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## MULTI-OBJECTIVE OPTIMIZATION OF SMALL WIND TURBINE USING METAHEURISTIC ALGORITHMS

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**Abstract.** Gather the continuous increase of greenhouse emissions is the required effort of policies and government investments to fulfill agreements against climate change. One viable way is based on renewable energy sources, and despite it corresponds to about 14.00% of the global matrix this percentage should still increase in near future. Aiming in wind energy utilization - which plays an important role in it –, this paper is the first of a series concerning optimized turbines development. In this first approach, the main objective is to investigate turbine performance and replicate its operation, and then find the optimal design parameters for small wind turbines. Literature correlations were applied through algorithms to perform the optimization process. In comparison with an existing SWT, it would be possible to find a turbine 2.66% smaller and 5.53% more efficient on its pick.

**Keywords:** power generation, electricity, renewable energy, wind energy, small wind turbine, validation, power curve, optimization, artificial intelligence

### 1. INTRODUCTION

Both the short and long terms from Paris Agreement (2030 and 2050, respectively) can be translated to one goal: reduce greenhouse gas emissions in order to diminish their impacts on climate change. However, in the wrong way, a recent report regarding  $CO_2$  emissions pointed an annually average raise of 1.30% over last five years against a required reduction of around 3.50% per year, from 2019 until 2050 (IRENA, 2019b). Towards the stipulation, not only global investments but also public policies play an important role in it. According to IRENA (2019b), 110 trillion dollars must be invested until 2050 in energy systems, and an example of such policies effort was presented by the United Kingdom: the government adopted a goal to reduce 80.00%  $CO_2$  emissions by 2050, supporting programs for people's awareness of climate change and stimulating electricity low-carbon micro-generation (Bergman and Jardine, 2009). Therefore, renewable energies have been presenting themselves as an affordable solution.

In 2016, almost 20.00% of the world's electricity supply had a renewable source basis. Also, what is notable is its percentage growth in relation to five years before: almost 420.00% from photovoltaics (63,170 to 328,038 GWh), approximately 120.00% from wind turbines (436,010 to 957,694 GWh) and 16.00% from hydropower (3,597,861 to 4,170,035 GWh) (IEA, 2019). Although China and USA in absolute numbers represent roughly 45.00% of the 958 TWh power provided from wind, it must be pointed out countries where wind energy plays a role in their electricity matrix – which means an effective investment on renewable energy – : Spain (17.80%), Germany (12.10%) and UK (11.00%) (IEA, 2019).

Around Paris Agreement climate targets achievement, that representative tends to be even higher, once the wind is considered as one of the leaders on electricity sector transformation: at 2050, when renewable energies tend to be responsible for almost 50.00% of global electricity generation (IRENA, 2019b), it is estimated that 35.00% of electricity demand will be supplied by wind (IRENA, 2019a). Naturally it might attract investments and new technologies development, from onshore and offshore projects to small wind turbines (SWT). Making use of SWT and another renewable resource (mainly solar panels and wood-fueled boiler systems), Bergman and Jardine (2009) explicit in their study further contributions: transmission losses reduction and increase system resilience in a decentralized manner, for example.

By the end of 2015, according to WWEA (2017), there was a total of 990 thousand SWTs installed around the world – whose power generated was approximately 994 MW –, an increase of 5.00% comparing to the year before, mostly in countries as China, USA, and the UK; it is expected that number be twice as much until 2020. Those installations are

commonly placed as off-grid, which in other words means an electricity supply to isolated places and a contribution to its universal access (WWEA, 2017; IRENA and IEA-ETSAP, 2016). This is also a worldwide challenge, mostly in countries whose wide territorial area disables grid spread, such as Brazil. On the other hand, it tends to increase cost per kW, once off-grid installations are usually applied as stand-alone instead of wind farms (IRENA and IEA-ETSAP, 2016) and their efficiency is lower than that of larger turbines (Singh and Ahmed, 2013).

