Optimising the Geometry of an Empty Concentrator-Diffuser Augmented Wind Turbine Using Genetic Algorithm.

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Abstract. The growing demand for electricity in off-grid regions and rising global energy needs driven by population growth underscore the urgent need to explore renewable energy alternatives to fossil fuels, key contributors to carbon emissions and climate change. Wind energy offers a sustainable option, but is challenged by its variability and low-speed performance in certain regions. This study investigates a performance enhancement strategy using an empty concentrator-diffuser augmented wind turbine (CDaugWT) to boost wind speed at the rotor, enabling continuous operation in areas with average wind speeds below 4 m/s. A velocity augmentation model served as the objective function, correlating the augmentation ratio with six geometric parameters. A Genetic Algorithm (GA), an evolutionary optimisation method, was used to determine the optimal design. Results showed that wind speed at the throat could increase up to 1.981 times. These findings closely aligned with results from response surface methodology (RSM), with only a 1.4 % deviation, validating the accuracy of the GA approach. The optimised geometric values included a diffuser angle of 10.1°, a concentrator angle of 20.0°, a concentrator length of 396.3 mm (0.66R_{th}), a diffuser length of 994.8 mm (1.65R_{th}), a throat length of 74.5 mm (0.12R_{th}), and a flange height of 104.4 mm (0.17R_{th}), where R_{th} is the throat radius. Computational Fluid Dynamics (CFD) simulations further validated these results, showing only a 0.58% difference. The study confirms that integrating optimisation algorithms such as GA into the design process of CDaugWT systems can significantly enhance wind turbine performance, making wind energy more viable for low-wind-speed regions.

1 Introduction

Increased global energy consumption, particularly in rural and off-grid areas, has prompted researchers to explore sustainable alternatives to fossil fuels. Wind energy, being abundant and renewable, presents a promising solution. However, its efficiency is often constrained by variability and low wind speeds in many regions. To address this, researchers have explored augmented wind turbine technologies that enhance performance under suboptimal wind conditions. One of the most promising innovations in this field is the concentrator-diffuser augmented wind turbine (CDaugWT), also known as the wind lens turbine [1]. This technology enhances wind capture by incorporating concentrator and diffuser elements, sometimes with a flange, to reduce back pressure and increase wind speed through the rotor plane [2], [3]. Several studies have demonstrated the effectiveness of this approach. For instance, [4] reported a velocity augmentation ratio of 1.32 using converging-diverging ducts, although the design exhibited issues related to backflow. Ref. [5] developed a compact wind turbine with an adjustable diffuser, achieving a 39.75% average velocity augmentation. These studies highlight the suitability of CDaugWT systems for improving wind energy capture in low-resource environments.

To further enhance performance, single-objective evolutionary metaheuristic optimisation algorithms, such as genetic algorithms (GA), have been employed to optimise the geometrical configuration of CDaugWTs. For example, [6] used a multi-objective GA to maximise power output and simultaneously minimise drag and thrust force. Similarly, [7] applied a GA in conjunction with the response surface methodology (RSM) to optimise seven geometric parameters of a ducted turbine system, resulting in a velocity augmentation ratio of 2.18 at the throat.These optimisation algorithms typically rely on surrogate models to serve as objective functions. Ref. [8], for example, employed computational fluid dynamics (CFD) and the response surface methodology (RSM) to develop quadratic surrogate models, achieving a velocity augmentation ratio of up to 2.16 at the throat with high accuracy ($R^2 = 0.9937$). Likewise, Ref. [9] constructed a response surface-based velocity augmentation model with high accuracy ($R^2 = 0.9581$). Importantly, this model accounts for interaction effects among all geometrical parameters, a feature often neglected in earlier studies, thus providing more precise optimisation outcomes.

This study uses the model obtained by Ref. [9] as the objective function for a genetic algorithm (GA) aimed at optimising the geometry of an empty CDaugWT under low wind speed conditions (≤ 2 m/s).

2 Materials and Methods

This study employed a structured approach to optimise the geometry of a CDaugWT. A quadratic surrogate model based on RSM was used as the objective function, with the velocity augmentation ratio as the target metric. The optimisation was performed using GA, and results were validated through computational fluid dynamics simulations in ANSYS Fluent 2022R1 software. MATLAB codes for the GA optimisation were developed and executed successfully in MATLAB R2021a. Detailed steps are outlined in Sections 2.1 to 2.4.

