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OPTIMIZATION OF SMALL-SCALE WIND TURBINE PMSG USING STATIC PSO AND DYNAMIC PSO ALGORITHMS FOR VOLUME MINIMIZATION

Prashanth N.A

Assistant Professor, Department of EEE, BMSIT & Management

Avalahalli, Yelahanka

Bengaluru- 560064

prashanthna@bmsit.in

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ABSTRACT:

The wind turbine generators employed in modern wind power plants should have high power factor, high efficiency, high power density and reliability, low volume and weight. In multi-pole induction generators, the length of the air gap is large and hence the efficiency and power factor of induction generators decline with the increase in the number of poles. As a result, their utilization, for direct drive wind power applications is limited. Permanent magnet synchronous generators are more suitable candidates for direct drive wind power applications compared to induction generators because of their high efficiency, high power factor, high torque, low cost, low speed, light weight, variable speed operation and scalable design to be able to construct generator of various sizes without significant changes in the design. In this research work, design of permanent magnet synchronous generator has been carried out to fulfill the desired output power for direct drive small-scale wind turbine applications. Even design care was taken to minimize the overall generator volume in order to reduce the cost. To model the problem, a minimization optimization with a constraint was proposed. Different variants of PSO such as Static Particle swarm optimization and Dynamic Particle swarm optimization have been considered separately as methods to estimate the optimal values of design parameters. In this comparative analysis, we evaluate the performance of Static Particle swarm optimization and Dynamic Particle swarm optimization algorithms in PMSG design optimization for minimizing volume while maintaining the output power at rated level.

KEYWORDS: Permanent magnet synchronous generators (PMSG), Dynamic particle swarm optimization, Static particle swarm optimization, small scale wind turbine

I. INTRODUCTION

In recent years, due to increased demand for clean, emission-free energy and also due to the foreseeable depletion of fossil fuel sources, wind energy has gained significant attention among other renewable energy sources as an important low-cost alternative to conventional fossil fuel energy sources. In recent decades, increased efforts have been made on research into wind energy to make it efficient and cost-effective.

Different types of wind turbine generators have been developed with the substantial increase in installed wind power capacity throughout the world and the consequent advancement of wind power technologies. These various types of wind generators have been developed with the objective of maximizing the energy capture with minimum costs involved. Permanent magnet synchronous generators (PMSG) are most commonly used for wind power generation since they have high efficiency, high power factor and increased power density. In permanent magnet synchronous generators instead of field winding excited by dc supply, the excitation is provided by permanent magnets. Permanent magnet generators require less maintenance when compared with induction generators and synchronous generators excited by DC supply.

Permanent magnet-synchronous generators with multiple poles have become especially attractive in small ratings for wind applications

Multi-pole Permanent magnet-synchronous generators have become especially attractive in wind power applications of small ratings. Permanent magnet Synchronous Generators (PMSG) are one of the best solutions for small-scale wind power plants among the various topologies of wind generators. Multi-pole low speed PMSG generators are maintenance-free and can be used in completely different climatic conditions. PMSG

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generators are simple and strong in construction and are highly efficient. With the availability of new high-energy density magnet materials such as NdFeB, it is possible to develop permanent magnet generators with special topologies. Most of the wind turbine generators currently installed in small scale levels are in directly driven system, variable speed, and power electronic converters with partial ratings. Choice of such system is to avoid failures in gearbox and result in long downtimes. For some new installations, Gearless full variable speed PM generators connected to the end user via a full rated power electronic converter are considered. In most of the tropical countries, due to low wind speed, synchronous generators with smaller or medium speed PM generator designs found to be important and given high consideration.

In recent years in several researches, Permanent magnet generators from small rating to large rating have been proposed for direct drive wind power applications. In order to improve the performance of PMSG, an optimal design of geometric dimensions and characteristics is very much essential and forms an emerging area of research for increasing the energy capturing capability of PMSG. Different objectives for the optimization of wind turbine PMSGs have been considered in recent years. Hence, in this research work, a design of permanent magnet synchronous generator has been carried out to meet the desired output power for direct drive wind turbines of small ratings. Design care has also been taken to minimize the overall volume of generator to reduce the cost using static PSO and dynamic PSO algorithms separately.

