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Aerodynamic Optimization of a Wind Turbine Blade for Maximum Annual Energy Production at Manjil Wind Farm

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To keep pace with current trends in the wind industry, this paper aims at the improvement of the annual energy production of a horizontal axis wind turbine by aerodynamic optimization of blades at the wind conditions of the Manjil site. To achieve this goal, the Riso wind turbine, whose characteristics are publicly available, is selected, and its twist angle and chord length distributions along the blades are optimized. The blade element momentum theory with appropriate corrections is used to predict the turbine output power. The genetic algorithm optimization tool and Weibull probability density function for wind regime representation are also utilized in this work. Optimization results show 9.4% and 11.6% increase in the annual energy production, for the blade with optimal twist angle and the blade with optimal chord length and twist angle distributions, respectively. Finally, the superiority of selecting annual energy production as the objective function is assessed in comparison with other objective functions.

Keywords: blade element momentum theory, genetic algorithm, Manjil wind farm, Weibull distribution, wind turbine optimization.

Nomenclature

Latin letters

a	Axial induction factor
a'	Angular induction factor
A	Weibull scale parameter [m/s]
B	Number of wind turbine blades
c	Blade chord [m]
C_d	Airfoil drag coefficient
C_l	Airfoil lift coefficient
F	Tip loss factor
F_D	Drag force [N]
F_L	Lift force [N]
F_N	Normal force [N]
F_T	Tangential force [N]
R	Blade radius [m]
T	Thrust force [N]
U	Free-stream wind speed [m/s]
U_{rel}	Relative wind speed [m/s]
z	Height [m]
k	Weibull shape parameter
r	Radial position [m]
Q	Torque [N.m]

Greek Symbols

α	Angle of attack [deg.], power-law exponent
θ	Twist angle [deg.]
ρ	Air density [kg/m^3]
φ	Flow angle [deg.]
Ω	Wind turbine rotational speed [rpm]

Abbreviations

AEP	Annual energy production [MWh]
BEM	Blade element momentum
GA	Genetic algorithm
WT	Wind turbine

Introduction

As today most nations struggle with energy problems, countries are attracted more than ever before to renewable energies, asking scientists to develop more efficient ways of utilizing them. No doubt, once renewable energies win the price competition over fossil fuels, they will replace conventional energy sources; since, besides their environmental problems, their price is also growing. The most widely used renewables are hydropower, wind power, and solar, in order of decreasing share in world energy supply. In 2018, renewables, excluding hydro, made a 4% share of world energy consumption. In Iran, as of 2018, renewables, including hydro, made a share of 0.87% in

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the country’s energy supply, and from that amount, 0.84% belonged to hydro, solely [1]. This happens while Iran has enormous wind energy potentials, especially at the Manjil site [2].

The challenge in wind energy development is making its cost comparable with that of other energy sources, especially fossil fuels. For wind, the cost of energy is found by summing WT cost, transportation, installation, and maintenance costs, and dividing that value by the produced power [3]. Therefore, one way of reducing the cost of wind energy is to maximize power production, and because of the natural behavior of wind differing from one location to another, wind turbines must be designed optimally for every specific site to maximize power.

This paper tries to modify an existing WT design and propose an optimum turbine whose output power supersedes all other designs of similar configurations and sizes for the Manjil site in the north of Iran. The proposed turbine aims to harvest the maximum possible amount of annual energy at the minimum design costs. To achieve this goal, the well-known Riso WT, designed by Riso laboratories in Denmark, is modified by a genetic algorithm seeking maximum AEP in Manjil. Twist and chord distributions along the blade are regarded as design variables. Meanwhile, the blade element momentum theory assists the output power estimation of candidate optimum wind turbines.

