

In this paper, a studying the performance of three optimization techniques include genetic algorithm, particle swarm optimization and differential evolution algorithm. They are designed to extract the maximum power point tracking and suggested in permanent magnet synchronous generator wind energy systems under randomly variable wind speed cases. The performance of the three algorithms is studied, assessed, and compared using key characteristics such as turbine power coefficient, convergence time, standard deviation, reliability, and turbine power under the same operating conditions. The tracking performances based on the three algorithms are assessed using MATLAB software. The results show that the differential evolution algorithm has a convergence to the global maximum power point that better solution quality while particle swarm optimization has a faster execution time in comparison with the genetic algorithm for solving the maximum power point tracking.

Keywords: Permanent magnet synchronous generator; maximum power point tracking; genetic algorithm; particle swarm optimization; differential evolution.

1. Introduction

The global warming and the harmful effects of fossil fuels emissions has encouraged the use of renewable energy to replace conventional fossil fuels to generate electricity [1]. Permanent magnet synchronous generator wind energy (PMSGWE) [2] has become to be one of the most significant renewable energy resources because of its long-term benefits, fast growing, unpolluted and lowest-priced today [3,4]. However, some obstacles are impeding the further use of PMSGWE systems such the low energy conversion efficiency and high initial investment cost [5]. To minimize the effect of these challenges, one of the most effective methods of boosting the efficiency of a PMSGWE system that should not be neglected is to improve the system's maximum power point tracking (MPPT) capabilities. Therefore, MPPT plays an important part in this progress [6,7]. The variable speed wind turbine needs to operate at MPPT under variable wind speed [8].

In past decades, the MPPT method has been studied and developed in industrial and academic fields. Each provides different benefits and disadvantages in terms of cost, sensor requirements, complexity, dependability, convergence speed, and hardware implementation [9,10]. Because of their simplicity and efficiency, the perturb and observe (P&O) technique [11] and incremental conductance (In-Cond) method [12] are the most common. However, their disadvantage is that they fail to track maximum power point (MPP) under rapidly changing conditions and may become entrapped in the global maximum [13,14]. Therefore, these issues have solved by evolutionary algorithms [15], which is become a very popular include genetic algorithm (GA), particle swarm optimization (PSO) and differential evolution (DE) [16]. In [15-17] the implementation of GA to MPPT method is proposed, but using a trial-and-error strategy for parameter setting in evolutionary computation

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technique takes more time to track MPP. An improved PSO technique [18-22]. The speed of convergence of PSO based MPPT is slow because it is dependent on candidate's initial position. Moreover, selection of many parameters in these techniques makes them complex and unreliable. In [23-26] is proposed a DE algorithm, which is basic and involves a small number of control variables yet performs well in terms of convergence, and independent of the initial conditions. The main contribution of this paper can be outlined as follows:

1. A comparative study of the three bio-inspired algorithms to evaluate their performance in searching for the MPPT.
2. GA, PSO and DE algorithm are successful designed to find the MPPT for PMSG wind turbine. Their performance is assessed and compared using key characteristics such as turbine power coefficient, convergence time, standard deviation, reliability, and turbine power under the same operating conditions.
3. DE algorithm shows a significant capability over other algorithms to find the MPPT.
4. This paper is organized as follows: PMSG wind turbine system is explained in detail in Section 2. Section 3 describes the MPPT method. Section 4 shows Simulink verifications of a PMSG wind system using the algorithms. Finally, Section 5 concludes this paper.

2. Wind Turbine model

The mechanical power harvested by a wind turbine P_m is expressed as [5,6]

$$P_m = C_p(\alpha, \beta) \frac{\rho A}{2} v_w^3 \quad (1)$$

where v_w is wind speed, A is the swept area of wind turbine blades, ρ is density of air, α is the tip speed ratio, β is the pitch angle, C_p is wind turbine power coefficient.

