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OPTIMISATION OF WIND TURBINE BLADE STRUCTURES USING A GENETIC ALGORITHM

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ABSTRACT

The current diminution of fossil-fuel reserves, stricter environmental guidelines and the world's ever-growing energy needs have directed to the deployment of alternative renewable energy sources. Among the many renewable energies, wind energy is one of the most promising and the fastest growing installed alternative-energy production technology.

In order to meet the production goals in the next few decades, both significant increases in wind turbine installations and operability are required, while maintaining a profitable and competitive energy cost. As the size of the wind turbine rotor increases, the structural performance and durability requirements tend to become more challenging. In this sense, solving the wind turbine design problem is an optimization problem where an optimal solution is to be found under a set of design constraints and a specific target.

Seen the world evolution towards the renewable energies and the beginning of an implementation of a local wind industry in Quebec, it becomes imperative to follow the international trends in this industry. Therefore, it is necessary to supply the designers a suitable decision tool for the study and design of optimal wind turbine blades.

The developed design tool is an open source code named *winDesign* which is capable to perform structural analysis and design of composite blades for wind turbines under various configurations in order to accelerate the preliminary design phase. The proposed tool is capable to perform a Pareto optimization where optimal decisions need to be taken in the presence of trade-offs between two conflicting objectives: the annual energy production and the weight of the blade. For a given external blade shape, *winDesign* is able to determine an optimal composite layup, chord and twist distributions which either minimizes blade mass or maximizes the annual energy production while simultaneously satisfying design constraints. The newly proposed graphical tool incorporates two novel VCH and KGA techniques and is validated with numerical simulation on both mono-objective and multi-objective optimization problems.

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NOMENCLATURE AND ABBREVIATIONS

a	Induction factor
ACO	Ant Colony Optimization
AEP	Annual Energy Production
AoA	Angle of attack (º)
as	Speed of sound (m/s)
BEM	Blade Element Momentum theory
$\mathbf{b_m}$	Buckling margin
C_{comp}	Component cost ($)
CanWEA	Canadian Wind Energy Association
C_D	Drag coefficient
C_L	Lift coefficient
C_L/C_D	Lift-to-drag ratio
C_P	Rotor power coefficient
$\mathrm{C_P}$	Pressure coefficient
C_{mc}	Pitching moment coefficient
C_{WT}	Total wind turbine cost
CHT	Constraint-Handling Technique
CFD	Computational Fluid Dynamics
CLT	Classical Lamination Theory
CoE	Cost-of-Energy
DB	Davies-Bouldin validity index
DE	Differential Evolution
DES	Detached Eddy Simulation
DNS	Direct Navier-Stokes
D_R	Diameter of the wind turbine rotor (m)
EA	Evolutionary Algorithms
E_{AP}	Annual Energy Production (kWh)
ECGA	Extended Compact Genetic Algorithm
ES	Evolutionary Strategy
$f(V)$	Wind speed distribution
F_D	Drag force applied on the blade element (N)
F_L	Lifting force applied on the blade element (N)
F_n	Axial force applied on the blade element (N)
F_t	Tangential force applied on the blade element (N)

F_{WT}	Calibration factor for the cost model
FSF	Fatigue Safety Factor
$g_i(\vec{x})$	Inequality constraints
GA	Genetic Algorithm
GBA	Gradient-Based Methods
$h_i(\vec{x})$	Equality constraints
HAWT	Horizontal Axis Wind Turbine
IEC	International Electrotechnical Commission
K	Number of clusters
KGA	K-means Genetic Selection
KGA$_f$	K-means Genetic Selection process with a fixed number of clusters
KGA$_o$-DB	K-means Genetic Selection using the Davies-Bouldin validity index
KGA$_o$-S	K-means Genetic Selection using the Silhouette validity index
KMA	K-means Algorithm
LES	Large Eddy Simulation
LU	Lebanese University
M	Shaft torque applied on the blade element (N.m)
M_{max}	Maximum permissible shaft torque on a blade element (N.m)
MN	Mach number
MN_{tip}	Mach number at the wing tip
MOOP	Multi-objective Optimization Problem
MOEA	Multi-objective Evolutionary Algorithm
N	Number of revolutions per minute (rpm)
NCGA	Neighborhood Cultivation Genetic Algorithm
Ncross	Number of crossover-ed individuals during the evolution process
Nelite	Number of elite individuals selected during the evolution process
Nmt	Number of mutated individuals during the evolution process
NPGA	Niched Pareto Genetic Algorithm
NREL	National Renewable Energy Laboratory
NSGA	Non-dominated Sorting Genetic Algorithm
n	Number of revolutions per second (rps)
$P(V)$	Power curve
PAES	Pareto Archived Evolution Strategy
PopNum	Population length in a genetic population
PSO	Particle Swarm Optimization
RANS	Reynolds Averaged Numerical Simulation
S	Silhouette validity index
SA	Simulated Annealing

S_f	Safety gap factor between ω_{1f} and ω_{3p}
SLP	Sequential Linear Programming
SPEA	Strength Pareto Evolutionary Algorithm
SQP	Sequential Quadratic Programing
S_R	Swept area of the rotor (m^2)
T	Thrust generated by a blade element (N)
T_{max}	Maximum permissible thrust on a blade element (N)
U	Wind velocity or wind velocity spectrum (m/s)
UQAC	Université du Québec à Chicoutimi
UQAR	Université du Québec à Rimouski
V_{tip}	Velocity of the blade tip (m/s)
$V_{tip,max}$	Maximum blade tip velocity (m/s)
VCH	Violation Constraint-Handling technique
VEGA	Vector-Evaluated Genetic Algorithm
WT	Wind Turbine
WTDP	Wind Turbine Design Problems
WTO	Wind Turbine Optimization
$\vec{x}$	Vector of design variables
$\vec{x}_{lower}$	Lower bound vector of the design variables
$\vec{x}_{upper}$	Upper bound vector of the design variables
λ	Tip speed ratio
Δ	Tolerance between two design variables of the same nature
θ	Angle between the relative flow and the chord line
σ	Normal stress generated on a blade element ($N.m^{-2}$)
ρ	Density (kg/m^3)
σ_{ult}	Ultimate permissible stress ($N.m^{-2}$)
ω	Natural frequency (Hz)
ω_{1f}	First blade flap natural frequency at rotor rated speed (Hz)
ω_{3p}	Three-per-rev frequency at rotor rated speed
ω^*	Target frequency of the rotor at rated speed
ω_{lower}	Lower bound of the natural frequency of the blade (Hz)
ω_{upper}	Upper bound of the natural frequency of the blade (Hz)
ε_{50}	Strain at 50-year extreme conditions
γ	Safety factor on the strain
ε_{cr}	Critical buckling strain
ε_{ult}	Ultimate strain
η_{GB}	Gearbox efficiency

DEDICATION

This thesis is the product of a four-year journey, during which numerous life lessons were acquired. This short dedication does not and will not recognize the many individuals throughout this journey; nonetheless it is a brave attempt to do so.

It all started at the Faculty of Engineering of the Lebanese University in Beirut, fall of 2011, inside Professor Mazen Ghandour's office where we both had a long discussion about a numerical simulation study of a VAWT which I conducted earlier in the summer of 2011. Little did I know that this meeting would be a milestone event, after which I was introduced to Hussein Ibrahim (Ph.D) and Professor Rafic Younes. During my final year of undergraduate studies and under the supervision of Rafic Younes, we conducted a comparative study of the performance of textile composite materials wind turbine blades. During my two-months internship in Gaspé and Rimouski, I had the pleasure to discover Hussein Ibrahim's work, his area of expertise and his personal journey throughout his doctoral studies. At the same time, my internship in Quebec exposed me to the growing market of renewable energy, particularly wind energy, and hybrid storage. I recall meeting Professor Adrian Ilinca for the first time in the cafeteria of the UQAR. No promises were given at the time, but together we spoke about the possibility of a doctoral project together.

Fast forward a year later, dragging two suits in both hands and carrying a laptop in my backpack, I set forth towards a town 200 km north of Quebec City by the name of Chicoutimi (Saguenay). I can still recall arriving in January 2014 and giving instructions to the taxi driver to transport me towards the LIMA AMIL laboratory at the Université du Québec à Chicoutimi. I was welcomed by Elizabeth Crook and Professor Jean Perron. Boiling emotions run through my body as I recall my first few days and weeks in Chicoutimi.

My first year in Chicoutimi was full of technical and personal challenges. If I am required to attribute a label to the 2013-2014 academic year, it would be: Hope. The hope that beyond the confusion, chaos, the many variables in the playing ground, there is a clearer sight ahead.

The outcome of that year was a complete review of performance optimization techniques applied in the design of wind turbines. Remaining hopeful paid-off.

Highly motivated to tackle the trials of my second year, I successfully completed my doctoral exam with the conclusion that our doctoral research required a minor adjustment. My mindset was to strive for success and greatness. The product of my second year was a novel technique for constraint-handling in genetic algorithms. Developing optimization algorithms became an obsession.

Going into my third year, I was dealing with a personal crisis following a series of events and incorrect choices. It was clear from the beginning of year 2016 that it would be one filled with obstacles of a different taste and magnitude. I recall sitting with Professor Perron, reassuring me that this is a normal and necessary state of mind called '*la traversée du désert'*. I would be a hypocrite to claim that I overcame my obstacles all alone, with ease and no negative impact on productivity. Adel Chehouri, Hussein Ibrahim, Ahmad Chamseddine, Ibrahim Bitar and Zein Saleh, you all have superhero powers, word can't express how grateful I am to have your support, guidance and mentoring. Finding my way out of the desert, breaking through many constraints and in search of a work-life balance, I gathered my thoughts and set forth a higher objective: silence the doubters and strive for success. Working in parallel with Rafic Younes and my supervisors, we pushed forward the research project and set a plan for the remaining calendar.

September 2016, I reverted to my childhood passion and love: general aviation – a reunion 9 years in the making. I had two priorities for the year of 2016-2017: complete my PhD studies and receive my private pilot license. I label this year as 'Trusting the Process'. At the final stage of my doctoral studies, a Transport Canada private pilot license in one hand and a solid curriculum vitae in the other, I was ready to begin scripting my next chapter.

There is something about the month of May, great things always seem to occur for me in May. With the same suits cases, same laptop in my backpack, Ahmad Chamseddine's SUV filled with boxes, I departed Saguenay in the direction of my hometown, Montreal – and began my career journey with Hatch.

To my Brother, Parents, Sister…

To Eleanor Barbara Chehouri…

From the heart of suffering, heroism is born.

Bruce Wayne: *I wanted to save Gotham. I failed.*

Alfred Pennyworth: ***Why do we fall sir**? So that we can learn to pick ourselves up.*

WHY DO WE FALL?

INTRODUCTION

The depletion of fossil-fuel reserves, stricter environmental regulations and the world's ever-growing energy needs have steered to the deployment of alternative renewable energy sources. Among the various renewable energy alternatives, wind energy is one of the most promising and the fastest growing installed alternative-energy production technology (M. Grujicic et al., 2010).

CanWEA reports that the province of Quebec is Canada's second-biggest market for wind power with 3510 MW of installed capacity. Their 2030 energy policy aims to increase renewable energies by 25 % and decrease fossil fuel by 40 % over the next year. In fact, it is anticipated that by 2025, at least 20% of Canada's electricity demand will be met by various onshore and offshore wind-farms (Lafrance, Nolet, & Cote). Achieving this vision will deliver huge paybacks:

- Generating $79 billion in Canadian wind energy investments, in a $1.8 trillion global wind industry.
- Creating at least 52,000 full-time jobs.
- 55,000 MW of clean energy injected into the electrical grids.
- Cutting Canada's annual greenhouse gas emissions by 17 %.

In order to meet the 20% production goal in the next 10 years, both significant increases in wind turbine installations (offshore and inshore farms) and an increase in wind turbine operability are required, while maintaining a profitable and competitive energy cost (Lindenberg, Smith, & O'Dell, 2008). To reduce the cost of energy (typically expressed in $/kWh), commercial wind turbines have grown considerably in size over the last 30 years. This is economically profitable because as the hub-height and rotor radius increase, the average wind speed captured increases due to wind shear. Hence this development has made it possible that less wind turbines units are required to meet the power production for the set-up of wind farms, which inevitably leads to a reduction in operation costs.

As the size of the wind turbine rotor increases, the structural performance and durability requirements tend to become more challenging. Presently it is still unclear the ultimate rotor diameter which can be attained with the current material and manufacturing technologies (M. Grujicic et al., 2010). In addition to the aforementioned structural performance and durability requirements the wind turbine has to meet with the evolving energy policies, international treaties, legislations and regulations set by the governments (Saidur, Islam, Rahim, & Solangi, 2010).

In this sense, solving the wind turbine design problem is an optimization problem where an optimal solution is to be found under a set of design constraints and a specific target. Seen the world evolution towards the renewable energies and the beginning of an implementation of a local wind industry in Quebec, it becomes imperative to follow the international trends concerning the integration of ***composite material*** in this industry. Therefore, it is necessary to supply the designers a suitable ***decision tool*** for the study and design of ***optimal*** wind turbine blades

As reported in Seminar 1 and 2, the primarily goal of our research is to propose a wind turbine design tool with an interactive interface. It is important to mention that throughout our doctoral research; the topic has evolved from an early focus towards its current form. Initially, the intention was oriented towards the study of textile composites inside the structure of the wind turbine blades. After completing a literature review on the optimization techniques applied in WTOP, we concluded that our efforts should be oriented towards building an optimization tool capable of handling multiple technical specifications. The developed design tool is an open source code named *winDesign* which is capable to perform:

- Structural analysis and design of composite blades for wind turbines under various configurations in order to accelerate the preliminary design phase.

- The proposed *winDesign* tool should perform a Pareto optimization where optimal decisions need to be taken in the presence of trade-offs between two conflicting objectives: AEP and the weight of the blade.
- For a given external blade shape, *winDesign* should determine an optimal composite layup, chord and twist distributions which either minimizes blade mass or maximizes the annual energy production while simultaneously satisfying design constraints.

Admitted into the PhD in engineering program at UQAC in January 2014, this report includes 10 trimesters of research studies on the subject of: *optimization of the structure of wind turbine blades using a genetic algorithm*, under the supervision of:

1. Professor Jean Perron, UQAC: doctoral advisor/director
2. Professor Rafic Younes, LU: co-director and main scientific advisor
3. Professor Adrian Ilinca, UQAR: co-director of research

This dissertation is divided into 6 main chapters in which the following key elements are discussed:

- A **literature review** of the most relevant wind turbine optimization studies is presented in chapter 1.
- Survey of the **mathematical models** applied in wind turbine performance optimization problems are presented in chapter 2.
- Two main **original contributions** for the proposed genetic algorithm of *winDesign* are discussed in this chapter. In section 3.3, a new constraint-handling technique named ‘Violation Constraint-Handling’ (VCH) is introduced. Likewise, section 3.4 presents a selection process mechanism using clustering analysis for genetic search called KGA.
- In chapter 4, we will focus on existing wind turbine blade design codes, tools and software solvers, which played a major role in building the proposed *winDesign* platform.

- The newly proposed *winDesign* graphical tool which incorporates the novel VCH and KGA techniques, is presented in chapter 5 with results from both mono-objective and multi-objective numerical simulations.
- Finally, we terminate this dissertation with chapter 6, where a detailed discussion, conclusion and a projection of future works are presented.

CHAPTER 1

WIND TURBINE OPTIMIZATION: LITERATURE REVIEW

1.1 WIND ENERGY STATUS: GENERAL OVERVIEW

Since early recorded history, humans have harnessed the kinetic energy of the wind. Wind energy propelled boats along the Nile River as early as 5000 B.C. By 200 B.C., windmills in China and Persia were pumping water, while vertical-axis windmills were grinding grain in the Middle East.

With the development of electrical power, wind power found new applications in residential lighting away from power plants. Throughout the 20th century, small wind turbine plants, suitable for farms and homes, along with larger wind farms connected to the grid were developed.

In the 1980's, while wind energy's growth in North America was slow, wind energy in Europe expanded in part due to environmental concerns in response to scientific studies about global climate change and global warming.

Today, wind power operates in various size range, from small turbines for isolated residences to large hundred of megawatt-size wind farms that generate electricity to the transmission grid.

As of the 21st century began, fossil fuel is still relatively inexpensive, but rising concerns over global warming and the eventual fossil fuel depletion has led to an expansion of interest in renewable energy. Since wind power can only generate electricity rather than liquid fuels, it cannot substitute for petroleum in transportation in the immediate future.

Canada, with its massive landmass and diversified geography, has significant renewable resources including: water, wind, biomass, solar, geothermal and ocean energy (Basbous, Younes, Ilinca, & Perron, 2012; Hussein Ibrahim, Ilinca, Younes, Perron, & Basbous, 2007; H

Ibrahim, Younès, Basbous, Ilinca, & Dimitrova, 2011; Hussein Ibrahim, Younès, Ilinca, Dimitrova, & Perron, 2010; Hussein Ibrahim et al., 2011). In 2016, renewable energy sources currently provided 19% of the total Canadian energy demand with 96 636 MW of installed capacities. Hydropower is the most important renewable energy source in Canada, accounting for more than 59% of Canada's electricity generation. In fact, Canada ranks as the second largest producer of hydroelectricity in the world (Adib et al., 2016).

Canada has large areas with excellent wind resources and therefore a potential for wind turbine projects. Much like other sites, the highest potential areas are offshore and along the coastlines. Until now, no offshore wind farms have been built in Canada. In 2016, Canada added 1.5 GW for a total of 11.2 GW, ranking sixth globally for additions and seventh for total capacity. The installed wind power capacity was enough to supply 5% of Canada's electricity demand.

The 2030 energy policy set by CanWEA aims to increase renewable energies by 25 % and decrease fossil fuel by 40 % over the next year. In fact, it is anticipated that by 2025, at least 20% of Canada's electricity demand will be met by various onshore and offshore wind-farms (Lafrance et al.). In order to meet the 20% production goal in the next 10 years, both significant increases in wind turbine installations (offshore and inshore farms) and an increase in wind turbine operability are required, while maintaining a profitable and competitive energy cost (Lindenberg et al., 2008). To reduce the cost of energy (typically expressed in $/kWh), commercial wind turbines have grown considerably in size over the last 30 years. As the size of the wind turbine rotor increases, the structural performance and durability requirements tend to become more challenging. In addition to the aforementioned structural performance and durability requirements the wind turbine has to meet with the evolving energy policies, international treaties, legislations and regulations set by the governments (Saidur et al., 2010).

In this sense, solving the wind turbine design problem is an optimization problem where an optimal solution is to be found under a set of design constraints and a specific target.

Therefore, our literature review search must begin from a survey of wind turbine optimization studies.

1.2 WIND TURBINE OPTIMIZATION: TIMELINE & COMPONENTS

The rapid growth in the number of research publications on wind turbine design optimization since 1990 highlights the status of the field of WTO (Figure 1). In the past, some authors have compared the impact of different optimization objectives on the quality of the solution, others have reviewed the optimization algorithms, energy policies, economics, environmental impacts of wind turbines but numerous researchers have proposed different optimization methodologies and resolution strategies.

None of the manuscripts in the literature reviewed the techniques of performance optimization of wind turbines. Therefore, the purpose of our published literature review in the journal of *Applied Energy* was to review the optimization techniques applied to wind turbines.

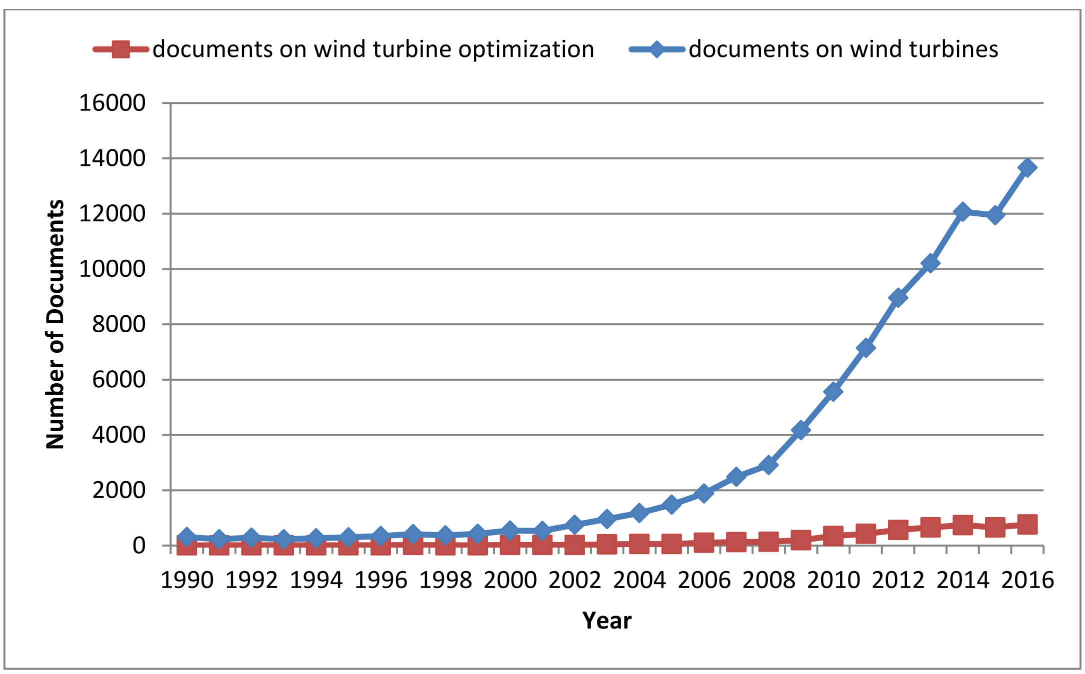

Figure 1 : Number of published documents on wind turbine design in the last 40 years (reproduced from Scopus database).

1.3 SURVEY OF WIND TURBINE OPTIMIZATION STUDIES

We begin by examining the most relevant wind turbine performance optimization studies conducted in the last 20 years. The reader is invited to refer to '*review of performance optimization techniques applied to wind turbines*' for a complete overview of the performance optimization techniques applied to horizontal wind turbines.

1.3.1 REVIEW OF AIRFOIL SHAPE OPTIMIZATION IN WIND TURBINE DESIGN STUDIES

The design of new airfoils families suited for wind turbines is an imperative field of research for the development of the wind energy industry (Björck, 1990; Peter Fuglsang, Bak, Gaunaa, & Antoniou, 2004; J. L. Tangler & Somers, 1995; Timmer & Van Rooij, 2003). During the last two decades, a series of airfoil design guidelines have been proposed by national energy laboratories and international commissions (Dutton, Bonnet, Hogg, & Lleong, 2010; P Fuglsang, 2002; Veritas, 2002). According to Ju and Zhang (Ju & Zhang, 2012), a desirable wind turbine airfoil should satisfy the following aerodynamic requirements:

1. High lift-to-drag ratio (C_L/C_D) and high lift coefficient (C_L)
2. Good performance during stochastic behavior of wind speed
3. Low sensitivity to leading edge roughness

A reduced sensitivity to the roughness (mainly leading edge roughness) means that the wind turbine blade should be efficient in dirty conditions (Sagol, Reggio, & Ilinca, 2013). In addition, the moment coefficient cannot be too high because this will increase blade torsion. In contrast, in pitch regulated wind turbine, a low moment coefficient causes a reduction in control forces. Because of wind gusts, the local angle of attack can suddenly change and be in pre-stall or stall zones (F. Grasso, 2011). Hence, the selection of the airfoil families is crucial in the design of wind turbine blades. Therefore, it is crucial to examine in this section the prominent approaches in wind turbine airfoil shape optimization. Below, we will review the most relevant airfoil shape optimization studies in the last two decades.

The desirable airfoil characteristics for wind turbine blades can be divided into two main categories: structural and aerodynamic. Throughout the wind turbine blade length distribution, different physical characteristics are key at the root, mid and tip. The root is mainly designed with regards to structural concerns, whereas the tip is determined for aerodynamic considerations (Bizzarrini, Grasso, & Coiro, 2011). The most significant structural parameters are the maximum airfoil thickness and its chord-wise location (F. Grasso, 2011). The airfoil thickness must be able to provide the required blade strength and stiffness. The location of the maximum thickness along the chord ensures a better penetration of the spar inside the airfoil sections. As for the tip region, the main aerodynamic parameter is the lift-to-drag ratio. This ratio is mainly related to the stall behavior and the $C_{L,max}$ of the airfoil. A relatively high value of the lift coefficient allows the designer to reduce the chord and consequently the loads in parked conditions at high speeds. A lower chord near the tip also reduces the weight of the blade and the amplitude of fluctuating load resulting from wind gusts (F. Grasso, 2011).

Burger and Hartfield (Burger & Hartfield, 2006) examined the feasibility of using the combination of the vortex lattice method with a genetic algorithm to optimize the aerodynamic performance of a horizontal axis wind turbine blade.

Li et al. (J. Y. Li, Li, Gao, & Huang, 2010) presented an improved optimization technique using response surface methods to improve the lift-to-drag ratio for 2D wind turbine airfoils.

In (Bizzarrini et al., 2011; F. Grasso, 2011; Francesco Grasso, 2012) the authors focused on the airfoil design at the tip region of the blade using numerical models. Grasso (Francesco Grasso, 2012) presented a hybrid optimization platform based on genetic and gradient based algorithms to design a new family of airfoils dedicated to the root region of the wind turbine blade. The motif was to enhance the aerodynamic efficiency $(\frac{L}{D})$ together with the sectional moment of resistance (I_{xx}) of the airfoil section. Because these two parameters are conflicting with each other, Grasso combined both objectives using a weighted linear combination (Eq. 1.1):

$$\min f(\vec{x}) = k\left(\frac{L}{D}\right) + (1-k)I_{xx} \qquad [1.1]$$

where $\boldsymbol{k}$ is a weighting parameter varying between 0 and 1, $\boldsymbol{L/D}$ the ratio of lift over drag, $\boldsymbol{I_{xx}}$ is the sectional moment of resistance.