In 2006, Méndez and Greiner performed an optimization of twist angle and chord length distributions of the Riso WT blade. Using GA as the optimization tool and setting its objective function to annual energy yield, they improved it by 2.66% W.R.T initial Riso WT. They used BEM as the turbine power output computation engine [4]. In 2008, Ceyhan optimized chord length and twist angle distributions of the Riso WT, and also performed blade profiles optimization by selecting the most suitable airfoil from a family of collected airfoils for the same WT. In doing so, Ceyhan used BEM and GA; the objective function was power production at some specific wind speed, and 40-80% improvement was gained depending on the optimization variables [5]. Polat and Tuncer in 2013, based on GA and BEM, optimized the aerodynamic shape of a 1 [MW] WT. Shape variables were sectional chord length, twist angle, and blade profiles at the root, mid, and tip of the blade. Their work resulted in a 10% increase in power production at the speed of 10 [m/s] [6]. Combining BEM with an algorithm that seeks the pitch angle distribution whose power extraction at the installation site is to the maximum, Sharifi and Nobari in 2013 proposed five optimum pitch angle distributions for five different representative sites. On one sample WT, they gained a 2.1-58.9% boost in electrical power for those five sites [7]. In 2013, Mirghaed and Roshandel optimized some wind turbine parameters, including hub height, tip speed ratio, rotor diameter, and generator capacity, using BEM and an iterative optimization algorithm. Performing optimization for three sites of Manjil, Ahar, and Khaf in Iran, they obtained three different turbines with optimum size parameters for those sites. Although their work is regarded as an attempt at optimization for Iran wind conditions, they merely proposed size parameters of the turbines, and no specific turbine was optimized [8]. Kaviani and Nejat, in 2017, carried out aeroacoustic and aerodynamic optimization of a WT using multi-objective particle swarm optimization algorithm and BEM. They optimized blade twist and chord distributions, section profiles, and rotational speed of the selected WT. Their results showed a 6% power increase and 1 [dB] noise decrease [9]. In 2019, Yang et al. performed integrated aero-structural optimization of a 2.1 [MW] commercial WT using BEM and airfoil integrated theory. Using particle swarm optimization algorithm, they succeeded in increasing the AEP of the selected turbine by 7.96% by changing airfoil profiles, chord, and twist distributions along the blade [10].

Although optimization attempts have been discussion topics of various papers for the rest of the world, as reviewed previously, there has not been such an attempt in Iran for Manjil, especially one optimizing with the least costs, proposing the least changes while maximizing the AEP.

The wind energy industry in Iran is at the beginning of its way, and almost all current operational turbines are imported from other countries whose design constraints did not take account of specific wind conditions in Iran. To go further in the way of developing wind energy extraction in Iran, instead of starting to design from scratch, which requires plenty amount of time and trial and error, and also increases expenses, WT manufacturers can start at globally known designs, and try to optimize them for Iran wind metrics. This optimization can become complicated and expensive by including many design parameters, like structures or acoustics, or can be simple yet efficient by reducing those variables while giving a handy measure on extracting the maximum possible amount of energy with currently available WT designs and least changes. This paper tries to convince WT manufacturers in Iran that by performing minor modifications to the current turbines, with the minimum computational cost and geometry modifications, they can harness much more energy. To achieve this goal, the Manjil site whose wind conditions are well-proved to be suitable for WT installation is selected, and one publicly available wind turbine, i.e., the Riso turbine, is optimized for having the most suitable twist angle and chord length distributions to extract the maximum amount of energy at the Manjil site.

This paper starts with a description of the Riso WT, continues with mathematical tools used, including BEM and multiple corrections applied on it, Weibull probability density function, and genetic algorithm. Then performs two main optimization attempts with maximizing AEP as the objective function; one optimizes twist angle distribution, and the other optimizes both twist angle and chord distributions along the blade. At last, two other optimization cases, with power production in Manjil at the most probable wind speed and the average wind speed, are performed, and their corresponding AEP value is compared with the AEP of the main optimization case.