An easy way to priorly evaluate equipment performance subjected to real conditions, in a costless and timeless manner, is to make use of numerical simulations, either algorithms or *Computational Fluid Dynamics* (CFD). The first is helpful when an overview is needed, whose analysis is well-used regarding tangible parameters and initial designs; if a deeper investigation is required, the second fulfills better. Both might give useful data for decision-makers at project development, allowing them to perform their tasks even more accurately. Additionally, electronic components evolution, faster code languages, and processors, allowed problems investigation to become more sophisticated, and techniques such as machine learning and artificial intelligence could be developed.

As part of the last, optimization methods can be highlighted, or in other words, an equation maximization/minimization under specific criteria (Sierksma, 2002), mostly built from genetic theories and swarm-based intelligence methods, based on the collective behavior of social animals. In an effort to overcome SWTs disadvantages, this paper analyses their performances and possible optimal design making use of alike methods and numerical simulation. The main target is to reach optimal parameters subjected to the same operational conditions from an already existing one and compare them regarding efficiency and structural parameters.

## 2. METHODOLOGY

In order to optimize an already existed small wind turbine, it is required to previously replicate its performance through models present in literature and described in Section 2.1 via algorithms coded in Python language. This reproduction is considered faithful through comparison, not only with other author's simulation results but also from experimental data available in the literature.

Then, optimization is made by techniques described in Section 2.2, whose aim is to provide the same electric power as the experimental turbine. Those techniques were also compared with each other on computational cost and result accuracy matter, whose objective functions were set regarding the power coefficient maximization and inertia minimization thus starting torque for operation initialization is reduced. The inputs and its constraints are different from earlier studies: rotor diameter, number of blades, and rotational speed.

### 2.1 Performance validation

From the previous theories called *Disk Actuator* (Rankine, 1865; Froude, 1889) and *Blade Element Theory* (BET) (Froude, 1878; Drzewiecki and Paryż, 1892), which tried to replicate rotating machines operation, Glauert (1935) postulated his optimal rotor theory, which is also the most generalized and the most applied nowadays on turbine projects: the *Blade Element Momentum* (BEM). It consists in determining the triangle of velocities – whose angles are correlated by Eq. (1) – proposed by BET and directly affected by induction factor of *Disk Actuator Theory* and *BET* (Eq. (2)); thus, it is enabled to calculate the inflow angle ( $\phi$ ) and loads at each blade section. In this way, an iterative loop is started, once a uniform load distribution along the blade section is assumed and new values for induction factors are found - until a stop criterion is achieved.

$$\phi = \alpha + \theta \quad (1)$$

$$\tan \phi = \frac{(1 - a)}{(1 + a')\lambda_r} \quad (2)$$

$$\lambda_r = \frac{r\omega}{U_0} \quad (3)$$

Where  $\alpha$  is the angle of attack,  $\theta$  blade twist,  $a$  axial and  $a'$  tangential induction factors, and  $\lambda_r$  is the local tip-speed ratio (Eq. (3)), in which  $r$  is the radial coordinate from blade section,  $\omega$  turbine rotational speed and  $U_0$  wind free-stream velocity. From an understanding that circulation is mainly a consequence of lift force along the blade, Wilson and Lissaman (1974) have included it on its formulation presented at Eq. (4) – and also dealt on the same rotor plane as developed by Glauert (1935) on *BEM* theory. Moreover, against over-predicted values due to wake expansion, Buhl (2005) experimentally proposed a correction for axial induction factor higher than 0.4 (Eq. (5) and Eq. (6)); it can be remarked that Marten *et al.* (2010) made use of this method in his research.

$$\frac{aF(1 - aF)}{(1 - a)^2} = \frac{\sigma C_L \cos \phi}{4\sin^2 \phi} \quad (4)$$

$$a = \frac{18F - 20 - 3\sqrt{C_T(50 - 36F) + 12F(3F - 4)}}{36F - 50} \quad (5)$$

$$C_T = \begin{cases} 4aF(1 - a) & \text{for } a \leq 0.4 \\ \frac{8}{9} + \left(4F + \frac{40}{9}\right)a + \left(\frac{50}{9} - 4F\right)a^2 & \text{for } a > 0.4 \end{cases} \quad (6)$$