In recent years, blunt trailing edge or flatback airfoils have been suggested for the inboard regions of large wind-turbine blades since they provide some structural and aerodynamic performance advantages (ASHWILL, 2003; Jackson, Zuteck, Van Dam, Standish, & Berry, 2005; Standish & Van Dam, 2003; Van Rooij & Timmer, 2003). Chen et al. (X. Chen & R. Agarwal, 2012) apply a multi-objective genetic algorithm code for the optimal design of flatback series. The two objectives were the maximum lift coefficient and maximum lift-to-drag ratio. It was shown that the multi-objective scheme generated flatback airfoils with better performances than those obtained using a single objective GA algorithm in (X. Chen & Agarwal, 2010; X. M. Chen & R. Agarwal, 2012).

Ribeiro et al. (Ribeiro, Awruch, & Gomes, 2012) coupled a RANS equation in steady state with one equation turbulence model and an optimization algorithm. Single and multi-objective genetic algorithms are employed, and artificial neural networks were used as a surrogate model to generate optimal airfoil shapes.

Jeong et al. (Jeong, Park, Jun, Song, & Lee, 2012) minimized the fluctuation of the unsteady aerodynamic load under turbulent wind condition. It was noted that the out-of-plane fluctuating unsteady aerodynamic load is more significant than the in-plane loads for structural fatigue of the blade. The *rms* of the out-of-plane bending moment was reduced by about 20% and its mean was reduced by about 5% (Jeong et al., 2012).

Ju et al. (Ju & Zhang, 2012) developed a robust design optimization (RDO) for wind turbine airfoils by maximizing the C_L/C_D and C_L of the airfoil along with a sensitivity minimization of the roughness at the leading edge associated with the geometry profile uncertainty.

1.3.2 REVIEW OF WIND TURBINE BLADE OPTIMIZATION STUDIES

In this section, we examine the most relevant wind turbine blade optimization studies conducted in the last 20 years.

One of the early studies was performed in 1996 by Selig and Coverstone-Carroll (M. S. Selig & Coverstone-Carroll, 1996). They examined the maximization of energy production with no or few constraints on the loads.

A year later, Giguère et Selig (Giguere & Selig, 2000) presented a multi-disciplinary optimization platform for the optimal blade geometry of HAWT's (refer to Figure 2). A combination of two objectives was used to obtain a trade-off curve, captured by the use of a sharing function. Only the structure of the blade was considered but the effects of the rotor on other components are represented in the cost model. These components include the hub, drivetrain, controller, nacelle and the tower. The cost of each component is modeled using the relative approach where the cost is obtained from a baseline model. In addition, the cost of each component is correlated with the corresponding design variables and normalized with the value from the baseline (except for the controller, which does not rely on baseline cost).

The following procedure was used to estimate the blade weight and resulting cost, as indicated in Figure 2.

1. The flap-bending load at each segment is determined from the thrust distribution for the given load condition (specified by the user or the IEC 50-year extreme wind speeds). An IEC load factor of 1.35 is applied to the static flap-bending loads.

2. The required moment of inertia of each segment is calculated using the flap-bending load to counterpart a prescribed stress level $\boldsymbol{\sigma_p}$ (one for the hub and skin and another for the spar) along the blade.
3. The required hub and spar thickness is found, neglecting the inertia of the skin and spar and that of the shear webs about their own axis of rotation.
4. The required number of plies from the skin thickness distribution is chosen.
5. Calculation of the tip deflection.
6. The cross-sectional area at each segment is calculated.
7. The volume of the material is estimated from a linear extrapolation of the cross sectional-area.
8. Finally, the blade weight is estimated from the number of blades $\boldsymbol{N}$, volume $\boldsymbol{MV_B}$ and density $\boldsymbol{\rho_B}$.

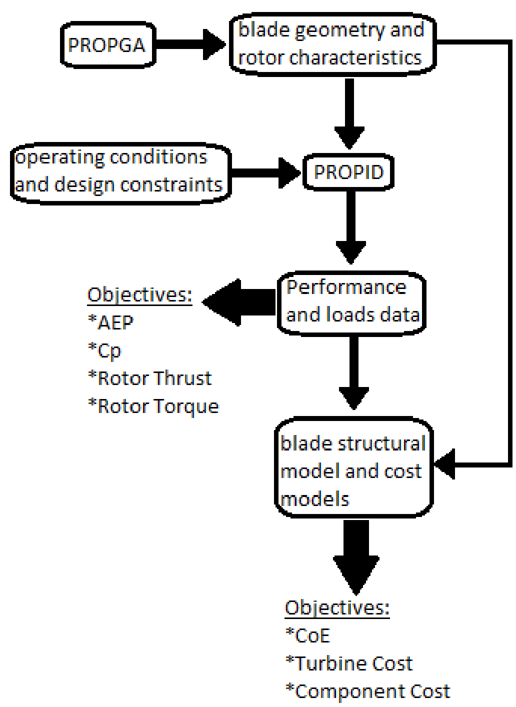

Figure 2 : Flowchart of Giguère et Selig (Giguere & Selig, 2000) (Reproduced from (Giguere & Selig, 2000)).

The optimization flowchart proposed by Giguère et Selig (Giguere & Selig, 2000) motivated researchers to conduct more studies in the field of wind turbine optimization. In the same way, Fuglsang and Madsen developed a famous code (P. Fuglsang & Madsen, 1999) for the multi-disciplinary optimization of HAWT rotors (refer to Figure 3) based on their previous work at Risø National Laboratory (P Fuglsang & Aagaard Madsen, 1994; Peter Fuglsang & Aagaard Madsen, 1995). The design variables are divided into 3 categories: rotor shape, airfoil characteristics, and blade regulation. The design method demonstrated that the change in rotor shape resulted in a maximum allowable strain on more than 80 % of the blade and a reduction of 3.5 % in energy cost.

Similarly, Maalawi and Badr (K. Y. Maalawi & Badr, 2003) developed a computer program and a new mathematical formulation based on dimensionless quantities to generate an optimum rotor configuration with the highest power output. The aerodynamic analysis is based on (H. Glauert, 1935; K. Y. Maalawi & Badawy, 2001; Pandey, Pandey, & Ojha, 1989; Robert Elliott Wilson, Lissaman, & Walker, 1976) and the design parameters are the chord and twist distributions, number of blades, family of the airfoil sections, hub size and the tip speed ratio.

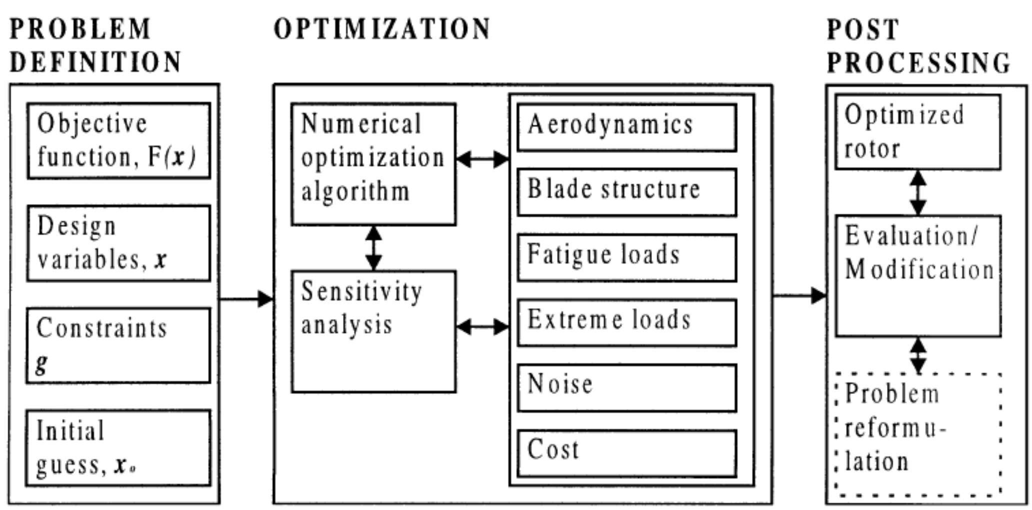

Figure 3 : Numerical algorithm applied by Fuglsang and Madsen (P. Fuglsang & Madsen, 1999).

A fast forward to 2005, Jureczko et al. (Jureczko, Pawlak, & Mezyk, 2005) studied the optimization of a wind turbine blade as a purely structural problem assuming a fixed aerodynamic shape. However, the model is only effective in modal, static and linear transient analysis. The formulation of the multi criteria discrete optimization problem forced the authors to take into account multiple criteria that can be contradictory at times. Jureczko et al. (Jureczko et al., 2005) formulated the optimization problem based on 5 different criterions:

1. Minimization of the generated blade vibrations
2. Maximization of the generated output
3. Minimization of blade material costs
4. Ensure local and global stability of the blade structure
5. Ensure strength requirements of the blade structure

The reason behind the first criterion is that minimal blade vibration guarantees a higher stability. However, caution must be taken when separating the natural frequency of the blade from the harmonic vibration associated with rotor rotation to prevent the occurrence of resonance. High vibration amplitude leads to the destruction of the wind turbine structure. Nevertheless, the vibration amplitude is a function of the material density, shell thickness and the arrangement of the structural ribs along the blade. Hence, when minimization of blade vibration is considered, proper care must be taken to ensure the required stiffness. This formulation of the optimisation problem also satisfies the second criterion; maximization of the generated output, since the output of a wind turbine depends also on the optimum shape. The third and fourth criterions are a difficult task to meet since the minimization of the costs of the blade materials is achieved by the minimization of the blade mass. A conflict between both principles arises because weight minimization puts the stability of the blade at risk, and in order to obtain better stability, the weight should be maximized. Finally, to meet the strength requirement, a limiting condition on the displacement in the transverse direction is added.

Méndez et Greiner (Méndez & Greiner, 2006) prepared a method to obtain the optimal chord and twist distributions in wind turbine blades. The distributions are calculated to maximize the mean power depending on the Weibull wind distribution. To optimize chord and twist distributions, an efficient implementation of the BEM theory (Burton, Jenkins, Sharpe, & Bossanyi, 2011; Jason Mark Jonkman, 2003; Martin, 2008) is used.

Liu et al. (Liu, Chen, & Ye, 2007) develop an optimization model based on an extended compact genetic algorithm (ECGA) to maximize the annual energy output of a 1.3 MW stall-regulated wind turbine. Compared to the original blades, the designed blades demonstrated a better aerodynamic performance. In fact, the results confirmed that at a lower wind speed, the power is nearly twice of that yielded by the original blades. An increase of 7.5 % in the annual energy output was recorded.

Lee et al. (Lee et al., 2007) presented a robust optimization procedure for wind turbine blades in the offshore Korean peninsula. The blade shape is optimized to obtain the maximum annual power production. The method consists of two steps; the operating condition optimization (step 1) and the geometric blade shape design and blade performance analysis optimization (step 2).

A multidisciplinary design feasible (MDF) (Cramer, Dennis, Frank, Lewis, & Shubin, 1994) approach is used for solving the optimization problem of a wind turbine blade by Kenway and Martins (Kenway & Martins, 2008). The blade is constructed using 7 design variables: chord, twist, spar (thickness, location, and length), airfoil thickness and rotation rate. To demonstrate the potential for site-specific optimization, a 5-kW wind turbine case was used with results showing a possible output increase of 3-4 %.

In 2009, Ceyhan et al (Ceyhan, 2008; Ceyhan, Sezer-Uzol, & Tuncer, 2009) studied the aerodynamic performance of horizontal axis wind turbine blades using BEM theory (Moriarty & Hansen, 2005) and genetic algorithm. An increase of 40 to 80 % in power production was recorded on a 100 kW HAWT. In the same year Clifton-Smith and Wood (Clifton-Smith & Wood,

2007) applied a numeric method of differential evolution (DE) to maximise both power and starting performance. Results show that the starting time can be improved by a factor of 20 with a small reduction in power coefficient. Similarly, Belessis et al. (Belessis, Stamos, & Voutsinas, 1996), investigated the capabilities of a genetic algorithm based wind turbine design tool demonstrating a 10% gain of annual energy for 100, 300 and 500 kW wind turbines.

Xudong et al. (W. Xudong, Shen, Zhu, Sorensen, & Jin, 2009; Wang Xudong, Shen, Zhu, Sørensen, & Jin, 2009) presented a design tool for optimizing wind turbine blades, coupling between an aerodynamic and an aeroelastic code to account for the structural dynamics represented by 11 degrees of freedom. The chord, twist and relative thickness of the blade were optimized. A three-bladed wind turbine was optimized, taking into consideration three eigenmodes (first and second flapwise modes and the first edgewise mode) along with the axial displacement of the whole rotor and the azimuth displacement of the blades. Further details concerning the aerodynamic/aeroelastic code can be found in (Omri, 2003; J. S. Schepers, H., 2007; H Snel, 2001; H. S. Snel, JG

Montgomerie, B, 2007), about the aerodynamic model in (H. Glauert, 1935) and the cost model in (Rasmussen & Kretz, 1994). In this study, Xudong et al (W. Xudong et al., 2009) restricted the fitness function to the cost of the rotor, where the total costs of producing, transporting and erecting the wind turbine rotor are evaluated. The relative value of the total rotor cost is defined as:

$$f(\vec{x}) = CoE = \frac{C_{rotor}}{AEP} \quad [1.2]$$

$$C_{rotor} = b_{rotor} + (1 - b_{rotor})w_{rotor} \quad [1.3]$$

where $\boldsymbol{b_i}$ is the fixed part of the rotor cost (assumed 0.1) and $\boldsymbol{w_{rotor}}$ is the weight parameter of the rotor calculated from the chord and blade mass distributions:

$$w_{rotor} = \sum_{i=1}^{N} \frac{m_i c_{i,opt}}{M_{tot} c_{i,org}} \quad [1.4]$$

where $\boldsymbol{m_i}$ is the mass of the *i*-th cross-section of the blade; $\boldsymbol{c_{i,opt}}$ is the averaged chord of the *i*-th cross section of the optimized blade; $\boldsymbol{c_{i,or}}$ is the averaged chord of the *i*-th cross-section of the original blade; $\boldsymbol{M_{tot}}$ is the total mass of the blade (W. Xudong et al., 2009).

The wind turbine is assumed to operate 8700 hours per year, and its AEP is evaluated as follows:

$$AEP = 8760 \sum_{i=1}^{n} \frac{1}{2} [P(V_{i+1}) + P(V_i)] f(V_i < V < V_{i+1}) \qquad [1.5]$$

where $P(V_i)$ is the power at the wind speed of V_i.

Inspired by Xudong et al. (Wang Xudong et al., 2009), Eke and Onyewudiala (Eke & Onyewudiala, 2010) applied a GA to optimize the shape parameters (chord, twist and relative thickness) using the same cost model and AEP formulation of (W. Xudong et al., 2009; Wang Xudong et al., 2009). Their results displayed a decrease of 0.8% in annual energy production and a decrease of 1.9% in the rotor cost, hence a decrease of 1.115% in rotor energy cost.

Grujicic et al. (M. Grujicic et al., 2010) developed a two-level optimization scheme consisting of an inner and outer level. In the inner level, for a given aerodynamic design of the blade; the blade mass is minimized). In the outer level, a cost assessment analysis is employed. Also, in the outer-level optimization loop the cost of energy is evaluated as the ratio of the blade material and production costs and the calculated AEP. This procedure is repeated until suitable objective function minima are found for both the outer-level and the inner-level optimization loops.

Wang et al. (L. Wang, Wang, & Luo, 2011) presented a multi-objective algorithm where the maximum power coefficient $\boldsymbol{C_P}$ at the design wind speed (9 m/s) and the minimum blade mass are taken as conflicting objectives. The aerodynamic loads acting on the blade are calculated using the modified BEM theory (Dai, Tang, & Wang, 1988). The mass distribution and the total mass of the blade are obtained from the normal stress equations in the condition of a free-bending thin-walled beam. The two objectives can be formulated as follows:

$$f_1 = \max(\mathbf{C_p} | V = 9\ m.s^{-1}) \quad [1.7]$$

$$f_2 = min \int_{R_{hub}}^{R} \mathbf{m_i} dr \quad [1.8]$$

In 2013, Chen et al. (J. Chen et al., 2013) recently established an optimized model to optimize the thickness and the location of the spar caps coupling a finite element program and a PSO algorithm. The initial ply design of the composite blade structure is composed of the combination of 6 laminate materials (refer to Figure 4):

1. A unidirectional laminate
2. Bi-axial laminate
3. Tri-axial laminate
4. Coating material
5. Extra resin
6. Foam core material

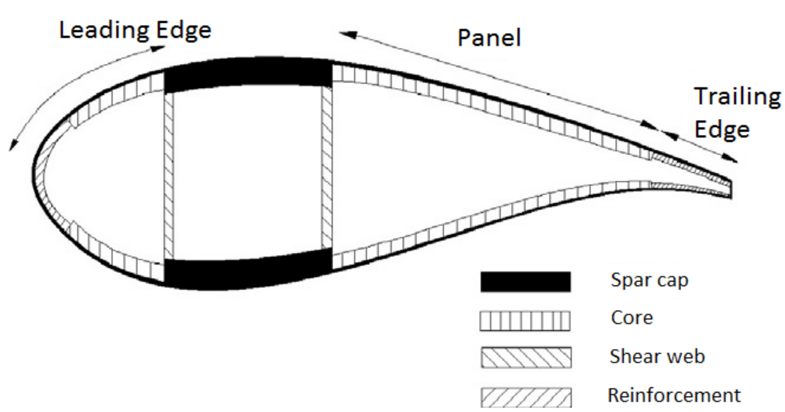

Figure 4 : Blade material of Chen et al. (J. Chen et al., 2013) (reproduced from (J. Chen et al., 2013)).

1.3.3 REVIEW OF WIND TURBINE PERFORMANCE OPTIMIZATION STUDIES

Diveux et al. (T Diveux, Sebastian, Bernard, Puiggali, & Grandidier, 2001) used a global cost model for the wind turbine and its components, inspired by the parameters of (Thierry

Diveux, 2000; Harrison & Jenkins, 1994) to develop a custom optimization design tool for wind turbines near the Mediterranean. The total wind turbine cost $\boldsymbol{C_{WT}}$ is the sum of all the components costs $\boldsymbol{C_{comp}}$ tampered by a calibration factor $\boldsymbol{F_{WT}}$ of 1.1, which take into account some unknown parameters such as the manufacturer's margin. The annual operation and maintenance costs are fixed to 2-5% of the initial investment cost and an actualization factor ***a*** was included (T Diveux et al., 2001) as follows:

$$C_{\mathrm{WT}} = F_{\mathrm{WT}} \sum_{i=1}^{N} C_{\mathrm{comp}} \qquad [1.9]$$

$$Total\ cost = (a + 0.025) C_{\mathrm{IT}} \mathrm{Z} \qquad [1.10]$$

The annual electrical energy output is determined by the integration of the wind speed distribution (Weibull) and the energy output for 1 year [kWh]. Diveux et al. use an empirical model for the power coefficient based on Wilson and Lissaman (Robert Elliott Wilson et al., 1976) :

$$E_{AP} = 8.76 \frac{\rho_{air}}{2} S_R \int_{V_1}^{V_2} V^3 f(V) C_p(V) \eta_{GB}(V) dV \qquad [1.11]$$

where $\boldsymbol{E_{AP}}$ is the annual energy production, with $\boldsymbol{S_R}$ is the swept area of the rotor (m^2), $\boldsymbol{f(V)}$ is the Weibull density function of the wind speed, $\boldsymbol{\eta_{GB}}$ is the gearbox efficiency (Harrison & Jenkins, 1994), $\boldsymbol{\eta_G}$ is the generator efficiency (Harrison & Jenkins, 1994). The results of Diveux et al. (T Diveux et al., 2001) indicated that the optimal wind turbines for the given Mediterranean conditions require larger power parameters.

Benini et al. (Benini & Toffolo, 2002) apply a multi-objective evolutionary algorithm (MOEA) for the design optimization of stall regulated wind HAWT with a trade-off between the ratio of ***AEP*** over the wind park area (to maximize) and the cost of energy (to minimize). An alternative objective function that is explored instead of the annual energy is the ***AEP*** density; ratio of this latter and the wind park area $\boldsymbol{R^2}$, a parameter that the designer seek to maximize in (Benini & Toffolo, 2002). The motif behind using this metric comes from the fact that the number of turbines that can be installed in a given area is inversely proportional to the square of turbine radius Therefore, the ***AEP*** density is defined as [kWh/m^2]:

$$AEP_{density} = \frac{AEP}{R^2} \qquad [1.12]$$

where ***AEP*** is the annual energy production and ***R*** the radius of the wind park.

The MOEA handles the chosen design parameters and searches for the group of optimal solutions following a set of Pareto concepts and basic principles of genetic programming (David Edward Goldberg, 1989; Schwefel, 1993). The chosen design variables are the tip speed, hub/tip ratio, chord and twist distributions. The airfoil parameters such as C_L and C_D that are function of the angle of attack are extracted from (Bertagnolio, Sørensen, Johansen, & Fuglsang, 2001). The shell thickness along the blade, coning angle, tilt angle and number of blades are all assumed constant during the optimization.

Fuglsang et al. (Peter Fuglsang et al., 2002) present a numerical optimization algorithm that is coupled with an aeroelastic and cost model, allowing the optimization of stand-alone flat terrain and offshore wind farm wind turbines for different operations and wind conditions (refer to **Error! Reference source not found.**). The work is used to identify the potentials in site specific design for offshore wind turbine farms by means of site specific design optimization of a reference 1.5 MW stall regulated wind turbine considering the hub height, rotor speed, rotor diameter and rated power as the design variables.

In 2010, Bottasso et al. (Bottasso, Campagnolo, & Croce, 2010) exercised a thorough description of a multi-disciplinary design optimization procedure. The optimization is realized through the maximizing of a merit function under constraints respecting relevant design requirements (Commission, 2005, 2006). Bottasso et al. (Bottasso et al., 2010) assumed that the weight is correlated to the cost but does not use a particular cost model, arguing that a reliable cost model is not offered to the public. The multi objective design is not formulated as a Pareto optimal problem, but rather as a combined cost defined as the ratio of the annual energy production to the total weight. The optimization task is a nested constrained optimization problem that has among its constraints a second set of constraints. Since the direct solution of the problem may require a significant computational effort, Bottasso et al. (Bottasso et al.,

2010) applied a sequential constrained optimization where the procedure is divided into two stages. In the first stage, the maximum ***AEP*** for minimum blade weight is calculated.

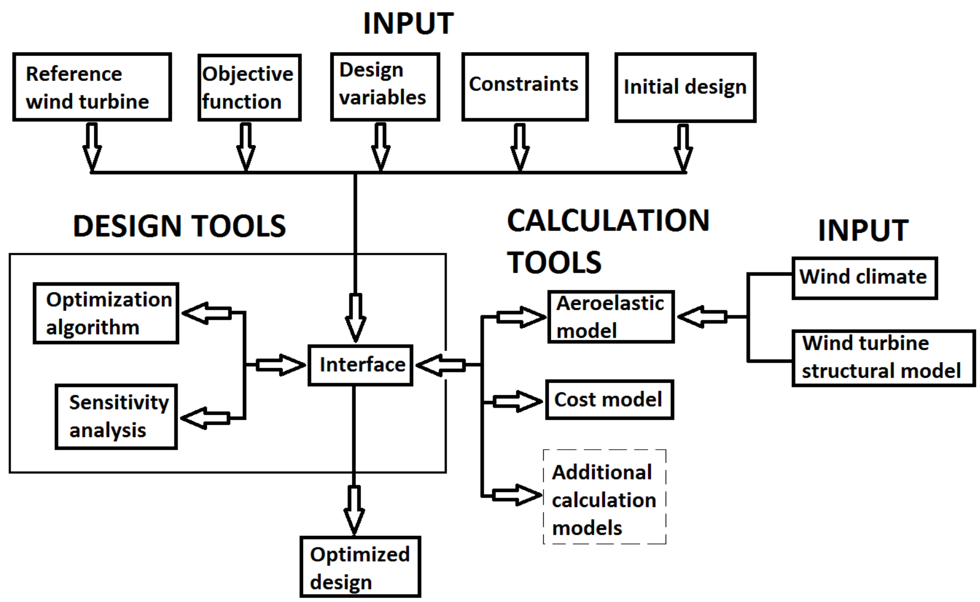

Figure 5 : Design tool of Fuglsang et al. (Peter Fuglsang et al., 2002) (reproduced from (Peter Fuglsang et al., 2002)).

Kusiak et al. (Kusiak, Zhang, & Li, 2010) introduced a data-driven approach to study the impact of turbine control on their vibrations and power output. The authors developed model for prediction of vibrations and the produced power using neural networks. To illustrate the importance of the three objectives (two vibrations and the power output), a weighted sum of these objectives is minimized:

$$min\left(w_1 y_1(t) + w_2 y_2(t) + w_3 \frac{1}{y_3(t)}\right) \qquad [1.6]$$

where $\boldsymbol{y_1(t)}$ is the estimated vibration of the drive train; $\boldsymbol{y_2(t)}$ tower vibration model; $\boldsymbol{y_3(t)}$ estimated power output model.

Maki et al. (Maki, Sbragio, & Vlahopoulos, 2012) conducted a new multi-level system design algorithm (MLS) for the analysis of a wind turbine. Similar general engineering design optimization models are introduced in (Fletcher, 2013; Papalambros & Wilde, 2000) (refer to Figure 6).