II. LITERATURE SURVEY

Permanent magnet synchronous generators (PMSG) are commonly employed for generation of wind power since they have high efficiency, high power factor and increased power density [1-2]. In permanent magnet synchronous generators instead of field winding the excitation is provided by permanent magnets. Permanent magnet generators require less maintenance when compared with induction generators and synchronous generators excited by DC supply [3].

Permanent magnet synchronous generators use permanent magnets for excitation, instead of field winding excited by DC. Large air gaps characterize permanent magnet machines which decrease the flux linkage even in machines with multiple magnetic poles [4]-[5].

[6] and [7] have reported the design aspect of PMSG to achieve better performance of PMSG at the cost of minimum permanent magnet material. This paper discusses design optimization of PMSGs that are used in small wind turbines. In fact, goal-oriented design optimization of PMSGs is not well covered in literature. The influence of various geometrical parameters of the PMSG and of the material properties on the useful magnetic flux has been analyzed in [8]. The authors have considered stator slot opening, tooth width and permanent magnet dimensions in the analysis. The calculations are carried out using the 2D Finite Element Method and the results were used to optimize the design of a permanent magnet synchronous generator.

PSO [9] is inspired by nature and a computational search for optimization developed by Eberhart and Kennedy in 1995 on the basis of the behavioral aspects of flocking birds or fish schooling. PSO is an iterative optimization algorithm based on population, inspired by the collective behavior of bird flocks and fish schools. The Differential Evolution algorithm [10] has emerged as one of the powerful tools for real parameter optimization, under the roof of evolutionary algorithms and was developed by Storn and Price more than two decades ago. The main objective of the DE algorithm is to generate a new location for an individual based on calculating vector differences between members of the population

III. PMSG DESIGN MODELING

The generator output in terms of fundamental parameters is given by

$$P_{out} = \frac{D^2 L\, n_s \sigma_p}{\varepsilon} \tag{1}$$

Where

$$\sigma_p = \frac{\Pi^2 k_w A_m B_{mg1} cos\phi}{2}$$

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$$B_{mg1} = \frac{4}{\Pi} B_{mg} sin\left(\frac{\Pi}{2}\alpha_i\right)$$

Hence final expression for P_{out} can be written as follows

$$P_{out} = \frac{D^2 L\, n_s\, \Pi^2 k_w A_m \frac{4}{\Pi} B_{mg} sin\left(\frac{\Pi}{2}\alpha_i\right) cos\phi}{2\, \varepsilon} \tag{2}$$

$$P_{out} = \frac{2\, D^2\, L\;\; n_s\, \Pi\; k_w\, A_m\, B_{mg}\; sin\left(\frac{\Pi}{2}\alpha_i\right)\, cos\phi}{\varepsilon} \tag{3}$$

Where:

P_{out} is the generator power output. ε is the no-load to rated load terminal phase voltage ratio. σ_p is the output coefficient, cosϕ is the load power factor, *D* is the diameter of the airgap (inner diameter of the stator), *L* is the stack length of the stator, n_s is speed of rotation in rev/sec , $kw1$ is the fundamental winding factor , *Bmg*1 is the maximum value of the first harmonic component of the magnetic flux density in the air gap, *Bmg* is the peak value of the air gap magnetic flux density and αi is the ratio of the pole-shoe arc to pole pitch and *Am* is the maximum value of the linear current density of the stator respectively.

The total volume of generator can be represented as function of inner diameter of stator (D), axial length of generator (L), slot depth(hs) and stator back-iron(hbis) as given in Eq4.

$$Vol_{tot} = \Pi L\left[\frac{D}{2} + 2(h_s + h_{bis})\right]^2 \tag{4}$$

The definition of objectives can be stated as: for a desired value of Generator power, find the design parameters *D, L, Am, Bmg and* α_i so that generated power could meet the objective of desired one and at the same time care has been taken to reduce the cost by minimizing the volume of generator as much as possible.

IV. OBJECTIVE FUNCTION

To achieve the objectives, problem is modeled as a problem of minimization with constraint, where obtained optimal values of five parameters *D, L,* A_m, *Bmg and* α_i could deliver the Pout at rated level as it is considered as constraint and reduction of volume by minimizing the Eq.4 with removal of h_s and h_{bis}.

$$Vol = min\left\{\Pi\; L\left[\frac{D}{2}\right]^2 + 1000 * abs(P_{out} - P_{rated}\,)\right. \tag{5}$$

Equation (5) is the objective function of this study. The aim of optimization is to minimize it. Table 1 displays the design variables considered for optimization of the PMSG volume and their associated boundaries.

