Optimization of a Small Passive Wind Turbine Generator with Multiobjective Genetic Algorithms

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Abstract. In this paper Multiobjective Genetic Algorithms (MOGAs) are used for the design of a small wind turbine generator (WTG) coupled to a DC bus through a diode bridge. The originality of the considered system resides in the suppression of the Maximum Power Point Tracker (MPPT). The poor efficiency of the corresponding passive structure is considerably improved by optimizing the generator characteristics associated with the wind turbine in relation to the wind cycle. The optimized configurations are capable of matching very closely the behavior of active wind turbine systems which operate at optimal wind powers by using a MPPT control device.

Key words: Multiobjective Optimization, Genetic Algorithms, Wind Energy, Vertical Axis Wind Turbine

1. Introduction

The optimization of wind energy transfer is generally achieved by controlling the speed of a Wind Turbine Generator (WTG). In particular, the rotor speed should vary in accordance with the wind speed by maintaining the tip speed ratio to the value that maximizes aerodynamic efficiency. For that purpose, many different Maximum Power Point Tracking (MPPT) control strategies have been developed, allowing to regulate the Permanent Magnet Synchronous Generator (PMSG) voltage [1][2]. The high efficiency of these generators is counterbalanced with higher costs and greater complexity of the electronic devices. On the other hand, simpler system structures consist in only using a passive rectifier directly connected to the DC bus (see Fig 1). Such system is characterized by very low cost but usually offers poor efficiency relatively to the wind power. However, thanks to a suitable choice of the system design variables associated with the wind turbine generator sizing (especially electrical and geometrical parameters) it is possible to improve significantly the global system efficiency. In this paper, we propose an original approach based on Multiobjective Genetic Algorithms for sizing a small passive WTG. The whole system mass and the extracted output power are considered as optimization criteria. The obtained power efficiency is finally close to the one offered by active WTGs coupled with MPPT control devices.

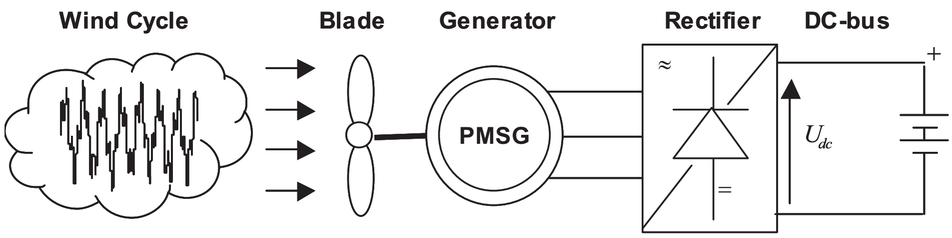


Fig. 1 : Synoptic of the passive wind turbine generator (without MPPT control system)

2. The Sizing and Simulation Models of the Wind Turbine Generator

Two classes of models have been developed for sizing and simulating the WTG. On the one hand, fine accurate models based on the use of empirical equations, finite elements and a complete circuit representation of the WTG have been used for the system analysis and validation. On the other hand, surrogate models which approximate the system behavior have been employed in the optimization process in order to reduce computing times.

2.1. The Wind Cycle

The wind Cycle is represented by a typical wind speed sample $V_W(t)$ which is approximated with the empirical relation

$$V_W(t) = 10 + 0.2\sin(0.105t) + 2\sin(0.367t) + \sin(1.293t) + 0.2\sin(3.665t)\,. \quad (1)$$

2.2. The Wind Turbine Characteristics

A Savonius Vertical Axis Wind Turbine of radius R = 0.5 m and height H = 2 m is considered as case study. Its power coefficient C_p is defined by the following empirical interpolation:

$$C_p = -0.1299\lambda^3 - 0.1168\lambda^2 + 0.4540\lambda\,, \tag{2}$$

where λ denotes the tip speed ratio, depending on the turbine rotational speed Ω and the wind speed V_W.