The tip-speed ratio of the turbine is defined by

$$\alpha = \frac{\omega_t}{v_w} R \quad (2)$$

where ω_t is rotor speed, R is the wind turbine radius

The curves depend on the blade design and are given by the wind turbine manufacturer

$$C_p(\alpha) = c_1 \left(\frac{c_2}{\alpha_i} - c_3 \beta - c_4 \right) e^{\left(\frac{-c_5}{\alpha_i} \right)} + c_6 \alpha \quad (3)$$

where $c_1 = 0.5176$, $c_2 = 116$, $c_3 = 0.4$, $c_4 = 5$, $c_5 = 21$, $c_6 = 0.0068$ and

$$\alpha_i = \left(\frac{1}{\alpha + 0.08\beta} - \frac{0.035}{1 + \beta^3} \right)^{-1} \quad (4)$$

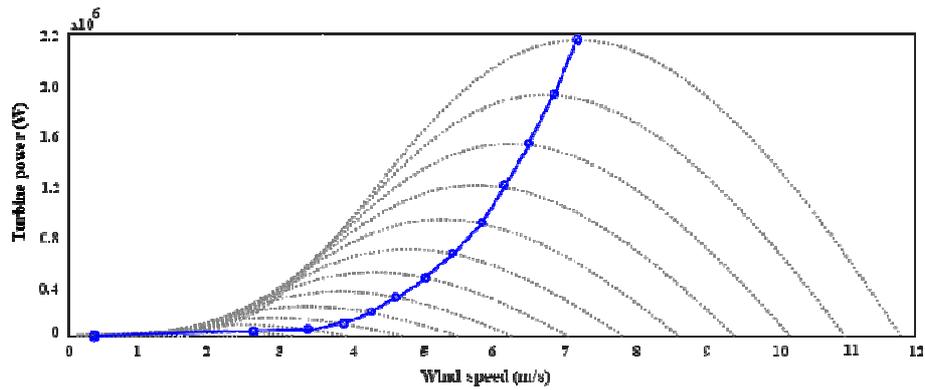


Figure 1. Turbine power characteristics

In Fig.1. Clearly demonstrates the relationship between the turbine power at variable wind speed. The turbine power for a given wind speed is maximized at that wind speed, which is referred to as the optimal wind speed. The blue curve is termed by means of optimal tracking curve. For maximum power, the turbine must always operate at an optimal tip speed ratio. This is accomplished by regulating the rotational speed of the turbine such that it always rotates at the optimal speed [2]. The collected wind power varies with wind speed and is related to a specified working zone within a wind speed range-restricted between connected wind speed (v_w cut-in) and disconnected wind speed (v_w cut-out). Otherwise, wind turbines must be prevented to operate above connected wind speed (v_w cut-in) or below disconnected wind speed (v_w cut-out) for safety conditions. The turbine should not run outside of this range for the sake of the turbine's and generator's safety. The rated power (P_{rated}) of a wind turbine is obtained at a given wind speed (v_{rated}). As a result, there are four major operational regions, which is illustrated as Fig.2. [9].

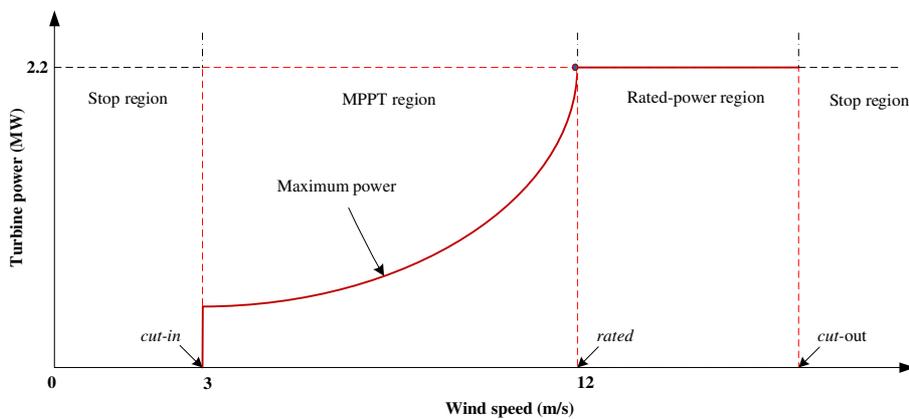


Figure 2. Turbine operating regions

To avoid the generator implements, the first and fourth regions are below (v_w cut-in) and above (v_w cut-out), respectively, that wind turbines must be stopped and disconnected from the grid. The second zone is between (v_w cut-in) and (v_w rated), and it is in this region that a wind turbine controller applies the maximum power point tracking (MPPT) approach below

rated wind speed to obtain the best power during changing wind speed. The third area is between (v_w rated) and (v_w cut-out), where the pitch controller is employed to limit mechanical power output and decrease mechanical stress to make wind turbines safe. The wind speed in region 2 is surveyed in this article. As a result, the MPPT method must concentrate on the second area.