Table 1. Minimum and Maximum ranges of design variables

SI No.	Variable	Minimum	Maximum
1.	Stator inner diameter(D)(m)	0	1
2.	Stator stack length(L)(m)	0	1
3.	Maximum value of the magnetic flux density in air gap(Bmg)(T)	0	1
4.	Maximum value of the stator linear current density(Am)(A/m)	0	100000

A penalty concept has been applied if there is violation in the constraint by increasing the objective function value by large number in terms of 1000x$|P_{out} - P_{rated}|$, where P_{out} is the generated output with obtained values of parameters. The population size is selected as 200. The considered wind turbine generator has power rating Pout=3500w, rated shaft speed [rpm] =250, Kw/ε= 0.7432 and power factor is taken as 1. Wind speed is assumed to be around 10m/s.

V. DESIGN OPTIMIZATION

5.1. Particle Swarm Optimization (PSO) Algorithm

In this section, firstly, Particle swarm optimization (PSO) algorithm is discussed. In addition, Differential Evolution Algorithm (DE) is briefly explained. Then, optimization process and selected case study are surveyed. Then optimization results are presented and discussed by these two algorithms.

To minimize the volume of PMSG and at the same time maintain the generated power output at rated level, a novel multipopulation based strategy of PSO is applied. PSO and Evolutionary Computation techniques are similar in that, a population of individual solutions to the problem considered is used to search the promising regions of the solution space or search space. In PSO, on the other hand, each individual in the entire population has an adaptable velocity (change in position), and it travels accordingly within the solution space. In addition, each individual of the population has a *memory*, which helps to remember the best position of the solution space it has visited so far. Therefore the movement of each individual member of the population is gravitated towards its best position visited previously and towards the best individual of a topologically interacting neighborhood companions. PSO algorithm was developed with two variants. The first variant with a global neighborhood and second variant was with a local neighborhood. As per the global variant type, each individual travels towards its best previously visited position and towards the best performing individual in the entire swarm. In contrast, as per the local variant of PSO, each individual in the swarm moves towards its best previously visited position and towards the best performing individual in its restricted neighborhood. The global variant of PSO is exposed in the following paragraphs. In global variant PSO technique, by assuming that the current searching space is having D dimensions, then the position of the i-th particle of the swarm is denoted by a vector, $Xi = [xi1, xi2, \ldots \ldots xiD]$ having D dimensions. The flying *velocity* (change in position) of this particle can be denoted by another vector $Vi = [vi1, vi2, \ldots viD]$ having D dimensions. The previous best position of the i-th particle in the swarm is represented as $Pi = [pi1, pi2, \ldots piD]$. Let '$g$' denote the index of the best performing particle in the entire swarm (i.e., best is the g-th particle),'n' is the best seen by that particular particle and let the superscripts represent the iteration number, then in the global variant of PSO, the swarm is manipulated using the following two equations.

$$V_{id}^{(n+1)} = \chi\,[w\, V^{n}_{id} + C1\, r1\, (P_{id}^{n} - X^{n}_{id}) + C\,2\, r2\, (P^{n}_{gd} - X^{n}_{id})] \qquad (6)$$

$$X^{(n+1)}_{id} = X^{n}_{id} + V^{(n+1)}_{id} \qquad (7)$$

where w is the *inertia weight*; $c1$is called *cognitive constant* and $c2$ *social* constant respectively; and *constriction factor* is denoted by χ. Each particle in the swarm travels towards the best performing particle of its neighborhood in the local variant of PSO. Space calculations are done by the swarm in PSO concept over series of time steps. The population responds to the quality factors implied by each particle's personal best position and the global best, thereby allocates the responses in such a way that ensures diversity. In case of global variant of PSO, the swarm changes its behavior or state only when the best performing particle in the entire swarm changes. In case of local variant of PSO, the swarm changes its behavior or state when the best performing particle in the neighborhood changes. Therefore, it is stable as well as adaptive.

5.2. STPSO and DYPSO

In this section two different development environments that have been considered for optimization are discussed.

(a) In static PSO the value of inertia weight is kept constant at w=0.4, cognitive constant c1 and social constant c2 are maintained a constant value of 0.5.