Baseline wind turbine

In this study, the known Riso WT is selected as the initial design to be optimized for Manjil. It is well described in the famed and beneficial ECN annexes xiv [11] and xviii [12] databases: It is a 3 blade stall regulated horizontal axis wind turbine with upwind rotor, tapered and twisted blades, a hub height of 30 [m], and the rotor diameter is 19 [m]. The profiled blade section starts at a radius of 2.7 [m] with NACA 63-225 airfoil to a radius of 9.5 [m] using NACA 63-212 airfoil. The nominal power of the Riso turbine is 100 [kW]. Cut-in wind speed is 4 [m/s], cut-out is assumed to be 25 [m/s], and rotational speed is 47.5 [rpm]. The field measured power curve of Riso WT is presented in annexes xiv or xviii, and validation of some existing BEM codes against measurements is investigated in [4] and [5].

Mathematical modeling and tools

This section tries to give a short review of mathematical tools used; they include the blade element momentum theory and its validation against experimental measurements, Weibull distribution for the annual energy production calculation, and the genetic algorithm optimization tool.

Blade element momentum theory

When it comes to the performance calculation of wind turbines, the blade element momentum theory is a widely accepted method. Assuming that working meteorological conditions and also the geometry of the turbine are known, BEM can predict the performance of the turbine accurately. More on BEM can be found in [13], but here, for the sake of conciseness, only a summary of BEM fundamentals and formulations are given.
BEM method combines blade element and momentum theories. Blade element theory analyses the forces on separate sections along the blade as a function of geometry, and momentum theory balances the forces on a rotating annular stream tube using the actuator disk concept. By combining separately obtained forces and moments from those two methods, velocities and induction factors at the blade will be obtained, leading to turbine overall thrust and torque calculations. The current paper sticks to classical BEM theory, along with common corrections, as described in [13] and [14].
The rotor induces two velocities in the flow, one axial and one tangential. The axial velocity component equals aU in the opposite direction of the free stream, and the angular component equals $a'\Omega r$ in the opposite direction of rotor rotation, where r denotes some radial position along the blade; a and a' are known as axial and angular induction factors, respectively. Thus, the overall axial velocity of the rotor becomes $U(1-a)$, and the overall rotational component is the vector sum of blade section velocity, Ωr, and angular component, $a'\Omega r$. The blade section geometry and its variables are shown in figure 1.
Blade element theory defines the differential normal and tangential forces on a section at some radial position of r as:

$$dF_N = (1/2)B\rho U_{rel}^2(C_l cos\varphi + C_d sin\varphi)cdr \qquad (1)$$

$$dF_T = (1/2)B\rho U_{rel}^2(C_l sin\varphi - C_d cos\varphi)cdr (2)$$

On the other hand, momentum theory gives the differential contribution of each section to the overall thrust and torque as:

$$dT = 4F\rho U^2 a(1-a)\pi r dr \qquad (3)$$

$$dQ = 4F\rho U a'(1-a)\pi r^3 \Omega dr \qquad (4)$$

Where F is known as the Prandtl tip loss factor, whose role is simulating airflow from blade pressure side to suction side at the tip, and thus reducing power production, as well as accounting for the finite number of blades. Prandtl tip loss factor is given by:

$$F = (2/\pi)cos^{-1}\left[exp\left(-\left\{\frac{(B/2)[1-(r/R)]}{(r/R)sin\varphi}\right\}\right)\right] \quad (5)$$

By equating differential normal forces and thrusts from blade element and momentum theories, equations (1) and (3), and solving for a, the following formula for axial induction factor is obtained:

$$a = \frac{1}{\frac{4F sin^2\varphi}{(Bc/2\pi r)(C_l cos\varphi + C_d sin\varphi)}+1} \qquad (6)$$

By first multiplying equation (2) with r, to yield differential torque, and comparing it with the equation (4), angular induction factor is found to be:

$$a' = \frac{1}{\frac{4F sin\varphi cos\varphi}{(Bc/2\pi r)(C_l sin\varphi - C_d cos\varphi)}+1} \qquad (7)$$

Because of interdependencies among BEM variables, the problem becomes implicit; thus, equations **Error! Reference source not found.** and (7) must be solved iteratively. This paper uses an iterative code developed in FORTRAN, which after convergence of induction factors for all sections along the blade, calculates forces and moments using numerical integration. Convergence check is set to be the sum of change of both induction factors W.R.T past iteration equal or less than $1e^{-6}$. During this iteration process, lift and drag coefficients for all sections along the blade are needed, which are provided from experimental measurements for the interval of $[0^{\circ}, 90^{\circ}]$ in the annex xviii [12]. The iterative solver also needs aerodynamic coefficients at some negative angles of attack, $[-6^{\circ}, 0^{\circ}]$, which were obtained from XFOIL solver [15].