3. Bio-inspired algorithms based on MPPT

The power generated (P_m) by wind turbine in equation (1) is dependent on C_p , ρ and turbine parameters, which are selected based on its design and ρ is a constant value. Therefore, the P_m is mainly dependent upon the value of C_p and it can be said that the maximum turbine output power (P_{mmax}) can be generated when C_p is maximum (C_{pmax}). If the wind turbine is operated at C_{pmax} , then α will be optimum as observed in equation (3) and (4), so the rotor speed will be maximum as shown in equation (2). Thus, it can also be observed from Fig.2 the output turbine power can be maximized by regulating the rotor speed to its maximum value at each various wind speed.

3.1. Genetic Algorithm

GA that introduced to broader audiences in 1975 by John Holland, a University of Michigan professor of psychology, electrical engineering, and computer science [15]. GA have become most well-known, and most widely used in a recent year. GAs are simulations of natural selection that can a wide range of optimization issues that are not well suited to traditional optimization techniques, such as those with discontinuous, nondifferentiable, stochastic, or highly nonlinear goal functions. These special characteristics which is interested by researchers to wind energy system applications where discontinuities may be wind speed [16]. The fundamental thought of GA is to mirror the natural selection. In GA, each person is assigned a fitness rating along each route and the best individuality is chosen as a chromosome. Natural selection is the process of producing new optimum individuals in GA, and this cycle is accomplished via repeated applications of genetic operators such as selection, crossover, and mutation [17]. The first thing, the best individuals are chosen to pattern parents to produce new individuals. The individuals with better fitness are chosen more than the individuals with poorer fitness, and that is rule facsimiled the survivor who is the fittest. Then the parents' individuals are chosen, and the crossover mixes the parents' individuals to generate new individuals. Because better individuals which is chosen so the new population may be same after several generations, and this might result in population stagnation. Mutation is an instrument to infuse variety into the populace to keep away from stagnation [18]. The parameters of GA algorithm used in simulation is depicted in Table 1.

Table 1 : GA parameters used in simulation

Depiction	Value
Particle number of a generation, <i>Npop</i>	10
Maximum number of generations, <i>itermax</i>	50
Crossover probability	0.75
Mutation probability	0.1
Length of chromosome	2

Algorithm 1 Pseudo-code for the GA

- Input v_w
 Output the optimal Power (P_m)
1. Pop = $w_{rmin} + \text{rand}(w_{rmax} - w_{rmin})$
 2. while iter < max generation count (jenerasyon)
 3. iter = iter + 1
 4. Initial population selection based on optimal cost function
 5. crossover (cost)
 6. mutation (cost)
 7. pop = Individuals should be chosen depending on crossover and mutation.
 8. end

3.2. Particle Swarm Optimization

The PSO algorithm is like a genetic algorithm in that the first phase is initialization, in which a population of random solutions is used to produce the first swarm of particles and Kennedy and Eberhard offered a PSO paper for the first time at the Congress on Evolutionary Computation in 1995 [18,19]. The solution is represented as a particle in a genetic algorithm, and the population of solutions is referred to as a swarm of particles. Each particle has two primary properties: location and velocity. It takes the advantages of PSO algorithm are the competence to exit from a global optimum fast convergence and easy implementation and it is not necessary to sort the fitness values of solutions in any procedure [20]. Each particle in PSO travels to a new place using velocity, which is compared to the particle's previous best fitness value and the swarm's previous best fitness value, and the personal best and global best positions are changed as necessary. The velocity of each particle is then changed based on the particle's experiences. The process is continued until a condition for halting is fulfilled [21, 22]. The parameters of PSO algorithm used in simulation is depicted in Table 2.

Table 2 : PSO parameters used in simulation

Depiction	Value
Particle number of a generation, <i>Npop</i>	10
Maximum number of generations, <i>itermax</i>	50
Inertia weight, w	0.25
Acceleration coefficients, c_1 and c_2	$c_1 = c_2 = 2$
Independent random sequences, r_1 and r_2	rand (0,1)
Initial particles' positions	rand (0,1)
Initial particles' velocities	rand (0,1)

Algorithm 2 Pseudo-code for the PSO

- Input v_w
 Output the optimal Power (P_m)
1. Pop = $w_{rmin} + \text{rand}(w_{rmax} - w_{rmin})$