(b) (B) The time-varying inertia weight called dynamic PSO (DYPSO) is proposed for improving the performance of PSO in this problem. This inertia weight decreases linearly with respect to time. In general, large inertia weight to enhance global exploration (search for new area) is recommended for the initial stages of the search process, while the inertia weight for local exploration is reduced for the final stages (fine tuning of the current search area). Inertia weight ‘w’ is linearly decreased from 1 to 0.1 in steps of 0.1 as given by Eq. (8).

$$w = M_{xw} - n * (M_{xw} - M_{nw})/(\lfloor 0.75 * M_{xn} \rfloor) \quad (8)$$

where M_{xw} and M_{nw} are maximum and minimum inertia weight values, n is iteration number and M_{xn} is maximum number of iterations.

VI. OPTIMIZATION RESULTS

The algorithms STPSO and DYPSO were independently run for 5 trials to obtain the optimal design parameters and minimum value of generator volume along with satisfying the required rated power. The constants for STPSO algorithm are taken as ‘w’=0.4, C1=0.5 and C2=0.5. The optimal parameter values and the corresponding performance to minimize the volume for given power rating using STPSO algorithm under 5 different trials have been shown in Table 2. and Table 3. The optimal parameter values and the corresponding performance to minimize the volume for given power rating using DYPSO algorithm under 5 different trials has been shown in Table 4. and Table 5. The total volume and absolute value of difference between generated power and rated power obtained by STPSO and DYPSO algorithms are recorded separately. During each trial, the required computation time is also recorded independently so that comparative benefit can be measured. The number of iterations is taken as 200 and the convergence characteristics for STPSO and DYPSO algorithms are shown in Fig.1 and Fig.3 respectively.

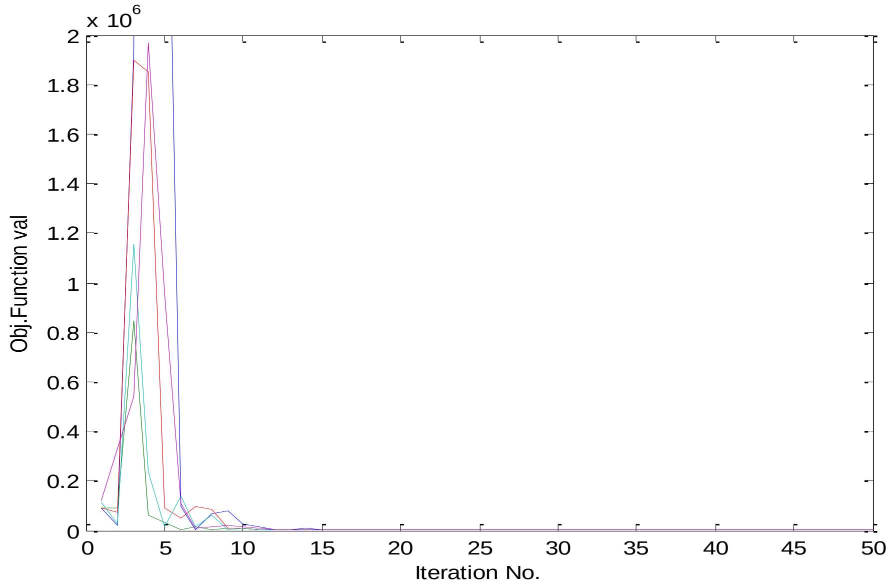

Figure 1. Objective function value versus iterations by STPSO in first 50 iterations for 5 trials

Table 2. Parameters values given by STPSO for 5 trials

Sl.No	**D (mm) ($\times 10^3$)**	**L(mm) ($\times 10^3$)**	**A_m (A/m) ($\times 10^5$)**	**B_{mg} (T)**	**α_i**
1	6.9849e-001	4.2418e-002	4.7028e-001	1.9843e-001	7.6282e-001
2	2.0763e-001	4.7129e-001	5.0298e-001	2.9101e-001	4.1351e-001
3	2.5781e-001	5.5669e-001	3.1021e-001	4.2600e-001	2.3982e-001
4	8.5837e-002	6.9103e-001	6.9074e-001	6.1080e-001	6.3180e-001
5	3.6773e-001	4.1865e-001	6.7380e-001	5.4363e-001	5.5290e-002

