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A MULTIOBJECTIVE AERODYNAMIC OPTIMIZATION OF A MICRO SCALE VERTICAL AXIS WIND TURBINE

Hakan Usanmaz [1]
Yeditepe University
Istanbul, Turkey

Emre Alpman [2]
Marmara University
Istanbul, Turkey

ABSTRACT
This study contains a two-objective aerodynamic optimization of a small scale vertical axis wind turbine. The design variables are the helix angle of the blades, and height and the radius of the rotor. The optimizations are performed to obtain maximum power prediction at low torque ripple amplitude. These objectives are computed using the open source wind turbine design and analysis code QBlade while the optimizations are performed using an NSGA-II algorithm code. During the optimizations objective function predictions are performed with Ordinary Kriging meta model which uses a database generated using QBlade. The optimization parameters for the database are created via the Latin Hypercube Sampling. Comparing the performances of different Pareto optimum designs shows that a multiobjective optimization approach is necessary in order to obtain design which could sufficiently satisfy both objectives.

INTRODUCTION
The idea of "producing clean energy where it is needed" paved the way for the use of small or micro-scale turbines (blade radius and rated power not exceeding 1.5m and 0.5 kW, respectively [Wood, 2011].) that can be used on top of the buildings in the urban environments. However, the wind turbines placed in urban environments may be subjected to winds with varying directions [Kalidelis, et al. 2012; Cace et al, 2007]. In a vertical axis wind turbine (VAWT) the blades rotate in a direction perpendicular to the oncoming wind speed. This basic design allows them to accept wind from any direction therefore; they do not suffer from yawing error as the horizontal axis wind turbines do [Paraschivoiou, 2002]. Also they allow the generator and gearbox located close to the ground [Eriksson et al. 2008]. However, the blades of a VAWT are subject to unsteady angle of attack even when they operate in steady wind conditions [Paraschivoiou, 2002]. As a result, huge variations in the torque produced (torque ripple) may be experienced [Paraschivoiou, 1983]. This issue may be addressed by sweeping the blades of the turbine [McIntosh and Babinsky, 2009].

[1] Student, Mechanical Engineering Department, Email:0216.hakan@gmail.com
[2] Associate Professor, Mechanical Engirneering Department, Email: emre.alpman@marmara.edu.tr

This paper includes a multi objective aerodynamic optimization of a micro-scale vertical axis wind turbine with helically swept blades. The design parameters will be helix angle, rotor height and the rotor radius. This way, in addition to the helix angle, the aspect ratio of the blades, rotor solidity and tip speed ratio would also be controlled. The cross section of the blades will be constructed using the CLARK Y 11.7% smoothed airfoil [https://m-selig.ae.illinois.edu/ads/coord_database.html]. Although this airfoil is basically designed for general aviation purposes, it is selected in this study due to its relatively smooth stall characteristics. Also the airfoil has a nearly flat lower surface which may be advantageous for manufacturing purposes [http://wikivisually.com/wiki/Clark –Y].

In the many of the previous VAWT design and optimization studies [Carrigan et.al, 2012; Castillo, 2011; Bedon and Benini, 2017], the major purpose was to maximize the steady torque (or power) without considering the torque ripple which may have serious negative effects on the drive train and the generator [Bati and Luk, 2015]. Therefore, in this study, the aerodynamic optimization seeks to maximize the average power produced while minimizing the torque ripple. For this purpose, blade helix angle, rotor height and rotor radius were selected as the optimization parameters while the chord length and airfoil sections of the blades were kept constant. The resulting two objective optimization problem is solved using a genetic algorithm which is very suitable for such multiobjective optimization problems with complex design spaces [Deb et.al. 2002].