$$\lambda = \frac{R\Omega}{V_W}\,. \tag{3}$$

The associated wind turbine power can be expressed as:

$$P_{WT} = \frac{1}{2} C_p \rho A V_W{}^3\,, \tag{4}$$

where ρ denotes the air density (ρ= 1.205 kg.m^{-3}) and where the swept rotor area A is approximated as:.

$$A = 2R \times H\,. \tag{5}$$

The corresponding torque T_W produced by the wind turbine is:

$$T_{WT} = \frac{P_{WT}}{\Omega} \tag{6}$$

and the electromagnetic torque of the generator is defined as:

$$T_{em} = T_{WT} - J_{WT}\frac{d\Omega}{dt} - F_{WT}\Omega\,, \tag{7}$$

where the wind turbine inertia and the damping coefficient are J_{WT} = 16 kg.m² and F_{WT} = 0.06. N.m.s/rad.

Note that the wind power is maximum when the power coefficient is maximum ($C_p{}^* \approx 0.22$), i.e. for the optimal tip speed ratio ($\lambda^* \approx 0.82$). For various wind speed values, the rotor speed should be adapted to operate at the optimal tip speed ratio. Therefore, in order to extract the maximum wind power, a MPPT strategy associated with a static converter structure is generally employed to control the rotor speed according to the wind speed such as $\Omega = \lambda^* V_W/R$. This can be made by using a PWM Voltage Source Rectifier or a passive diode bridge coupled with a DC-DC chopper that tunes the extracted power [1].

2.3. The Permanent Magnet Synchronous Generator

An analytical model allows us to extract all sizing variables of the PMSG from geometrical features (i.e. the radius length ratio R_{rl}, the number of pole pairs p, the number of slots per pole per phase N_{spp}) and energetic characteristics (the sizing voltage V_b, the current density J_c in a slot, the magnetic flux density B_y in the yoke, the typical sizing power P_b at the base point). For reason of complexity and space limitation, this model is not explained in detail in the paper. We invite the reader to refer to [3], [4] for more information. Note that contrary to [4] the generator is sized for a specific base speed:

$$\Omega_b = \frac{\lambda^* < V_W >}{R}, \tag{8}$$

where $<V_W>$ denotes the average speed of the wind cycle. The PMSG electric parameters (i.e. main inductance, stator resistance, magnetic flux, base current) are then deduced from empirical relations [3] or by using the Finite Element Method (FEM). For the system simulation, the PMSG is represented in a ABC reference frame and the diode rectifier is modeled in instantaneous value by considering ideal switches but taking into account the diode overlapping during the commutation interval. Furthermore, this model includes the thermal behavior of the synchronous generator in each component (slot copper, slot insulators, stator yoke) evaluated from the magnetic and electrical losses. Joule losses are classically computed from the generator current and the stator resistance, and magnetic losses are estimated from hysteresis and eddy current losses in the stator parts (i.e. yoke and teethes) according to [4]. Since the computational cost associated with this global circuit model and the use of finite elements is rather high, surrogate models have been developed for the optimization process in order to reduce computing times. In particular, for the system simulation, a simplified causal model is used where the synchronous generator with the diode bridge association is replaced with an energetically equivalent DC model valid in average value. The synoptic of this model is given in Fig. 2b. Note that the causality is symbolized by arrows specifying which physical variables (energetic efforts or flows) are applied in each part of the system. The correspondence of this model with the synchronous generator circuit of Fig. 2a is given in Table 1. We also mention in the following the characteristics of each block in the synoptic. The electromechanical conversion is represented by:

$$\begin{cases} T_{em} = p\Phi_{DC} I'_{sDC} \\ E_{sDC} = p\Phi_{DC}\Omega \end{cases}, \tag{9}$$

where p denotes the pole pair number of the generator. The armature reaction in the generator is modelled with a voltage drop without power losses:

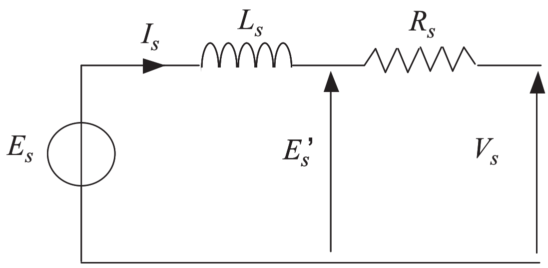
$$\begin{cases} E'_{sDC} = \sqrt{E_{sDC}^2 - (L_{DC}\omega I_{sDC})^2} \\ I'_{sDC} = E'_{sDC} I_{sDC} / E_{sDC} \end{cases}, \tag{10}$$

where ω denotes the electric angular pulsation associated with the rotor. The transient electric mode leads to a DC current in the generator defined as:

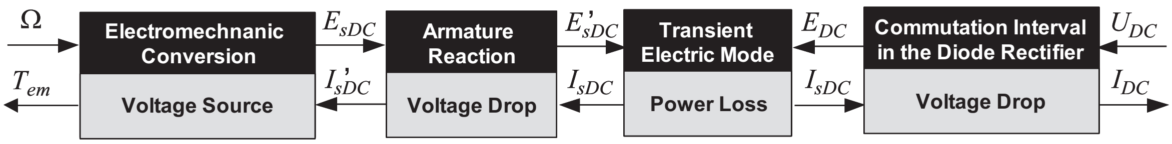
$$L_{DC}\frac{dI_{sDC}}{dt} + R_{DC} I_{sDC} = E'_{sDC} - E_{DC}. \tag{11}$$

Finally, the diode overlapping during the commutation interval is represented by a power conservative voltage drop:

$$\begin{cases} U_{DC} = E_{DC} - \dfrac{3}{\pi} L_s \omega I_{DC} \\ I_{DC} = E_{DC} I_{sDC} / U_{DC} \end{cases} . \tag{12}$$



(a) The synchronous generator equivalent circuit



(b) The causal synoptic of the equivalent DC model

Fig. 2 : The energetic equivalent DC model for the synchronous generator

Table 1 : Correspondence between the synchronous generator circuit and the equivalent DC model

Variable	Synchronous Generator	Equivalent DC – Model
Voltage	V_s	$U_{DC} = \frac{3\sqrt{6}}{\pi} V_s$
Current	I_s	$I_{DC} = \frac{\sqrt{6}}{\pi} I_s$
Flux	Φ_s	$\Phi_{DC} = \frac{3\sqrt{6}}{\pi} \Phi_s$
Inductance	L_s	$L_{DC} = 3\left(\frac{\sqrt{6}}{\pi}\right)^2 L_s$
Resistance	R_s	$R_{DC} = 3\left(\frac{\sqrt{6}}{\pi}\right)^2 R_s$
Electromotive Force	E_s	$E_{sDC} = \frac{3\sqrt{6}}{\pi} E_s$

3. Multiobjective Optimization of the Wind Turbine Generator by Genetic Algorithms

3.1. Design Variables, Objectives and Constraints

The design variables considered for the wind turbine optimisation and their associated bounds are shown in Table 2. Note that five variables are continuous parameters (i.e. R_{rl}, P_b, V_b, B_y, and J_c) and two are discrete (i.e. p and N_{spp}).

Table 2 : Design Variable Characteristics

Design Variable	Nature	Bounds
Sizing Voltage [V]	Continuous	$V_b \in [1, 200]$
Radius/Length Ratio	Continuous	$R_{rl} \in [0.1, 10]$
Number of Pole Pairs	Discrete	$p \in \{1,.., 60\}$
Current Density [A/mm^2]	Continuous	$J_c \in [0.5, 10]$
Sizing Power [W]	Continuous	$P_b \in [1, 700]$
Yoke Induction [T]	Continuous	$B_y \in [1.2, 2.2]$
Number of Slots per Pole per Phase	Discrete	$N_{spp} \in \{1,..,6\}$