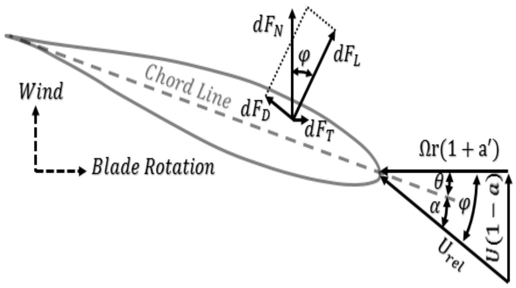

Figure 1: Blade section geometry and related variables.

BEM theory modifications

The simplicity of BEM suggests some inherent limitations, and hence, to overcome those, there are some modifications introduced into BEM equations to make it more practical. At high values of the axial induction factor, the equation (3) is not valid anymore; this is known as the momentum theory break down, and there are some empirical relations available in the literature to counteract it. One such famous relation is known as the high thrust correction model of Spera [14]; when the axial induction factor from equation **Error! Reference source not found.** exceeds a particular value of $a_c = 0.2$, the following formula is used for axial induction factor calculation instead:

$$a = 1 + (1/2)[K(1-2a_c)] - (1/2)\left[\sqrt{(K(1-2a_c)+2)^2 + (4Ka_c^2 - 1)}\right]$$
$$K = \frac{4F\sin^2\varphi}{(Bc/2\pi r)(C_l\cos\varphi + C_d\sin\varphi)} \tag{8}$$

As [14] recommends, the following formula is used instead of eq. (7) for angular induction factor:

$$a' = (1/2)\left[\sqrt{1 + \frac{4a(1-a)}{(r\Omega/U)^2}}\right] \tag{9}$$

BEM code validation

In nature, BEM theory breaks each blade into some sections or strips, and that is why it is sometimes referred to as strip theory [13]. All geometric and aerodynamic variables must be provided for each strip along the blade. Simpler blade geometries need a smaller number of strips, and as the blade becomes more complex, in terms of twist and chord distributions, the number of strips must be increased for BEM to yield accurate results. After some trial and error regarding output power accuracy and computation time, this paper uses 39 strips along the Riso WT blade, and their corresponding data are interpolated from what is initially given in annex xviii [12]. Comparison of current BEM code versus experimental data of output power, and also two other existing BEM codes of Mendez and Greiner [4], and Ceyhan [5], is plotted in figure 2; current BEM results agree with experimental data satisfactorily, and thus, current BEM code can function as a turbine power estimator for optimization process whose input is blade geometry, more specifically, blade twist angle and chord length distributions.

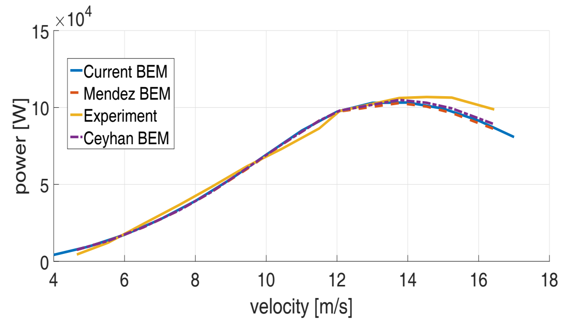

Figure 2: Comparing output power prediction of current BEM code with experimental results and two other BEM codes.