METHODOLOGY

Two-objective optimization studies are performed for micro-scale VAWTs which seeks to maximize the average power produced while minimizing the torque ripple. The resulting optimization problem was solved using the fast and elitist non-dominated sorting genetic algorithm NSGA-II [Deb et.al. 2002], which is considered to be one of the state of the art genetic algorithms for multiobjective optimization. For this purpose an NSGA-II Matlab code developed by Mostapha Kalami Heris [http://yarpiz.com/56/ypea120-nsga2] is modified to accept the fitness function values from an outside source. Since the code aims to minimize the objectives, the amount of the torque ripple and the reciprocal of the average power are selected as the fitness functions. The rotor height and radius, and the helix angle of the blades are selected as optimization parameters. In order to select suitable ranges for the values of these parameters, geometric data of some of the existing small scale VAWTS are considered. [Castillo, 2011, Table 8]. According to this, the rotor height changes between 2.5m and 4m, the rotor radius changes between 1.5m and 2.5m and finally the helix angle changes between 0° and 60°. The population size is set to be 50 and optimizations were performed for 5000 generations

The average power and the amount of torque ripple for a selected geometry are calculated using the open source wind turbine design and analysis code QBlade. [http://q-blade.org/]. This code can perform unsteady aerodynamics simulations for VAWTs using a nonlinear lifting line model [Marten et.al., 2015]. Here, unsteady predictions were performed until a quasi-steady condition where the average power becomes constant is reached.

Although QBlade can give quick predictions for a selected geometry, running this software for every member of the population for each generation would be time consuming. Therefore, fitness function predictions are performed using a meta model like a response surface [Cavazzuti, 2013]. A database, created using a design of experiment method, is needed for this purpose. In this study the database is created using Latin Hypercube Sampling methodology [Cavazzuti, 2013]. The number of elements in the database was selected to be 35 which is the number of experiments required to construct a cubic response surface for three design variables (See .Table 3.1 of [Cavazzuti, 2013]). The resulting helix angle (theta), rotor height (length) and rotor radius are listed in Table 1along with the corresponding blade aspect ratio and solidity.

Table 1. Design Parameters of the elements of the database

Profile number	Theta	Lenght	Radius	Aspect ratio	Solidity ratio
1	45.5825	3.8405	2.0139	1.05	0.01
2	43.1584	4.4913	1.9132	0.85	0.01
3	21.4963	3.4775	2.3334	1.34	0.01
4	16.4041	3.7839	2.0894	1.10	0.01
5	48.6473	4.1528	2.1174	1.02	0.01
6	57.0515	3.0626	2.3192	1.51	0.01
7	35.4383	3.1225	1.6003	1.03	0.02
8	56.5666	3.2221	2.0265	1.26	0.01
9	26.8209	3.6592	1.6962	0.93	0.02
10	24.9728	3.211	1.6429	1.02	0.02
11	0.2069	3.5558	2.177	1.22	0.01
12	6.1448	3.4026	1.7466	1.03	0.02
13	17.3938	3.3004	1.8428	1.12	0.02
14	12.9928	3.8602	1.7857	0.93	0.01
15	2.3493	3.7207	2.2322	1.20	0.01
16	27.7248	3.4392	1.6199	0.94	0.02
17	9.158	4.175	2.1861	1.05	0.01
18	7.4871	4.3017	1.7099	0.79	0.01
19	29.3736	4.2061	2.4063	1.14	0.01
20	19.9474	4.0371	2.4602	1.22	0.01
21	11.2944	4.0103	2.0713	1.03	0.01
22	41.8017	3.956	1.8654	0.94	0.01
23	14.7498	4.1004	2.3769	1.16	0.01
24	23.0718	4.3635	2.2681	1.04	0.01
25	54.1042	4.4167	2.1429	0.97	0.01
26	49.9624	3.3618	2.2881	1.36	0.01
27	47.3243	3.9211	1.5376	0.78	0.02
28	59.2425	3.1529	1.9327	1.23	0.02
29	33.7203	3.7455	2.4289	1.30	0.01
30	36.1035	3.6388	2.4839	1.37	0.01
31	31.5249	3.0091	1.9773	1.31	0.02
32	4.2677	3.2668	1.8811	1.15	0.02
33	52.2972	4.4093	1.5618	0.71	0.01
34	39.5321	4.2572	1.5059	0.71	0.01
35	38.5915	3.5809	1.7694	0.99	0.02