Two conflicting objectives have to be improved: the useful power has to be maximized while minimizing the total mass of the system. The useful power is defined as the power extracted from the wind cycle reduced from all losses in the wind turbine system (i.e. mechanical losses in the turbine, Joule and iron losses in the generator and conduction losses in the diode rectifier). As underlined previously, all losses in the synchronous generator are computed according to [4] and the conduction losses P_{cond} in a diode of the rectifier are classically evaluated as follows:

$$P_{cond} = u_d i_d + R_d i_d^2 , \tag{13}$$

where u_d.denotes the diode voltage drop and R_d represents the diode internal resistance (typically $R_d = 3.4$ mΩ and $u_d = 0.8$ V). Note that switching losses have been neglected. The total mass of the system is obtained by considering the wind turbine mass as constant ($M_{WT} \approx 48$ kg) and the generator mass. This mass is computed from the volume of each constitutive component (iron, magnet, copper windings) and the corresponding mass density according to [4]. Note that the rectifier mass has been neglected. Moreover, five constraints have to be fulfilled to ensure the wind turbine feasibility and to allow complying with the wind cycle. These constraints concern the number of wires per slot, the maximum temperature associated with the copper windings in the generator, the demagnetization limit of the magnets and the maximum temperature in the semiconductor junctions. They are computed similarly to [4].

3.1. The Optimization Process

The Nondominated Sorting Genetic Algorithm (NSGAII) [5] is applied for the optimization of the full passive wind turbine generator. To take into account the design constraints in the NSGA-II, the Pareto-dominance rule is modified as follows:

- if two individuals are non-feasible, the Pareto-dominance is considered in the constraint space.

- if two individuals are feasible, the Pareto-dominance is considered in the objective space.

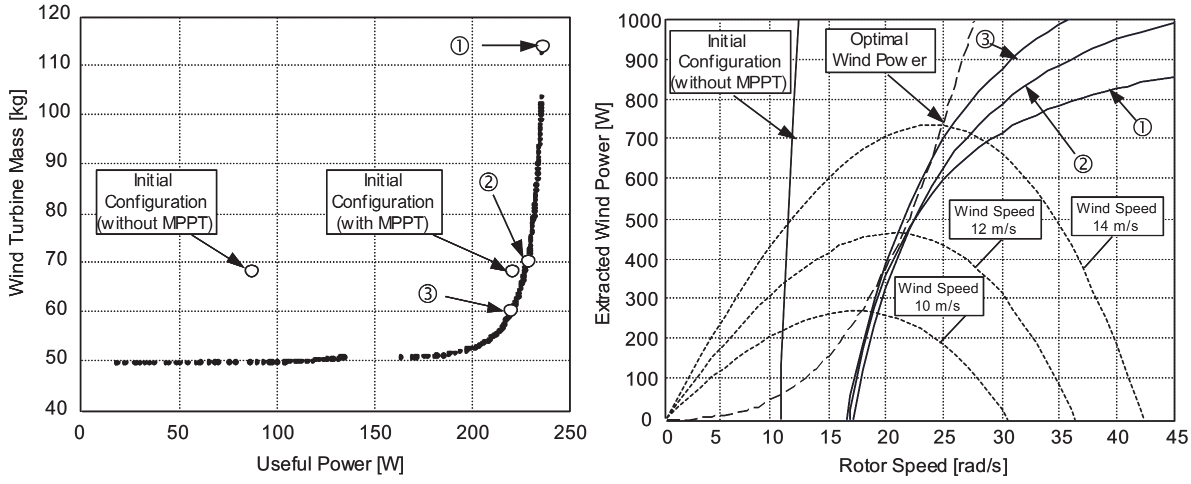
- if one individual is feasible and the other non-feasible, the feasible individual dominates the non-feasible individual.

In this manner, Pareto ranking tournaments between individuals include the constraint minimization as well as the objective minimization. Note that in the case of the NSGA-II, for non-feasible individuals belonging to a given front in the constraint space, the computation of the *I*-distance density estimator [5] is carried out in relation to all constraints [4]. In this way, niching will occur in the two different spaces (i.e. constraint and objective spaces) and diversity will be preserved to avoid premature convergence.

