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(Research Article)

Wind power optimization using modified memetic algorithm

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Abstract

This research paper introduces an approach for optimizing the design of wind turbines to enhance their electrical output. To efficiently convert wind energy into electrical energy, a specific turbine design is essential. The study employs a modified shuffled frog-leaping algorithm (MSFLA), an improved variant of the memetic algorithm, to determine the optimal wind power coefficient by adjusting rotor speed at various wind velocities (including rated, cut-in, and cut-out speeds). MSFLA combines global and local search techniques, following divide-and-conquer principles, to achieve better results. By imposing specific turbine constraints, the simulation demonstrates that the wind power coefficient can be increased under optimized conditions.

Keywords: Memetic algorithm; Frog leaping algorithm; Wind turbine; Power optimization.

1. Introduction

Renewable energy has the potential to play an important role in the future energy supply as the rising prices of oil and gas and their potential shortages have raised uncertainties about security in the future, which has serious repercussions on the growth of the national economy. The increasing use of fossil fuels also causes serious environmental problems.

In order to meet future energy demands while ensuring quality and pollution-free supply, the world's current focus is on adopting natural, clean, and renewable energy sources. Among various non-conventional energy sources, wind energy plays a crucial role. By harnessing the kinetic energy present in the wind, we can operate wind turbines, with the output power directly dependent on wind speed. Typically, turbines require wind speeds within the range of 5.5 m/s (20 km/h). However, only a few land areas experience significant prevailing winds. Nevertheless, wind power remains one of the most cost-competitive renewable energy options today. Its long-term technical potential is estimated to be five times the current global energy consumption or forty times the current electricity demand.

Nowadays extensive research work has been done to maximize wind turbine output. In [1] blade pitch profiles are considered for maximizing power production where a static wind model for a three-bladed, horizontal axis, pitch-controlled wind turbine is used. Detailed information is provided in [2] for calculations of wind turbine & values of different parameters and discussed about blade chord profile selection. The electrical analogy concept is used to increase wind turbine blade efficiency [3]. [4] Proposes a model for wind turbine placement based on the wind distribution. In [5] a method is shown to obtain optimal chord and twist distributions in wind turbine blades by using genetic algorithms. In [6] an evolutionary computation approach is presented for the optimization of power factor and power output of wind turbines & it shows the evolutionary strategy algorithm solves the data-derived optimization model. Fuzzy set-based modeling of wind power generation [7] provides information about the cost-effectiveness of wind power. A site specification optimization of rotor sizing is carried out by Kirk Martin in [8]. In [9] main objective was to fully control the wind turbine system with an induction generator to maximize power generation. MSFLA

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techniques are newly introduced in [12]. The applications of MSFLA are found in [13-17]. It combines the advantages of the genetic-based memetic algorithm (MA) and the social behavior-based Particle Swarm Optimization (PSO) algorithm. Recent research [18-19] has demonstrated techniques for quantifying uncertainty in graph cut solutions. These studies focus on computing min-marginal energies related to label assignments in random fields, leveraging newly developed algorithms based on dynamic graph cuts. Additionally, robust optimization methods [20-22] are employed to assess the uncertainty associated with input parameters and wake models [23-24]. These factors play a crucial role in determining the optimal layout and are likely to significantly influence the results.

In this study, we introduce a novel soft computing-based optimization technique aimed at maximizing wind power output. Specifically, we employ a memetic algorithm, known as Modified Shuffled Frog-Leaping Algorithm (MSFLA), which addresses the inherent complexities of non-smooth optimization problems with intricate and non-convex characteristics. These challenges arise due to the presence of substantial equality and inequality constraints. Our primary objective is to identify the global optimum, which proves to be a formidable task.

The proposed algorithm effectively optimizes power generation within the specified wind velocity range. Simulation results demonstrate its robust performance, making it a valuable tool for wind turbine design. By harnessing maximum energy, this approach contributes to enhancing overall electrical output.

2. Power co-efficient (C_P) modelling

The detailed mathematical formulation of C_p (power coefficient) is discussed here.