Annual energy production calculation

The most accepted method of representing wind regime in a specific area is the Weibull probability density function, given by:

$$h_W(U_0) = (k/A)(U_0/A)^{k-1}exp(-[U_0/A]^k) \tag{10}$$

Where $A[m/s]$ is the Weibull scale parameter, mainly dependent on the average wind speed, and k is the non-dimensional shape parameter. Both parameters are specific to each site and must be obtained empirically. Using equation (10), the probability that the speed U_0 lies within the interval $[U_i, U_{i+1}]$ is:

$$f(U_i < U_0 < U_{i+1}) = exp(-[U_i/A]^k) - exp(-[U_{i+1}/A]^k) \tag{11}$$

Once the Weibull parameters are estimated empirically, the turbine annual energy yield is obtained by:

$$AEP = (8760)(1/2)\sum_{i=1}^{N-1}[P(U_{i+1}) + P(U_i)]f(U_i < U_0 < U_{i+1}) \tag{12}$$

Where $P(U_i)$ is the turbine power at speed U_i and 8760 is the number of hours in a year [16].

Genetic algorithm optimization tool

In the 1950s and 60s, several computer engineers separately started to investigate evolutionary systems; the motivation behind it was to use evolution as an optimization tool and, in the way of doing so, to promote candidate solutions of a problem by natural selection and genetic variation. This led to the birth of the genetic algorithm by John Holland and his students and colleagues at the University of Michigan in the 1960s. GA relies on some operators to evolve individual solutions over many generations; these are selection, cross-over, and mutation [17].

As was stated earlier, BEM theory equations are complex, and providing the optimization method with derivative of objective function (AEP in this case) W.R.T design variables (blade twist and chord distributions) gets complicated and almost impossible; thus, traditional gradient-based optimizers cannot be applied to WT blade optimization problem. WT optimization algorithm must seek within a large number of possible solutions to find the global optimum and not to get trapped by local optima, and among known methods of optimization, GA is proved to be suitable for WT applications. GA can deal with many continuous variables and find the global optimum without even an initial design point [18], [19].

This paper relies on the genetic algorithm available in the optimization toolbox of MATLAB, release R2016b [20], and the BEM code in FORTRAN is coupled to MATLAB GA via MEX filing. The computation algorithm follows the flow chart of figure 3. Convergence check is function tolerance, as described in [20]. The objective function is set as minus of AEP since the MATLAB GA tool can only operate as a minimizer.

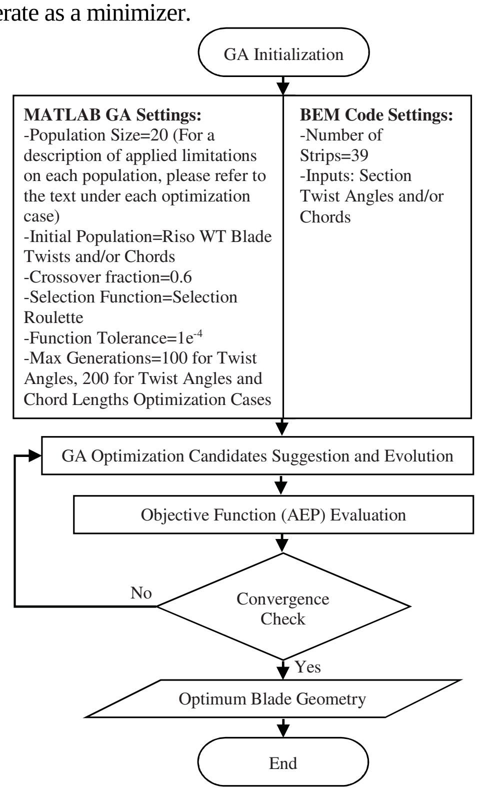

Figure 3: Algorithm of GA optimization and BEM coupling.

Manjil wind site

Manjil city, located in Gilan Province, north of Iran, at $N36^{\circ}41'42''$- $N36^{\circ}45'18''$and $E49^{\circ}23'6''$- $E49^{\circ}31'48''$, is one of the most globally suitable wind sites. Manjil average wind speed in fall and winter is about 6 [m/s], and in spring and summer reaches as high as 14 [m/s], at the height of 40 [m]. Thus, it is regarded as a high potential for installing wind turbines [2]. Currently, Manjil has the largest number of wind turbines installed in Iran. The wind map of Iran at 40 [m] is shown in figure 4, and the Manjil site is bolded on it. For Manjil, Weibull parameters of wind data are available at the height of 40 [m] in [8], and when interpolated to the hub height of Riso WT, i.e., 30 [m], the result is $A = 10.8036$, $k = 1.943$, which is plotted in figure 5.