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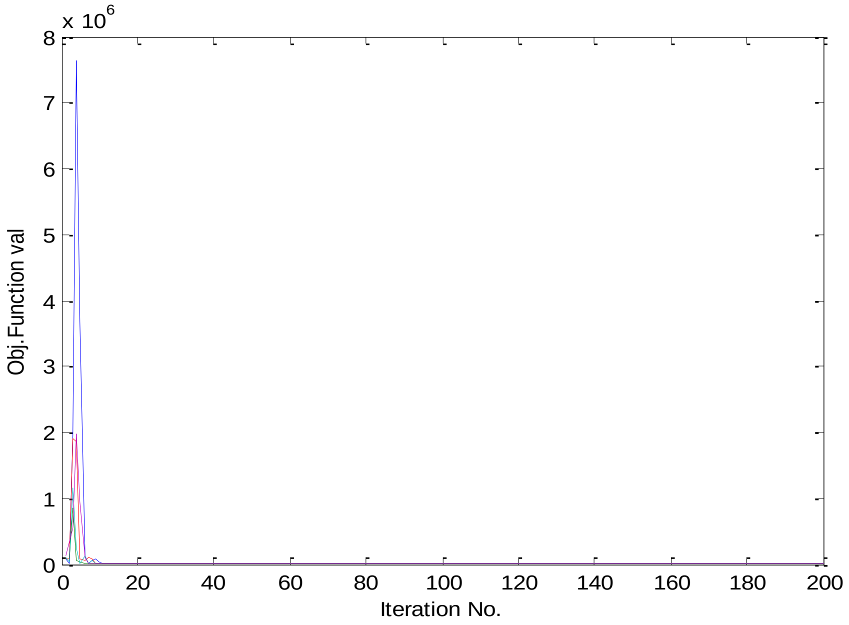

Figure 2. Objective function value versus iterations by STPSO in 200 iterations for 5 trials

Table 3. Corresponding performance by STPSO

Sl.No	**P_{out} (W)**	**P_{abs} = abs(Pout –Prated)**	**Volume (m^3)**	**Vol+1000*D**	**Computational time (Sec)**
1	3.5000e+003	0	1.6254e-002	1.6254e-002	1.02
2	3.5000e+003	0	1.5957e-002	1.5957e-002	1.01
3	3.5000e+003	0	2.9061e-002	2.9061e-002	0.96
4	3.5000e+003	0	3.9989e-003	3.9989e-003	0.99
5	3.5000e+003	0	4.4464e-002	4.4464e-002	1.02
mean	**3.5000e+003**	0	**2.1947e-002**	**2.1947e-002**	**1.00**
std	**0**	0	**1.5395e-002**	**1.5395e-002**	