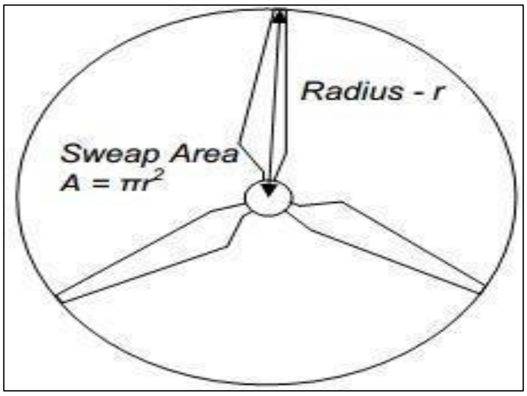

Figure 1 Wind turbine blade

From Fig 1, Swept area of a turbine blade A= πr^2 ………… (1)

If the air of mass m flowing through area A with a velocity V then mass flow rate is given by, $\frac{dm}{dt} = \rho A \frac{dx}{dt}$ …………(2)

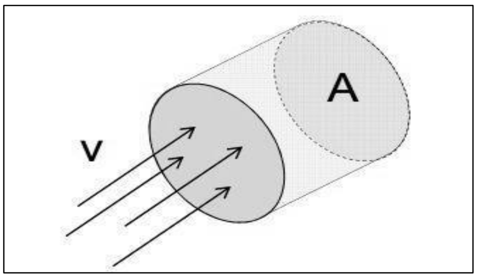

Figure 2 Wind flow direction across cross-sectional area of rotor blade

Or, $\frac{dm}{dt} = \rho AV$ ……(3) [since, $\frac{dx}{dt} = V$]

The kinetic energy of the flowing air of mass m,

$= E = \frac{1}{2} mV^2$ ………………(4)

Power present in the wind,

$P_w = \frac{1}{2} V^2 \frac{dm}{dt}$ ………………(5)

Now,

$\frac{dm}{dt} = \rho A \frac{dx}{dt}$ ………………..(6)

Hence,

$\frac{dm}{dt} = \rho AV$ ....(7)

Then, from equation (6) we get,

$P_w = \frac{1}{2} \rho AV^3$ ………………..(8)

We can represent swept area in terms of blade width and length, then swept area is given by A=DH.

Hence,

$P_w = \frac{1}{2} \rho DHV^3$ ………………..(9)

This is the equation of wind power in terms of wind speed, air density and swept area.

According to Betz limit no wind power can convert more than 59.3% of K.E. of the wind into mechanical energy turning a rotor. Now,

$C_p = \frac{P_r}{P_w}$ ……………………..(10)

Hence,

$P_r = F.U$ ………………………(11)

Or, $P_r = FU \cos\theta$

Most familiar type of aerodynamic force is drag; direction of the drag force is parallel to the relative wind *i.e.* $\theta = 0$ rad.Hence,

$P_r = FU$ …………………..(12)

Therefore,

$$C_p = \frac{2UF}{\rho DHV^3} \quad \text{.....................................(13)}$$

Equation (13) is considered as objective function.