Where  $F$  is the tip-loss factor,  $\sigma$  the section solidity,  $C_L$  the lift and,  $C_T$  is the thrust coefficients. Aerodynamic coefficients, such as drag and lift, can be dealt as constants in project planing. Otherwise, when replicating turbine performance, flow regimes are changed and those coefficients are directly affected – achieving even the stall. Despite of operational conditions, a good prediction method is capable of accurately estimate them, and Martínez *et al.* (2005) work presented satisfactory results on this matter. Additionally, de Vries (1979) pointed out an inconsistency at Eq. (4) regarding non-orthogonality between induced and relative velocities. Against it, their method differs from Wilson and Lissaman (1974) only in the proposed tangential factor, presented in Eq. (7).

$$\frac{a'F(1 - aF)}{(1 - a)(1 + a')} = \frac{\sigma C_L}{4 \sin \phi} \quad (7)$$

Shen *et al.* (2005) treated *BEM* bi-dimensionality in the non-annulment of forces at the tip, which should tends to zero once fluid directly passes from the pressurized blade side to suction one. Therefore, it was proposed a semi-empirical tri-dimensional model among involved forces, resulting in a new expression for the tip-loss factor (Eq. (8)).

$$F = \frac{2}{\pi} \cos^{-1} \exp \left( -g \frac{B(R - r)}{2r \sin \phi} \right) \quad (8)$$

$$g = \exp \left[ \frac{1}{8} (B\lambda - 21) \right] + 0.1$$

$$\lambda = \frac{R\omega}{U_0} \quad (9)$$

Where  $B$  is the number of blades,  $R$  rotor radius and  $\lambda$  tip-speed ratio (Eq. (9)). In the end, an alternative power coefficient prediction is shown as Eq. (10) (Brasil Junior *et al.*, 2019).

$$C_P = \frac{8}{\lambda^2} \int_0^\lambda a'(1 - a) \left( 1 - \frac{C_D}{C_L} \cot \phi \right) \lambda_r^3 d\lambda_r \quad (10)$$

Where  $C_D$  is the drag coefficient.

## 2.2 Optimization methods

The aim of optimization problems is to find a solution that better fits a desired minimal or maximal value from an objective function, whether subjected or not to domain constrains, also particular to each case. In other words, the variables are responsible for varying sets of images produced according to a function. This can be not only treated as *Single Objective*, demanding less computational effort and complexity to solving, but also *Multi-Objective*, whose approach is peculiar: outputs compete against themselves in order to supply a set of optimal solutions.

Methods are mainly separated into two fields: deterministic and heuristic, differing from an exact or approximated outcome, respectively. An example from the first is a technique called *Gradient Descent*, which makes use of calculus theories and is mostly applied in the learning process of artificial neuron networks. However, once it needs complete knowledge of function behavior – for example, its derivatives –, it becomes unable to get a feasible solution effortless. Hence the heuristic approach is commonly used, predominantly in a randomized search manner through the entire domain. From that kind of method can be cited the *Artificial Bee Colony* (ABC), *Flower Pollination Algorithm* (FPA), and *Particle Swarm Optimization* (PSO).

PSO method was created by Kennedy and Eberhart (1995), who had been inspired from birds food exploration: each bird flock individually looks for a source with more food abundance, and communicate each other in order to check whether that is the most plentiful or not; the birds should follow the one, which has found it. In a computational background, the source is a synonym of an optimal solution and birds are treated as particles with spacial position and velocity among the entire – or constrained – domain. These are updated each epoch according to cognitive and social parameters, previously set. Due to its low computational cost and complexity, PSO has been used to optimize engineering problems, as for example, Borhanazad *et al.* (2014) investigated an optimal hybrid-grid layout containing photovoltaic cells, wind turbine and diesel moto-generator.