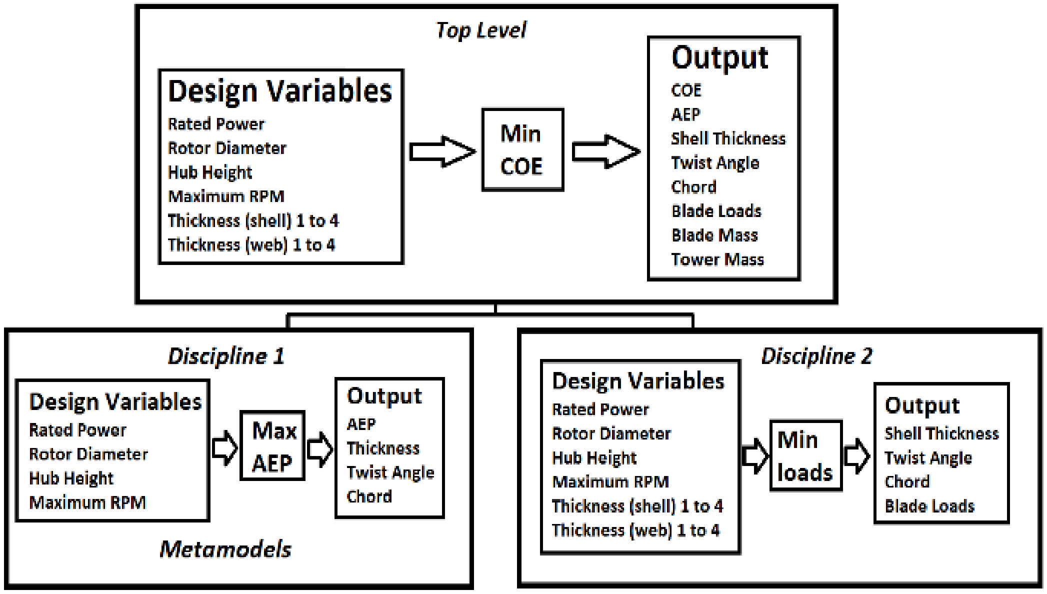

Figure 6 : Flowchart of the optimization scheme of Maki et al. (Maki et al., 2012) (reproduced from (Maki et al., 2012)).

The cost of energy is the overall system level objective, arguing that the work that optimize the ratio of lift to drag do not reflect the least cost of energy. Maki et al. inspired their work from other areas in engineering that seek one overall global optimum design such as in naval architecture (Cox et al., 2001; Moraes, Vasconcellos, & Almeida, 2007), automotive engineering (H. M. Kim, Michelena, Papalambros, & Jiang, 2003; Sinha, 2007), mechanical engineering (I. Y. Kim & de Weck, 2005; Venkayya, 1989), in biomedical engineering (Moles, Mendes, & Banga, 2003) and others (Jouhaud, Sagaut, Montagnac, & Laurenceau, 2007; Lewis, 2001). The design variables (rotor diameter, rotational speed, maximum rated power, hub height, structural characteristic of the blade, geometric characteristic of the blade) are separated into blade parameters and rotor parameters to find the minimum cost of energy of the entire system. The system design analysis was developed using the NREL tools (NREL) with a cost and scaling model from the work of Fingersh et al. (Fingersh, Hand, & Laxson, 2006). The two technical design disciplines that compose the design optimization of the wind turbine are:

1. The optimal design of the blade geometry for maximum annual energy production

2. Structural design of the blade for minimum bending moment at the root

In a compelling study conducted by Ning et al. (A. Ning, Damiani, & Moriarty, 2013), the authors study the impact of various objective functions on the quality of the optimal solutions. Three different optimization objective functions were examined:

1. Maximization of the Annual Energy Production (AEP)
2. Minimization of the turbine mass to AEP ratio
3. Minimization of the cost of energy (CoE)

Ning et al. (A. Ning et al., 2013) assumed that the weight loads are added to the aerodynamic loads at 0 degree pitch and the 3 o'clock azimuthal position, which is considered the worth case for edgewise loads. The 2D airfoil correction take account the rotational effects in the solver using a Du-Selig (Du & Selig, 1998) for lift and Eggers(Eggers, Chaney, & Digumarthi, 2003) for drag. The method proposed by Viterna (Viterna & Janetzke, 1982) was used for the extrapolation of the results for the -180^o to $+180^o$ range. The NREL 5MW geometry was used as a reference (Jason Mark Jonkman, Butterfield, Musial, & Scott, 2009) with a preliminary evaluation by NUMAD for the initial layup (Resor, 2013) and the materials were derived from the database carried by Mandell (Mandell & Samborsky, 1997). A parameterization of the chord, twist and spar cap distribution along the blade length was completed to ensure the efficiency and flexibility in describing the geometry. The cost model used in (A. Ning et al., 2013) was proposed by Fingersh (Fingersh et al., 2006) but some modifications were implemented in the optimization tool. One of the main adjustments was the computation of the blade mass using structural models and not scaling laws. Another modification is that the blade cost was supposed to be a linear function of the blade mass and the mass of the tower was estimated using physics-based scaling arguments.

The first objective function Ning et al. (A. Ning et al., 2013) examined was a sequential maximization of the AEP followed by a minimization of the blade mass. The AEP can be conducted using different strategies, namely as follows:

1. deprived of a blade mass computation
2. with mass constraints by the use of surrogates

When maximizing the AEP using the first method, the optimization strategy lead to the design of multiple blades with the same AEP for different blade masses; meaning the existence of weak local optimum solutions.

The blade mass constraints were imposed in diverse forms. One possibility of constraining the blade mass is limiting the root bending moment. However, the root bending moment constraint does not alter the solution since the primary objective is to maximize the AEP, which tends to decrease the root bending moment. Another surrogate is inspired from aircraft design, using wing weight portion scaling, where the weight of the wing is divided into a portion that scales with the planform area and another that scales the required loading (S. A. Ning & Kroo, 2010). In this strategy, the optimal solution is realized by decreasing the root chord in exchange for a larger chord at maximum chord location. The aerodynamic performance of the blade is improved but structurally worth, therefore a restriction on the stress at the blade root is set. This surrogate alters the optimization problem; applying a sequential algorithm where the maximization of the AEP is followed by the minimization of the blade mass. An alternative approach is forcing the structural analysis to dictate the blade shape whereas the aerodynamic analysis only dictates the airfoil shape; this is known as blade shape and airfoil decoupling. This approach changes the optimization because the structural analysis must be repeated one final time to guarantee that the constraints are satisfied. The results of each surrogate were compared with the minimum cost of energy formulation and a maximum energy reduction of 0.35% was recorded from the blade & airfoil decoupling and a 0.3% reduction in portion scaling. Although both approaches lead to decreases in cost of energy, they are still inferior to metrics that combine the aerodynamic and structural performance.

Ning et al. (A. Ning et al., 2013) deduced that maximizing AEP and then minimizing the mass sequentially is ineffective. When designers are fixed with material selection, a reasonable choice is to minimize the ratio of the turbine mass to the annual energy production. Results showed that even if a proper nacelle and tower model are not used, a constant estimate of their mass must be included; otherwise potential decreases in rotor mass are overemphasized, which can lead to exaggerated aerodynamic performance. If a fixed tower mass is chosen, then the optimization showed good results at a fixed rotor diameter, but for a variable-diameter design, inaccurate diameters were predicted. On the other hand, when the tower is allowed to resize, caution must be taken because the tower mass consists a large portion of total mass, but tower cost is a rather small to the total cost. Thus, minimizing the ***m/AEP*** ratio may risk overemphasizing the role of the tower if careful care in the construction of the problem is not pursued. Equivalently, the objective function may over incentivize the solver to decrease the tower mass at the expense of aerodynamic performance

1.4 SUMMARY

Within the last 15 years, wind turbine technology has reached maturity. The growing world-wide market will culminate to further improvements. The advances in horizontal wind turbine performance strategies and techniques will result to further cost reductions and in the near future wind energy will be able to compete with fossil fuel. It can be anticipated that the number of research publications that use optimization techniques to solve for the optimal horizontal wind turbine blade, airfoil shape and rotor design problems have increased significantly in recent years.

The parameters that designers seek to optimize under a set of design constraints have evolved in recent years. Wind turbines are designed using an integrated design process where several important parameters are included such as annual energy production, extreme and fatigue loads, as well as a turbine component cost model. Ultimately, the objective is to minimize the cost per kilowatt-hour.

Lately, we have witnessed an increased awareness of improving the wind turbine performance. Practical constraints associated with physically harnessing the kinetic energy in wind to generate electricity relate to the suitability of:

1. Wind speeds
2. Land, access and ecological issues
3. Residential annoyance and shadow flicker
4. Structural and mechanical limitations

All of the above setbacks will interfere the wind farm project if not carefully taken into consideration during a preliminary design phase. Therefore, in order to build an efficient and reliable wind turbine blade design tool, the various optimization strategies and design constraints have to be identified. The latter will the topic of discussion in the next chapter.

CHAPTER 2

MATHEMATICAL MODELS OF THE WIND TURBINE OPTIMIZATION PROBLEMS

2.1 INTRODUCTION

In the previous chapter, we presented the most relevant studies conducted in the field of wind turbine optimization. In order to present an efficient and reliable wind turbine blade design tool, a thorough examination of the mathematical models must be conducted. Accordingly, in this chapter, we will inspect the structure of the mathematical models used in WTOP. At the outmost, the objective functions are assessed followed by a taxonomy of the wind turbine design constraints.

2.2 OBJECTIVE FUNCTIONS

The parameters that designers seek to optimize have evolved in recent years. In the early days, designers focused on the maximization of the power coefficient $\boldsymbol{C_P}$ (the fraction of power in the wind that can be extracted by the wind turbine). This optimization strategy had a direct impact on the blade shape, resulting in larger root chords, larger taper and very high blade twist. With the increase of the rotor size for higher power production, the problems occurring in transportation and production began to interfere with the design. As the maximization of the power coefficient occurs at a particular tip speed ratio on fixed speed stall regulated turbines, the tendency shifted towards a second optimization parameter - the maximization of energy production. The maximization of the energy production is achieved over a given period of time (e.g. one year) and wind speed spectrum rather than a particular wind speed. Increased knowledge about the influence of rotational effects in stall brought a new generation of wind turbine blades with smaller root chords and less twist.

Since wind energy is still unable to compete with traditional fossil fuel energy sources and to increase its economics, the main objective has shifted toward minimization of the cost of energy (CoE: ratio of the total costs and the annual energy production). In this strategy, loads are translated into costs by introducing a cost model and by slightly reducing the power coefficient, loads on the wind turbine can be largely reduced. This type of optimization resulted in slender blades, with lower solidity. The design of a wind turbine rotor is complex, since design variables are dynamic, and some have conflicting behaviors within the definition of the CoE. For example, the rotor diameter is increased for a higher energy capture but this result into higher loads that increase the cost of energy.

In (Ashuri, Zaaijer, van Bussel, & van Kuik, 2010; Bak, 2013; Benini & Toffolo, 2002; Eke & Onyewudiala, 2010; P Fuglsang & Aagaard Madsen, 1994; Peter Fuglsang & Aagaard Madsen, 1995; Peter Fuglsang et al., 2002; P. Fuglsang & Madsen, 1999; Giguere & Selig, 2000; M. Grujicic et al., 2010; Maki et al., 2012; A. Ning et al., 2013; W. Xudong et al., 2009), the authors argue that the main objective in wind turbines is towards the minimization of the cost of energy rather than the maximization of the aerodynamic performance of the wind blade in order to make wind energy competitive with other energy sources. One of the earliest approaches was to restrain the blade weight growth with the increase of its length by limiting the chord length and increasing instead the lift coefficients of wind turbine airfoils. This strategy is inspired by the fact that the blade is one of the most important components of wind turbines and its structure has significant impact on the stability and the cost of the wind turbine. Hence to lower the cost, the weight should decrease but in order ensure the stability, the weight has to be increased. So, designing a blade with minimal blade mass requires the right balance between the mass and the stability. Wind turbines dimensions are becoming larger and it can be assumed that gravity and inertia loads become as significant as aerodynamic loads, hence the importance of weight reduction. However, common alternatives for the choice of the objective function are the maximization of the annual energy production or the power coefficient, blade mass minimization and maximization of the rotor thrust and torque.

In this chapter, the objective functions that were explored are divided in four main categories: minimization of cost of energy, maximization of the power production, minimization of the blade mass and the group of multi-disciplinary optimizations. The reader is referred to

(Bak, 2013; Benini & Toffolo, 2002; Eke & Onyewudiala, 2010; P Fuglsang & Aagaard Madsen, 1994; Peter Fuglsang & Aagaard Madsen, 1995; Peter Fuglsang et al., 2002; P. Fuglsang & Madsen, 1999; J. Y. Li et al., 2010; Liao, Zhao, & Xu, 2012; Maki et al., 2012; Morgan & Garrad, 1988; A. Ning et al., 2013; H. Snel, 2003; L. Wang et al., 2011; W. Xudong et al., 2009) for further discussions concerning the choice of the objective function in wind turbine optimization.

2.2.1 MINIMIZATION OF THE COST OF ENERGY

The cost of energy (CoE) is a parameter that is examined as the main and overall objective function in the following references (Arroyo et al., 2013; T Diveux et al., 2001; Eke & Onyewudiala, 2010; P Fuglsang & Aagaard Madsen, 1996; Peter Fuglsang et al., 2002; P. Fuglsang & Madsen, 1999; Giguere & Selig, 2000; Philippe Giguère, Tangler, & Selig, 1999; Hendriks, Schepers, Engelen, Stern, & Boerstra, 1996; Kenway & Martins, 2008; Maki et al., 2012; A. Ning et al., 2013; W. Xudong et al., 2009; Wang Xudong et al., 2009). It is essentially expressed as a ratio between the total annual cost C_{TA} and the annual energy production (AEP). Because the operation and maintenance costs account a small percentage of the capital cost and since a well-designed wind turbine with a low cost of energy has an aerodynamically efficient rotor, the objective function is sometimes restricted to the cost of the rotor (Eke & Onyewudiala, 2010; W. Xudong et al., 2009; Wang Xudong et al., 2009).

$$CoE = \frac{C_{TA}}{AEP} \qquad [2.1]$$

In offshore wind energy, the objective is to maximize the difference between the value of the energy (depending on the expected payback period) and the energy cost. For example, Snel (H. Snel, 2003) states that in offshore wind turbine farms, the turbine cost is not dominant, since other elements such as the foundation, installation, and electrical cable costs are high, and hence the designer pursues larger rotor sizes for a more economically attractive system.

2.2.2 MAXIMIZATION OF THE ANNUAL ENERGY PRODUCTION

The purpose behind an aerodynamic optimization is the absence of a reliable structural and cost model. Although the most popular objective for the current wind turbine optimization is minimization of the cost of energy, some trends are directed toward optimizing the aerodynamic performance of a wind turbine by either:

1. Maximization of the power production at a fixed wind speed
2. Maximization of the AEP for a given wind distribution

The maximum annual energy for a given distribution was investigated in the following references (Belessis et al., 1996; P Fuglsang & Aagaard Madsen, 1994; Peter Fuglsang & Aagaard Madsen, 1995; Lee et al., 2007; Liu et al., 2007; K. Y. Maalawi & Badr, 2003; Méndez & Greiner, 2006; A. Ning et al., 2013; M. S. Selig & Coverstone-Carroll, 1996; Xuan, Weimin, Xiao, & Jieping, 2008). The annual energy is usually calculated by integration of the wind turbine power combined with a wind speed distribution (e.g. Weibull) over the wind speed spectrum.

$$AEP = \int_{V_{min}}^{V_{max}} P(V) f(V) dV \qquad [2.2]$$

here, *P(V)* is the power curve of the wind turbine, *f(V)* is the wind speed distribution.

2.2.3 MINIMIZATION OF THE WIND BLADE MASS

In (Chehouri, Younes, Hallal, & Ilinca, 2013, 2014; J. Chen et al., 2013; Jureczko et al., 2005; Liao et al., 2012; Pirrera, Capuzzi, Buckney, & Weaver, 2012; Zhu, Cai, Pan, & Gu, 2012), minimum blade mass was defined as the primary objective function. Jureczko et al. (Jureczko et al., 2005) developed a numerical model of the wind turbine blade to perform a multi-criteria discrete-continuous optimization of wind turbine blades with the blade mass as the main objective function and the criteria’s translated into constraints. Liao et al. (Liao et al., 2012) developed a multi-criteria constrained design model integrating a particle swarm optimization algorithm with FAST (Jason M Jonkman & Buhl Jr, 2005).

Ning et al. (A. Ning et al., 2013) inspected the minimization of the turbine mass to AEP ratio as one of three examined objective functions. In a recent journal, Chen et al. (J. Chen et al., 2013) argue that a lighter blade mass will be beneficial to improve fatigue life based on requirements of blade's strength and stiffness. Therefore, the minimum mass of the wind turbine blade was chosen as objective function.

2.2.4 MULTI-OBJECTIVE OPTIMIZATION FORMULATIONS

In references (Benini & Toffolo, 2002; Bottasso et al., 2010; Deb, 2001; Giguere & Selig, 2000; Philippe Giguère et al., 1999; M. Grujicic et al., 2010; Ju & Zhang, 2012; Kusiak et al., 2010; M. S. Selig & Coverstone-Carroll, 1996; L. Wang et al., 2011), the authors apply a multi-objective optimization model.

Giguère et Selig (Giguere & Selig, 2000) selected to simultaneously optimize the blade geometry for two objectives among the following choices:

- Minimize the cost of energy of the turbine or any component
- Maximize the AEP or power coefficient
- Minimum rotor thrust or torque

The AEP & CoE are combined by means of appropriate weights in (Philippe Giguère et al., 1999; M. S. Selig & Coverstone-Carroll, 1996). But since both metrics have conflicting objectives, the variation of the AEP as a function of the CoE is fundamental. This is known in optimization as the search for a set of Pareto Optimal design solutions.

Benini et al. (Benini & Toffolo, 2002) try to achieve the best trade-off between two metrics; the ratio of the annual energy production and the wind park area, a parameter that is maximized simultaneously with minimization of the cost of energy.

Bottasso et al. (Bottasso et al., 2010) presented a multi-disciplinary optimization of a wind turbine as a multi-objective design problem (Deb, 2001) where a compromise between the maximization of the annual energy production (AEP) and weight minimization.

Kusiak et al. (Kusiak et al., 2010) presented a multi-objective optimization model considering three objectives: wind turbine power output, drive train and tower vibrations.

The same year, Kusiak et Zheng (Kusiak & Zheng, 2010) presented a bi-objective optimization, a trade-off between the power coefficient and the energy output of the wind turbine.

Grujicic et al. (M. Grujicic et al., 2010) developed a multidisciplinary design optimization procedure based on a two-level optimization scheme. Wang et al. (L. Wang et al., 2011) presented a multi-objective algorithm combining the maximum power coefficient and the minimum blade mass.

2.3 CONSTRAINTS APPLIED IN WIND TURBINE DESIGN PROBLEMS

In engineering optimization, a constrained optimization is the mathematical process of optimizing an objective function with respect to a vector of design variables under a set of constraints. In general terms, imposing constrains to the problem increases the difficulty of the formulation with the risk of complicating the design. In this section, we enumerate the design constraints used in the performance optimization of wind turbines. After a critical survey of the literature, the constraints applied in wind turbine design studies into three categories: geometrical, aerodynamic and physical constraints.

2.3.1 GEOMETRICAL CONSTRAINTS

Below we list the different geometrical constraints identified in the literature.

2.3.1.1 GROUND CLEARANCE

In the following references (Bizzarrini et al., 2011; Bottasso et al., 2010; J. Chen et al., 2013; F. Grasso, 2011; Hillmer, Borstelmann, Schaffarczyk, & Dannenberg, 2007; Jeong et al., 2012; Jureczko et al., 2005; Kong, Bang, & Sugiyama, 2005; Liao et al., 2012; A. Ning et al., 2013; Zhu et al., 2012), limitations on the displacement of local nodes (***u***) and/or a maximum tip deflection (***δ***) are employed.

Two sets of displacement constraints were set by Jureczko et al. (Jureczko et al., 2005). The first displacement constraint is set for the individual nodes in the numerical model of the blade to ensure global stability. The second constraint is on the blade tip to guarantee a local stability.

$$u(\overrightarrow{x}) \leq u_{max} \tag{2.3}$$

$$\delta \leq \delta_{max} \tag{2.4}$$

where ***u(x)*** and ***δ*** are respectively the local displacements and the tip deflection of the nodes along the blade model, u_{max} (0.1 m) and δ_{max} (0.15 m) are the limits.

Liao et al. (Liao et al., 2012) choose to consider one load case to predict the tip deflection in the optimal design; the one that generates the same tip deflection for the initial blade after the analysis by FOCUS5.

Ning et al. (A. Ning et al., 2013) calculated the deflection of the structure at rated speed in the 3 o'clock azimuth position; which is assumed to be the worst loading case, constraining the deflection to be within 10% of the baseline tip deflection δ_0 (2.44 m).

$$\delta \leq 1.1\delta_0 \tag{2.5}$$

In order to prevent security problems, a ground clearance between the blade tip and the ground is set. For instance, Diveux et al. (T Diveux et al., 2001) set a safety clearance of 15 m.

$$\frac{D_R}{2} + 15 \leq H_{hub} \tag{2.6}$$

where D_R is the rotor diameter, H_{hub} is the hub height.

2.3.1.2 STRAIN

Similar to the generated stresses in the structure, the strains are restrained in the following references (Bottasso et al., 2010; Maki et al., 2012; A. Ning et al., 2013; Zhu et al., 2012) expressed by the following inequality:

$$\epsilon(\vec{x}) \leq \epsilon_{ult} \qquad [2.7]$$

where $\boldsymbol{\varepsilon}$ is the local strain at the local nodes of the blade model and $\boldsymbol{\varepsilon_{ult}}$ is the ultimate strain.

Bottasso et al. (Bottasso et al., 2010) constrains the maximum strains of the sectional airfoils evaluated using an anisotropic beam theory (Giavotto, Borri, Mantegazza, & Ghiringhelli, 1983). Ning et al. (A. Ning et al., 2013) added a maximum strain condition where the ultimate strain $\boldsymbol{\varepsilon_{ult}}$ is bounded by the strain at 50-year extreme wind condition tampered by a partial safety factor for loads $\boldsymbol{\gamma_f}$ and a partial safety factor for materials $\boldsymbol{\gamma_m}$ as per the IEC requirements (Commission, 2005).

$$-\gamma_f \gamma_m \epsilon_{50} \leq \epsilon_{ult} \leq \gamma_f \gamma_m \epsilon_{50} \qquad [2.8]$$

Maki et al. (Maki et al., 2012) ensured that the largest strain in the blade, in each of the four chosen sections of the blade do not exceed the limit of 0.003

2.3.1.3 SOLIDITY

Lee et al. (Lee et al., 2007) included a lower limit for the solidity that can be modified by changing the number of blades or more realistically by altering the blade chord (Burton et al., 2011).

$$\sigma = \frac{B \int c(r) dr}{\pi R^2} \geq \sigma_{LL} \qquad [2.9]$$

where $\boldsymbol{\sigma}$ is the solidity of the blade, $\boldsymbol{B}$ the number of blades, $\boldsymbol{c}$ the chord distribution, $\boldsymbol{R}$ is the radius of the blade and $\boldsymbol{\sigma_{LL}}$ is the maximum solidity 0.0345.

2.3.2 AERODYNAMIC CONSTRAINTS

Below we list the various aerodynamic constraints identified in the literature.

2.3.2.1 SHELL AND AIRFOIL THICKNESS

A feasibility condition is forced on the shell thickness and the surface of the airfoil of the wind turbine blade in the following references (Benini & Toffolo, 2002; Bizzarrini et al., 2011; F. Grasso, 2011; Francesco Grasso, 2012; Ju & Zhang, 2012; Maki et al., 2012; Petrone et al., 2011). For example, Benini and Toffolo restricted the shell thickness to half of the blade profile thickness at any radius.

In addition, Grazzo (F. Grasso, 2011) also imposes a minimum trailing edge thickness of 0.25 and a minimum leading edge radius of 0.015c to ensure airfoil's feasibility and ensure a proper trailing edge separation. In (Francesco Grasso, 2012), a minimum airfoil thickness of 35% of the chord and a minimum shell thickness at the trailing edge of 1% (to take into account manufacturing requirements) of the chord were chosen.

Bizzarrini et al. (Bizzarrini et al., 2011) and Grasso (F. Grasso, 2011) impose a minimum airfoil thickness of 18 % of the chord at the tip a trailing edge thickness of 0.25% of the chord to ensure airfoil's practicability and feasibility from manufacturing point of view.

Maki et al. (Maki et al., 2012) ensured that the thickness of the shell $\boldsymbol{t}_s$ and web $\boldsymbol{t}_w$ are decreasing along the span. Two additional inequality constraints on their thicknesses in terms of the maximum sectional thickness $\boldsymbol{t}$ were added as follows (refer to Figure 7):

$$t_s \leq \frac{1}{2}t \qquad t_w \leq 2t \tag{2.10}$$

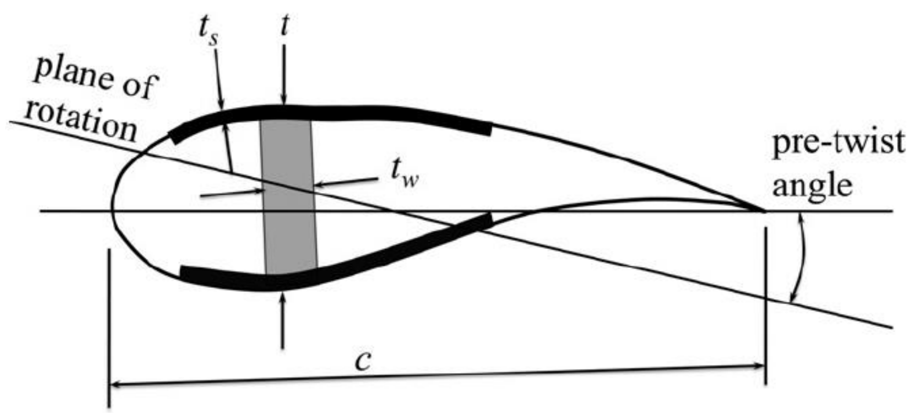

Figure 7 : Blade section diagram (source (Maki et al., 2012)).