For Weibull scale parameter interpolation, the power law is used as [21]:

$$U_z = U_r(z/z_r)^{\alpha} \quad (13)$$

At which U_z is the wind speed at height z, U_r is the measured wind speed at the height z_r and α is the power-law exponent; here, $\alpha = 0.15$ was accepted. For Weibull shape factor interpolation, the following empirical formula is used [22]:

$$k_z = k_r \left[\left\{ 1 - c ln \left(\frac{z_r}{z_{ref}} \right) \right\} \Big/ \left\{ 1 - c ln \left(\frac{z}{z_{ref}} \right) \right\} \right] \quad (14)$$

Where k_z is the shape parameter at height z, k_r is the shape parameter at height z_r, and $z_{ref} = 10\ [m]$, $c = 0.088$ are constants.

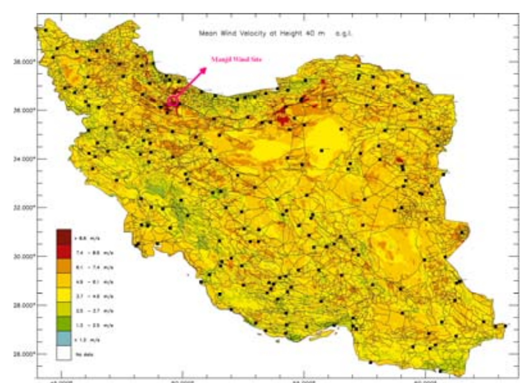

Figure 4: Iran wind map at 40 [m] height, with the Manjil site bolded on it.

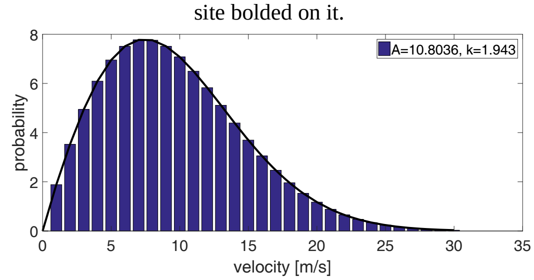

Figure 5: Weibull plot representing wind regime at Manjil site.

Optimization results

After running the MATLAB GA tool nine times on each optimization case, and making sure they all arrive at the same verified solution, one of them with smoother twist and chord distributions is chosen as the final solution. First, twist angle distribution along the blade is optimized, and then, twist angle and chord distributions are optimized; in both cases, the objective function is maximum AEP. Then, by performing two similar optimizations but with different objective functions, one for the average wind speed in Manjil and the other for the most probable wind speed and a common objective function of output power at those speeds, and comparing AEP of all cases, maximizing AEP is verified as the most suitable objective function.

Twist angle distribution optimization

Aimed at maximizing AEP in Manjil, the GA optimization process starts with the Riso WT twist distribution as the initial population and promotes possible solutions on five section twists as design variables; they must lie within the interval of $-20^{\circ} \leq \theta(r) \leq +30^{\circ}$, a range wide-enough for all probable solutions, and additionally, they must decrease from the root to the tip, or $\theta(r_{i+1}) \leq \theta(r_i)$, which omits meaningless solutions. Optimization follows the flow chart of figure 3, and more on GA settings parameters is also provided in the same figure. It is worth noting that for obtaining a smooth distribution of twist distribution along the blade, GA design parameters are selected as five twist angles.

As the result, 9.4% optimization in AEP is gained, i.e., from 440.66 [MWh] of the Riso WT to 482.14 [MWh] of the Manjil optimum. A graph of GA convergence is shown in figure 6, showing that GA has converged after almost 60 iterations. Optimum twist angle distribution along the blade is plotted in figure 7, pointing that the Manjil optimum blade has a higher range of twist angles compared to the initial Riso blade; the reason being the high wind speed range in Manjil.