Similarly, the ABC technique was developed by Karaboga (2005) and it is based on nectar search from a swarm of bees. Their strategy consists in divide them into three groups: employed, onlooker, and scout bees. The last is responsible to locate possible nectar sources surround hive, as soon as the onlooker bees send employed to rummage it. Then, it is reported – through the so-called waggle dance – where and how good the nectar source is, in order to the onlooker evaluate and decide whether that source should be considered as the main one or not. From a computational perspective, food resource is a possible optimal solution and is measured as a probability manner, taking into account its nectar quantity and its distance from the hive. Yildiz (2013) made use of this method in structural problem optimization, which dealt with an automotive component.

FPA procedure occurs likewise the ABC, being differentiated on its search methodology. Developed by Yang (2012), it was inspired by plants reproduction mechanism, which pollen – treated as optimal solution – is transferred until a flower gamete is reached. First, a global search is made, called biotic pollination, through a probabilistic distribution, the Lévy flight; second, from a possible optimal source, a local search – or abiotic pollination – is proceed in order to check vicinities solutions. And third, these solutions are compared to the minimum (or maximum) value already found. For example, a study carried to compare the preceding method among others alike was made by Bekdaş *et al.* (2015), who looked for optimize truss weight.

At this work, an investigation was made around with not only turbine power coefficient ( $C_P$ ) optimization, but also with its mass in order to turn its manufacturing costless and its movement unresistant as possible – in other words, translated into blade inertia. Equation (11) was developed by Mesquita *et al.* (2014), who proposed a method to determine it.

$$J = B \sum_{i=1}^N m_i r_i^2 \quad (11)$$

Where  $J$  is the turbine inertia,  $i$  represents each profile section and  $m$  the mass partition between actual and previous profile section. This can be described by Eq. (12) reported by Drela *et al.* (2006).

$$m = \rho_m K_A c t d r \quad (12)$$

Where  $\rho_m$  is blade materials density,  $K_A$  profile area coefficient – usually approximated as 0.60 Drela *et al.* (2006) –,  $c$  section chord and  $t$  maximum profile thickness. Chord can be obtained by thrust coefficient provided by classical *BEM* theory Silva *et al.* (2017) and is presented at Eq. (13).

$$c = \frac{2\pi r}{B} \frac{C_T}{C_n} \left( \frac{U_0}{W} \right)^2 \quad (13)$$

$$W = \sqrt{[U_0(1-a)]^2 + [r\omega(1+a')]^2} \quad (14)$$

Where  $C_n$  is the normal force coefficient – determined by *BET* calculation at each blade section –, and  $W$  relative velocity. Both of optimized parameters ( $C_P$  and  $J$ ) were combined into a multi-objective manner as similar as applied by Wood (2011), in which each of them is normalized and weighted in a single function. In order to guarantee turbine power specification, a parabolic function penalized the cost function when it did not provide power demand. The cost function and penalty function are presented in Eq. (15) and Eq. (16).

$$O = \gamma \left( (1-\varepsilon) \frac{C_{P_{ref}}}{C_P} + \varepsilon \frac{J}{J_{ref}} \right) \quad (15)$$

$$\gamma = 9.999 \frac{P}{P_{ref}} - 19.998 \frac{P}{P_{ref}} + 10 \quad (16)$$

Where sub-script *ref* refers to reference values and  $\varepsilon$  variable weight, initially set as 0.5 and  $P$  the turbine power.