Petrone et al. (Petrone et al., 2011) inserted a geometrical constraint to avoid the intersections of the upper and lower airfoil surfaces. In addition, the curvature change of the upper and lower surfaces of the airfoil is restricted (Bak, 2013; Petrone et al., 2011). For instance, the inner part of the blade is designed with thicker airfoil to withstand loads whereas the outer part can be made with a thinner airfoil (Bak, 2013).

2.3.2.2 AIRFOIL CHARACTERISTICS

Two different aerodynamic constraints are imposed to control the airfoil behavior near stall in (Bizzarrini et al., 2011). The first is achieved by imposing a separation point, guarantying the robustness of the airfoil performance in case of gust. Second, in order to control the nature of the stall, the absolute value of the slope beyond the stall angle is limited to a certain threshold value. Similarly, Grasso (F. Grasso, 2011) imposes a minimum value of -0.08 for the moment coefficient C_{mc} as to limit the blade torsion based on a comparative analysis made in (Timmer & Van Rooij, 2003; Van Rooij, 1996). Likewise, a maximum value of C_{mc} -0.15 was assigned at the design condition (6 degrees of angle attack) in (Francesco Grasso, 2012).

Grasso (F. Grasso, 2011) also imposes -a minimum range of 7 degrees between the start of a significant separation and the AoA by forcing the position of the separation point on the suction side to be at minimum 90 % of the chord at 14 degrees AoA. Finally, to avoid abrupt stall, the design is performed by fixing a transition condition, a length of 0.01c on the suction side and 0.1c on the pressure side are taken for the occurrence of flow separation (stall) on the airfoil. In the airfoil design for the inner part of the blade, Grasso (Francesco Grasso, 2012) adds a upper limit of 1.8 for the lift coefficient at 15 degrees AoA and a maximum drop in C_L less than 0.3 between 15 and 16 degrees (based on (Hoerner, 2012; Hoerner & Borst, 1985; Timmer & Van Rooij, 2003)) all of this to avoid excessive lift performance that may lead to an abrupt stall. Ju et al. (Ju & Zhang, 2012) limit the drag coefficient value in the airfoil geometry optimization to prevent it from undesirably becoming higher during the optimization of the C_L/C_D and C_L of the airfoil.

2.3.2.3 MAXIMUM CHORD

The maximum chord is a geometric dimension that should be set to ensure proper transportation of the blade across difficult landmarks such as tunnels and bridges (Bottasso et al., 2010; Petrone et al., 2011). As stated in (Bak, 2013; Petrone et al., 2011), this constraint is vital to consider if the wind turbine is to be installed on offshore sites.

2.3.2.4 NOISE LEVELS

Noise levels constraints were employed in the following references (T Diveux et al., 2001; P Fuglsang & Aagaard Madsen, 1994; Peter Fuglsang et al., 2002; P. Fuglsang & Madsen, 1999; Giguere & Selig, 2000; Lee et al., 2007; A. Ning et al., 2013; Xuan et al., 2008). Fuglsang and Madsen (P. Fuglsang & Madsen, 1999) constrain the noise level emitted by the wind turbine blades using semi-empirical aerodynamic noise models proposed by Brooks (Brooks, Pope, & Marcolini, 1989) and Lowson (Lowson, 1994) that are mainly function of: the stream flow, angle of attack and the turbulent inflow.

Giguère et Selig (Giguere & Selig, 2000) identify that the main sources of aerodynamic noise are the tip-vortex/trailing edge interaction, turbulent inflow and the trailing-edge thickness. The aerodynamic noise can be reduced by adopting a proper tip shape (H.A Madsen & Fuglsang, 1996) and a sharper trailing edge over the outboard section of the blades as per (J Tangler, 1997). However, Giguère et Selig (Giguere & Selig, 2000) choose to limit or fix the tip speed of the rotor rather than incorporating a noise model, to save computational time. In order to limit the noise level and sound pollution, Diveux et al. (T Diveux et al., 2001) fixed the maximum rotor tip speed to be 80 m/s. Similarly, different limits for the blade tip velocity are used in references (Bottasso et al., 2010) to contain noise emissions.

$$V_{tip} = \frac{\pi N D_R}{60} \leq V_{tip.max} \quad [2.11]$$

Lee et al. (Lee et al., 2007) considered the compressibility effect as a limitation of noise level and proposed a constraint based on the upper limit of the Mach number at the blade tip:

$$MN_{tip} = \sqrt{MN^2 + (\frac{\pi n D}{as})^2} \leq 0.3 \quad [2.12]$$

where, ***MN*** is the Mach number, ***as*** is the speed of sound, and ***n*** is the blade revolution per second (*rps*).

Xuan et al. (Xuan et al., 2008) conducted an airfoil optimization to minimize the noise level by constraining the lift to drag ratio and the maximum lift coefficient. Ning et al. (A. Ning et al., 2013) imposed a constraint on the maximum tip speed as an equivalent for noise limitation and implemented it directly into the analysis.

2.3.3 PHYSICAL CONSTRAINTS

Below we list the many physical constraints identified in the literature.

2.3.3.1 LINEAR INEQUALITY

To respect the design space where the objective function is valid, a linear inequality in the following form (Eq. 2.13) is generated to represent the upper and lower limits of the design variables (such as the chord, twist and relative thickness distributions), where $\vec{x}_{lower}$ is the column matrix of lower bound variables and $\vec{x}_{upper}$ is the column matrix of upper bound variables (Ceyhan, 2008; Ceyhan et al., 2009; Eke & Onyewudiala, 2010; Peter Fuglsang et al., 2002; Liao et al., 2012; Liu et al., 2007; L. Wang et al., 2011; W. Xudong et al., 2009; Wang Xudong et al., 2009; Zhu et al., 2012).

$$\vec{x}_{lower} \leq \vec{x} \leq \vec{x}_{upper} \quad [2.13]$$

Design variables such as chord, twist angle and relative thickness are very important for the aerodynamic performance of the rotor, hence upper and lower limits need to be set (Bottasso et al., 2010; W. Xudong et al., 2009). Furthermore, the rotor cut in speed should be low and properly selected to prevent excessive loads (Bak, 2013).

Méndez et Greiner (Méndez & Greiner, 2006) constrained the upper limit of the chord using a linear law between the blade sections to prevent the increasing of the blade area. Hence, a maximum of 10% in chord value changes and a range of 5º on the twist are imposed. Two measures that are used to approximate the cost of the blade; the spar mass and the surface area are constrained in the design process of Kenway et Martins (Kenway & Martins, 2008).

Bottasso et al. (Bottasso et al., 2010) also expressed the bounds of the structural parameters, such as the maximum relative position between the center of gravity and pitch axis of each airfoil section or even limits on the number of plies in a composite laminate imposed by the manufacturer. Liao et al. (Liao et al., 2012) constrained the number of layers that form the spar caps, limiting its maximum number to 50. Also, the locations of the first and last point in the spar caps are fixed, forming an equality constraint. Zhu et al. (Zhu et al., 2012) employ inequality equations to satisfy the manufacturing maneuverability and the continuity of the materials.

2.3.3.2 RATED POWER

Benini and Toffolo (Benini & Toffolo, 2002) imposed a fixed rated power. The power density is a function of the wind speed and rotor power coefficient $\boldsymbol{C_P}$ is determined for different values of tip speed ratio $\boldsymbol{\lambda}$ for wind speeds in the range $3<\boldsymbol{U}<25$ m/s. An upper bound of the maximum power was set by Kenway et Martins (Kenway & Martins, 2008) to match the maximum generator capacity. Xudong et al. (W. Xudong et al., 2009) suggested restricting the maximum output power since it has a direct influence on the cost of the rotor and its lifetime.

2.3.3.3 THRUST

Using blade momentum theory (Dexin, 2006; H. Glauert, 1935), Xudong et al. (W. Xudong et al., 2009) constrained the total thrust on the rotor based on axial force $\boldsymbol{F_n}$ on blades as follows:

$$F_n = F_L cos\theta + F_d sin\theta \tag{2.14}$$

$$T \leq T_{max} \tag{2.15}$$

where, $\boldsymbol{T_{max}}$: maximum thrust of the original rotor, $\boldsymbol{F_l}$: lift force, $\boldsymbol{F_d}$: drag force and $\boldsymbol{\theta}$ is the flow angle (see Figure 8).

2.3.3.4 SHAFT TORQUE

The tangential force $\boldsymbol{F_t}$ contributes mostly to the output power and shaft torque. A bigger torque will increase the load on the transmission system and reduce gearbox's lifetime. Therefore, the shaft torque distribution on the blades is constrained by Xudong et al. (W. Xudong et al., 2009) as:

$$F_t = F_L sin\theta - F_d cos\theta \tag{2.16}$$

$$M \leq M_{max} \tag{2.17}$$

$\boldsymbol{M_{max}}$: maximum shaft torque of the original rotor. Refer to Figure 8.

2.3.3.5 AXIAL INDUCTION FACTOR

A feasibility condition on the axial induction factor ***a*** (cannot exceed 0.5) was imposed by Benini and Toffolo (Benini & Toffolo, 2002) to prevent axial velocity beyond the rotor to become negative.

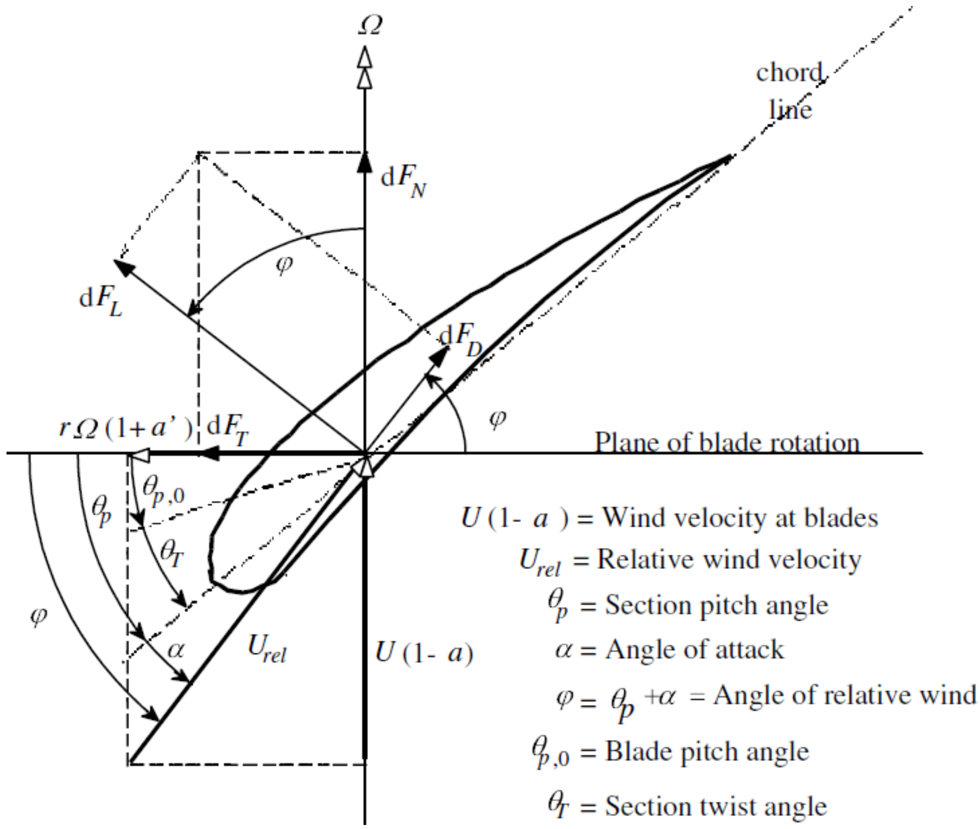

Figure 8 : Forces applied on a wind turbine blade element (source (Manwell, McGowan, & Rogers, 2010)).

2.3.3.6 STRESS

The stresses generated in the materials cannot exceed associated permissible strength requirements. To constrain the stress, the following references (Bottasso et al., 2010; Jureczko et al., 2005; Kenway & Martins, 2008; Liao et al., 2012; Zhu et al., 2012) expressed the constraint in the inequality form:

$$\sigma(\vec{x}) \leq \sigma_{ult} \qquad [2.14]$$

where $\sigma(x)$ and σ_{ult} are respectively the generated stresses and the ultimate permissible stresses.

Kenway and Martins (Kenway & Martins, 2008) imposed a Von Misses stress constraint, limiting the maximum stress limit to the yield stress of Aluminum (40 MPa). Bottasso et al. (Bottasso et al., 2010), constrained the maximum stresses to be lower than a given upper limit as per IEC requirements (Commission, 2005, 2006). A common way to select the external conditions and the guidelines are mentioned in (Armaroli & Balzani, 2007; Commission, 2005, 2006; Lloyd, 2003). Extreme loads are selected from the minimum and maximum values of the simulation series at specific radial stations that showed critical areas (e.g. the blade root and at 0.3x(blade radius) in (Hillmer et al., 2007)). The stresses at these selected stations are than used in constraint evaluation.

2.3.3.7 NATURAL FREQUENCY

The separation of the natural frequency of the blade from harmonic vibrations generated by rotor's rotation is introduced as a constraint to prevent resonance in (Bottasso et al., 2010; Jureczko et al., 2005; Liao et al., 2012; A. Ning et al., 2013; Zhu et al., 2012). Frequency separation was imposed in (Jureczko et al., 2005), whereas in (Bottasso et al., 2010) the authors forced some natural frequencies $\boldsymbol{\omega}$ to lie within an admissible bound [$\boldsymbol{\omega_{lower}}$; $\boldsymbol{\omega_{upper}}$]. Another requirement is that the first blade flap, $\boldsymbol{\omega_{1f}}$ natural frequency (and thus all further frequencies) to be larger than three-per-rev frequency at the rotor rated speed $\boldsymbol{\omega_{3p}}$ (Bottasso et al., 2010; A. Ning et al., 2013):

$$\omega_{1f} \geq S_f \omega_{3p}(\Omega) \qquad [2.15]$$

with $\boldsymbol{S_f}$ a safety gap factor between both frequencies.

Ning et al. (A. Ning et al., 2013) assumed a safety gap factor of 1.1 as per the IEC requirements (Commission, 2005) whereas Bottasso et al. (Bottasso et al., 2010) chooses a safety gap of 1.2. A similar approach has been used by Liao et al. (Liao et al., 2012) to reduce the vibration, by separating the natural frequency of the blade and the rotor speed, avoiding resonance. It is expressed as follows:

$$|\omega(x_i, t_i) \ - \omega^*| \leq \Delta \qquad [2.16]$$

where $\boldsymbol{\omega_1(x_i,t_i)}$ is the first flap frequency of the optimal blade, $\boldsymbol{\omega^*}$ is the target frequency and $\boldsymbol{\Delta}$ is the tolerance.

The reader is referred to (K. Y. Maalawi & Badr, 2010; Karam Y Maalawi & Negm, 2002) for the optimal frequency design of wind turbine blades, where the optimal design is pursued with respect to the maximum frequency design criterion.

2.3.3.8 BUCKLING

Ning et al. (A. Ning et al., 2013) computed the panel buckling using the simple method suggested by Bir (G. S. Bir, 2001). The buckling margin was computed as:

$$b_m = \frac{\epsilon_{50}\gamma_f - \epsilon_{cr}}{\epsilon_{ult}} \qquad [2.17]$$

where $\boldsymbol{b_m}$ is the buckling margin, $\boldsymbol{\varepsilon_{50}}$ strain at 50-year extreme condition, $\boldsymbol{\gamma}$ is the safety factor, $\boldsymbol{\varepsilon_{cr}}$ critical buckling strain, $\boldsymbol{\varepsilon_{ult}}$ is the ultimate strain.

2.3.3.9 BLADE FATIGUE

A fatigue analysis to wind turbine blades that includes a rain flow cycle counting analysis, definition of a Goodman diagram and Miners degradation is provided in (M. Grujicic et al., 2010; M Grujicic et al., 2010). Ning et al. (A. Ning et al., 2013) computed the fatigue strength at the root for a 20-year lifetime. To simplify the fatigue estimation, the S-N curve for the root section is parameterized as:

$$S_f = aN^b \qquad [2.18]$$

where $\boldsymbol{b}$ is assumed to be -10 (glass reinforced composite materials (Mandell & Samborsky, 1997)) and *a* is calibrated so that after 20 year, the root stress had a 10% margin to the fatigue stress ($\boldsymbol{\sigma_{root}}$ = 0.9$\boldsymbol{S_f}$).

Ning et al. (A. Ning et al., 2013) argues that a full lifetime fatigue analysis is a complex process, instead a simpler approach is to use the edgewise gravity loads since they can be more significant than the flapwise aerodynamic loads in determining the fatigue of large blades (Griffith & Ashwill, 2011). Liao et al. (Liao et al., 2012) use a fatigue safety factor (FSF) to judge whether the blade is safe or not. When the FSF is larger than 1, the blade structure is safe and it is computed by FOCUS5 (Duineveld, 2008).

2.3.3.10 DAMAGE AND STATIC FAILURE

In the process of the optimizing the structural design of the blade, it is important to meet the requirements of the structural strength and to prevent failure. Orifici et al. [98] presented a review of failure models of composite materials.

Bottasso et al. (Bottasso et al., 2010) included a constraint for the damage caused by loads during turbulent wind as per the design load conditions (Commission, 2005). A multi-axial damage criterion is applied according to references (Philippidis & Vassilopoulos, 2002a, 2002b). The damage is calculated for multiple points for cross sections of interest and a damage vector is formed, which is bounded by the upper limit of 1.

2.4 SUMMARY

A decision can be made in agreement with (Ashuri et al., 2010; Bak, 2013; Benini & Toffolo, 2002; Eke & Onyewudiala, 2010; P Fuglsang & Aagaard Madsen, 1994; Peter Fuglsang & Aagaard Madsen, 1995; Peter Fuglsang et al., 2002; P. Fuglsang & Madsen, 1999; Giguere & Selig, 2000; M. Grujicic et al., 2010; Maki et al., 2012; A. Ning et al., 2013; W. Xudong et al., 2009), that the most suitable choice of objective functions in wind turbines is aimed towards the minimization of the cost of energy rather than the maximization of the aerodynamic performance. This is mainly due to the fact that we still require that the wind energy systems compete with other energy sources.

Despite the fact that minimum cost of energy was chosen as the single main objective in most of the articles that we have reviewed, many solved the performance optimization of wind turbines using multi-objectives in the optimization process using Pareto-optimization techniques to treat the competing objectives with trade-off curves that reveal weaknesses, anomalies and rewards of the targets to the wind turbine designers. Thus, it is seen useful in the early stage of wind turbine design, both minimum cost of energy and maximum annual energy production are pursued. For these reasons, we can anticipate that future optimization problems will be set as multi-disciplinary (or multi-objective) problems. In fact, in our review we noticed that less than 25 % of wind turbine performance optimization problems were solved using a multi-objective algorithm.

It is not always practical for developers to stipulate the exact turbine characteristics prior project approval. This is largely because various unpredictable factors and influences such as physical, geometrical and aerodynamic constraints. A thorough evaluation is required to examine the above issues and identify the final wind turbine blade design. Accordingly, a developer might seek flexibility in the blade design and each environment might identify several potentially suitable models.

One of the key complications in engineering optimization is the design of the fitness function. When dealing with constrained problems such as WTOP, we must find a mean to estimate the closeness of an infeasible solution to the feasible region. Therefore, the main proposal of the authors in the following chapter is to suggest a constraint-handling technique that preserves the notions of the GA. When coupled with the Co-Blade preliminary design tool, the proposed genetic algorithm, the graphical *winDesign* tool enables developers to compute the optimal design of wind turbine blades under the set of different constraints.

CHAPTER 3

THE PROPOSED GENETIC ALGORITHM

3.1 INTRODUCTION

In the previous chapter, we presented the mathematical models incorporated to solve the wind turbine optimization problems. The main target was to highlight the significance of the objective function and the design constraints when solving a WTOP. With this knowledge in hand, the external shape of the wind turbine blade design tool can be drawn. In this chapter, we will focus on the computational algorithm responsible of generating optimal solutions throughout the evolutionary process. Two main original contributions will be presented: a novel penalty-free constraint-handling technique for genetic algorithms and a selection process using clustering analysis to promote a more efficient selection pressure throughout the evolution process.

3.2 COMPUTATIONAL ALGORITHMS APPLIED IN WIND TURBINE DESIGN PROBLEMS

The selection of the optimization algorithm is an important task in engineering optimization that depends on the nature of the problem and the characteristics of its design space. The choice of the optimization algorithm is central in wind turbine performance optimization because the final results depend on the specific algorithm in terms of accuracy and local minima sensitivity.

Throughout the years, the algorithms used to solve optimization problems in wind turbine design have evolved. At first, most of the methods derived directly from the BEM theory, typically from Wilson and Lissaman (Robert Elliot Wilson & Lissaman, 1974) momentum (BEM) theory. In the 1990s, Selig and Coverstone-Carroll (M. S. Selig & Coverstone-Carroll, 1996) were one of the first to suggest a method based on GA into the field of wind turbine blade design. With the necessity to complete a multi-disciplinary or multi-objective optimization design, Wood (Wood, 2004) and Sale et al. (Danny Sale, Jonkman, & Musial, 2009) simplified the multi-objective problem into a single objective question using a weighted method. In multi-objective optimization, there is no single solution that is optimal under the imposed constraints, and only non-dominated solutions exist (called Pareto optimal solutions). The approaches for solving conventional multi-objective design problems include:

- objective weighted method
- hierarchical optimization method
- *ε* constraint method
- goal programming method

All the above algorithms convert the multi-objective problem to a single-objective problem. In the last decades, in order to solve complicated optimization problems, evolutionary algorithms have been suggested such as:

- Niched Pareto genetic algorithm (NPGA) (Horn, Nafpliotis, & Goldberg, 1994)
- Pareto archived evolution strategy (PAES) (Knowles & Corne, 1999)
- Strength Pareto evolutionary algorithm (SPEA) (M. Kim, Hiroyasu, Miki, & Watanabe, 2004)
- Neighborhood cultivation genetic algorithm (NCGA) (Watanabe, Hiroyasu, & Miki, 2002)
- Non-dominated sorting genetic algorithm (NSGA)-II (Deb, Agrawal, Pratab, & Meyarivan, 2002).

In the case of blade geometry optimization, there is a large number of design variables, which are continuous (e.g. chord and twist distributions, blade pitch, etc.) and discrete (e.g. airfoil family, number of blades, etc.). Moreover, some of these design variables are mutually dependent (e.g. chord and twist), as well as competing objectives within the definition of the cost of energy.

According to Ribeiro et al. (Ribeiro et al., 2012), the optimization algorithm fall under two categories: gradient based methods (GBA) and heuristic algorithms, whereas Endo (Endo, 2011) separates the optimization methods between genetic and non-genetic algorithms.

Meta-heuristics are general algorithms often inspired from the nature, designed to solve complex optimization problems, and this is a growing research field since the last few decades. Meta-heuristics are emerging as alternatives to more classical approaches also for solving optimization problems such as optimization of wind turbine. Meta-heuristic algorithms can be classified according to their strategies (local search improvement or learning component), population-based search or single solution approach, hybrid or parallel meta-heuristics (see Figure 9).

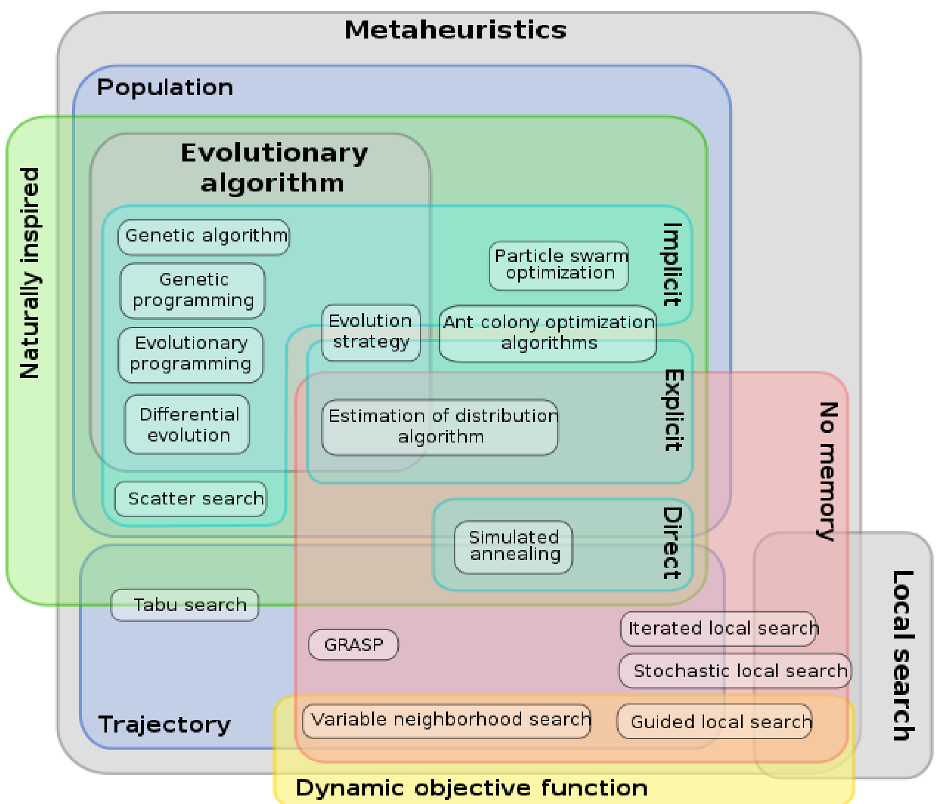

Figure 9 : Classification of meta-heuristic algorithms (source (Dréo, 2007)).