3. Modified shuffled frog leaping algorithm

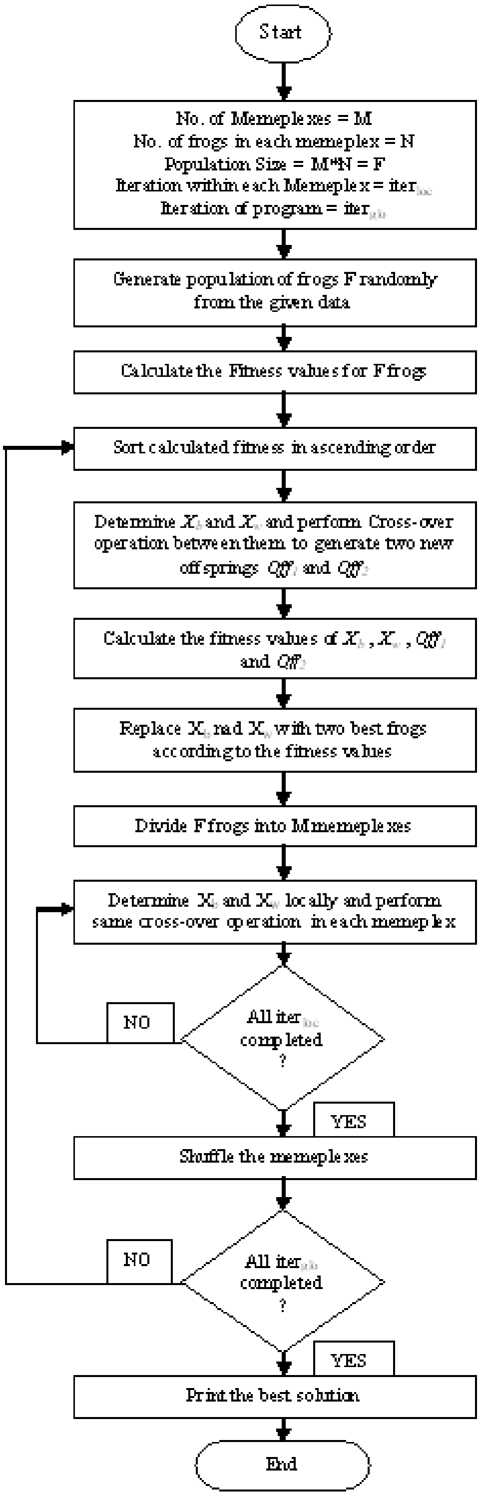

Figure 3 Outline Flowchart of MSFLA

In 2005, Muzaffar Eusuff and Kevin Lansey introduced the concept of SFLA [12]. SFLA metaphorically mirrors the evolutionary behavior of a group of frogs as they forage for the location with the maximum available food. This approach draws inspiration from the exchange of memes among interactive individuals within the frog population. Notably, SFLA combines the strengths of both gene-based memetic algorithms (MA) and social behavior-based Particle Swarm Optimization (PSO) algorithms.

Key characteristics of SFLA include its simplicity, minimal parameter requirements, swift convergence, robust global search capabilities, and straightforward implementation. Building upon this foundation, we propose the Modified Shuffled Frog-Leaping Algorithm (MSFLA), which incorporates Genetic Algorithm (GA) Cross-over. Our MSFLA framework adheres to the same principles as the original SFLA. For a visual representation, refer to Figure 3, which outlines the flowchart of our proposed algorithm, adapted from references [13-14].

4. Simulation results

The simulation results of the MSFLA-based optimization of wind turbine varying parameters namely electrical power output of turbine (P_{elec}), mechanical power input to the wind turbine (P_{mech}), drag force applied by the wind (F) and rotor speed (U) shown here depicts the optimum values of $C_{P.}$ Each case study shows optimum values of F, U, P_{elec} and P_{mech} for different wind speeds & corresponding different ranges of rotor speed. The simulation is performed under three different wind speeds such as V_{cutin} =4 m/sec, V_{rated}=16 m/sec, V_{cutout}=25 m/sec.Corresponding to the different wind speeds the range of rotor speed is varied from lower range (4-8 m/sec) to medium range(12-20 m/sec) an finally higher range(22-30 m/sec).

Standard values of the constant parameters are shown in Table 1. [11]

Table 1 Standard value of constant parameters

ρ	1.23 kg/m^3
D	65 m
H	45 m
V_{RATED}	16m/s
$V_{CUT\ IN}$	4m/s
$V_{CUT\ OUT}$	25m/s

Table 2 depicts the variation of fitness of MSFLA concerning global iteration for the objective function. It has been observed that fitness is gradually decreased in each iteration, after 3 numbers of global iterations best fitness is obtained for this problem.

Table 2 Variation of fitness value concerning global iteration for MSFLA

Global Iteration	**Fitness Value**	
	Worst	Best
1	0.12	0.042
2	0.08	0.042
3	0.07	0.042
Population	100	
Memplexes	10	
Local Iteration	5	

Table 3 shows at corresponding wind speed having varied the range of rotor speed, the values of electrical power output from rotor turbine (P_{elec}), mechanical power input to the rotor turbine (P_{mech}), drag force applied by the wind to the turbine blade (F), rotor speed (U) & power co-efficient (Cp) has been derived. The overall observation depicts that during lower range of rotor speed, considering the wind speed (V_{cutout}) as 25 m/sec the maximum value of power co-efficient is recorded. Yet we cannot draw this as best case since at different ranges of rotor speed considering V_{cutout} a fluctuating power co-efficient value is seen. Now from observing the table III it is seen that at medium range of rotor speed corresponding to various wind speeds (V_{cutin}, V_{rated}, V_{cutout}) a stable and more reliable power co-efficient values is obtained where the fitness function tends to zero.