2.1 Geometry and Parameters

The concentrator-diffuser system geometry was defined using six key parameters recognised through literature studies: diffuser angle (θ_d), concentrator angle (θ_c), concentrator length (L_c), diffuser length (L_d), throat length (L_{th}), flange height (H_f) [10], [11]. All dimensions were normalised with respect to the throat radius (R_{th}) to allow generalisation of the results. Figure 1 illustrates the geometry of the CDaugWT design.

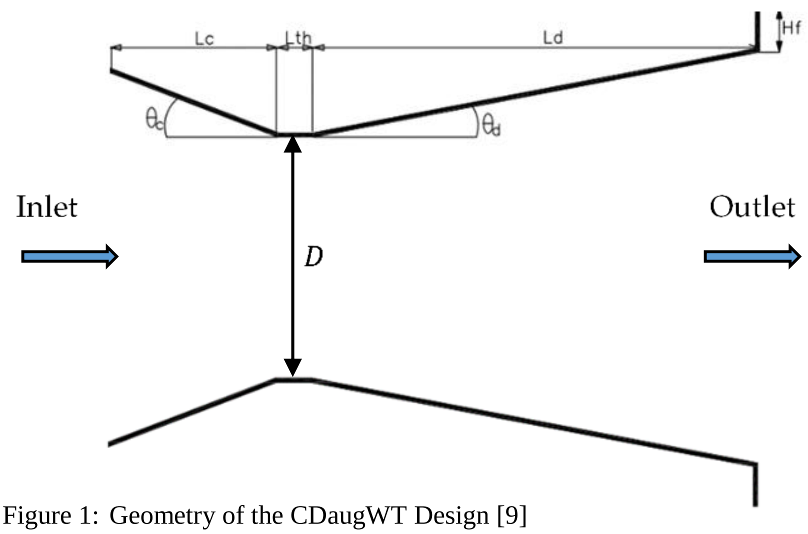

Figure 1: Geometry of the CDaugWT Design [9]

2.2 Objective Function $\left(\frac{V_{th}}{V_\infty}\right)$

A velocity augmentation model was used as the objective function. The goal was to maximise the velocity augmentation ratio, $A_v = \frac{V_{th}}{V_\infty}$, where V_{th} is the velocity at the throat, and V_∞ is the free-stream velocity. This model, derived in [9], is a quadratic regression metamodel based on six geometric design parameters. It serves as the fitness function in a genetic algorithm (GA) used to optimise the concentrator-diffuser augmented wind turbine (CDaugWT) geometry for maximum wind speed augmentation. The velocity augmentation model is given as shown in Equation 1.

$$\frac{V_{th}}{V_\infty} = -0.752974 + 0.355948\,A + 0.280702\,B - 0.00431128\,C - 0.00217402\,D - 0.0133117\,E + 0.000363692\,F + 0.000214108\,(A\cdot C) + 4.976\times10^{-6}\,(C\cdot D) + 1.447\times10^{-5}\,(D\cdot E) - 0.0218753\,A^2 - 0.00701959\,B^2 - 3.20027\times10^{-6}\,C^2. \quad (1)$$

This function estimates throat wind speed, guiding the GA to maximise velocity augmentation by optimising turbine geometry. The six design parameters (A–F) used in optimisation are continuous variables, each constrained within specific ranges. These include the diffuser angle (θ_d), ranging from 9.0° to 10.5° (A), and the concentrator angle (θ_c), ranging from 19.0° to 20.5° (B). The concentrator length (L_c) varies between 327.10 mm and 397.90 mm (C), while the diffuser length (L_d) ranges from 927.10 mm to 997.90 mm (D). The throat length (L_{th}) spans 60.40 mm to 74.60 mm (E), and the flange height (H_f) is bounded between 90.40 mm and 104.60 mm (F). These ranges define the design space for the genetic algorithm used in optimising the CDaugWT Design geometry.