2. $Pop = v_{min} + \text{rand}(v_{max} - v_{min})$
3. while the termination requirement has not been met, do
4. Assess each particle $exi(t) = fob(xi(t))$
5. Keep the greatest personal solution up to date $pi(t)$
6. Update the most effective worldwide solution $P_m(t)$
7. For $i=1$ to n do
8. Compute update velocity $vi = f(px, P\ bestx, Gbestx)$
9. Compute update position $xi = f(px, vx)$
10. $t = (t + 1)$
11. end
12. end

3.3. Differential Evolution

Like all genetic algorithms, DE, which sprang from such a highly competitive form more than a decade ago, is one of the most often used optimization algorithm in use today [23]. Since 1995, the earliest published journal papers on DE were likely one of R. Storn and K. V. Price's technical report for continuous search space global optimization [24]. In DE algorithms for optimizing functions in an N-dimensional continuous area. Every type in the population is an N-dimensional vector that represents the problem solving. DE is based on taking the differentiation vector between two kinds and a scaled version of the distinguishing vector was added to a third person to produce another applicant arrangement. This process is illustrated for a process create a new candidate solution [25]. The first step is to construct a mutant vector is created by connecting three arbitrarily chosen vectors from the number of residents in vectors keeping out the goal vector. This consolidation cycle of three random vectors was used to make the mutant vector [26].

The trial vector is then created by conducting a hybrid in the middle of the mutant vector and the target vector. In DE, two hybrid methods are commonly used: binomial hybrid and exponential hybrid [23]. The hybrid probability must be specified here. A little amount of hybrid probability drives a trial vector that resembles the target vector more closely, whereas the mutant vector, on the other hand, is preferred by the opposing side [26]. After trial vectors have been created as described above, the most fit vector in each pair is kept for the next DE generation, and the least fit is discarded. The parameters of DE algorithm used in simulation is depicted in Table 3.

Table 3 : DE parameters used in simulation

Depiction	Value
Particle number of a generation, N_{pop}	10
Maximum number of generations, $iter_{max}$	50
Crossover probability	0.2
Lower Bound of scaling factor	0.2
Upper Bound of scaling factor	0.8

Algorithm 3 Pseudo-code for the DE

Input v_w

Output the optimal Power (Pm)

1. Pop = $w_{min} + \text{rand}(w_{max} - w_{min})$
2. For the termination requirement has not been met, do
3. For $i = 1$ to n do
4. Mutation
5. Select the best particle [y(t) best]
6. Select the parent
7. Crossover
8. For $j = 1$: numel (x) do
9. if (j=0 rank < =pCR) then
10. z(j)= y(j)
11. else
12. z(j)= x(j)
13. end
14. end
15. Update Best Cost
16. end
17. end

4. Simulation results

The simulation for evaluating the performance of the GA, PSO, and DE algorithms based the MPPT method applied to PMSG that is implemented using MATLAB/Simulink. Furthermore, its optimum rotor speed is sought by the GA, PSO and DE algorithm based MPPT method, at where generated maximum turbine power. In addition, we simulate under the same condition as follows: the sample count have been set to 30 and the amount of times its iterated has been set to 50 for three algorithms. In this paper, the analysis of each algorithm based MPPT method are performed on the case of same wind speed data, which are selected randomly between 3 and 12 m/sec as illustrated in Fig.3a. Some of the parameters of the generator and turbine that are used for the simulation are shown in Tables 4 and 5. In this paper, the comparison has been carried out by observing the power coefficient, turbine power, standard deviation, and the relationship between turbine power at variable rotor speed in three algorithms. The turbine power coefficient (C_p) obtained by each algorithm based MPPT method is depicted in Fig.3b. It can be showed that, when the wind speed varies quickly, the C_p in DE algorithm, which is not oscillation and remains almost constant at 0.48 while GA algorithm is unstable and widely oscillation. Furthermore, the waveform of C_p in the PSO algorithm that is unstable too and oscillation, but it is low. Simulation results for peak value wind speed during 0–120 sec in Fig.3b have been zoomed for clearly differentiate the results obtained by each algorithm based MPPT method.