The turbine geometries corresponding to the design parameters listed in Table 1 are constructed using QBlade and the corresponding average power and torque ripple values are then calculated. Here all of the designs have three blades. Aerodynamic analyses are performed at the wind speed of 5m/s and at a tip speed ratio of 3. Figure 1 shows the variations of momentary rotor torque (top) and average power (bottom) with respect to time for one of the designs in the database. The simulation is performed for 10 rotor revolutions. It is clear that the averaged power becomes almost constant after about 4 seconds the oscillations are evident in the momentary torque. In this study the reciprocal of the arithmetic average of the average power values obtained after the 6th second is taken as the first objective while the standard deviation of the momentary torque predicted after the 6th second is taken as the second objective. For some of the geometries in the database such quasi-steady conditions were not obtained after 10 rotor revolutions. In those cases the simulations were continued for at least two more seconds, and the average and the standard deviation were computed after the 8th second.

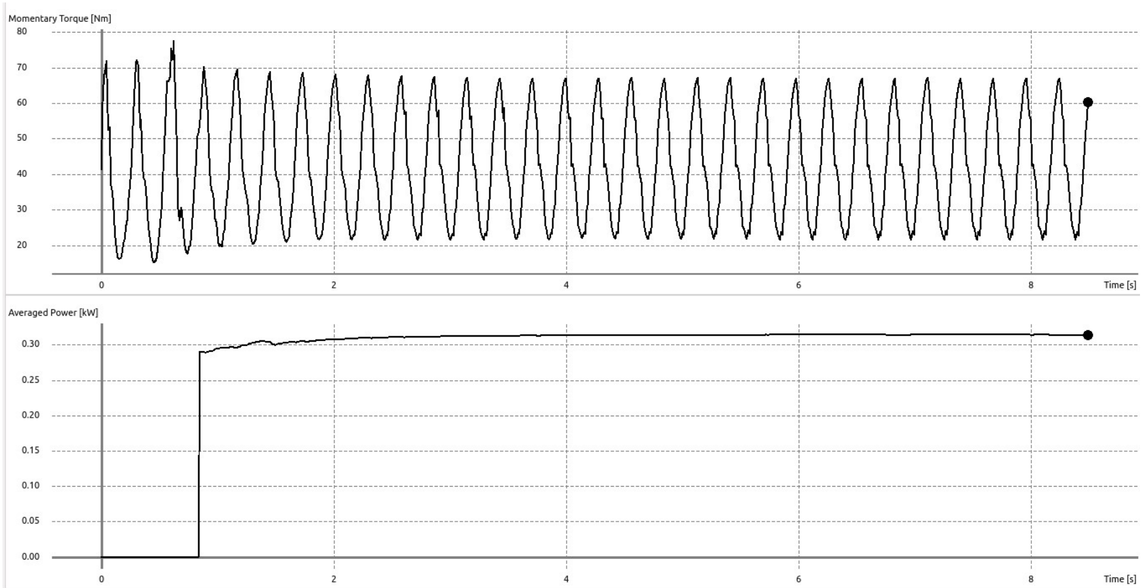


Figure 1. The variation of momentary rotor torque (top) and average power (bottom) with respect to time for one of the designs in the database.

Once the database is complete the NSGA-II code employs the Ordinary Kriging methodology [Cavazzuti, 2013] for fitness function estimations. Here, the Ordinary Kriging method is applied separately for each fitness function. Once the maximum number of generations is reached, a Pareto front consisting of the non-dominated solutions is obtained. Since every point on the Pareto front can be considered as an optimum design one may need to select a specific point for particular turbine geometry. The flowchart of the whole process is displayed in Figure 2.