### 3. RESULTS

#### 3.1 Turbine validation

The experimental data to be used in the validation process were obtained by Maniaci *et al.* (2015), who looked for aerodynamic parameters operation of a small wind turbine called G1, whose wind tunnel test was developed at the Technical University of Munich (TUM). Its rotor has a radius of 0.5500 m, while the hub radius is 0.0540 m, and was designed with 3 blades for a tip-speed ratio( $\lambda$ ) equals to 6.6 (or rotational speed of 850 rpm) - otherwise, in this study all results were evaluated with an operational condition of 7.0. The majority of its profile section – 86.00% – is built

as RG14 and the first 14.00% is constituted of a cylindrical and a transition section. Also, RG14 maximum thickness is 8.50% of chord. By applying models presented in Section 2.1, a power coefficient curve is predicted in order to validate the performance replication. Moreover, a comparison is provided between the results from this work and the curve from an open-source software called *QBlade* (Marten *et al.*, 2013), developed at the Technical University of Berlin (TU Berlin), which is widely referenced in such researches as this. Convergence criteria was set as  $3 * 10^{-2}$  and results are shown in Fig. 1.

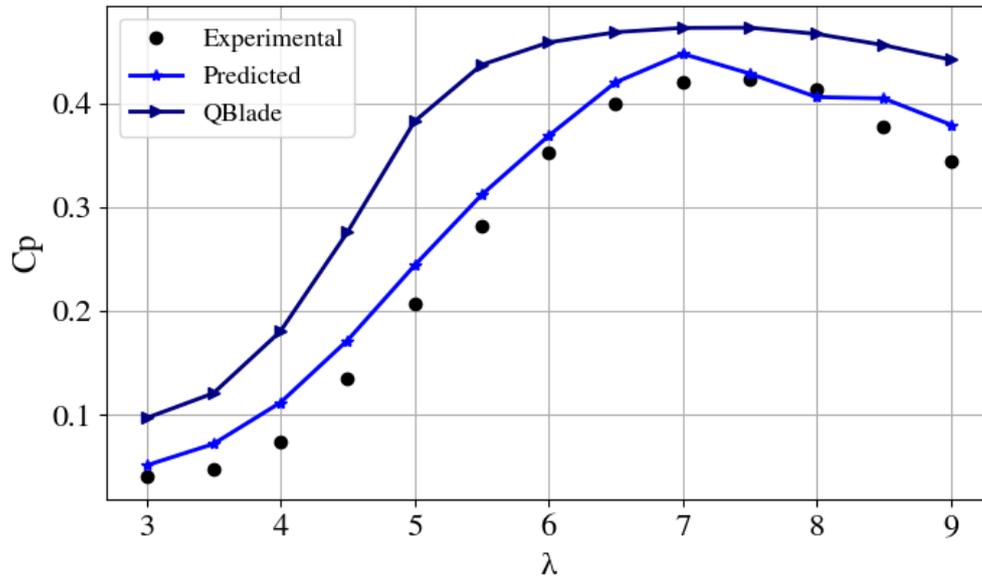


Figure 1. G1 turbine performance prediction developed by this work, compared with the commercial software *QBlade* and experimental data (Maniaci *et al.*, 2015).

Predict the power coefficient under environmental conditions is a well helpful tool in turbine projects and also tends to be a tough task. Even though the tolerance of  $3 * 10^{-2}$  previously specified appears to be high, this number was the minimum which allowed the algorithm to converge. The resulted power coefficient prediction, otherwise, is far from an inaccuracy that lower tolerances could mean: the curve not only followed experimental behavior of a decrease coming after a starting increase, but also reached a pick at the same tip-speed ratio ( $\lambda$ ). This design point  $C_p$  has shown a difference of 5.07%, while the maximum difference of 51.57% was encountered at tip-speed ratio of 3.5: a prediction of 0.0723 against an experimental of 0.0477. This gap coincide the operation range, whose aerodynamic effects are prominent and hard to predict, such as stall; as higher the operational parameters, softer that effect is and aerodynamic parameters are better filled, even achieving a minimum divergence of 1.19% at 7.5 of tip-speed ratio.

Furthermore, it must be pointed out how closer predicted the values from a constructed algorithm for this work were in relation to experimental data, in comparison with a consolidated software as *QBlade*. Thus, among an overall variation, the turbine power coefficient is considered as well-replicated in order to keep research.