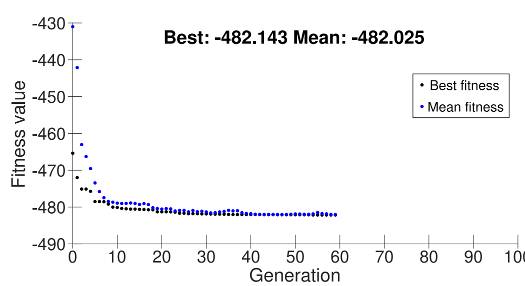

Figure 6: GA convergence graph for twist angle distribution optimization.

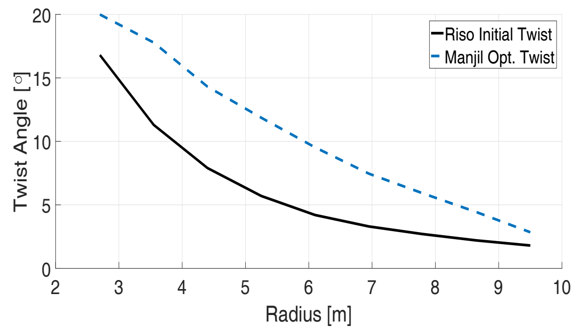

Figure 7: Optimal twist angle distribution along the blade for the Manjil site.

Chord length and twist angle distribution optimization

While twist angle optimization settings are set the same as previous section, GA is set to find optimum chords in the interval of $(1-\delta_c)c_0(r) \leq c(r) \leq (1+\delta_c)c_0(r)$, where $c_0(r)$ is the Riso WT chord distribution, and $\delta_c = 0.1$ is constant, as advised in [4]. Two constraints are imposed on candidate chord solutions: $c(r_{i+1}) \leq c(r_i)$ and $\int c(r)dr = (1/2)\sum(c_{i+1}+c_i)(r_{i+1}-r_i) \leq A_0$; the former ensures chords decrease from the root to the tip, and the latter sets blade area of candidate solutions equal to, or smaller than, the initial Riso WT blade area; this constraint, while allows for minor changes to increase AEP, also makes optimum blade chords as much similar as possible to the initial chord, in order to prevent structural failure. GA design parameters are selected as five twist angles and five chord lengths along the blade for a smoother distribution.

After convergence of GA after almost 130 iterations, as plotted in figure 8, AEP is improved over 11.6%, from 440.66 [MWh] to 492.10 [MWh]. Optimal twist angle and chord length distributions are plotted in figures 9 and 10, respectively. Optimal twist angle distribution closely resembles the results obtained in the previous section and plotted in figure 7, which is of no surprise; however, by comparing optimization percentages of the two cases quantitatively, almost 2.2% increase, i.e., from 9.4% to 11.6%, is solely gained by chord length distribution variation, which proves the importance of blade shape in wind turbine blade designs. Optimal chord length remains similar to the initial design of Riso WT, mainly because of strict constraints applied to it, and it tends to increase the blade area on the outer part of the blade to gain more power.

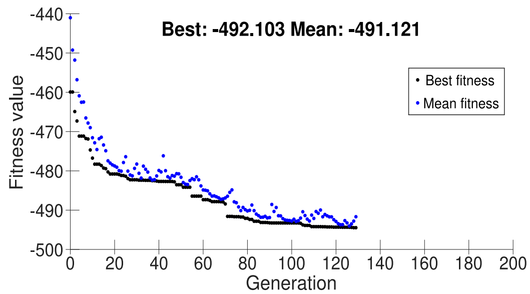

Figure 8: GA convergence graph for chord and twist angle distributions optimization.

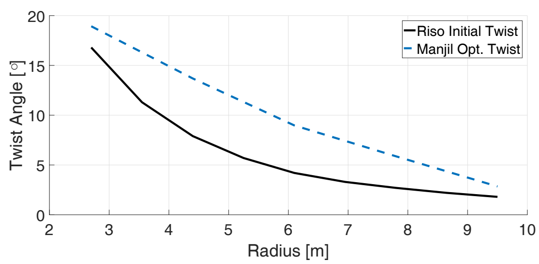

Figure 9: Optimal twist angle distribution along the blade for Manjil site, obtained from chord length and twist angle distribution optimization case.