RESULTS AND DISCUSSION

Using the constructed database consisting of 35 different VAWT designs the resulting NSGA-II code was run for 300 generations for a population size of 50. Figure 3 shows the objective functions of the individuals in the population at different generations. It is clear that there is little or no change between the 200th and the 300th generations. Therefore, the algorithm can be assumed to have converged. Note that all of the individuals of the 100th, 200th, and the final generation are on the Pareto front, hence they are non-dominated

The fitness functions of the individuals on the final Pareto front along with the original database of the 35 individuals are displayed in Figure 4. The improvements in the designs are evident from this figure. However, one can easily see that two of the solutions in the database (marked by red circles) dominate the Pareto front yielded by the optimization code. This is basically due to the prediction error made by the ordinary Kriging method for fitness function evaluations. In order to check the prediction capabilities of this method, the fitness functions of three selected individuals are re-calculated using QBlade. The results are compared in Table 2. These individuals are selected using a weighted summation technique where the weight pairs for the objective functions were (1,0), (0,1) and (0.5, 0.5). In the table “Theta”, “H”, and “R” denote the helix angle, rotor height and rotor radius, respectively. “Error1” and “Error2” percent relative error values for reciprocal of power and torque ripple. The averages of these errors are given in bold face below them. It is clear that there are some differences between the results. Therefore, in an attempt to improve the predictions capabilities of the ordinary Kriging method, these three new QBlade predictions are also added to the database and optimization process is repeated. The prediction comparisons of the similarly selected three individuals are displayed in Table 3. According to this table, increasing the database size by adding individuals decreased the discrepancy between the ordinary Kriging and QBlade predictions. These predictions are also displayed in Figure 5. Although further increasing the database size might improve the predictions of the meta model, the database size of 38 is assumed to be sufficient for ranking purposes by considering the closeness of the solutions especially at the middle point in Figure 5.