In the over two hundred publications we have reviewed in the field of performance optimization of wind turbine, we concluded that the use of optimization methods to solve the problems has increasingly developed in the last decade. This same conclusion was drawn by Baños et al. (Baños et al., 2011), stressing that in recent years, wind and solar energy showed an increase in the use of optimization methods: linear programming, Lagrangian relaxation, quadratic programming, heuristic optimization (precisely genetic algorithm and particle swarm optimization). From the examined literature, the main optimization methods used in the performance optimization of wind turbine can be categorized into two:

- Gradient based approach methods (GBA)
- Meta-Heuristic methods (GA and PSO)

3.2.1 GRADIENT-BASED APPROACHES

Gradient based approach algorithms have been compared to genetic algorithms in terms of calculation time and the choice of objective functions. They are mainly used because of their speed and however they are very sensitive to the initial condition (Bizzarrini et al., 2011) and in this sense they are not robust (Obayashi, 1996). On the other hand, gradient based algorithms can lack in global optimality, but they allow multiple constraints, which can be very useful for complex engineering designs. More often for complicated problems, it is difficult to obtain a global optimal because conventional algorithms (such as feasible direction methods) are susceptible to converge to the local optimal point (Mitsuo Gen & Cheng, 2000). Therefore, the user is prompted to interfere in the design process and adjust the design parameters or shift the initial feasible domain.

For example, Fuglsang et al.(Peter Fuglsang et al., 2002) apply a Sequential Linear Programming (SLP) (Fleury & Braibant, 1986) when the design vector was feasible and the Method of Feasible Directions (MFD) (Vanderplaats & Moses, 1973) was used to return the design vector to the feasible domain when it was unfeasible. Kenway et Martins (Kenway & Martins, 2008) use SNOPT (Perez & Behdinan, 2007), an optimizer based on the Sequential

Quadratic Programing (SQP) approach. Similarly, Ning et al. (A. Ning et al., 2013) use central differencing and a multi-start approach to improve the convergence behavior of the SQP algorithm.

Hybrid methods between GA and GBA have been investigated by (Bizzarrini et al., 2011; Duvigneau & Visonneau, 2004; Foster & Dulikravich, 1997; Francesco Grasso, 2012; Vicini & Quagliarella, 1999). Grasso (Francesco Grasso, 2012) implement this scheme by first using the GA to explore large domain that contain less local optima problems, and an optimal solution is found. This latter is used as the initial configuration for the GBA which searches for an accurate optimal solution in the smaller design space. Bizzarrini (Bizzarrini et al., 2011) compares the results of a hybrid scheme and a single-algorithm (GA) and shows that the hybrid is more effective with higher accuracy and low sensitivity to local minima.

3.2.2 GENETIC ALGORITHMS

Genetic algorithms are the most popular evolutionary algorithms because of their robustness and reliability. Evolutionary algorithms are less sensitive to local minima; however, they are time consuming and constraints have to be included as a penalty term to the objective function. Usually, evolutionary algorithms are less sensitive to local minima, but they are time consuming and constraints have to be included as a penalty term to the objective function.

A genetic algorithm is an optimization method that mimics Darwin’s principle of the survival of the fittest over a set (population) of candidate solutions (individuals) that evolves from one generation to another. Individuals with a large “fitness” according to the specified objective function for the optimization process have a superior probability to “reproduce” in forming the new generation compared with those with a smaller fitness value. Similarly to a DNA chain, each individual is coded in one string and uses reproduction, crossover, and mutation operators to direct the search over the generations.

We summarize the fundamental steps of genetic algorithms in Figure 10. In genetic algorithms, each individual (or solution vector) is encoded as an either a binary bit string or a real-value vector, both referred to as a chromosome. The standard representation of each individual is a binary array of bits, to facilitate the crossover and mutation operations.

An initial population is generated according to a heuristic rule or randomly. The population size typically depends on the nature of the optimization problem. Often, the initial population is generated in a matter to allow a larger range of possible solutions inside the given search space. If the population size is too small, there is not enough evolution going on and consequently there is a risk of premature convergence towards a local optimum and ultimately extinction of the population. However, a larger population will cost more computational time and fitness evaluations.

Genetic Algorithm

Objective function $\boldsymbol{f}(\vec{\boldsymbol{x}})$, $\vec{x} = (x_1, \ldots, x_d)^T$
Encode the solutions into a set of chromosomes
Generate the initial population
Initialize the crossover and mutation probabilities
While (*t* < Max number of generations OR Stopping criteria)
Evaluate fitness function of each individual
Selection of the current best for the next generation
Reproduction by crossover and mutation
Update $t = t + 1$
End while
Display the optimal solution $\vec{x}^*$

Figure 10 : Pseudo-code of a standard genetic algorithm.

At each successive generation, a percentage of the existing population is ‘selected’ to breed a new generation, therefore ensuring the continuity of the population. Thus, a selection function chooses ‘parents’ based on a fitness-based selection process, where ‘fitter’ solutions are more likely to be selected. An individual can be selected more than once, in which case it transfers its genes to more than one offspring.

At each generation, the GA uses the current generation to create the new offspring that will define the next generation. The algorithm will apply a set of genetic operators (crossover and mutation) on the parents selected by the selection function to generate the children. Recombination (or crossover) is the combination of a pair of parents, analogous to biological reproduction. Mutated children are created by a random change (or mutation) of the genes of a single parent. Both genetic operators are essential for the success of optimization search. Crossover enables the algorithm to preserve the best genes from different individuals and recombine them into possibly fitter children. This allows a better ‘exploitation’ of the search space. Whereas mutation increases the diversity of the population and permits a further ‘exploration’ of the search domain. The crossover probability is usually between 0.7 and 1.0, while the mutation probability is lower 0.001 ~ 0.05. Mutation probability is dependent upon the representation type and number of genes. For instance, for an *n* bit representation, the suggested mutation rate is 1/*n*. In natural systems, if the mutation rate is too high under a high selection pressure, the population might go extinct. A suitable elitist selection function must be employed to avoid loss of good solutions. Selection, crossover and mutation are iteratively applied to the population until a stopping condition is satisfied.

The following references have applied a GA to solve their wind turbine optimization problems (Belessis et al., 1996; Bizzarrini et al., 2011; Ceyhan et al., 2009; T Diveux et al., 2001; Eke & Onyewudiala, 2010; Endo, 2011; Giguere & Selig, 2000; Liu et al., 2007; Méndez & Greiner, 2006; M. S. Selig & Coverstone-Carroll, 1996; H. Wang, Wang, & Bin, 2010; L. Wang et al., 2011; Xuan et al., 2008). In blade geometry optimization, the usefulness of a GA is due to its robustness in the case of a multimodal design space. In addition, the population-based search of a GA yields a population of optimum solutions, which is important in the event that there is a large area of the design space that yields optimum results with no clear optima. Also, GA has the advantage in exploring, non-linear, non-derivable, non-continuous domains and they are less sensitive to the initial domain. For more details concerning genetic algorithms in airfoil design, the reader is referred to (Bizzarrini et al., 2011; López, Angulo, & Macareno, 2008; Ribeiro et al., 2012; Shahrokhi & Jahangirian, 2007). Diveux et al. (T Diveux et al., 2001) use a genetic algorithm inspired by Holland (Holland, 1975) (see Figure 11). Jurecsko et al.

(Jureczko et al., 2005) formulate their discrete-continuous multi-objective problem using the ε-limitations method (Marler & Arora, 2004) and solve it by means of a genetic algorithm.

Liu et al. (Liu et al., 2007) argue that an extended compact genetic algorithm (ECGA) gives more accurate results with smaller population size and fewer function evaluations compared to simple genetic algorithm.

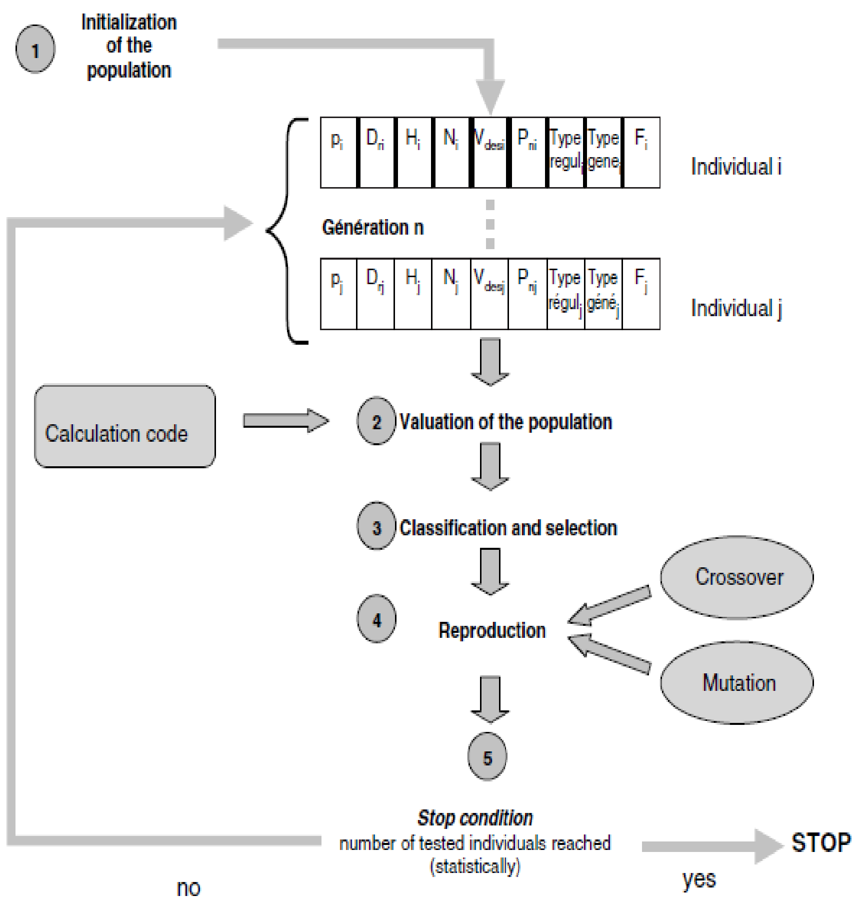

Figure 11 : Optimization scheme using a genetic algorithm (source (T Diveux et al., 2001)).

In Kusiak et al. (Kusiak et al., 2010; Kusiak & Zheng, 2010), the multi-objective optimization model was solved with an Evolutionary Strategy (ES) algorithm (Deb, 2001; Z. Song & Kusiak, 2009; Zitzler & Thiele, 1999), particularly using SPEA (Zitzler & Thiele, 1999).

In 1996, Selig and Coverstone-Carroll (M. S. Selig & Coverstone-Carroll, 1996) and a year later Giguère and Selig (P Giguère & Selig, 1997) developed a computer program designed to optimize the chord and twist as well as the blade pitch for maximum annual energy production called PROPGA. Throughout the years, PROPGA evolved and considers additional design variables with the possibility of solving multi-objective problems, making it possible to obtain trade-off curves between competing blade design objectives. In brief, PROPGA is an efficient optimization tool to use prior an aeroelastic or finite element numerical simulation used in the work of (Giguere & Selig, 2000; M. S. Selig & Coverstone-Carroll, 1996).

3.3 PROPOSED CONSTRAINT-HANDLING TECHNIQUE (VCH) – ORIGINAL CONTRIBUTION

3.3.1 MOTIF

In section 1.3, we presented various WTO problems and demonstrated that they highly nonlinear, containing a mixture of discrete and continuous design variables subject to a set of constraints. Such problems are known as constrained optimization problems or nonlinear programming problems in which traditional calculus-based methods struggle to solve. These numerical optimization methods are highly deterministic and are convenient in finding the global optimum for simple problems by improving the solution in the vicinity of a starting point. However, they have major drawbacks with complex engineering problems i.e.: difficulty in computing the derivatives, sensitivity to the initial conditions, and a large memory requirement.

Because of these downsides, over the years, several heuristic and meta-heuristic algorithms were proposed. They are now emerging as popular methods for the solution of complex engineering problems. These algorithms are purely stochastic and consist of approximate methods but on the contrary, are derivative-free techniques.

Heuristic methods try to find decent solutions that are easily reachable but are not necessarily the best solutions by means of trial and error. Further developments of heuristics are the so-called meta-heuristic algorithms: a higher level of optimization compared to heuristic algorithms.

The meta-heuristic techniques include: genetic algorithms (GA, Holland (Holland, 1975)), simulated annealing (SA, Kirkpatrick et al. (Kirkpatrick & Vecchi, 1983)), particle swarm optimization (PSO, Eberhart et al. (Eberhart & Kennedy, 1995)), ant colony optimization (ACO, Dorigo et al. (Dorigo, Maniezzo, & Colorni, 1996)), tabu search (Glover (Glover, 1977)) etc. Among all meta-heuristics, genetic algorithms (proposed by Holland (Holland, 1975) in 1975) are one of the most popular EA's. By mimicking the basic Darwinian mechanism from the famous book "The Origin of Species", Charles Darwin (Darwin & Bynum, 2009) defined *natural selection* of biological systems or the principle of the *survival of the fittest*. GA's try to evolve the population of *chromosomes* that are fitter by applying three key evolutionary operators: selection, crossover and mutation. The attempt is to produce a new generation or *descendants* with a better *fitness* value than their parents.

Most engineering optimization design problems are difficult to solve using conventional algorithms since they comprise problem-specific constraints (linear, non-linear, equality or inequality). Despite the success of GA in a wide-range of applications, solving constrained optimization problems is no easy task. The most common technique is to apply penalty functions. As a result, the problem is converted from a constrained to an unconstrained optimization problem. The major drawback of these penalty functions is the requirement of a definition and proper tuning of their parameters, which can be challenging and problematic.

Hence, the aim of this proposed technique is to answer one of the most stimulating questions encountered in meta-heuristics: constraint-handling in evolutionary algorithms. In this section, we will use a custom GA as a numerical tool to propose a constraint-handling technique that eliminates the use of penalty functions. We present a parameter-free constraint-handling technique for GA using the violation factor; hence, the method will be referred to as VCH (Violation Constraint-Handling).

3.3.2 CONSTRAINT-HANDLING TECHNIQUES – LITERATURE REVIEW

Below we list the most relevant constraint-handling techniques used in EA's. The reader is referred to the following surveys (Coello, 2002; Coello & Carlos, 1999; Dasgupta & Michalewicz, 1997; Mitsuo Gen & Cheng, 1996; Michalewicz, 1995a, 1995b; Michalewicz & Schoenauer, 1996; Yeniay, 2005) for further details, explanations and comparison.

1. Penalty Methods

The penalty methods are the most common approaches for constraint-handling in EA. Penalty functions were initially suggested by Courant (Courant, 1943) and later extended by Carroll (Carroll, 1961) and Fiacco et al. (Fiacco & McCormick, 1966). Generally, the penalty term is determined from the amount of constraint violation of the solution vector. The formulation of the exterior penalty functions can be expressed as:

$$\psi(\vec{x}) = f(\vec{x}) \pm \left[\sum_{i=1}^{n} a_i \times G_i + \sum_{j=1}^{m} b_j \times H_j\right] \qquad [3.1]$$

where, $\psi(\vec{x})$ is the new fitness function to be optimized, G_i and H_j depend on the inequality constraints and equality constraints respectively. a_i and b_j are called penalty factors.

The determination of the magnitude of the penalty term is a vital concern. The penalty term cannot be too high or else the algorithm will be locked inside the feasible domain and cannot move towards the border with the infeasible area. Too low, the term will be irrelevant in regard to the objective function and the search will remain in the infeasible region. Knowing how to exploit the search space in order to guide the search in the utmost desired direction is still unclear and rather challenging.

2. Static Penalty

In this group, the penalty factors remain constant during the evolution process and do not vary during each generation. A popular method is to define several levels of violation and attribute to each higher level a greater penalty coefficient A_{ki}. Homaifar et al. (Homaifar, Qi, &

Lai, 1994) proposed to convert the equality constraints into inequality constraints and evaluate the following:

$$\psi(\vec{x}) = f(\vec{x}) + \sum_{i=1}^{m+n} (A_{k,i} \times \max[0, g_i(\vec{x})]^2) \qquad [3.2]$$

Other researchers (Hoffmeister & Sprave, 1996; Morales & Quezada, 1998) have proposed interesting static penalties, but the main downside in these approaches are the necessity of a high number of parameters. They are difficult to describe and may not always be easy to obtain for real-world applications.

3. Dynamic Penalty

In this category, the penalty function depends on the generation number and usually the penalty term will increase over each generation. Joines and Houck (Joines & Houck, 1994) evaluate each individuals using the following expressions:

$$\psi(\vec{x}) = f(\vec{x}) + (0.5 \times t)^{\alpha} \times SVC(\beta, \vec{x})$$

$$\mathrm{SVC}(\beta, \vec{x}) = \sum_{i=1}^{n} A_i^{\beta}(\vec{x}) + \sum_{j=1}^{m} B_j(\vec{x})$$

and

[3.3]

$$A_i(\vec{x}) = \begin{cases} 0, & \text{if } g_i(\vec{x}) \le 0 \\ |g_i(\vec{x})|, & \text{otherwise} \end{cases}$$

$$B_j(\vec{x}) = \begin{cases} 0 & \text{if } -\epsilon \le h_j(\vec{x}) \le \epsilon \\ |h_j(\vec{x})|, & \text{otherwise} \end{cases}$$

The cooling parameters α and β are user defined constants; g_i and h_j are the inequality and equality constraints respectively.

A common dynamic penalty function is based on the notion of simulated annealing (Kirkpatrick & Vecchi, 1983; Michalewicz & Attia, 1994), where the penalty term is updated on every occasion the solution is locked in near a local optimal. Dynamic penalties that learn from the search process are called adaptive penalty functions. An incorrect choice of the penalty factor may lead to a local feasible solution or an infeasible solution (Back, Fogel, & Michalewicz, 1997). As for simulated annealing, the solution is extremely sensitive to the cooling parameters.

4. Co-Evolution

Coello (Coello, 2000b; Coello Coello, 1999) proposed to evaluate the following fitness function with only inequality constraints as follows:

$$\psi(\vec{x}) = f(\vec{x}) - (\mathrm{CV} \times w_1 + \mathrm{Viol} \times w_2) \qquad [3.4]$$

with w_1 and w_2 two integers considered as penalty factors, *Viol* is an integer that is incremented for each violated constraint and *CV* is the sum of all violated constraints expressed as:

$$\mathrm{CV} = \sum_{i=1}^{n} \max\,[0, g_i(\vec{x})] \qquad [3.5]$$

The idea of this method is to use a population to evolve the solution vector and another to develop the penalty factors w_1 and w_2. This technique still requires the definition of four parameters and according to the author, they must be empirically determined. A major drawback of this penalty method is that it is very subtle to variations in the parameters in addition of their rigorous definition and high computational cost.

5. Death Penalty

A major concern in optimization algorithms in general and in EA's in particular is the element of 'infeasible solutions'. The simplest way is to reject the individual (hence 'death') when at least one constraint is violated. A new point is generated until a feasible solution is found, therefore making this approach a lengthy process with the high risk of stagnating.

6. Separation of Objectives and Constraints

There are more than a few proposed approaches that separate the amount of constraint violation and the objective function. For instance, Powell and Skolnick (Powell & Skolnick,

1993) scale the objective function $f(\vec{x})$ into the interval]-∞,1], whereas $g_i(\vec{x})$ and $h_j(\vec{x})$ are scaled into the interval [1, +∞[and when the solution is unfeasible the objective function is not combined with the penalty term. During the search, each individual is assessed according to the following form:

$$\psi(\vec{x}) = \begin{cases} f(\vec{x}) & \text{if feasible} \\ 1 + A\left(\sum_{i=1}^{n} g_i(\vec{x}) + \sum_{j=1}^{m} h_j(\vec{x})\right) & \text{otherwise} \end{cases} \quad [3.6]$$

with *A* a constant to be determined by the user.

The main difficulty with Powell and Skolnick (Powell & Skolnick, 1993) is not the definition of the penalty factor *A* but rather with the concept of superiority of feasible over infeasible solutions. Deb (Deb, 2000) uses a similar separation approach and evaluates the individuals using:

$$\psi(\vec{x}) = \begin{cases} f(\vec{x}) & \text{if feasible} \\ f_{worst} + \sum_{i=1}^{m+n} k_i(\vec{x}) & \text{otherwise} \end{cases} \quad [3.7]$$

where, f_{worst} is the worst feasible solution in the population and $k_i(\vec{x})$ include the inequality constraints and the transformed equalities. The constraints are normalized since they are each expressed in different units and to avoid any preference.

3.3.3 PROPOSED 'VCH' METHOD

One of the key complications in using GA for practical engineering optimization applications is the design of the fitness function. When dealing with constrained problems, we must find a mean to estimate the closeness of an infeasible solution to the feasible region. By simply examining the previously proposed constraint-handling techniques, several key points can be derived about the existing methods. Initially, they are diverse, yet require the definition and fine-tuning of at least one parameter.

Apart of being an arduous procedure to define and control the penalty terms, we claim that such methods deviate from the essence of the philosophy of the evolutionary algorithms (i.e., techniques based on the principle of natural selection). Arguably, the most widely used algorithm is the genetic algorithm developed by Holland (Holland, 1975). Despite the success of GA’s as optimization techniques in many engineering applications, they are mostly applied on unconstrained problems.

Therefore, the main proposal of the authors is to suggest a constraint-handling technique that preserves the notions of the GA. The key motif is to keep the fitness function equivalent to the designer’s objective and eliminate any additional penalty functions. The core structure of GA is analogous to the theory of biological evolution mimicking the principle of the survival of the fittest. The proposed constraint-handling technique is directly inspired from the nature of genetic algorithms, since the objective function is preserved during the evolution process. In this study, we will implement the proposed VCH method inside a genetic algorithm due to its advantages:

a) **Adaptability**: Does not oblige the objective function to be continuous or in algebraic form.
b) **Robustness**: escapes more easily from local optimums because of its population-based nature.
c) **Equilibrium**: provide a good balance between exploitation and exploration. Do not need specific domain information but can be further exploited it if provided.
d) **Flexibility**: GA’s are simple and relatively easy to implement.

We are interested in the general nonlinear programming problems (NLP); a minimization or maximization of a constrained optimization problem in which we want to:

Find $\vec{x}$ which optimizes $f(\vec{x})$

subject to certain set of constraints:

$$g_i(\vec{x}) \leq 0, \qquad i = 1, \ldots, n$$

$$h_j(\vec{x}) = 0, \qquad j = 1, \ldots, m$$

$$\vec{x}_k^L \leq \vec{x}_k \leq \vec{x}_k^U, \quad k = 1, \ldots, p$$

where $\vec{x}$ is the solution vector with *p* variables, *n* is the number of inequality constraints, *m* the number of equality constraints and the k^{th} variable varies in the range $[\vec{x}_k^L, \vec{x}_k^U]$; the lower and upper bounds for each variable.

These constraints can be either linear or non-linear. Most constraint-handling approaches tend to deal with inequality constraints only. Therefore, a customary approach is to transform equality to inequality constraints using the following expression:

$$\left|h_j(\vec{x})\right| - \epsilon \leq 0 \qquad [3.8]$$

which is equivalent to $h_j(\vec{x}) - \epsilon \leq 0$ and $-h_j(\vec{x}) - \epsilon \leq 0$, where ϵ is the tolerance (usually a very small value, user-defined). This is justified by the fact that obtaining sampling points that satisfy the equality exactly is very difficult and hence, some tolerance or allowance is used in practice.

We shall first illustrate the overall procedure of the VCH technique for GA. In the subsequent, we assume the following:

- *PopNum*: Population length
- *Nelite*: Number of elites
- *Ncross*: Number of crossover-ed individuals
- *Nmut*: Number of mutated individuals (Bmut = PopNum – Nelite – Ncross)
- Real-coded GA according to which each chromosome is a string of the form $\langle d_1, d_2, \ldots, d_m \rangle$, where d_1, d_2 …, d_m are real numbers

Step 1: Initialization of the population

The design variables are randomly initialized to satisfy the upper and lower constraints as follows:

$$\vec{x} = \vec{x}_k^L + [\vec{x}_k^U - \vec{x}_k^L] * \text{rand}(0,1) \qquad [3.9]$$

Step 2: Evaluation of the fitness function, normalized constraints and constraint violation

For each individual $\vec{x}$, the fitness function $f(\vec{x})$ is calculated along with the resulting constraints. All the equality constraints are converted into inequalities using Eq. 3.10, hence a total of *n*+*m* inequality constraints. These equations are all normalized and therefore become in the form of:

$$G_i = C_i(\vec{x}) - 1 \leq 0 \qquad [3.10]$$

$\mathrm{i} = 1, \dots \mathrm{n}$ (inequality constraints)

$$G_j = h_j(\vec{x})/\epsilon - 1 \leq 0 \qquad [3.11]$$

$\mathrm{j} = \mathrm{n} + 1, \dots \mathrm{n} + \mathrm{m}$ (equality constraints)

Furthermore, the amount of Constraint Violation (C.V) of the normalized constraints G_k, (k = 1, …n+m), is determined using:

$$\text{C.V} = \sum_{i=1}^{i=n+m} \max(0, G_i) \qquad [3.12]$$

In addition, the number of violation is defined as the percentage of violated constraints for a given solution:

$$\text{N.V} = \frac{number\ of\ violated\ constraints}{n + m} \qquad [3.13]$$

Step 3: Sorting of the population

The population is separated into two families; feasible solutions (V_0) and unfeasible (V_1) consisting of individuals that violate at least one constraint. The first set (V_0) is sorted with respect to the fitness value (ascending order, assuming a minimization problem). The second family (V_1) is sorted according to the proposed pair-wise comparison rules. In the VCH approach, we adopted a feasibility-based rule, a set of rules to evolve the population at each generation:

- If one individual is infeasible and the other is feasible, the winner is the feasible solution
- If both individuals are feasible, the winner is the one with the highest fitness value
- If both individuals are infeasible, the winner is the one with the lowest Number of Violations (N.V)
- If both individuals are infeasible with the same (N.V), the one with the lowest Constraints Violation (C.V) value wins

Step 4: Formation of Elites

The sorted families V_0 and V_1 form the new population. The first *Nelite* individuals are the elites, which are kept intact to the next generation with no alteration. This selection operator, one form of elitism consists of a driving force for self-organization or convergence and is essentially an intensive exploitation.