### 3.2 Design optimization

An investigation is then attempted concerning a local and isolated power generation through a small wind turbine. A hypothetical environmental condition of  $25.00^\circ C$  and free stream wind velocity equals to 7.4176 m/s - which was obtained from tip-speed ratio ( $\lambda$ ) and turbine's rotational speed experimental data. Assuming drag and lift coefficient distribution presented by Maniaci *et al.* (2015), it was found an optimal ratio of 48.1838 (respective numbers of drag and lift coefficient are 0.0150 and 0.7222) at  $5.22^\circ$  angle of attack ( $\alpha$ ). Chord and twist at each section were determined according to, respectively, Eq. (13) and Eq. (1).

Design variables were analyzed within a constrained domain delimited from turbine G1 power, roughly 100.95 W. Equation (17) allows calculation of diameter boundary values, where  $P$  is power generated,  $\rho$  is fluid density (air in this case and  $1.2250 \text{ kg/m}^3$ ) and  $A$  rotor area. Assuming a minimum power coefficient value of 0.2000 and a well-known maximum possible power coefficient, determined by Betz, evaluated as 0.5793. In this way, rotational speed limits can be determined considering the tip-speed ratio ( $\lambda$ ) values of 3 and 10. Finally, the number of blades is between 3 and 12; a summary of all design constraints can be seen at Tab. 1.

$$P = \frac{1}{2} \rho A U_0^3 C_P \quad (17)$$

Table 1. Optimization constrains for each input.

Input	Minimum value	Maximum value
Rotor diameter (m)	0.9420	1.6030
Number of blades	3	12
Rotational speed (rpm)	451.090	883.500

It should be noted that, although aerodynamic coefficients do not show significant difference as Reynolds number changes due to different rotational speeds (Martínez *et al.*, 2005; Wood, 2011), it was minimized any similar effect applying lower tip-speed ratio ( $\lambda$ ) on the smallest rotor diameter instead. From an operational manner, it would be improper such higher boundary values. Regarding blade mass, its length is directly affected by hub diameter; hence, the same ratio between rotor diameter was considered – 9.80%. Despite material density plays an important role in internal loads, it was neglected as soon as such an approach did not take part of this research.

Reference values for Eq. (15) were Betz power coefficient – 0.5793 – and  $9.4380 \times 10^{-5}$  – outcome from Vaz *et al.* (2018) divided by its blade material (Singh, 2014). Optimization methods were performed according to parameters presented in Tab. 2 and a tolerance criteria equaled to  $1 \times 10^{-6}$ . Furthermore, simulations from randomized methods like *ABC* and *FPA* are commonly repeated in order to guarantee a reasonable solution, and at this work 50 times each were redone. Table 3 presents optimization solutions from methods attempted.

Table 2. Optimization constants from each method.

Constant	Value
Initial population	100
<i>ABC</i>	
Maximum trials	100
<i>FPA</i>	
Switch probability	0.80
<i>PSO</i>	
Inertia coefficient	1.00
Deceleration coefficient	0.99
Cognitive coefficient	2.00
Social coefficient	2.00

Table 3. Optimal design according to each method.

Result	Original	<i>ABC</i>	<i>FPA</i>	<i>PSO</i>
Cost Value ( $\times 10^{-3}$ )	3.7803	4.1080	3.9420	3.8830
Power coefficient	0.4250	0.4267	0.4494	0.4485
Total inertia ( $\times 10^{-4}$ kg*m <sup>2</sup> )	5.8491	6.2562	6.2158	6.1104
Rotor diameter (m)	1.1000	1.0968	1.0699	1.0707
Hub diameter (m)	0.1080	0.1075	0.1048	0.1049
Number of blades	3	4	4	3
Rotational speed (rpm)	850.000	873.124	875.243	883.500
$\lambda$	6.60	6.76	6.61	6.68
Power output (W)	100.95	100.79	100.99	100.95
Simulation time (s)	-	988.12	1402.43	5687.77