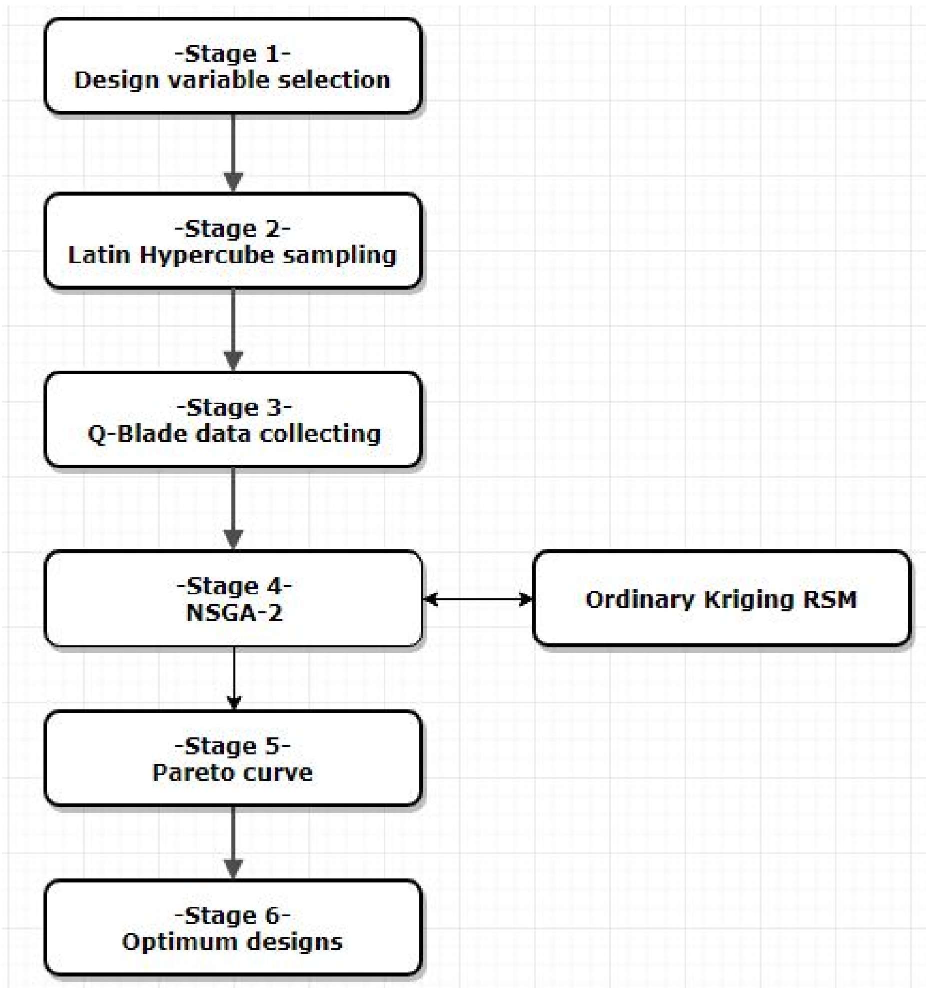


Figure 2. Flowchart of the optimization process

Since any point on a Pareto front can be considered as an optimum solution, one may need to compromise between the objectives to select a particular solution. In this study, for comparisons in Table 2 and 3, this was done using a weighted summation method with three different weight pairs. In fact, the design shown in the first row of Table 3 yields maximum power, the one in the second row yields minimum torque ripple, and the design in the third row can be considered as an optimum solution which assumes that both objectives has equal importance. It is clear from Table 3 that increasing the blade helix angle successfully decreases the amount of the torque ripple. However, it is also evident that if one wants to optimize the geometry for maximum power production, then the resulting design may yield a lot of torque ripple. Also trying to decrease torque ripple alone may lead to turbines with poor power generation. Therefore, it is necessary to use a multiobjective optimization technique in order to produce maximum possible power at low torque ripple. Conceptual views of these selected turbines can be seen from Figure 6. Unsteady power predictions for these three selected designs obtained using QBlade are displayed in Figure 7. Predictions are plotted for 10 rotor revolutions. It is clear that the first design yields a high average power at the expense of high torque ripple while the second design does the opposite. The third design tries to find an optimum solution by compromising between these objective functions.

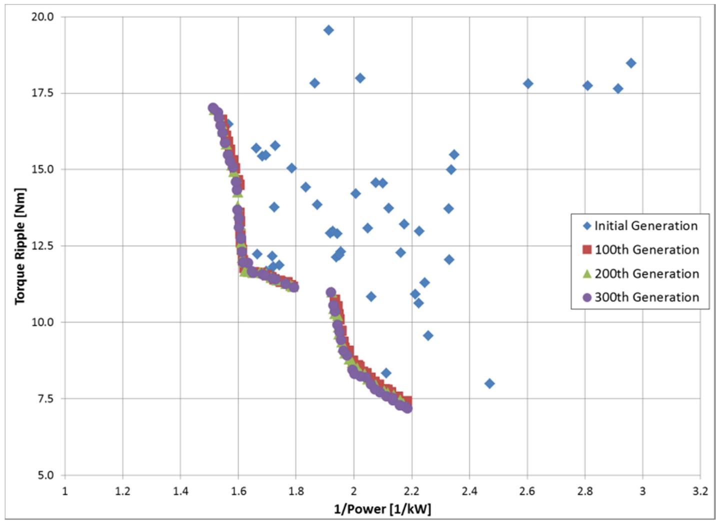


Figure 3. Objective functions of the individuals in the population at different generations