Step 5: Reproduction by crossover and mutation:

A tournament-based technique is used to perform the crossover among the individuals of the population. Whole arithmetic crossover (Michalewicz & Janikow, 1996; Michalewicz & Nazhiyath, 1995; Michalewicz & Schoenauer, 1996) is applied in our algorithm. It is composed of a linear combination of two parent vectors (**A** and **B**) to be crossed (as shown in Eq. 3.14). This genetic operator uses simple static parameter ∅ (a random number between 0 and 1). Any linear combination of two feasible points in a convex domain will produce another feasible point (Michalewicz, 1992).

$$\mathbf{A} \otimes \mathbf{B} = \mathbf{A} * \emptyset + \mathbf{B} * (1 - \emptyset) \qquad [3.14]$$

with $\emptyset = \text{rand}(0,1)$

The reproduction and crossover operators are programmed to imitate the paradigm of the survival of the fittest. The crossover operator is a recombination of two chromosomes, an operation that ensures an efficient exploitation in the local search within a subspace. Therefore, the offspring are spread over the entire feasible space. The crossover-elitism pair eases the achievement of global optimality. In contrast, the mutation operator is a randomization mechanism for global search and exploration.

Step 6: Stopping criteria

Steps 2-5 are repeated until either the stopping criteria is respected, or the maximum number of generation is attained. We implemented a severe stopping criterion on the best solution of each generation; the relative error between the present and the past generation for each design variable must remain less than the user-defined tolerance for at least *N* amount of generations.

As the population evolves, the proposed VCH process will lead the search to reach feasible regions, much similar to a severe penalty function. Nonetheless, in order to maintain infeasible solutions near the feasible region, at each generation, the infeasible solution with the lowest C.V and best objective function value will be kept in the population for the next generation. As a result, the population will most likely have fewer infeasible solutions located in promising areas of the search space.

The VCH approach does not use any penalty function to handle the constraints. Instead, it can be seen to have a mechanism that encourages the solutions close to the feasible region in favorable areas of the design space to remain in the population. This does not add substantial computational cost.

An optimization problem is called a convex programming problem if the objective function and the constraint functions are both convex. Originally, EAs were developed to solve unconstrained problems. Constrained optimization is a computationally challenging task, mainly if the constraint functions are nonlinear and/or nonconvex. A positive feature of the proposed VCH approach is that it does not care about the structure of the constraint functions (linear or nonlinear, convex or nonconvex).

An accelerated VCH technique for convex optimization problems is to generate an initial population with only feasible solutions. Thereafter, the reproduction by means of an arithmetic crossover (as per expression 15) will continue to generate feasible solutions (Michalewicz, 1992). Testing for convexity or concavity can be done by evaluating if the Hessian matrix $\mathbf{H}(\mathbf{X}) = \left[\frac{\partial^2 f(\mathbf{X})}{\partial x_i \partial x_j}\right]$ is positive semi definite (for minimization problems). The accelerated genetic algorithm for the solving of constrained problems in the case of convex design and objective spaces would not require the use of any feasibility-rules. Rather, solutions with high fitness values are preferred since all the individuals of the population are feasible (as described in Figure 12).

3.3.4 NUMERICAL VALIDATION OF 'VCH'

In order to validate the proposed constraint handling technique, several examples taken from the literature will be used. These numerical examples are all constrained optimization problems that include linear and nonlinear constraints. These are benchmark optimization problems that have been previously evaluated by other GA-based techniques, which is useful to investigate and demonstrate the quality and usefulness of the proposed VCH approach.

The algorithm is implemented in MATLAB (R2013 a Student Version 8.1.1.604) run by a 2.90 GHz Intel® Core™ i7-3520M CPU (4 Duo processor) with 4096 MB of Random Access

Memory (RAM). The number of crossover-ed and mutated individuals in the population (100 chromosomes) are 94 and 5 respectively.

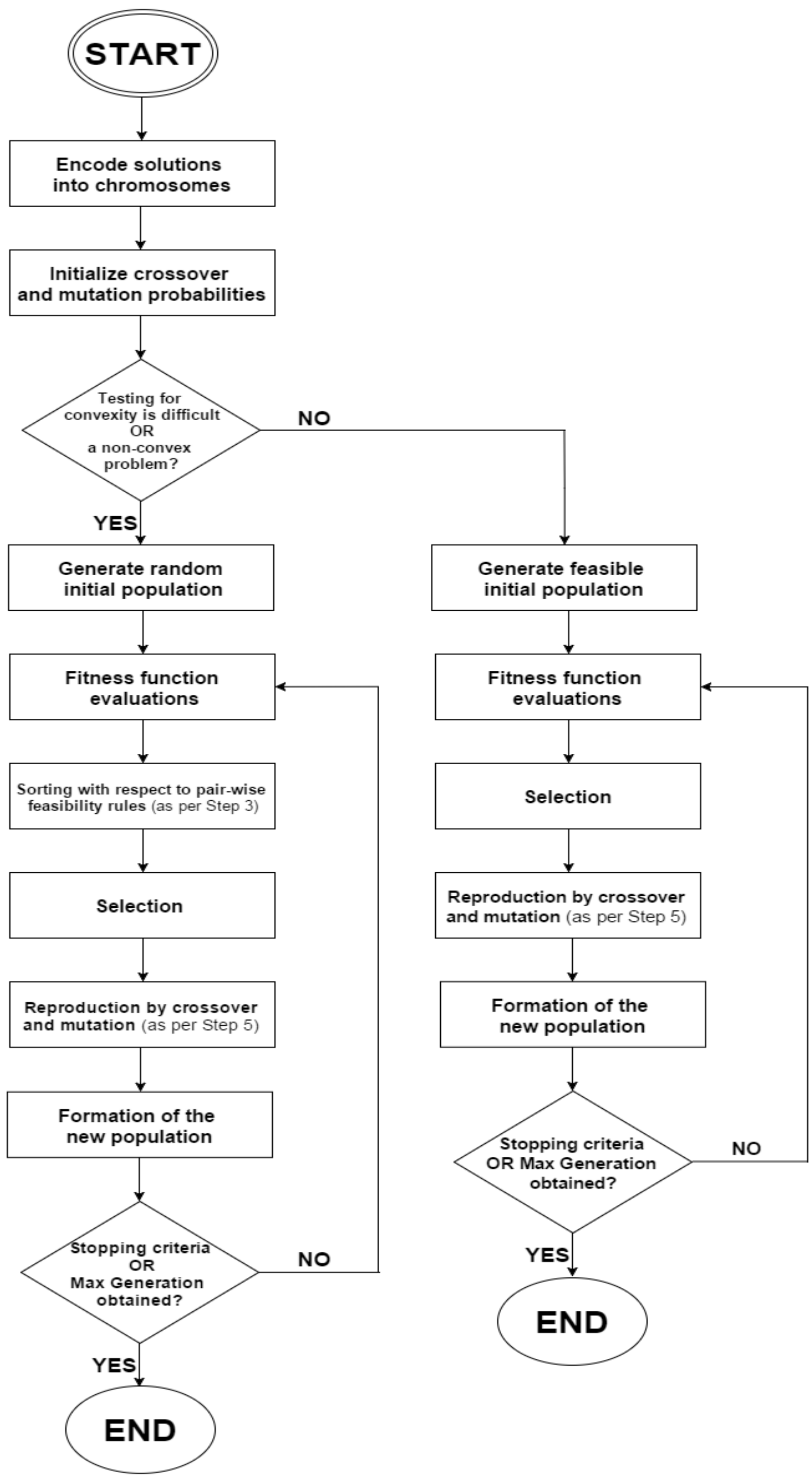

Figure 12 : Complete flowchart of the proposed GA.

That means only one individual is preserved to the following generation based on elitism. The termination criterion is taken as either the reach of the maximum number of generations (set to 500 in all examples) or the achievement of the relative error on the design vector (set to be equal to 10^{-6}). To demonstrate the effectiveness of the proposed VCH, the best, mean, median, worst and fitness evaluations are recorded for 20 independent runs. We are concerned with the efficiency of the technique in terms of CPU time, because we are particularly interested in solving engineering optimization problems, for which the cost of fitness evaluations is generally high. However, it is more convenient to adopt the number of fitness evaluations since it is independent of the implemented hardware. The stopping condition employed in the numerical simulations is identical to the criteria described in step 6.

3.3.4.1 HIMMELBLAU'S NONLINEAR OPTIMIZATION PROBLEM

This problem was originally proposed by Himmelblau (Himmelblau, 1972) and has been widely used as a point of reference for nonlinear constrained optimization problems and several other constraint handling techniques that use penalties. In this formulation, there are five design variables [x_1, x_2, x_3, x_4, x_5], six nonlinear inequality constraints and 10 boundary conditions.

The problem can be stated as follows:

Minimize $\boldsymbol{f(\vec{x}) = 5.3578547x_3^2 + 0.8356891x_1x_5 + 37.293239x_1 - 40792.141}$

Subject to:

$g_1(\vec{x})$ = 85.334407 + 0.0056858x_2x_5 + 0.00026x_1x_4 $-$ $0.0022053\mathrm{x}_3\mathrm{x}_5$ $-$ $0.0022053\mathrm{x}_3\mathrm{x}_5$

$g_2(\vec{x})$ = 80.51249 + 0.0071317x_2x_5 + 0.0029955x_1x_2 + $0.0021813\mathrm{x}_3^2$ + $0.0021813\mathrm{x}_3^2$

$g_3(\vec{x})$ = 9.300961 + 0.0047026x_3x_5 + 0.0012547x_1x_3 + 0.0019085x_3x_4

$$0 \le g_1(\vec{x}) \le 92 \qquad 90 \le g_2(\vec{x}) \le 110 \qquad 20 \le g_3(\vec{x}) \le 25$$

The best solution was found to be $f(\vec{x}) = -30988.95$, with 15000 evaluations only. The design vector is: $x_1 = 78.00$, $x_2 = 33.08$, $x_3 = 27.35$, $x_4 = 44.61$ and $x_5 = 44.26$. The mean is $f(\vec{x}) = -30845.42$, with a standard deviation of 48.60 (as listed in Table II). The worst solution found was $f(\vec{x}) = -30800.89$, which is better than 75% of the reviewed methods as per Table I. The significantly fewer function evaluations reduced the computational cost of the optimization procedure to an average CPU time of 0.52 s/run for 20 independent runs.

Table 1 : Optimal results for Himmelblau's nonlinear problem.

Methods	Design Variables x_1	x_2	x_3	x_4	x_5	$f(\vec{x})$
Present study	78.00	33.08	27.35	44.61	44.26	-30988.9
Coello (Coello, 2000a)	78.59	33.01	27.64	45.00	45.00	-30810.3
Deb (Deb, 1997)	NA	NA	NA	NA	NA	-30665.5
Deb (Deb, 2000)	78.00	33.00	29.99	45.00	36.77	-30665.5
Homaifar et al. (Homaifar et al., 1994)	NA	NA	NA	NA	NA	-30575.9
Bean and Ben Hadj-Alouane (Bean, 1994; Ben Hadj-Alouane & Bean, 1997)	NA	NA	NA	NA	NA	-30560.4
Gen and Cheng (M Gen & Cheng, 1997)	81.49	34.09	31.24	42.20	34.37	-30183.5
Coello and Cortés (Coello & Cortés, 2004)	NA	NA	NA	NA	NA	-30665.5

Table 2 : Statistical results for Himmelblau's nonlinear problem.

Methods	Mean	Worst	Std	Fitness Evaluation
Present study	-30845.4	-30800.8	48.6	15000
Coello (Coello, 2000b; Coello Coello, 1999)	-30984.2	-30792.4	73.6	900000
Coello (Coello, 2000a)	NA	NA	NA	16000
Deb (Deb, 2000)	-30665.5	-29846.6	NA	250000
Homaifar et al. (Homaifar et al., 1994)	-30403.8	-30294.5	64.1	40000
Bean and Ben Hadj-Alouane (Bean, 1994; Ben Hadj-Alouane & Bean, 1997)	-30397.4	-30255.3	-73.8	NA
Gen and Cheng (M Gen & Cheng, 1997)	NA	NA	NA	NA
Coello and Cortés (Coello & Cortés, 2004)	-30654.9	-30517.4	32.6	150000

3.3.4.1.1 MINIMIZATION OF THE WEIGHT OF A TENSION/COMPRESSION SPRING

This optimization problem was described by Arora (Arora, 1989) and Belegundu (Belegundu, 1983) and it consists of minimizing the weight of a tension/compression spring, subject to constraints on minimum deflection, shear stress, surge frequency, outside diameter and on the design variables. The later are the wire diameter *d* (= x_1), the mean coil diameter *D* (= x_2) and the number of active coils *N* (= x_3).

The problem is expressed as follows:

Minimize $\boldsymbol{f(\vec{x}) = (x_3+2)x_1^2 x_2}$

Subject to:

$$g_1(\vec{x}) = 1 - \frac{x_2^3 x_3}{71785 x_1^4} \leq 0 \qquad g_2(\vec{x}) = \frac{4x_2^2 - x_1 x_2}{12566(x_1^3 x_2 - x_1^4)} + \frac{1}{5108 x_1^2} - 1 \leq 0$$

$$g_3(\vec{x}) = 1 - \frac{140.45 x_1}{x_2^2 x_3} \leq 0 \qquad g_4(\vec{x}) = \frac{x_1 + x_2}{1.5} - 1 \leq 0$$

The optimal solution for this problem is at: $x_1 = 0.0513$, $x_2 = 0.348$, $x_3 = 1.802$, with an optimal fitness value of $f(\vec{x}) = 0.0126$, obtained after 28000 evaluations (as per Table III and IV). The mean is 0.01269 with a low standard deviation of 8.32×10^{-6}.

Table 3 : Optimal results for spring design problem.

Methods	Design Variables x_1	x_2	x_3	$f(\vec{x})$
Present study	0.05134	0.3483	11.8026	0.01267
Coello and Mezura-Montes (Coello & Montes, 2002)	0.05198	0.3639	10.8905	0.01268
Mezura-Montes and Coello (Mezura-Montes & Coello, 2005)	0.05283	0.3849	9.8077	0.01268
Mezura-Montes and Coello (Coello, 2000b; Coello Coello, 1999)	0.05148	0.3516	11.6322	0.01270

Table 4 : Statistical results for spring design problem.

Methods	Mean	Worst	Std	Fitness Evaluation
Present study	0.01269	0.01270	8.328E-06	28000
Coello and Mezura-Montes (Coello & Montes, 2002)	0.01274	0.01297	5.9E-05	80000
Mezura-Montes and Coello (Mezura-Montes & Coello, 2005)	0.01316	0.01407	3.90E-04	30000
Coello(Coello, 2000b; Coello Coello, 1999)	0.01276	0.01282	3.939E-05	900000

3.3.4.2 DESIGN OF A PRESSURE VESSEL

This problem was originally proposed Sandgren (Sandgren, 1988, 1990) for the design of a pressure vessel with minimal overall cost (material, forming and welding). The air storage tank has a working pressure of 2000 psi and a maximum volume of 750 ft^3. There are four design variables namely; T_S (= x_1) thickness of the shell, T_h (= x_2) thickness of the head, R (= x_3) inner radius and L (= x_4) length of the cylindrical section of the vessel, not including the head. T_S and T_h are integer multiples of 0.0625 inch and R and L are continuous.

The following pressure vessel design problem is taken from Kannan and Kramer (Kannan & Kramer, 1994) as follow:

Minimize $f(\vec{x}) = 0.6224 x_1 x_3 x_4 + 1.7781 x_2 x_3^2 + 3.1661 x_1^2 x_4 + 19.84 x_1^2 x_3$

Subject to:

$g_1(\vec{x}) = -x_1 + 0.0193 x_3 \leq 0$ $\quad$ $g_2(\vec{x}) = -x_2 + 0.00954 x_3 \leq 0$

$g_3(\vec{x}) = -\pi x_3^2 x_4 - \frac{4}{3}\pi x_3^3 + 1{,}296{,}000 \leq 0$ $\quad$ $g_4(\vec{x}) = x_4 - 240 \leq 0$

It has been observed from Table V, that the best solution is found to be $f(\vec{x}) =$ 6059.79164, at $x_1 = 0.8125$, $x_2 = 0.4375$, $x_3 = 42.0978$, $x_4 = 176.644$. Based on the information from Table VI, our approach provided the best performance in an average computational time of 1.46 sec, a mean of 6060.0618 and standard deviation of 0.128.

Table 5 : Optimal results for pressure vessel design problem.

	Design variables				
Methods	x_1	x_2	x_3	x_4	$f(\vec{x})$
Present study	0.8125	0.4375	42.0978	176.64	6059.79
Mezura-Montes and Coello (Mezura-Montes & Coello, 2005)	0.8125	0.4375	42.0984	176.63	6059.71
Coello and Mezura-Monte (Coello & Montes, 2002)	0.8125	0.4375	42.0974	176.65	6059.94
Coello and Cortes (Coello & Cortés, 2004)	0.8125	0.4375	42.0869	176.79	6061.12
Coello (Coello Coello, 2000)	0.875	0.5000	42.0939	177.08	6069.32
Coello (Coello, 2000b; Coello Coello, 1999)	0.8125	0.4375	40.3239	200.00	6288.74
Deb (Deb, 1997)	0.9375	0.5000	48.3290	112.67	6410.38
Yun (Yun, 2005)	1.125	0.6250	58.2850	43.72	7198.42
Wu and Chow (Wu & Chow, 1995)	1.125	0.6250	58.1978	44.29	7207.49

Table 6 : Statistical results for pressure vessel design problem.

Methods	Mean	Worst	Std	Fitness Evaluation
Present Study	6060.06	6060.21	0.1284	24250
Mezura-Montes and Coello (Mezura-Montes & Coello, 2005)	6379.93	6820.39	2.10E+02	30000
Coello and Mezura-Montes (Coello & Montes, 2002)	6177.25	6469.32	130.92	80000
Coello and Cortes (Coello & Cortés, 2004)	6734.08	7368.06	457.99	150000
Coello (Coello Coello, 2000)	6177.25	6469.32	130.92	50000
Coello (Coello, 2000b; Coello Coello, 1999)	6293.84	6308.14	7.4132	900000

3.3.4.3 WELDED BEAM DESIGN PROBLEM

The welded beam problem has been used as a benchmark problem originally proposed by Rao (Rao, 1996). The beam is designed for minimum cost subject to constraints on shear stress (τ), bending stress in the beam (σ), buckling load on the bar (P_c) end deflection of the beam (δ) and side constraints. In this problem, there are four design variables namely; thickness of the beam *h* (= x_1), length of the welded joint *l* (= x_2), width of the beam *t* (= x_3) and thickness of the beam *b* (= x_4). It is important to note that in this problem, there are several models in the overviewed literature, with different number of constraints and variable definitions. In the present study, the results for the following optimization formulation are presented:

Minimize $\boldsymbol{f(\vec{x}) = 1.1047 x_1^2 x_2 + 0.04811 x_3 x_4 (14 + x_2)}$

Subject to:

$$g_1(\vec{x}) = \tau(\vec{x}) - \tau_{max} \le 0 \qquad g_2(\vec{x}) = \sigma(\vec{x}) - \sigma_{max} \le 0 \qquad g_3(\vec{x}) = x_1 - x_4 \le 0$$

$$g_4(\vec{x}) = 0.10471 x_1^2 + 0.04811 x_3 x_4 (14.0 + x_2) - 5.0 \le 0$$

$$g_5(\vec{x}) = 0.125 - x_1 \le 0 \qquad g_5(\vec{x}) = 0.125 - x_1 \le 0 \qquad g_7(\vec{x}) = P - P_c(\vec{x}) \le 0$$

where, τ is the shear stress in the weld (it has two components namely primary stress τ' and secondary stress τ''), τ_{max} is the allowable shear stress of the weld (= 13600 psi), σ the normal stress in the beam, σ_{max} is the allowable normal stress for the beam material (= 30000 psi), P_c the buckling load, P the load (= 6000 lb) and δ the beam end deflection:

$$\tau(\vec{x}) = \sqrt{(\tau')^2 + \frac{2\tau'\tau'' x_2}{2R} + (\tau'')^2}\,, \qquad \tau' = \frac{P}{\sqrt{2} x_1 x_2}\,, \qquad \tau'' = \frac{MR}{J}\,, \qquad M = P\left(L + \frac{x_2}{2}\right),$$

$$R = \sqrt{\frac{x_2^2}{4} + \left(\frac{x_1 + x_3}{2}\right)^2}, \qquad \sigma(\vec{x}) = \frac{6PL}{x_4 x_3^2}, \qquad J = 2\left\{\sqrt{2} x_1 x_2 \left[\frac{x_2^2}{12} + \left(\frac{x_1 + x_3}{2}\right)^2\right]\right\},$$

$$\delta(\vec{x}) = \frac{4PL^3}{E x_3^3 x_4} \qquad P_c(\vec{x}) = \frac{4.013E\sqrt{x_3^2 x_4^6/36}}{L^2}\left(1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}}\right)$$

$L = 14$ in $\delta_{max} = 0.25$ in $E = 30 \times 10^6$ psi $G = 12 \times 10^6$ psi

The presented algorithm has been tested on this optimization problem and compared with the best solutions by previous methods reported in Table VII. The optimal design vector was found to be: $x_1 = 0.2057$, $x_2 = 3.4729$, $x_3 = 9.0292, x_4 = 0.2060$ with an optimal fitness value $f(\vec{x}) = 1.7267$. In average, the time elapsed for one execution of the program is 1.82 sec and the average number of fitness evaluations for 20 runs is 30000.

Table 7 : Optimal results for welded beam design problem.

Methods	Design Variables x_1	x_2	x_3	x_4	$f(\vec{x})$
Present study	0.2057	3.4729	9.0292	0.2060	1.7267
Coello and Mezura-Montes (Coello & Montes, 2002)	0.2059	3.4713	9.0202	0.2064	1.7282
Coello (Coello, 2000b)	0.2088	3.4205	8.9975	0.2100	1.7483
Siddall (Siddall, 1972)	0.2444	6.2189	8.2915	0.2444	2.3815
Ragsdell and Philipps (Ragsdell & Phillips, 1976)	NA	NA	NA	NA	2.3859
Deb (Deb, 1991)	0.2489	6.173	8.1789	0.2533	2.4331

Table 8 : Statistical results for welded beam design problem.

Methods	Mean	Worst	Std	Fitness Evaluation
Present study	1.727	1.728	0.00042	30000
Mezura-Montes et al. (Mezura-Montes, Coello Coello, Velázquez-Reyes, & Muñoz-Dávila, 2007)	1.725	1.725	1.00E-15	24000
Coello and Mezura-Montes (Coello & Montes, 2002)	1.792	1.993	0.0747	80000
Coello (Coello, 2000b)	1.771	1.785	0.0112	900000

3.3.5 DISCUSSION OF THE 'VCH' METHOD

Genetic algorithms try to mimic the principle of the survival of the fittest, where newer generations are evolved in attempt to produce descendants with a better 'fitness'. Because at all times the fitness function is equal to the objective function to be minimized, our proposed VCH technique is more conforming with the biological fundamentals of genetic algorithms. A major drawback of many techniques in the literature is that the constraint handling method requires a feasible initial population.

For some problems, finding a feasible solution is NP-hard, and even impossible for the problems with conflicting constraints. In the VCH approach, it is not required to have a feasible initial population. There are available techniques that ensure feasibility of the population when dealing with linear constraints such as [53, 54] by means of mathematical programming.

Compared to other constraint-handling techniques based on penalty functions, the VCH method was able to provide a consistent performance and demonstrated to be simpler, faster and delivered reliable optimal solutions without any violation of the constraints. As the population evolves, the VCH method will lead the search to reach faster feasible regions. This is revealed in Figure 13, with the convergence of the average constraint violation of the elites towards zero (no violation) as the population evolves.

The VCH method allows the closest solutions to the feasible region in favorable areas of the search space to remain in the population. Specific methods such as the reduced gradient method, cutting plane method and the gradient projection method are appropriate. However, they are only fitting either to problems having convex feasible regions or with few design variables. Furthermore, the overall results suggest that the proposed approach is highly competitive and was even able to contest (some cases improve) the results produced by other methods, some of which are more difficult constraint-handling techniques applied to genetic algorithms. The VCH algorithm was tested on several benchmark examples and demonstrated its ability to solve problems with a large number of constraints.