It is remarkable a specific result obtained from the optimization methods: most of them – excepting *ABC* – have provided a higher power coefficient than from original turbine and its prediction, highlighting the approximately 5.00% increase of design provided by *FPA* in comparison with prediction. As well designed as it is, can also be noted among the values of the diameters a slight decrease from the original, which gathered to a higher rotational speed lead to a possibility of an optimum range of tip-speed ratio, around 6.6. Regarding number of blades, it can be deduced that less blades provide a smaller inertia, as can be compared the *PSO* turbine with the others; and, the higher that number, the better power coefficient, once an infinity of blades take part of Betz theory. If both approaches are taking into account, as this work proposes, it tends to be non-mandatory the usual 3, rather is preferable not much more, once *ABC* and *FPA* have found turbines with 4 blades.

However, neither the trade-off between size and rotational speed, nor number of blades, are direct relationships with

a well-designed turbine according to parameters previously established in this work. All methods have showed a higher inertia and a possible reason is the chord formula, which was not optimized and based on classical *BEM* theory Silva *et al.* (2017). The one, which was capable to not only better balance  $C_P$  and inertia, but also to provide desired power, was *PSO* and is consequently translated to the lower cost value. Moreover, such analysis through methods that combined variables and provided many distinct turbines, but still could supply almost the same power, only empowers this work and this approach. Fig. 2 and Fig. 3 compare normalize chord and twist angle distribution, respectively, between turbine optimized design from *PSO*, and original.

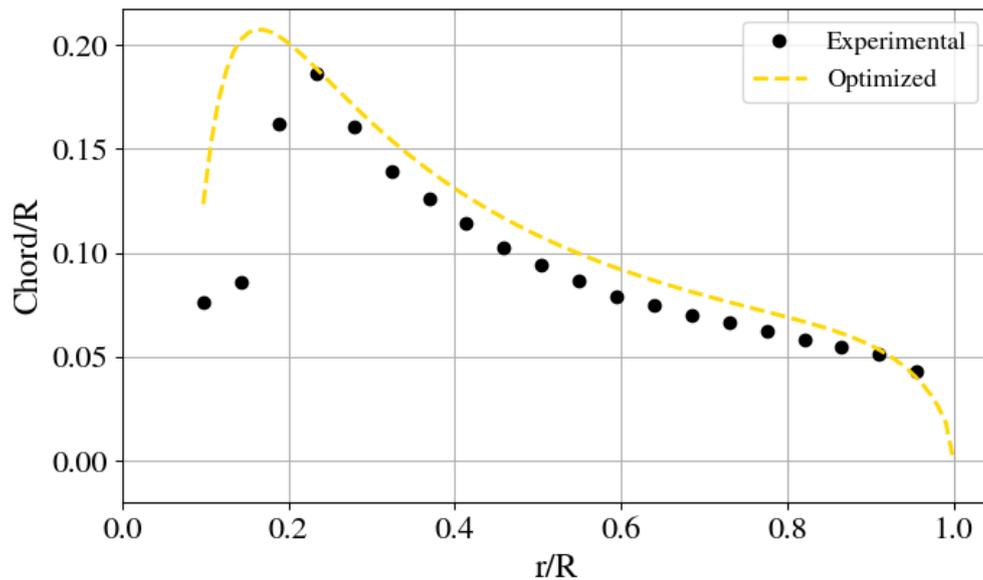


Figure 2. Normalized chord distribution comparison between optimized and original G1 turbine.