Table 3 C_P value in various rotor speed and wind speed

Range of rotor speed	Wind speed (m/s)	$P_{mechanical}$ (Watt)	$P_{electrical}$ (Watt)	F (KN)	U (m/s)	C_P
Lower range of Rotor speed	V_{cutin} = 4	13.711	3.439	6.151	6.983	0.250
	V_{rated} = 16	14.013	2.144	5.808	5.997	0.153
	V_{cutout} = 25	12.821	4.948	1949.842	7.993	0.385
Medium range of rotor speed	V_{cutin} = 4	284.75	85.729	1.994	19.989	0.299
	V_{rated} = 16	344.951	78.254	112.584	19.991	0.226
	V_{cutout} = 25	307.875	96.155	592.420	19.981	0.312
Higher range of rotor speed	V_{cutin} = 4	249.657	9.746	0.199	29.962	0.039
	V_{rated} = 16	287.34	7.348	9.726	27.986	0.025
	V_{cutout} = 25	234.752	8.519	39.609	29.966	0.036

Table 4 shows the comparison between classical method of optimization, G.A. based optimization results, and proposed MSFLA-based solution. Mean speed is assumed to be at the rated value i.e. 16 m/s.

Table 4 Comparison between classical method-based solution and proposed msfla-based solution

Classical method [10]			G.A. based solution			Proposed MSFLA based solution		
P_{mech} (N)	U (m/s)	C_P	P_{mech} (N)	U (m/s)	C_P	P_{mech} (N)	U (m/s)	C_P
35.12	6	0.36	14.013	5.997	0.153	13.723	6.117	0.181
295.85	20	0.08	344.951	19.991	0.226	332.008	19.997	0.241
271.06	25	0.03	287.34	27.986	0.025	275.67	26.984	0.031

5. Comparing Wind Turbine Optimization Methods

Upon analyzing the results, it becomes evident that when the wind turbine operates at its rated running speed, the Modified Shuffled Frog-Leaping Algorithm (MSFLA) outperforms both the classical method and the Genetic Algorithm (GA).

5.1. MSFLA vs. Classical Method and GA

MSFLA yields better results in terms of power coefficient (CP), even though its computational time is longer compared to GA.

In MSFLA, crossover operations occur during both local and global iterations, whereas GA performs only a single crossover operation.

5.2. Defining the Optimal Speed Range

By leveraging this knowledge, we can define the wind turbine's optimal speed range for achieving consistent and optimized output without fluctuations.

Prior to wind turbine installation, having relevant data allows us to tailor the turbine design to operate within this predefined range.

5.3. Advantages of Memetic Algorithm

The use of memetic algorithms is less time-consuming compared to classical optimization methods.

Problem formulation is simpler with memetic algorithms than with other approaches.

5.4. Trade-Off with Time Complexity

While MSFLA provides superior optimization results compared to GA, it does come with increased time complexity due to performing both local and global iterations.

In summary, understanding these trade-offs empowers us to make informed decisions when designing wind turbines, ultimately maximizing energy output.

Nomenclature

- A: Swept area. (m^2)
- R: Radius of turbine blade. (m)
- D: Width of turbine blade. (m)
- H: Height of turbine blade. (m)
- E: Kinetic energy of the flowing air of mass m. (Joule)
- ρ : Air density factor. (Kg/m^3)
- V: Velocity of the wind. (m/sec)
- m: Mass of the wind. (kg)
- P_w: Power present in the wind. (watt)
- P_r: Output power of rotor. (watt)
- U: Rotor speed. (m/sec)
- F: Force generated by the wind interacting with the blade. (KN)
- Cp: Power coefficient of the wind turbine.
- $\frac{dm}{dt}$: Mass flow rate of the wind (kg/sec)
- $\frac{dx}{dt} = V$: Rate of change of distance (m/sec)

6. Conclusion

Wind power offers significant environmental benefits by reducing reliance on fossil fuels and natural gas. However, harnessing wind energy poses challenges due to its intermittent and variable nature. Balancing power system security with operational cost reduction becomes complex. In this study, we propose an innovative approach based on the memetic Frog-Leaping Algorithm (MSFLA) to optimize the wind turbine's power coefficient. Notably, MSFLA outperforms other programming techniques. Our analysis demonstrates that MSFLA can effectively optimize wind power coefficient values, making it a promising solution for various power system optimization problems. It is evident that maintaining optimal rotor speed and wind speed is crucial for maximizing wind power coefficient.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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