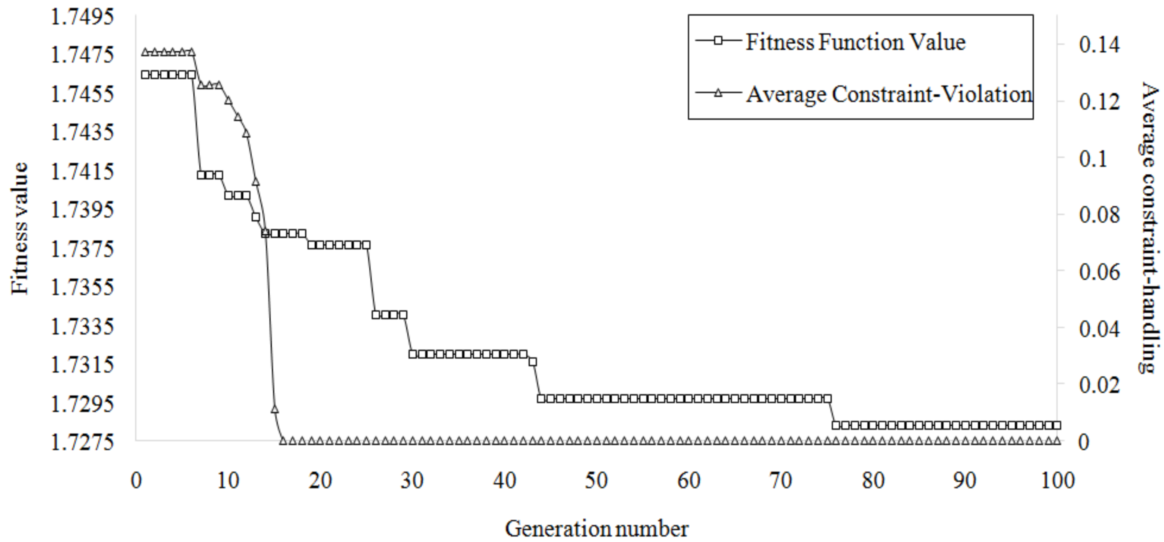

Figure 13 : Average constraint-handling (CV) and best fitness function obtained with the proposed VCH method for the welded beam design problem

3.4 PROPOSED SELECTION PROCESS USING CLUSTERING ANALYSIS – ORIGINAL CONTRIBUTION

3.4.1 MOTIF

Cluster analysis is the study of techniques and algorithms to organize data into sensible groupings (clusters) according to measured or apparent similarities. Clustering has been successfully applied in various engineering and scientific disciplines such as biology, medicine, machine learning, pattern recognition, image analysis and data compression (Krishna & Murty, 1999). The aim of clustering is to find a given structure among the series of data and is therefore exploratory in nature (Anil K Jain, 2010). The task of organizing a set of data using cluster analysis requires some dissimilarity measurement among the set of patterns. The dissimilarity metric is defined according to the nature of the data and the purpose of the analysis.

Many types of clustering algorithms have been proposed; the reader is referred to (Aggarwal & Reddy, 2013; Anil K Jain, 2010; Anil K Jain, Murty, & Flynn, 1999; Xu & Wunsch, 2005) for a taxonomy of clustering techniques, discussions on major challenges and key issues and useful surveys of recent advances. The simplest and most popular clustering algorithm is the K-means algorithms (KMA), and was originally published by Steinhaus (Steinhaus, 1956) in 1956. Even though it was first proposed 60 years ago, it is still the most widely used algorithm for clustering.

In this section, we propose a GA-based algorithm that utilizes clustering analysis to organize the population and select the parents for recombination. The performance of a newly proposed selection process named the K-means Genetic Algorithm Selection (KGA) process is investigated on a class of unconstrained optimization problems.

The KGA technique is composed of 4 essential stages: clustering, membership phase, fitness scaling and selection. We postulate that clustering the evolving population can help preserve a continuous selection pressure throughout the evolution process. A membership probability index is allocated to each individual subsequent the clustering phase. Fitness scaling alters the membership scores into a range suitable for the selection function; which selects the parents of the succeeding generation. Two versions of the KGA technique are examined: using a fixed number of clusters K (KGA_f) and via an optimal number of clusters K_{opt} (KGA_o).

The performance of each method is tested on 8 benchmark problems. The numerical simulations reveal that the proposed selection process is superior or competitive with the standard GA for the given problems. The reader is referred to our publication published in the journal of Algorithms for more details (Chehouri, Younes, Khoder, Perron, & Ilinca, 2017).

3.4.2 CLUSTERING ANALYSIS IN OPTIMIZATION ALGORITHMS

There are many algorithms that have been proposed in literature to solve the clustering problems. Some relevant studies that have explored the problem of clustering using various approaches include : evolutionary algorithms such as evolutionary programing (Sarkar, Yegnanarayana, & Khemani, 1997), particle swarm optimization (Cura, 2012; Das, Abraham,

& Konar, 2008; F. Yang, Sun, & Zhang, 2009), ant colony algorithms (Jiang, Yi, Li, Yang, & Hu, 2010; Shelokar, Jayaraman, & Kulkarni, 2004), artificial bee colony (C. Zhang, Ouyang, & Ning, 2010), simulated annealing (Maulik & Mukhopadhyay, 2010; Selim & Alsultan, 1991) and tabu search (Sung & Jin, 2000).

Conversely, there have been many attempts to use GAs to solve clustering applications (Agustı et al., 2012; Babu & Murty, 1993; Cowgill, Harvey, & Watson, 1999; Hall, Ozyurt, & Bezdek, 1999; He & Tan, 2012; Krishna & Murty, 1999; Maulik & Bandyopadhyay, 2000; Maulik, Bandyopadhyay, & Mukhopadhyay, 2011; Razavi, Ebadati, Asadi, & Kaur, 2015; Tseng & Yang, 2001). Maulik and Bandyopadhyay (Maulik & Bandyopadhyay, 2000) proposed a GA approach to clustering. They tested the performance of the algorithm on synthetic and real-life datasets. The GA-*k*-means algorithm was used to search for the cluster centres which minimize the clustering metric; showing results significantly superior to that of the *k*-means algorithm. Another genetic algorithm approach, the genetic *k*-means algorithm was presented by Krishna and Murty (Krishna & Murty, 1999); they defined a mutation operator specific to clustering problems. Recently, a novel optimization algorithm was proposed by Krishnasamy(Krishnasamy, Kulkarni, & Paramesran, 2014) referred to as K-MCI, inspired from natural and society tendency of cohort individuals of learning from one another.

Since the novelty of the proposed algorithm revolves around the notion of introducing clustering analysis in the selection stage of the genetic algorithm, this section will avoid the survey of clustering techniques. The reader is referred to (Anoop Kumar Jain & Maheswari, 2012; Mann & Kaur, 2013; Popat & Emmanuel, 2014) for detailed surveys of clustering algorithms. Consequently, in the remainder of this section we will review the most relevant optimization algorithms that have introduced clustering analysis in one way or another.

The process of genetic differentiation where the population subdivided was discussed in the literature. For instance, the island model (Latter, 1973) divides the population into discrete finite races, between which some migration occurs. The hypothesis is that multiple subpopulations help preserve a better genetic diversity, since each island can potentially follow a different search trajectory through the search space. Various ‘islands’ conserve some degree of independence and therefore explore different regions of the search space while sharing some information by migration.

Many researchers have investigated evolutionary algorithms for dynamic optimization problems (DOP’s) because EA’s are fundamentally inspired from biological evolution, which is always subject to an ever-varying environment. From the literature for DOP’s, the traditional approaches use the multi-population method to find the optimum solutions for multi-modal functions. The core notion is to divide the search space into different sub-spaces, and then separately search within these sub-spaces. The challenge with these multi-population methods (such as (Blackwell & Branke, 2004; C. Li & Yang, 2012; S. Yang & Li, 2010)), is how to choose an appropriate number of sub-populations to cover the entire search space. Three major difficulties rise using multi-populations methods: how to guide the particles towards different promising sub-regions, how to define sub-regions and how many sub-populations are required.

In order to overcome these questions, a clustering particle swarm optimizer (CPSO) was proposed in (C. Li & Yang, 2009; S. Yang & Li, 2010). In the CPSO algorithm, a proper number of sub-swarms which cover different local regions are created using a clustering method. A hierarchical clustering method is used to locate and track multiple optima and a fast-local search method is employed to find the near optimal solutions in a promising region in the search space.

Kennedy (Kennedy, 2000) originally proposed a PSO algorithm that uses a *k*-means clustering algorithm to identify the centers of different clusters of particles in the population, and then uses the centers to substitute the personal best or neighborhood best positions. The limitation of this approach lies in that the number of clusters must be predefined.

Similarly, a fuzzy clustering-based particle swarm (FCPSO) algorithm was proposed in (Agrawal, Panigrahi, & Tiwari, 2008) to solve multiobjective environmental/economic dispatch.

The clustering in the FCPSO technique ensures that the obtained Pareto front will have uniform diversity at all stages of the search.

In (J. Zhang, Chung, & Lo, 2007), clustering analysis was applied to adjust the probabilities of crossover p_x and mutation p_m in GAs. By applying the *k*-means algorithm, the population is clustered in each generation and a fuzzy system is used to adjust the values of the genetic operators. Regulations are based on considering the relative size between the clusters holding the best and worst chromosomes respectively.

Zhang et al. (X. Zhang, Tian, Cheng, & Jin, 2016) tackle the problem of large-scale many-objective optimization problems based on a decision variable clustering method. The proposed technique divides the decision variables into two clusters based on the features of each variable. The decision variable clustering method adopts the *k*-means method to divide the decision variables into two types: convergence-related variable and diversity-related variables.

3.4.2.1 PROBLEM DEFINITION

In essence, the basic object of any clustering algorithm is to find a global or approximate optimal for combinatorial optimization problems which are NP-hard (Vattani, 2009). The *k*-means algorithm is very likely to converge to a suboptimal partition. The main lead of stochastic optimization techniques over deterministic-methods is that they are able to avoid convergence to a local optimal solution. Therefore, stochastic approaches have been employed to solve clustering problems; algorithms such as simulated annealing, genetic algorithms, evolution strategies and evolutionary programming.

Inspired by the principles of natural selection and biological evolution, evolutionary algorithms seek to optimize a population of individuals by applying a set of evolutionary operators. They are population-based meta-heuristic optimization algorithms that make use of biological evolution operators such as selection, recombination and mutation.

In order to demonstrate the novelty in the use of clustering analysis in the selection process of the genetic algorithm, the performance of the proposed KGA techniques will be compared with existing GA methods. They were originally proposed by Holland (Holland, 1975), inspired by the principle of natural selection of biological systems or 'Darwinian evolution'. GAs have demonstrated their capability to solve a wide range of optimization problems such as revenue management, optimal engineering system designs, scheduling applications, image processing, quality control etc.

John Holland essentially formed the foundation of modern evolutionary computing by fundamentally defining three key genetic operators: crossover, mutation, and selection. These evolutionary operators provide a way to generate offspring from parent solutions.

Inspired from the notion that clustering (such as *k*-means) the evolving population can help avoid excessive exploitation and therefore escape local optimum (local minimum or local maximum). The role of clustering analysis is to improve the probability of discovering the global optimum by covering sufficiently the solution space (exploration) yet ensure sufficient pressure to obtain even better solutions from current individuals (exploitation). A detailed explanation of the proposed KGA technique is considered in the next section.

3.4.2.2 PROPOSED SELECTION PROCESS TECHNIQUE: KGA

We are interested in the unconstrained optimization problems in which we attempt to find $\overrightarrow{x^*}$ which optimizes $f(\vec{x})$ using GA based algorithms. Therefore, only the standard GA will be used to test the performance of the proposed KGA algorithms.

A general definition of clustering can be stated as follows: given a set of data composed on n objects, find K groups in such that the measure of similarities between objects in the same group is low while the similarities between objects in different groups are low.

K-means algorithm attempts to find a partition such that the squared error between the empirical mean of a cluster and the objects in the cluster is minimized. The goal is to minimize the sum of the squared error *J* over all *K* clusters, as follows:

$$J(X, C) = \sum_{k=1}^{K} \sum_{x_i \in c_k} \|x_i - \mu_k\|^2 \qquad [3.15]$$

where $X = \{x_i\},\ i = 1, \dots, N$ is the set of *N* *d*-dimensional points to be clustered into *K* clusters, $C = \{c_k\},\ k = 1, \dots, K$ and μ_k the mean of cluster c_k.

Minimizing the *K*-means objective function is an NP-hard problem (even for *K* = 2) (Drineas, Frieze, Kannan, Vempala, & Vinay, 2004), and therefore the algorithm can only converge to local minima. The main steps of K-means algorithm can be summarized as follows:

1. Choose an initial partition with *K* clusters.
2. Generate a new partition by assigning each pattern to its nearest cluster centroid.
3. Compute new cluster centroids.
4. If a convergence criterion is not met, repeat steps 2 and 3.
5. Clustering the population by *k*-means algorithm
6. Computing the membership probability (MP) vector (Eq. 3.16)
7. Fitness scaling of MP
8. Selection of the parents for recombination.

The following section presents a brief description of the proposed *k*-means genetic selection processes. We are interested in the unconstrained optimization problems in which we attempt to find $\overrightarrow{x^*}$ which optimizes $f(\vec{x})$ using GA based algorithms. Therefore, only the standard GA will be used to test the performance of the proposed KGA algorithms. Below, two distinct selection techniques KGA_f and KGA_o are presented.

3.4.2.2.1 *KGA$_f$*

The proposed KGA is different than the standard GA in several ways. Primary, the chromosomes of the population are partitioned into groups in a way that all individuals inside the same cluster are similar. This offers a novel approach to solve the two important issues in the evolution process of the genetic search: exploitation and exploration.

Exploration is responsible of population diversity by exploring the search space. While, exploitation attempts to reduce the diversity by focusing on individuals with higher fitness scores. Strong exploitation encourages premature convergence of the genetic search. Recombining individuals inside the same cluster reduces population diversity, and thus clustering the population can allow an enhanced balance between exploitation and exploration.

In the KGA_f algorithm, the number of clusters is kept the same throughout the evolution process. The 4 main stages of KGA_f are:

1. Clustering the population by K-means algorithm
2. Computing the membership probability (MP) vector
3. Fitness scaling of MP
4. Selection of the parents for recombination.

In general, we want to maintain an even selection pressure during the evolution of the genetic search. At the beginning, the search may be bias towards high fitness individuals. Near the end of the search, as the population is converging towards an optimal solution, there may not be much separation among individuals in the population. Neither situation is desirable, thus there is a necessity to scale the fitness in a manner to preserve the selection pressure the same throughout in the population.

The membership probability score (Eq. 3.16) of an individual is a measurement of its affiliation with respect to both designated and external clusters (refer to Figure 14). For a given solution *i* inside a cluster *j* of size m_j, the membership probability index is calculated as follows:

$$MP(i,j) = \frac{m_j}{m_j - 1} \times \frac{1}{Pop\ Size} \times \frac{S_j - f(x_i)}{S_j} \qquad [3.16]$$

And S_j is expressed as:

$$S_j = \sum_{k=1}^{m_j} f(x_k) \qquad [3.17]$$

where *Pop Size* is the population size and S_j is the sum of the fitness values $f(x_i)$ inside cluster *j*.

The key characteristics that are associated with the use of the membership probability function are the following:

- The sum of the membership probability scores of a given cluster *j* of size m_j is equal to $\frac{m_j}{Pop\ Size}$. Consequently, clusters with more individuals will be attributed a larger probability sum.

- An individual with a lower fitness value $f(x_i)$ inside a cluster of size m_j is awarded a higher *MP* score. This is translated in the $\frac{S_j - f(x_i)}{S_j}$ term, thus allocating fitter solutions a higher probability of selection.

- In order to reduce the probability of recombination between individuals from the same cluster, therefore avoiding local optimal traps, fitter individuals in smaller clusters are awarded a higher *MP* score. This is the direct effect of $\frac{m_j}{m_j - 1}$ term.

- The sum of all membership probability scores is equal to 1.

The general framework of the proposed KGA_f algorithm is shown in Figure 15.

Fitness scaling converts the membership scores in a range suitable for the selection function which selects the parents of the next generation. The selection function allocates a higher probability of selection to individuals with higher scaled values.

The range of the scaled values can affect the performance of the genetic algorithm. If the scaled values vary too extensively, higher scaled value individuals will reproduce too rapidly and prevent the GA from searching other regions in the search space. In contrast, little scaled value variations, all individuals will have an equal chance of reproduction and therefore will result into a very slow search progress.

3.4.1.1.1 *KGA$_o$*

It is obvious that a problem we face in the KGA$_f$ algorithm is to decide the optimal number of clusters. Visual verification of a large multidimensional data set (e.g. more than three) is difficult (Halkidi, Batistakis, & Vazirgiannis, 2002a). In order to find the optimal clustering scheme that best fits the inherent partitions of the data set, the concept of clustering validation has been subject of numerous research efforts. The fundamental concepts, drawbacks and applications of clustering validation techniques were discussed in (Halkidi, Batistakis, & Vazirgiannis, 2001; Halkidi et al., 2002a; Halkidi, Batistakis, & Vazirgiannis, 2002b; Vendramin, Campello, & Hruschka, 2010) .

Membership Probability Function

```
%% Combining individuals belonging to the same cluster

for i=1:K
    fit_per_cluster = 0;
    num_per_clus = 1;
    for j=1:length(idx)
      if (idx(j)== i)
          fit_per_cluster = Fitness(j) + fit_per_cluster;
          Matrix(num_per_clus,i) = j;
          num_per_clus = num_per_clus + 1;
      end
   end
    Matrix(end-2,i) = num_per_cluster - 1;
    Matrix(end-1,i) = fit_per_cluster;
end

 %% Evaluation of the probability membership vector

Vector = zeros(length(Population),2);
p = 1;
for i=1:K
```

```
        Matrix(end,i) = Matrix(end-2,i)/sum(Matrix(end-2,:));
         if Matrix(end-2,i)== 1
           Vector(p,1) = Matrix(end,i);
           Vector(p,2) = Matrix(1,i);
            p = p+1;
         else
      for j = 1:Matrix(end-2,i)
Vector(p,1) = Matrix(end,i)*((Matrix(end-1,i) - Fitness(Matrix(j,i)))/(Matrix(end-1,i)*(Matrix(end-2,i)-1)));
     Vector(p,2) = Matrix(j,i);
     p = p+1;
      end
    end
   end

 %% Sorting of the MP vector with respect to the probability index

 scores = sortrows(Vector,2);
 MP_Vector = scores(:,1);
```

Figure 14 : Function code of the membership probability vector.

In essence, there are three main approaches to examine cluster validity:

- External criteria: evaluation of the clustering algorithm results is based on previous knowledge about data.
- Internal criteria: clustering results are evaluated using a mechanism that takes into account the vectors of the data set themselves and prior information from the dataset is not required.
- Relative criteria: aim to evaluate a clustering structure by comparing it to other clustering schemes.

KGA_o attempts to answer the following questions:

1. In how many clusters can the population be partitioned to?
2. Is there a better “optimal” partitioning for our evolving population of chromosomes?

Two main approaches to determining the suitable number of clusters for a given data can be distinguished:

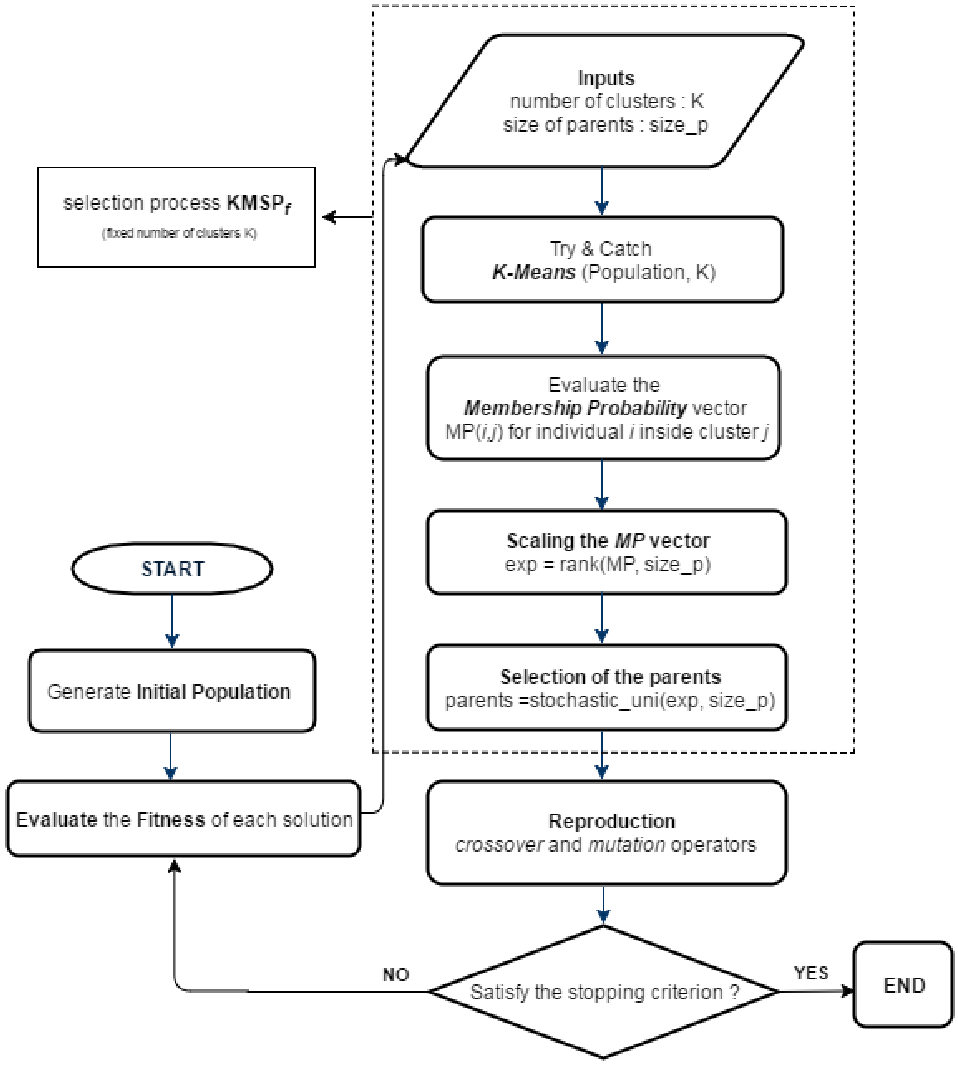

Figure 15 : Flowchart of the proposed KGA$_f$ technique.

- Compatible Cluster Merging (CCM): starting with a large number of clusters, and successively reduce the number by merging clusters which are similar (compatible) with respect to a similarity criterion.
- Validity Indices (VI's): clustering the data for different values of *K*, and using validity measures to assess the obtained partitions.

The CCM approach requires more computational operations than the use of a validity index to determine the optimal number of clusters. Moreover, the size of the evolving population is small (less or equal than 100 chromosomes), therefore there is no need to apply a CCM approach. On the other hand, the validity index is not a clustering algorithm itself, but rather a measurement of the results and thus suggests a scheme that best fits the data set. At each generation in the proposed KGA$_o$ technique, the optimal number of clusters is calculated using a validity assessment index. Different validity indices suitable for *K*-means clustering have been proposed in the literature.

Two different internal validity indices are applied in the KGA$_o$ technique: Silhouette(Rousseeuw, 1987) and the Davies-Bouldin index (Davies & Bouldin, 1979) explained below.

1. **Silhouette (S)** (Rousseeuw, 1987)

The silhouette technique assigns to the *ith* vector of cluster c_j $(j = 1,..K)$, a quality measure $s(i)$ known as the silhouette width defined as *S*:

$$s_j = \frac{1}{m_j}\sum_{i=1}^{m_j}\frac{(b(i) - a(i))}{\max\,[a(i), b(i)]} \tag{3.18}$$

$$S = \frac{1}{K}\sum_{j=1}^{K} s_j \tag{3.19}$$

where $a(i)$ is the average distance between the *ith* vector and the remaining elements inside the same cluster *j* of size m_j, $b(i)$ is the minimum average distance between vector *i* and all elements inside clusters c_k $(k = 1,..K; k \neq j)$. The optimal partition is expected to minimize the intra-group distance *a* while maximizing the inter-group distance *b*. Thus, maximize the silhouette width criterion *S*.

2. **Davies-Bouldin (DB)** (Davies & Bouldin, 1979)

The DB index aims to evaluate intra-cluster similarity and inter-cluster differences by computing the following:

$$BD = \frac{1}{K}\sum_{i=1}^{K} max_{i \neq j}\left[\frac{d(x_i) + d(x_j)}{d(c_i, c_j)}\right] \qquad [3.20]$$

where $d(x_i)$ and $d(x_j)$ are each the sum of all the distances between the centroid of the cluster and the elements of clusters *i* and *j* respectively, $d(c_i, c_j)$ is the distance between centroids of cluster c_i and c_j. A good partition composed of compact and separated clusters is represented by a small DB value. The Davies-Bouldin index presents decent results for dissimilar groups. However, it is not intended to handle overlapping clusters (Razavi et al., 2015).