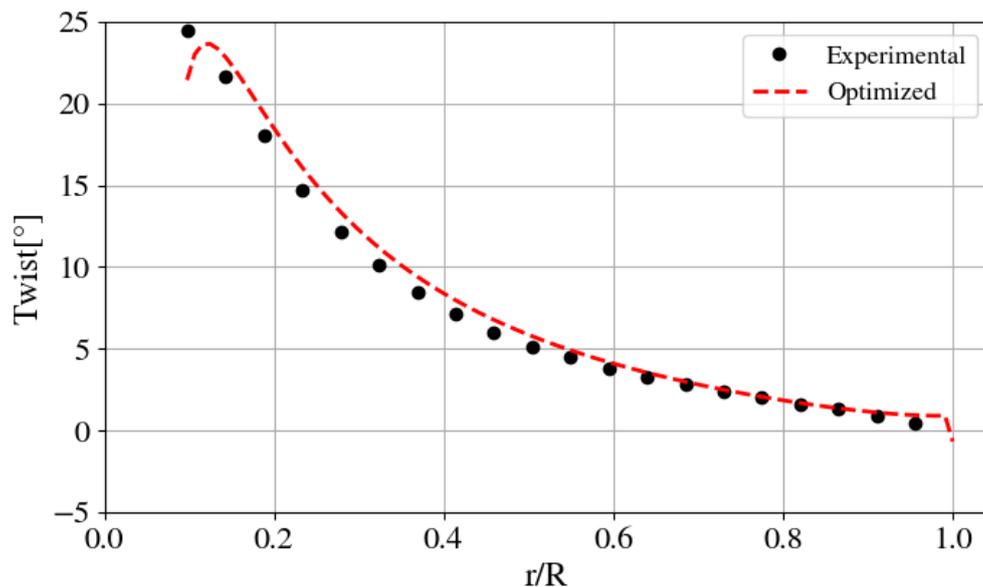


Figure 3. Twist distribution comparison between optimized and original G1 turbine.

According to Fig. 3, both twist distributions are slightly closer and it can be deduced, excepting  $\phi$  which is determined by turbine particularities and its influence on flow, that a same optimum angle of attack ( $\alpha$ ) was used. Finally, a comparison between the optimized and the original turbine, concerning their performance can be seen at Fig. 4. Among almost all operation range the optimized turbine provided a better  $C_P$  than G1, reaching even an increase of 21.04% at tip-speed ratio of 4.5; in general, if all  $\lambda$  are taken account, optimized is able to be 114.75% more efficient – both percentages were

evaluated in reference with Section 3.1 prediction, and assuming same discrepancy to a possible construction. Despite chord differences, through the entire investigation, it was possible to develop a more efficient and smaller turbine.

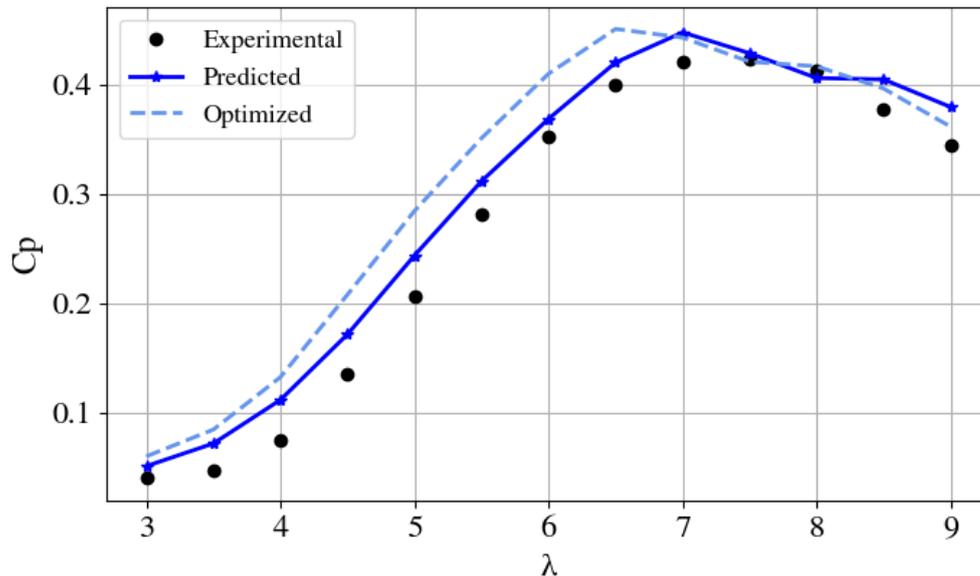


Figure 4. Power coefficient curve comparison between optimized, previously predicted and original G1 turbine.

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