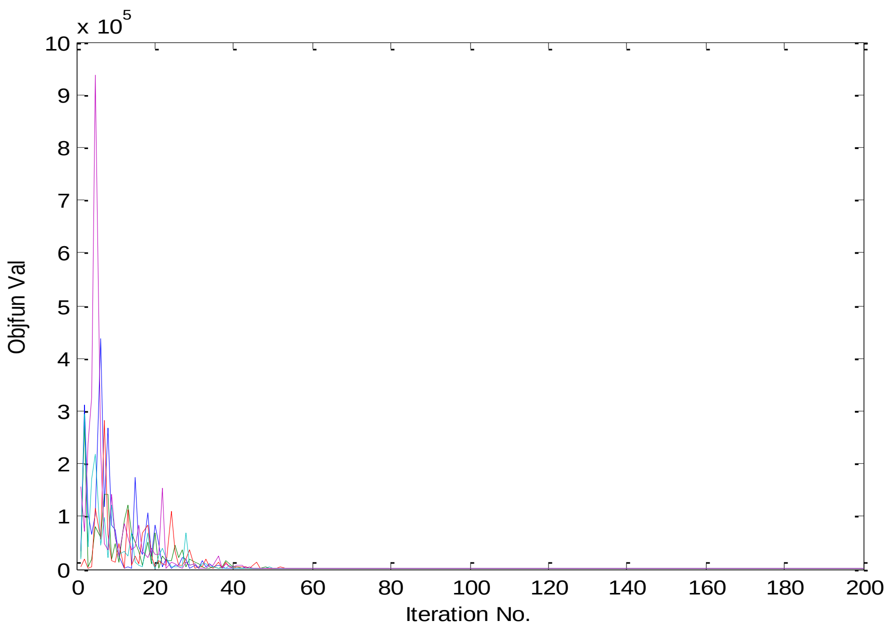

Figure 3. Objective function value versus iterations by DYPSO in 5 trials

Table 4. Parameters values given by DYPSO for 5 trials

Sl.No	D (mm) ($x10^3$)	L(mm) ($x10^3$)	A_m (A/m) ($x10^5$)	B_{mg} (T)	α_i
1	1.3452e-001	6.6175e-001	9.8977e-001	2.2895e-001	4.6127e-001
2	2.4123e-001	1.2112e-001	6.4451e-001	7.4439e-001	3.5707e-001
3	1.6990e-001	6.0434e-001	2.2875e-001	8.6121e-001	3.5065e-001
4	2.58261e-001	8.7686e-002	5.6078e-001	7.6515e-001	5.0878e-001
5	1.9288e-001	2.8913e-001	5.9670e-001	3.2064e-001	6.7702-001

Table 5. Corresponding performance by DYPSO

Sl.No	P_{out} (W)	P_{abs} = abs (Pout –Prated)	Volume (m^3)	Vol+1000*D	Computational time (Sec)
1	3.4999e+003	9.5496e-012	9.4061e-003	9.4062e-003	0.92
2	3.5000e+003	6.3664e-012	5.5358e-003	5.5358e-003	0.87
3	3.5000e+003	4.5474e-013	1.3701e-002	1.3701e-002	0.86
4	3.4999e+003	9.5496e-012	4.5934e-003	4.5934e-003	0.87
5	3.4999e+003	2.9103e-011	8.4482e-003	8.4483e-003	0.94
mean	**3.4999e+003**	**1.1004e-011**	**8.3371e-003**	**8.3371e-003**	**0.8920**
std	**1.3436e-011**	**1.0777e-011**	**3.5985e-003**	**3.5985e-003**	

It can be seen in Table 3 and Table 5 from the simulation results that the objective function in case of DYPSO algorithm is minimized to a larger extent as compared to the STPSO algorithm. The total volume of PMSG is minimized to a greater extent in case of DYPSO compared to the STPSO algorithm. STPSO delivers the outpower exactly at the rated level consistently. STPSO doesn’t have much exploration capability. After some iterations there will be no improvement in the objective function value and the focus of STPSO algorithm shifts towards delivering the rated output. Hence STPSO algorithm delivers the rated power output consistently. From the table it can be noted that the execution time for the DYPSO algorithm for different trials is less compared to the execution time of the STPSO algorithm.

Comparison of STPSO and DYPSO algorithms

(i) Convergence behaviors: The comparisons between mean convergence in STPSO and DYPSO have shown in different sections to get the clarity in progress. In case of STPSO algorithm, it can be observed that the algorithm has converged in less than 20 iterations.

(ii) Solution quality: The mean and standard deviation obtained from 5 trials for STPSO algorithm is 2.1947e-002 and 1.5395e-002 respectively. The observed mean is 8.3371 e-003 while standard deviation is 3.59e-003, for DYPSO algorithm. The standard deviation for DYPSO algorithm is less compared to STPSO which implies that there are less fluctuations in the final solution quality of DYPSO algorithm.

(iii) Robustness: To verify the robustness/consistency of STPSO and DYPSO approaches 5 trials were run independently for STPSO and DYPSO algorithms. The number of trials reaching minimum value of objective function is high and consistent for DYPSO algorithm. Hence DYPSO algorithm is more robust compared to STPSO algorithm.

VII. CONCLUSION

In this research paper, we present a detailed comparison of the performance of STPSO and DYPSO algorithms in order to minimize the volume of PMSG while preserving the power generated at the rated level. From the simulation results it is clear that DYPSO is better than STPSO in terms of solution quality, running time and chance of reaching the best solutions for different number of trials. PSO's better performance in terms of computational complexity and solution convergence may be attributed to its simple structure and minimal parameters. It is also interesting to note that DYPSO is more powerful than STPSO in computational terms. Swarm intelligence in the form of particle swarm optimization and its variant like STPSO and DYPSO can be utilized for optimization of wind turbine PMSG. The excellent characteristics of PSO and its variants may be applied successfully to optimize wind turbine PMSG to improve its performance.

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