2.3 *Optimisation Algorithm*

The Genetic Algorithm (GA), introduced by Holland (1975), is a nature-inspired optimisation technique based on natural selection and the principle of "survival of the fittest." GA is a semi-stochastic and semi-deterministic search method that evolves a population of candidate solutions across generations to find optimal or near-optimal results [6]. This study applied GA to optimise six geometric parameters of the CDaugWT design. The algorithm was implemented in MATLAB and structured around the following iterative steps [7]:

- Initialise the population with randomly generated individuals (design solutions).
- Evaluate each individual using a defined objective function derived from the velocity augmentation model.
- Select parents based on fitness scores.
- Crossover parent pairs to generate new offspring.
- Mutate offspring to introduce diversity.
- Repeat evaluation, selection, crossover, and mutation for multiple generations.
- Select the best solution based on the highest augmentation performance.

The algorithm was implemented in MATLAB with a population size of 100, a crossover rate of 0.8, a mutation rate of 0.05, and 200 generations. The fitness function used a negated objective to enable maximisation within GA's minimisation framework. A schematic of the GA process is shown in the figure below.

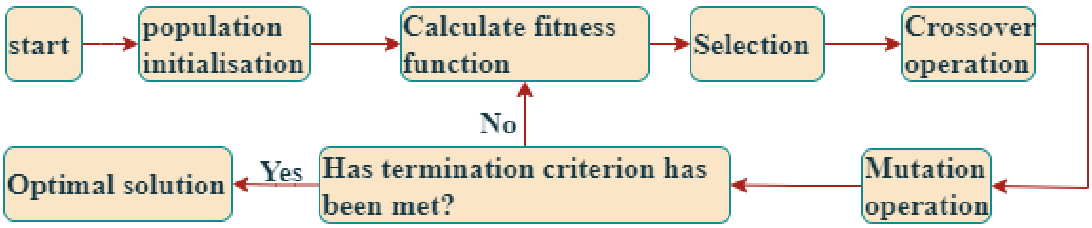

Figure 2: Flow chart of Genetic Algorithm

2.4 *Validation*

The Response surface methodology (RSM) results from [12] were used to validate and compare the GA optimisation results. Additionally, Computational Fluid Dynamics (CFD) was employed to simulate airflow through the CDaugWT system, as detailed in [9]. The simulations were conducted using ANSYS Fluent, solving the steady, incompressible Reynolds-Averaged Navier–Stokes (RANS) equations with the SST k-ω turbulence model, a hybrid of the k-ε and k-ω models selected for its balance between accuracy and computational efficiency [13]. Second-order upwind schemes were utilised for the convection-diffusion terms, and a convergence criterion of 1×10^{-6} was applied. This CFD analysis provided a detailed understanding of wind acceleration effects and was instrumental in verifying the GA optimisation results. The whole numerical procedure is available in [9].

3 Results and Discussion

3.1 Optimisation Results

The optimisation results presented in Table 1 show that the GA identified an optimal design with the following parameters: θ_d (Diffuser angle): 10.1°, θ_c (Concentrator angle): 20.0°, L_c: 396.3 mm ($0.66R_{th}$), L_d: 994.8 mm ($1.65R_{th}$), L_t: 74.5 mm ($0.12R_{th}$), H_f: 104.4 mm ($0.17R_{th}$). The RSM yielded slightly different optimal values, as shown in Table 1. The GA-predicted throat velocity was slightly higher than that of RSM, with a slight deviation of 0.58% when compared to CFD results, while the difference between GA and RSM predictions was 1.4%. These small discrepancies confirm the reliability and accuracy of the GA optimisation method. Moreover, the GA configuration achieved a maximum augmentation ratio of 1.981, indicating a near doubling of wind speed at the turbine's throat and demonstrating superior performance in enhancing flow velocity through geometric optimisation. Figure 3 depicts the 3D CDaugWT design generated in ANSYS Fluent, based on the optimal geometric parameters obtained from the GA optimisation.

Table 1: Optimised throat wind speed values validation with CFD results.