Five independent runs are made to take into account the stochastic nature of the NSGA-II. The population size and the number of non-dominated individuals in the archive are set to 100 and the number of generations is G=200. Mutation and recombination operators are similar to those presented in [6]. They are used with a crossover probability of 1, a mutation rate on design variables of $1/m$ (m denoting here the total number of design variables in the problem) and a mutation probability of 5% for the X-gene parameter used in the self-adaptive recombination scheme. The surrogate sizing and simulation models described in the previous section are exploited to evaluate the constraints and the objectives (i.e. the useful power and the total wind turbine mass) associated to the individuals in the NSGA-II population.

3.2. Results

The Pareto-optimal configurations determined from the five independent runs are displayed in Fig. 3a. Note that the global Pareto-optimal front is obtained by merging all fronts associated to these runs. We also represent in Fig. 3a the characteristics of three typical solutions and the initial configuration of the WTG which is actually used in our lab [1]. This generator is able to operate at optimal wind powers when it is associated with a MPPT control device but presents a "poor" efficiency if the MPPT is suppressed. As shown in Fig 3b, the power extracted from the wind cycle is strongly reduced in this case. The WTG optimization considerably improves both objectives. As it can be seen in Fig. 3, these passive optimized solutions can match very closely the behavior of active WTGs operating at optimal wind powers by using a MPPT control device. Some Pareto-optimal solutions are even slightly better than the initial configuration of the generator with an MPPT control device since all losses in the system are reduced thanks to the global optimization process (see Table 3 for justification).



(a) The Pareto-optimal Front (b) The extracted wind Power of three optimal solutions

Fig. 3 : Pareto-optimal configurations compared with a non-optimized wind turbine

Table 3 : Power assessment associated with the particular solutions of Fig 3

Solution	Extracted Wind Power (W)	Electromagnetic Power (W)	Iron Losses (W)	Joule Losses (W)	Conduction Losses (W)	Useful Power (W)
Initial Configuration (without MPPT)	124	123	19	16	3	85
Initial Configuration (with MPPT)	291	274	33	18	3	220
①	281	266	7	21	2	236
②	281	266	8	27	2	229
③	276	263	11	29	3	220

3.3. Model Sensitivity

To validate these results obtained with the surrogate sizing and simulation models, we compute the characteristics of the specific Pareto-optimal solutions of Fig. 3 with the accurate corresponding models. In particular, we compare in Table 4 the electric parameter values of the generator (typically the leakage and main inductances computed for one conductor per slot) obtained with the fully Analytical Model (AM) and the Finite Element Method (FEM). Moreover, we indicate the useful power computed from the FEM sizing and the classical synchronous model represented in a ABC frame. It can be noted that the results are globally in accordance since differences between the surrogate and accurate models are rather small. We also mention in this table the computing time associated with both models for a standard PC. Note that it is about 8 times higher for the accurate model. This justifies the use of the surrogate model in an optimization context since 100 000 runs have been performed to obtain the Pareto-optimal configurations.

Table 4 : Surrogate and accurate model comparison for the particular solutions of Fig. 3

Solution	Main Inductance L_p [μH]		Leakage Inductance L_l [μH]		Useful Power [W]	
	AM	FEM	AM	FEM	AM sizing + Equivalent DC Model	FEM sizing + Synchronous Model
①	33.8	33.4	2.4	2.7	236	231
②	29.5	29.7	5.8	6.4	229	220
③	25.6	26.5	14.3	15.6	220	207
Computing Time (s)	Negligible	120	Negligible	120	40	310

4. Conclusions

In this work, Multiobjective Genetic Algorithms have been applied to the design of a small passive WTG. For this purpose, surrogate and accurate models have been developed for the sizing and the simulation of the WTG. An optimization process based on the use of the NSGA-II in association with the implemented surrogate models has been exploited to improve the useful power and the mass of the WTG. Three Pareto-optimal solutions have been analyzed and compared with the accurate sizing and simulation models. Results show that the optimized configurations of the full passive WTGs are able to match very closely the behavior of active WTGs which operate at optimal wind powers by using a MPPT control device. In the outlooks of this work, the Pareto-optimal solution sensitivity to the wind cycle will be studied in order to take statistical information related to the WTG location. Note also that this problem can constitute an original benchmark for investigating design methodologies based on model hybridization such as Space Mapping Methods.

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