The relationship between the turbine power at variable rotor speed obtained by each algorithm is demonstrated in Fig.3c. It is clear to observe that, based on equation (2), when the wind speed varies the DE algorithm based MPPT method has the convergence time high and tracks the MPP very efficiently while the GA and PSO algorithm deviate

from the MPP, so it has the convergence time lower. In addition, simulation results have been zoomed for clearly differentiate the results for turbine power when rotor speed during 1.7455–1.748 rad/s that are illustrated in Fig.3c. It is clear to observe that under variable wind speed, the turbine power in DE algorithm which has the highest value while GA algorithm is the lowest and PSO algorithm is moderate which is illustrated in Fig.43. Furthermore, simulation results for peak value turbine power during 58.9758–59.02 sec in Fig.3d. have been zoomed for clearly differentiate the results obtained by each algorithm. According to Fig.4, there are two cases of standard deviation. Firstly, the sample count (Np) is below or equal 10 then the standard deviation of DE algorithm has higher than PSO algorithm. However, the sample count is above 10 then the standard deviation of DE algorithm has lower than PSO algorithm while the standard deviation of GA algorithm has always the highest value in two cases.

From the above analysis clearly indicates that the DE algorithm based MPPT method acquires the best performance among other algorithms considered in this paper. It has a higher success rate than GA and PSO algorithm based MPPT method since it does searching and finding the MPP more efficiently. Consequently, DE algorithm is simple, flexible and also more efficient. Table 6 summarizes the results of the preceding investigation.

Table 4 : Turbine parameters [2]

Depiction	Symbol	Value
Rated power	S_n	2.2MW
Rated current	I_n	2606A
Rated stator voltage	u_n	690V
DC-link voltage	V_{dc}	1200 V
Rated rotor speed	ω_m	2.355 rad/s
Number of poles	Z_p	26 N.m
Moment of inertia	T_e	934.1 kNm
Turbine damping	B	0.0041 Nms
Stator winding resistance	R_s	0.8e-3 Ω
Stator winding inductance	L_s	1.67 mH
Flux linkage	λ_r	9.18 Wb
Inertia of turbine rotor	J_n	0.5e6 kg.m ²

Table 5 : Generator parameters [2]

Depiction	Symbol	Value
Rated power	P_n	2MW
Rated rotor speed	ω_m	2.355 rad/s
Blade inertia	J_m	0.25e3 kg.m2
Blades length	R	37.1 m
Wind speed area	v_w	12m/s