Method	θ_d	θ_c	$L_c(mm)$	L_d(mm)	L_{th}(mm)	H_f(mm)	V_{th} (m/s)	CFDV_{th} (m/s)	% difference
RSM	10.0°	20.0°	375	975	70	100	3.906	3.8980	0.02
GA	10.1°	20.0°	396.3	994.8	74.5	104.4	3.961	3.9382	0.58

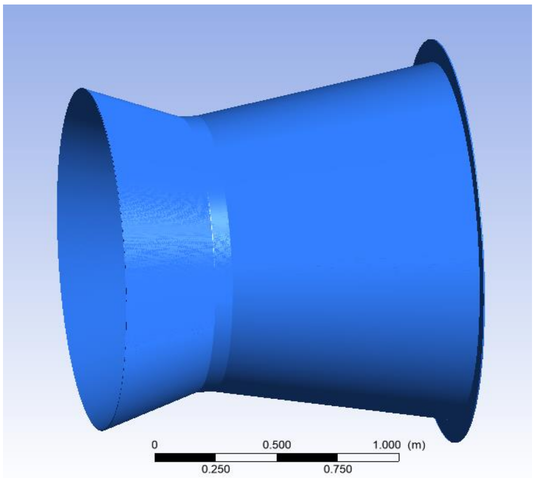

Figure 3. The CDaugWT design.

3.2 CFD Analysis

The CFD velocity streamlines confirmed significant flow acceleration through the throat region of the CDaugWT. The diffuser geometry facilitated controlled expansion and effective pressure recovery, while the concentrator section focused the incoming airflow, resulting in increased velocity at the throat. Figure 4 presents the velocity and pressure contour distributions and the corresponding axial velocity and pressure profiles for the CDaugWT configuration optimised using the GA.

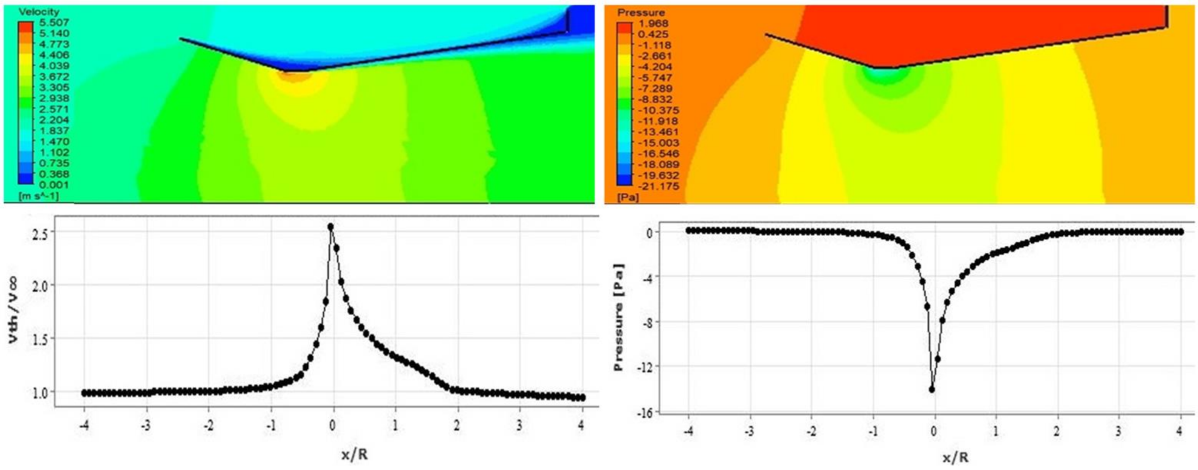

Figure 4: Velocity, pressure contour distributions, and axial profiles for the CDaugWT design using the GA.

4 Conclusions and Recommendations

This study demonstrates that the application of a genetic algorithm to optimise the geometry of a concentrator-diffuser augmented wind turbine design can substantially enhance turbine performance in low wind-speed regions. The optimised configuration achieved nearly a twofold increase in throat velocity, with results showing strong agreement with both response surface methodology and computational fluid dynamics validations. These findings suggest that well-designed CDaugWT systems have the potential to extend the operational capabilities of small-scale wind turbines, making them viable in areas previously considered unsuitable due to low wind speeds. Field testing of the optimised CDaugWT design geometry is recommended to validate the simulation results under real-world conditions. Future research could incorporate multi-objective optimisation approaches that consider structural integrity, cost, and material weight to enhance practical deployment. Additionally, exploring other artificial intelligence-based optimisation methods, such as particle swarm optimisation (PSO), whale optimisation algorithm (WOA), and grey wolf optimisation (GWO), may offer improvements in convergence speed and robustness, potentially leading to even more efficient design outcomes.

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