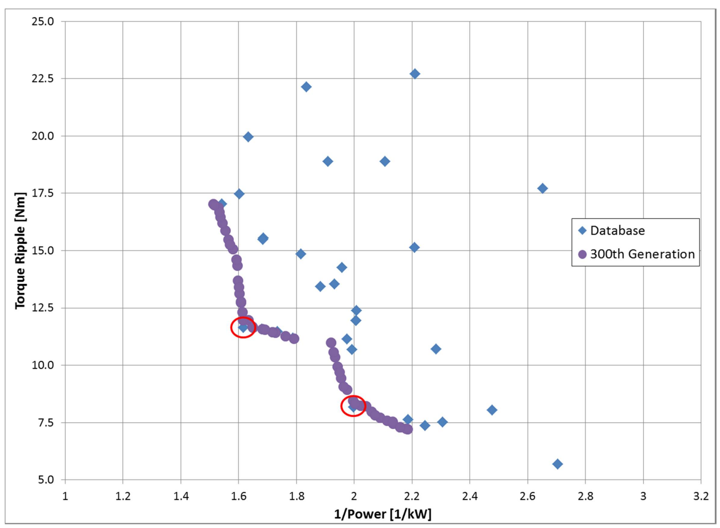


Figure 4. The fitness functions of the individuals in the database and the final Pareto front

Table 2. Comparison of QBlade and Ordinary Kriging predictions

Theta	H	R	1/P (Kri)	Ripple (Kri)	1/P (QB)	Ripple (QB)	Error1 (%)	Error2 (%)
23.0293	4.4743	2.2521	1.5119	17.0232	1.47809443	17.1108621	2.287105	0.512319
38.8461	3.5473	1.5946	2.1854	7.1983	2.32018561	7.0914881	5.80926	1.506199
11.1559	3.9408	2.0371	1.6501	11.628	1.5536391	16.3664113	6.208707	28.95205
							4.768357	**10.32352**

Table 3. Comparison of QBlade and Ordinary Kriging predictions for the enlarged database

Theta	H	R	1/P (Kri)	Ripple (Kri)	1/P (QB)	Ripple (QB)	Error1 (%)	Error2 (%)
23.0109	4.5	2.2898	1.4759	17.1742	1.46757022	18.2391183	0.56759	5.83865
38.8569	3.6018	1.5782	2.2965	7.1336	2.31515471	6.5774875	0.805765	8.454786
11.2355	4.0334	2.068	1.6159	11.7486	1.60483007	11.7454744	0.689788	0.026611
							0.687714	**4.773349**