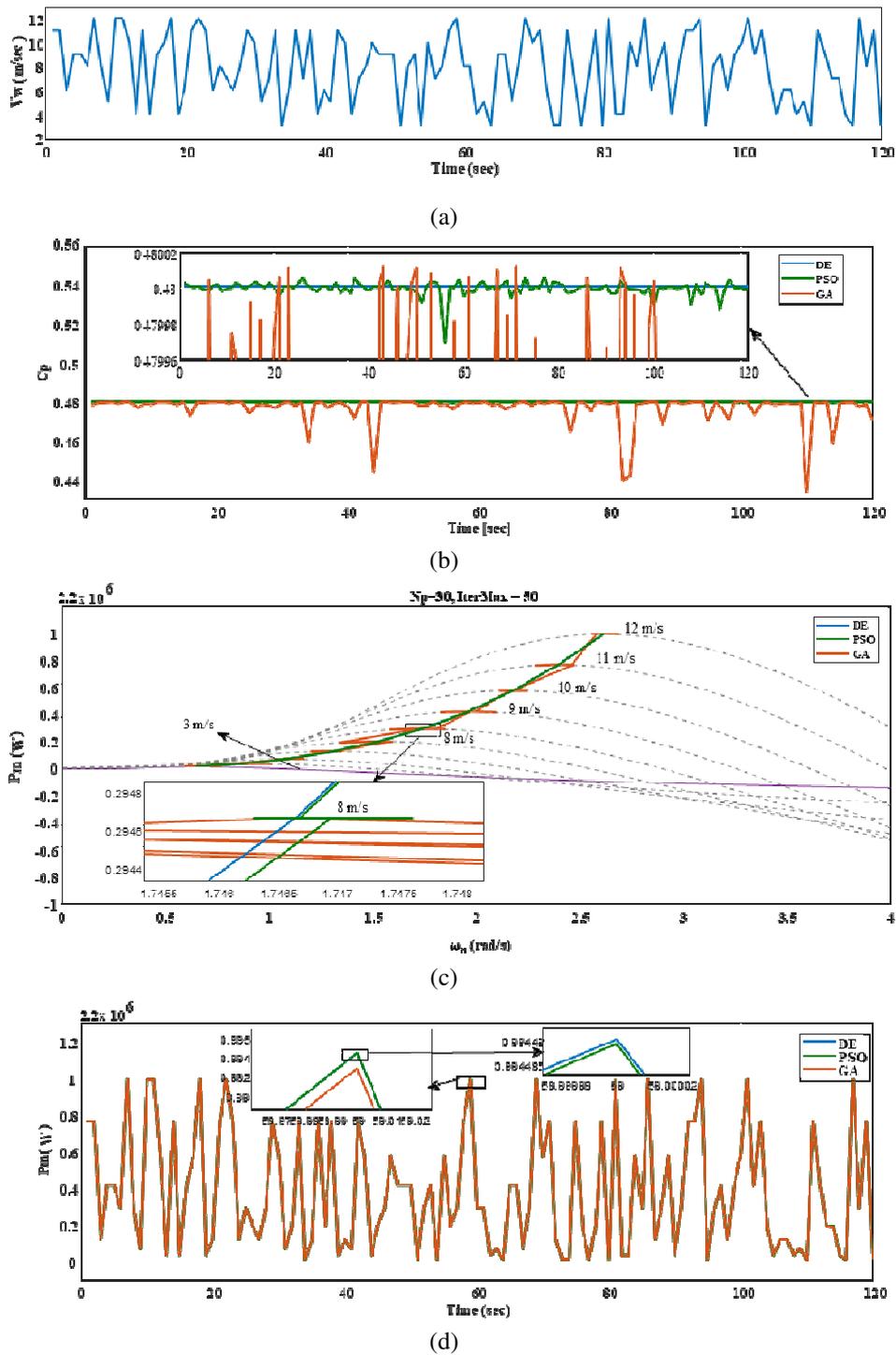


Figure 3. Simulation results of GA, PSO, DE algorithms (a) wind speed profile, (b) turbine power coefficient, (c) turbine power and rotor speed, (d) turbine power

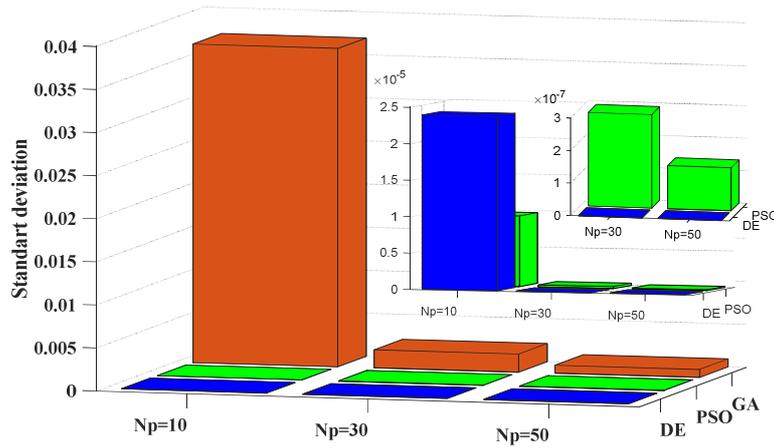


Figure 4. Standard deviation in the three algorithms

Table 6: Comparison of GA, PSO and DE algorithms based MPPT method

Evaluation parameters	(DE)	(GA)	(PSO)
Turbine power	High	Low	Moderate
Turbine power coefficient	High	Low	Moderate
Reliability	High	Low	Moderate
The convergence time	High	Low	Moderate
Influence of population size	No	Yes	No
Steady state oscillation	Low	High	Moderate
Standard deviation (Np <=10)	Moderate	High	Low
Standard deviation (Np >10)	Low	High	Moderate
Maximum power point tracking capability	High	Low	Moderate

5. Conclusion

In this paper, the performance of the three GA, PSO and DE optimisation algorithms based on MPPT technique are designed, analysed and evaluated. The methods given here are intended to enhance the efficiency of PMSG in WECS. The simulation results show that trackers based on GA, PSO, and DE algorithms have excellent correctness and stability in taking out the global MPP. From the above clearly analysis, it may be concluded that DE algorithm is very effective for finding out the MPPT in all the studied cases with the condition sample count above 10. In case the number of condition sample is less than or equal to 10, only the standard deviation of the DE algorithm will be more than PSO algorithm.

Although this paper is only focused on the PMSG, in future research, the proposed algorithms are equally applicable to other three-phase machines and multi-phase machines.

Acknowledgment

The authors would like to express their gratitude to the Industrial University of Ho Chi Minh City, Vietnam, for sponsoring this study.

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