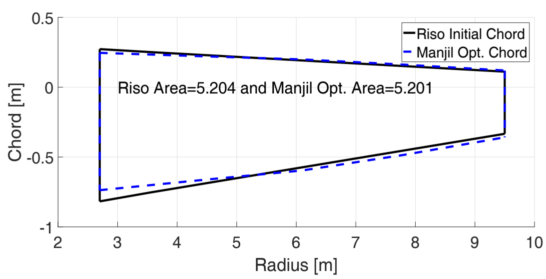

Figure 10: Blade shape and optimal chord length distribution along the blade for the Manjil site.

Objective function verification

Although the current paper deals with maximizing AEP as the optimization objective function; nevertheless, it must be verified to be the best possible solution. Therefore, in addition to AEP maximization attempts previously performed, two other extra optimization cases are proposed and assessed. One sets turbine output power at the most probable wind speed of Manjil, 7 [m/s], as GA objective function, and the other focuses on power at the mean wind speed of Manjil, 9.5 [m/s]. After successful convergence of the two other optimization cases, the corresponding value of AEP is calculated based on the geometry of the turbine obtained. Table 1 summarizes the results. Chord length distribution for different objective functions resembles the same as previous section, since the chord distribution along the blade is highly constrained by GA, but twist angles show significant differences, emphasizing the importance of selecting the appropriate objective function in GA. A plot comparing twist angles for different objective functions is drawn in figure 11. Now it is proved that optimizing a blade at a single speed does not guarantee maximum annual energy output, but other variables, including the range of wind speeds in a site, and of more significance, the probability of occurrence of those speeds must be taken into account; which is the case when optimizing for maximum AEP.

Table 1: AEP results of optimization with different objective functions.

Optimization case	Initial Riso	Max. power at 7 [m/s]	Max. power at 9.5 [m/s]	Max. AEP
AEP [MWh]	440.66	326.31	348.04	492.10

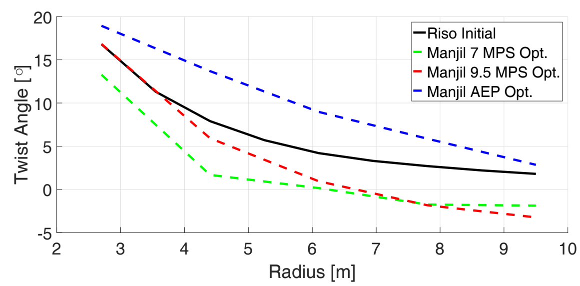

Figure 11: comparison of different twist angle distributions obtained for different objective functions in GA.

Conclusions

In this work, the geometric parameters of the Riso wind turbine blade, including twist angle and chord length distributions, have been optimized for maximizing the annual energy production at the Manjil wind farm in the north of Iran. It was an attempt to prove the idea that by making simple and cheap modifications to wind turbine blades optimal for each site, countries can harvest the maximum possible amount of energy and thus, reduce energy prices by making more of it.

This paper relies on a modified blade element momentum theory, which predicts output power of the Riso wind turbine satisfactorily, and when combined with the genetic algorithm for optimization and Weibull distribution for wind representation, it makes a robust tool for wind turbine blade optimization problems. Results show 9.4% and 11.6% improvements in the annual energy production, respectively, for the blade with optimal twist angle distribution and the blade with both optimal chord length and twist angle distributions. Finally, some extra optimization cases were carried out to maximize the output power at the most probable and the mean wind speeds at the Manjil site. But they both lag the results of optimizing for the maximum annual energy production. Thus, it was proved that in the process of optimizing wind turbines, not only wind ranges of a specific region, but also the probability of occurrence of each wind speed must be correctly accounted for, and this is achieved when the maximum annual energy production is used as the objective function.

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