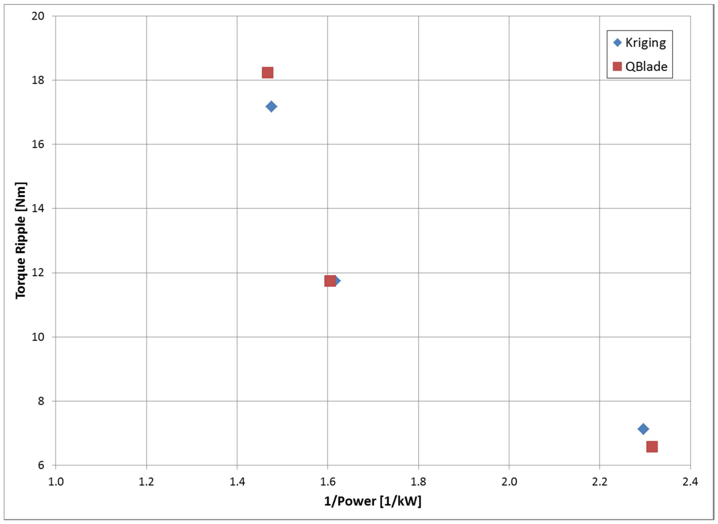
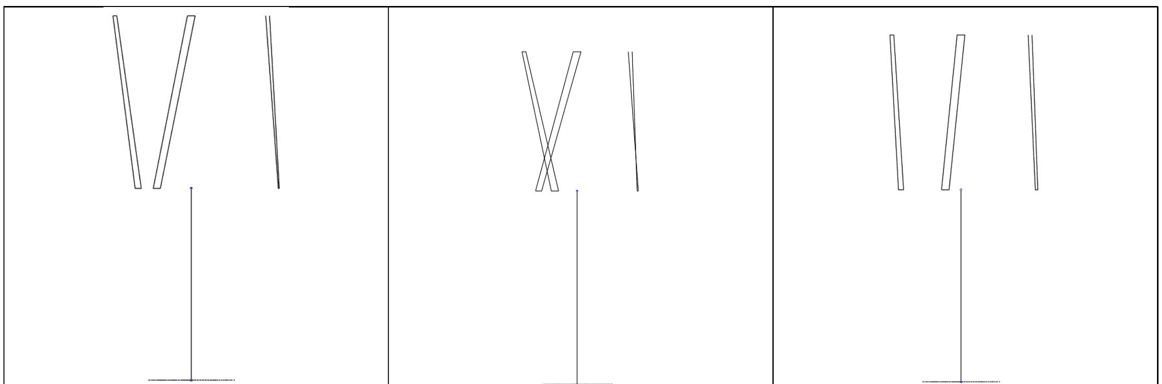
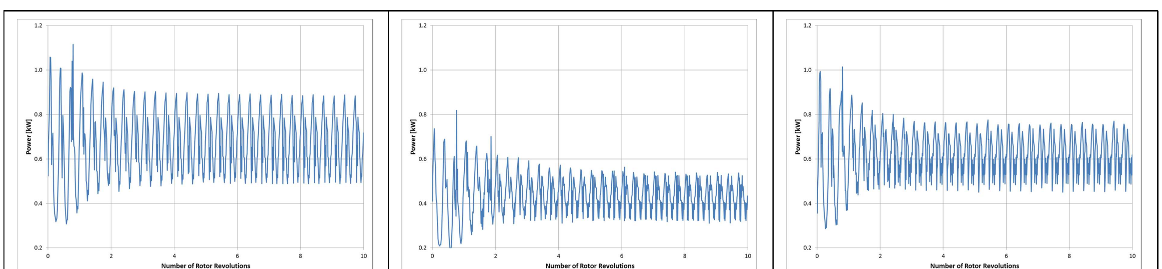


Figure 5. Comparison of QBlade and Ordinary Kriging fitness function predictions



Maximum Power	Minimum Ripple	Optimum

Figure 6. Conceptual views of the three selected designs



Maximum Power	Minimum Ripple	Optimum

Figure 7. Unsteady power predictions for the three selected designs

CONCLUSIONS

A two objective aerodynamic optimization study which aimed to maximize produced power while minimizing the torque ripple was performed for three bladed micro scale VAWTs. The rotor height, rotor radius and the helix angle of the blades were selected as the optimization parameters while the chord length and airfoil section of the blades were kept fixed. The NSGA-II algorithm was used for the optimizations while the aerodynamic analyses required to calculate the objectives were performed using the open source wind turbine design and analysis software QBlade. Since directly coupling the NSGA-II code with QBlade would be computationally expensive, fitness function predictions during the optimizations were performed using the ordinary Kriging method which used the database constructed using the QBlade software. 35 different design parameter values for the database were obtained using the Latin Hypercube Sampling method.

The optimization code was run for 300 generations. The fitness function values of three selected individuals were recalculated using QBlade in order to see the prediction quality of the employed ordinary Kriging method. Having seen the discrepancies between the kriging and QBlade predictions, these new QBlade predictions were added to the database and a new Pareto front was obtained. Increasing the database size by adding those selected individuals improved the ordinary Kriging predictions. Although further improvement was possible by increasing the step size more, the database size of 38 was assumed to be sufficient for the ranking purposes required by the optimization algorithm.

Comparing the performances of the Pareto optimum designs which yield the maximum power and minimum torque ripple with the so called optimum design which gives equal importance for both objectives showed that, trying to improve one of the objectives alone would lead to poor designs and the optimizations should be performed in a multiobjective manner. Depending on the user needs, different designs could be produced by assigning different weights to the objectives or using a different decision making methodology.

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