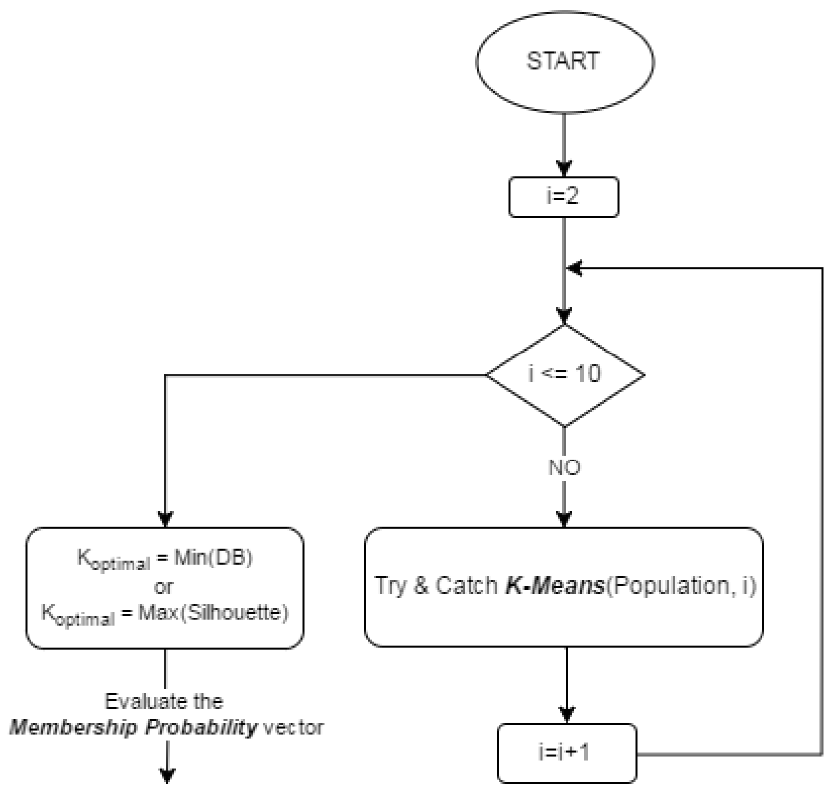

Figure 16 : Search for the optimal number of clusters.

Throughout the KGA_o technique, the evaluation of the validity index function is performed within a range of cluster numbers and then an optimal number is chosen. For instance, if the Silhouette index is applied, the number of clusters which maximizes S corresponds to the optimal partition. Whereas, the minimum DB value determines the optimal number of clusters for the clustering of the population. Since the size of the population is small, the maximum number of partitions is set to 10. Consequently, the search for the optimal partition varies between K = 2 and K = 10, as per Figure 16.

3.4.1.2 NUMERICAL SIMULATIONS

In this section, the performance of KGA techniques on 7 well-known test functions is investigated. In recent years, various kinds of novel computational intelligence methods have been proposed and the field is attracting more and more attention. To promote research on expensive optimization, the CEC 14' special session competition developed a set of benchmark optimization problems.

All test functions are minimization problems defined as following:

$$\min f(\mathbf{x}); \qquad \mathbf{x} = [x_1, x_2, \ldots, x_D] \tag{3.21}$$

D: dimension of the search space.

Most functions are shifted by $\boldsymbol{o}_i = [o_{i1}, o_{i2}, \ldots o_{iD}]$, a randomly distributed in $[-10{,}10]^D$. Some problems are rotated by a predefined rotation matrix **M** (Table IX).

Table 9 : Summary of the test functions.

No.	***Functions***	***Search ranges***	$\boldsymbol{f_i^*} = \boldsymbol{f_i}(\boldsymbol{x}^*)$
1	shifted sphere	$[-20{,}20]$	0
2	shifted ellipsoid	$[-20{,}20]$	0
3	shifted and rotated ellipsoid	$[-20{,}20]$	0
4	shifted step	$[-20{,}20]$	0
5	shifted Ackley	$[-32{,}32]$	0
6	shifted Griewank	$[-600{,}600]$	0
7	shifted rotated Rosenbrock	$[-20{,}20]$	0

1) shifted sphere function: $f_1(\mathbf{x}) = \sum_{i=1}^{D} x_i^2 \quad F_1(\mathbf{x}) = f_1(\mathbf{x} - \boldsymbol{o}_1)$
2) shifted ellipsoid: $f_2(\mathbf{x}) = \sum_{i=1}^{D} i x_i^2 \quad F_2(\mathbf{x}) = f_2(\mathbf{x} - \boldsymbol{o}_2)$

3) shifted and rotated ellipsoid: $F_3(\mathbf{x}) = f_2(\mathbf{M_3}[\mathbf{x} - \boldsymbol{o}_3])$

4) shifted step: $f_2(\mathbf{x}) = \sum_{i=1}^{D} |x_i + 0.5|^2 \quad F_3(\mathbf{x}) = f_3(\mathbf{x} - \boldsymbol{o}_4)$

5) shifted Ackley:

$$f_4(\mathbf{x}) = -20 \exp\left[-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right] - \exp\left[\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right] + 20 + e;\ F_5(\mathbf{x}) = f_4(\mathbf{x} - \boldsymbol{o}_5)$$

6) shifted Griewank: $f_5(\mathbf{x}) = \sum_{i=1}^{D} \frac{x_i^2}{4000} - \prod_{i=1}^{D} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \quad F_6(\mathbf{x}) = f_5(\mathbf{x} - \boldsymbol{o}_6)$

7) shifted rotated Rosenbrock:

$$f_6(\mathbf{x}) = \sum_{i=1}^{D-1}[100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2]\ ;\ F_6(\mathbf{x}) = f_6\left(\mathbf{M_7}\left[\frac{2.048(\mathbf{x}-\boldsymbol{o}_7)}{20}\right] + 1\right)$$

Results of the KGA techniques (KGA$_o$-S, KGA$_o$-DB and KGA$_f$) were taken for D = 10 and 20 and are compared to those of the standard genetic algorithm GA and the Group Counseling Optimizer (GCO) (Biswas, Eita, Das, & Vasilakos, 2014) presented at the IEEE Congress on Evolutionary computation (CEC 2014). In all experiments, common parameters such as population number, maximum generation number and stopping criterion were chosen the same for all algorithms. Population sizes of 50 and 100 were selected for dimensions 10 and 20 respectively. Each experiment is repeated 50 times to obtain the statistical features of the algorithms. A system with an Intel core i7 2.9 GHz processor and 4.096 GB RAM is used for implementing the MATLAB code for the proposed KGA techniques. All algorithms run the same number of fitness evaluations equal to 15,000 for D=10 and 20,000 for D=20, to ensure a fair comparison.

Table 10 : Comparison of statistical results of 4 algorithms for test problems 1–7 of dimensions *D*=10.

Problem		KGA$_o$ (S index)	KGA$_o$ (DB index)	Genetic Algorithm (GA)	KGA$_f$ (K=10)	GCO
1	Best	**8.82E-05**	1.95E-04	2.76E-04	5.06E-04	3.23
	Mean	2.45E-03	5.33E-03	8.29E-03	2.84E-02	1.23E+01
	Worst	1.13E-02	5.43E-02	1.08E-01	3.04E-01	2.96E+01
	SD	2.63E-03	8.39E-03	1.58E-02	5.01E-02	6.36E+00
2	Best	**2.91E-04**	3.34E-04	4.60E-04	2.08E-03	8.46
	Mean	7.12E-03	7.12E-03	4.75E-02	2.09E-01	4.14E+01
	Worst	6.27E-02	4.83E-02	7.20E-01	3.62	2.22E+02
	SD	1.07E-02	1.06E-02	1.17E-01	6.13E-01	4.61E+01
3	Best	5.55E-04	**2.27E-04**	5.32E-04	3.23E-03	1.56E+01
	Mean	1.00E-02	8.24E-03	5.01E-02	3.12E-01	8.85E+01
	Worst	5.42E-02	7.49E-02	2.58E-01	2.49	2.09E+02
	SD	1.25E-02	1.46E-02	6.72E-02	5.63E-01	5.53E+01
4	Best	4.00	**2.00**	1.50E+01	3.00	3.00
	Mean	9.14E+01	6.48E+01	1.31E+02	6.50E+01	1.00E+01
	Worst	3.86E+02	4.19E+02	3.83E+02	2.05E+02	2.70E+01
	SD	9.84E+01	8.38E+01	8.88E+01	5.42E+01	6.93
5	Best	**1.48E-03**	8.42E-03	1.21E-02	4.01E-02	3.92
	Mean	1.49	6.55	5.15	5.62	6.35
	Worst	1.26E+01	1.31E+01	1.24E+01	1.30E+01	9.94

	Problem	**KGA$_o$ (S index)**	**KGA$_o$ (DB index)**	**Genetic Algorithm (GA)**	**KGA$_f$ (K=10)**	**GCO**
	SD	2.28	4.52	3.62	4.12	1.71
6	Best	**4.94E-02**	4.97E-02	4.95E-02	5.04E-02	1.24
	Mean	6.41E-02	6.32E-02	6.38E-02	6.96E-02	2.11
	Worst	8.66E-02	8.56E-02	8.14E-02	1.00E-01	4.51
	SD	7.33E-03	6.73E-03	7.56E-03	1.07E-02	6.77E-01
7	Best	2.02E-01	**3.84E-03**	1.28	1.48E-01	4.42E+01
	Mean	3.77	3.65	3.22	4.59	9.28E+01
	Worst	7.77	8.81	5.09	1.55E+01	1.80E+02
	SD	1.48	2.12	5.94E-01	2.78	3.22E+01

***best solution for the given test problem**

Table 11 : Comparison of statistical results of 4 algorithms for test problems 1–7 of dimensions *D*=20.

Problem		KGA$_o$ (S index)	KGA$_o$ (DB index)	Genetic Algorithm (GA)	KGA$_f$ (K=10)	GCO
1	Best	**1.67E-03**	2.36E-03	1.05	4.51E-03	3.60E+01
	Mean	1.22E-02	1.53E-02	1.63	1.16E-01	1.19E+01
	Worst	6.32E-02	9.89E-02	2.43	6.42E-01	2.17E+01
	SD	1.45E-02	1.87E-02	3.13E-01	1.40E-01	5.88
2	Best	**3.76E-03**	5.68E-03	8.99	5.01E-02	7.79E+01
	Mean	1.17E-01	1.19E-01	1.02E+01	4.10	9.34E+01
	Worst	1.16	2.05	1.33E+01	2.75E+01	1.79E+02
	SD	2.17E-01	2.94E-01	1.48	6.05	4.75E+01
3	Best	1.96E-01	**5.50E-03**	1.49E+01	2.27E-02	3.33
	Mean	9.16E-01	3.33E-01	2.45E+01	2.04	1.44E+02
	Worst	3.19	4.59	3.53E+01	1.27E+01	2.62E+02
	SD	4.29E-01	6.85E-01	4.19	2.55	4.76E+01
4	Best	**7.00**	**7.00**	3.19E+02	1.70E+01	3.00
	Mean	7.91E+01	7.52E+01	4.89E+02	8.83E+01	8.48
	Worst	5.37E+02	3.32E+02	7.23E+02	3.17E+02	1.40E+01
	SD	9.23E+01	7.44E+01	9.99E+01	6.41E+01	3.01
5	Best	1.46	**1.32E-01**	9.83	1.55	1.28
	Mean	6.75	5.59	1.16	5.18	4.58
	Worst	1.26E+01	1.28E+01	1.25E+01	1.20E+01	8.94

Problem		KGA_o (S index)	KGA_o (DB index)	Genetic Algorithm (GA)	KGA_f (K=10)	GCO
	SD	3.69	3.58	7.38E-01	2.47	1.16
6	Best	2.72E-03	**1.37E-03**	1.04	6.77E-03	4.91E+01
	Mean	3.23E-02	2.93E-02	1.55	1.01E-01	1.89
	Worst	9.96E-02	7.65E-02	2.18	1.02	2.86
	SD	2.23E-02	1.80E-02	6.10E-01	1.95E-01	4.94E-01
7	Best	1.65E-02	**1.02E-02**	7.99	5.04E-02	3.10E+01
	Mean	1.87E+01	1.59E+01	2.63E+01	1.96E+01	1.13E+02
	Worst	7.54E+01	7.21E+01	6.15E+01	7.84E+01	1.72E+02
	SD	2.82E+01	2.74E+01	1.34E+01	2.97E+01	2.67E+01

***best solution for the given test problem**

The statistical results of the test problems are shown in Table X and Table XI. In all cases, the best solution was obtained with either the KGA_o-S or the KGA_o-DB. This demonstrates the significant feasibility and efficiency of the proposed techniques over the standard GA. The KGA techniques ensured a broader and more exhaustive search and prevent premature death of potential solutions.

The KGA methods implement an efficient partitioning of the population. They extend the diversity by intensifying the scope of the search process and reducing less favourable solutions. The recombination of two similar solutions will more likely generate a descendant with homogenous chromosomes. The evaluation of the membership probability vector inside the proposed selection process guarantees a more fitting parent selection.

In addition, the elitism strategy that results from partitioning the population into a number of clusters ensures that best solutions are always carried forward to the next generation. In fact, rather than obtaining one elite solution, *K*-strong optimal solutions are generated in each generation. In the long run, this enhances the exploration of future generations and reduces the possibility of premature convergence at local minima. The latter was recorded with the standard GA in problems 4-7 especially. Unlike the KGA_f, the KGA_o-S and KGA_o-DB are designed in such a way that there are no additional parameters to be fine-tuned.

The most frequently used statistical tests to determine significant differences between two computational intelligence algorithms are the t-test and Wilcoxon signed-ranks test (Wilcoxon, 1945). The later is a non-parametric counterpart of the paired t-test, which ranks the differences in performances of two algorithms over each data set. In brief, the test omits the signs, and compares the ranks for the positive and the negative differences. The differences are ranked based per their absolute values and in case of ties average ranks are calculated.

A Wilcoxon test is used for pairwise comparisons between the following pairs of algorithms: KGA_o (S index)- KGA_o (DB index), KGA_o (S index)-GA, KGA_o (S index)-KGA_f, KGA_o (DB index)-GA, KGA_o (DB index)- KGA_f, GA- KGA_f for test function 7 (Table XII)

As we can see, the *p*-values obtained by the paired Wilcoxon test indicate that the algorithms behave differently, since all *p*-values are less the level of significance $\alpha = 0.05$.

Table 12 : *p*-values for Wilcoxon test for benchmark function 7.

Comparison	R^+	R^-	alpha	z-score	p-value
KGAo (S index)- KGAo (DB index)	3.07E+02	9.68E+02	5.00E-02	3.19E+00	1.42E-03
KGA_o (S index)-GA	1.55E+02	1.12E+03	5.00E-02	4.66E+00	3.20E-06
KGA_o (S index)-KGA_f	7.40E+01	1.20E+03	5.00E-02	5.44E+00	5.34E-08
KGA_o (DB index)-GA	4.51E+02	8.24E+02	5.00E-02	3.80E+00	4.18E-02
KGA_o (DB index)- KGA_f	1.34E+02	1.14E+03	5.00E-02	4.86E+00	1.17E-06
GA- KGA_f	1.28E+03	0.00E+00	5.00E-02	6.15E+00	7.56E-10

3.5 SUMMARY

Two original contributions were presented in this chapter: VCH method and the KGA techniques:

The VCH method is a penalty-free constraint-handling method that only uses the violation factor to perform the sorting of the population with both feasible and infeasible individuals. In the proposed VCH method, at a given iteration, the individuals of the population are never compared in terms of both objective function value and constraint violation information. Essentially, the main motif is to keep the fitness function equivalent to the designer’s objective function and therefore the conversion of the constrained problem into an unconstrained one is no longer required.

The KGA methods implement an efficient partitioning of the population. They extend the diversity by intensifying the scope of the search process and reducing less favourable solutions. The recombination of two similar solutions will more likely generate a descendant with homogenous chromosomes. The evaluation of the membership probability vector inside the proposed selection process guarantees a more fitting parent selection.

In this chapter, the emphasis was on the computational algorithm responsible of generating optimal solutions throughout the evolutionary process. The VCH and KGA technique form the core mechanisms for the constraint-handling and selection process respectively. With this knowledge in hand, existing wind turbine blade design tools can now be dissected in the following chapter.

CHAPTER 4

WIND TURBINE BLADE DESIGN AND OPTIMIZATION TOOLS

4.1 INTRODUCTION

In the previous chapter, we emphasized on two original contributions in computational intelligence mainly and in genetic algorithms specifically. The proposed VCH method allow us to deal with WTOP design constraints without the need to define a penalized fitness function. Whereas the KGA techniques promote a more efficient selection process during the search for optimal wind turbine blades.

In this chapter, we will focus on existing wind turbine blade design codes, tools and software solvers, which played a major role in building the proposed *winDesign* platform. We overview commercial numerical tools and solvers that compute:

- Rotor aerodynamics (BEM and CFD)
- Airfoil preparation codes
- Rotor performance models
- Aerodynamic loads solvers
- Wind turbine structure design software

4.2 OVERVIEW OF WIND TURBINE ROTOR AERODYNAMICS

One of the core disciplines in wind energy is fluid mechanics, precisely aerodynamics. It is required to describe the flow field around the rotor from which the conversion system extracts energy. Beside the need for the performance description of the wind turbine, a proper description of the flow regimes is needed to develop an interaction with the deforming structure (aeroelasticity). Furthermore, it allows the designers to reduce noise production and the wake behind the rotor that must be evaluated to determine the inflow field for the downstream rotors. In this section, we examine the state of art in rotor aerodynamics used in numerical tools for wind turbine design studies. The solvers are divided into two classes:

1. Blade Element Momentum (BEM) theory
2. Computational Fluid Dynamic (CFD)

4.2.1 BLADE ELEMENT MOMENTUM SOLVERS

The momentum method originates from Froude (Froude, 1889), Lanchester (Lanchester, 1915), Betz (Betz, 1920) and Glauert (Glauert, 1948), where the flows are considered in a control volume consisting of the stream tube surrounding the actuator disc. Betz (Betz, 1958), derived the famous limit, the Betz limit, which states that the maximum energy that can be extracted from the wind is the 16/27th of its kinetic energy. This limit assumes the absence of axial pressure due to the pressure distribution on the external tube and the absence of radial forces on the flow. According to van Kuik (van Kuik, 1991), the second assumption does not hold, hereafter, the limit becomes slightly higher than Betz limit.

Later, Wilson and Lissaman (Robert Elliot Wilson & Lissaman, 1974), proposed a method combining the blade element momentum theory and a vortex theory assuming small perturbation. This later model, has been used in many tools for the calculation of the aerodynamic loadings because of its accuracy, simplicity and ease of intuitive understanding (A. Hansen, 1992). An excellent discussion of the wind turbine theory for both horizontal-axis and vertical-axis turbines is presented by Vries (Vries, 1979). The following references (Adkins & Liebeck, 1983; Benini & Toffolo, 2002; Bot & Ceyhan, 2013; Buhl, 2004; Ceyhan, 2008; Ceyhan et al., 2009; J. Chen et al., 2013; Clifton-Smith & Wood, 2007; T Diveux et al., 2001; P Fuglsang & Aagaard Madsen, 1994; Peter Fuglsang & Aagaard Madsen, 1995; Peter Fuglsang et al., 2002; P. Fuglsang & Madsen, 1999; P Giguère & Selig, 1997; Hillmer et al., 2007; Jureczko et al., 2005; Larrabee, 1979; K. Y. Maalawi & Badr, 2003; Méndez & Greiner, 2006; Moriarty & Hansen, 2005; A. Ning, 2013; A. Ning et al., 2013; S. Ning, 2013; Øye, 1996; DC Sale, 2010; J. Schepers et al., 2002; Michael S Selig & Tangler, 1995; H Snel, 1998; H. Snel, 2003; L. Wang et al., 2011; Xuan et al., 2008) applied the blade element momentum theory (mostly based on Wilson and Lissaman (Robert Elliot Wilson & Lissaman, 1974; Robert

Elliott Wilson et al., 1976)) for the aerodynamic analysis in their optimization codes or aerodynamic tools.

The axial momentum method presents major deficiencies (H Snel, 1998), and several improvements have been presented. One of the serious problems is the yaw behavior or yaw misalignment on controlled-yaw rotors and free-yaw rotors, a problem that has been reported as the second leading cause of failures in wind farms in California (Lynette, 1989). Hansen (A. Hansen, 1992) and Schepers et al.(J. Schepers, Snel, & Bussel, 1995) suggest than in addition of applying a basic annular momentum theory to the axial component of the wind speed, an azimuthal distribution is applied which is a function of the yaw angle. The form of this distribution may be from Glauert (H Glauert, 1935) or even by Gaonkar and Peters (Gaonkar & Peters, 1988). Readers interested in the improvements of the yaw misalignments models should review references (J. Schepers et al., 1995) and (H Snel, Schepers, & Nederland, 1995) for more details.

Another incorrect assumption of the axial momentum method is the time independence of the flow. Snel et al. (H Snel et al., 1995) justifies the absence of global equilibrium or also referred as wake equilibrium. In fact, the rotor is changing in time as a result of the variations in wind speed, wind direction, wind shear effects, blade dynamics and control. In addition, the momentum method has a major flaw during high rotor loading, where during this mode a sizeable amount of kinetic energy is converted into large-scale turbulence; known as “turbulent wake state”. This is usually resolved by introducing an empirical correction factor between the axial forces and the induction factor.

For more details concerning wind turbine blade correction factors, the reader is referred to Schepers (J. G. Schepers, 2012) Wilson and Lassaman (Robert Elliot Wilson & Lissaman, 1974), Prandtl and Betz (Prandtl & Betz, 1927), Shen et al. (Shen, Mikkelsen, Sorensen, & Bak, 2005), Clifton-Smith (Clifton-Smith, 2009; Clifton-Smith & Wood, 2007) and Hoadly (Hoadley, Madsen, & Bouras, 1993). Although modern corrections exist, the decision of introducing them in the codes is altered by the risk of increasing the complexity of the problem in terms of required computational time.

The blade element momentum theory can be expected to remain a useful aerodynamic model for aeroelastic calculations, but improvements will be made inspired from the numerical validation that the latest computational fluid dynamics flow calculations will provide (H. Snel, 2003; H. Yang, Shen, Xu, Hong, & Liu, 2014). Inverse design methods such as Larrabee (Larrabee, 1979) and Adkins et al. (Adkins & Liebeck, 1983), inherent limitations of the blade element theory and uncertainties in the prediction of the aerodynamic forces can reach as much as 20 % (J. Schepers et al., 2002). This error is mainly due to the basic assumptions made in the traditional BEM theory such as radial independence of flow effects, yaw flow effects negligence, 2D flow over the blade. Recently implemented and improved mathematical models for the fluid dynamics of wind turbine based on the blade element momentum theory can be found in (Lanzafame & Messina, 2007; Helge Aa Madsen, Bak, Døssing, Mikkelsen, & Øye, 2010; A. Ning, 2013).

4.2.2 COMPUTATIONAL FLUID DYNAMICS SOLVERS

In recent years, a common way during the rotor design is to produce a draft rotor from a preliminary analysis tool using a relatively simple method such as BEM and then evaluate it using an aeroelastic code (Timmer, 2013). The decision of carrying further evaluation using a CFD solver depends on the efficiency of the draft model and on the experience of the designer. Since the start of the 1990s CFD techniques for wind turbines (Dornberger, Büche, & Stoll, 2000; J. Johansen, Madsen, Gaunaa, Bak, & Sorensen, 2009; J. Michelsen, 1992; J. A. Michelsen, 1994; N. N. Sørensen, 1995) and reduced models where volume forces are included into the flow (Robert Mikkelsen, 2003; Sørensen & Shen, 2002), have been introduced aside from the commercially available CFD codes ("ANSYS, CFX," ; "ANSYS, Fluent,"). In the process of optimization, getting an accurate value of the objective function is important. We can summarize the performance of different calculation methods as follows:

- Direct Navier-Stokes (DNS)
- Euler Simulation (Inviscid calculation)
- Reynolds Averaged Numerical Simulation (RANS)
- Large Eddy Simulation (LES)
- Detached Eddy Simulation (DES)

The most rigorous way of analyzing the global flow field for wind turbines would be the use of time-dependent incompressible Navier-Stokes equations. However, this requires the solution of difficult set of equations. In fact a Direct Navier-Stokes (DNS) for a relevant value of Reynolds would require several centuries of computing time (H. Snel, 2003). The first work done by NASA-NREL applying the DES method can be found in (Jeppe Johansen, Sorensen, Michelsen, & Schreck, 2002).

The most common solution of the Navier-Stokes equations is achieved by separating the flow into an average part and a fluctuating part. The equations are then averaged; this is called the Reynolds Averaged Navier Stokes (RANS) method. The reader is referred to references (Castellani & Vignaroli, 2013; X. Chen & Agarwal, 2010; X. Chen & R. Agarwal, 2012; X. M. Chen & R. Agarwal, 2012; Ramachandran, Webster, & Zhuang, 2010; Ribeiro et al., 2012; J. Sørensen, 1999; N. N. Sørensen, Michelsen, & Schreck, 2002; Srinivasan, Ekaterinaris, & Mccroskey, 1995) for more applications of the RANS method in airfoil and wind turbine blade optimization. The RANS method gives accurate lift and drag coefficients at low angle of attack before separation.

For highly separated flow, problems with the RANS method arise, and it is recommended to use the Large Eddy Simulation (LES). According to Mellen et al. (Mellen, Fr-ograve, hlich, & Rodi, 2003) "when resolution requirements are specified, LES is able to produce the correct overall flow behavior". Details are provided on the structure of the flow and its time-dependant behavior that are not available from RANS calculations. However, meeting resolution requirements lead to calculations that are extremely expensive and currently not suitable for routine use". This latter method is combined with RANS, where the RANS is responsible for the attached flow whereas the LES resolves the far flow; the method is called the Detached Eddy Simulation (DES).

Johansen et al. (Jeppe Johansen et al., 2002) showed that the DES computations did not improve the predicted blade characteristics because the LES takes too much computational time. Instead of applying the Navier-Stokes equations, we can use the Euler equations; which is the non-viscous form of the Navier-Stokes (Huyse, Padula, Lewis, & Li, 2002; Vatandas & Özkol, 2008; Whitney, Sefrioui, Srinivas, & Périaux, 2002). The assumption of a constant density holds for the analysis of wind turbines since the flow speeds have a maximum cut out wind speed of approximately 25 m/s, even at the blade tip where the tip speed can reach 100 m/s. Hence, assumptions are taken on the flow, where the process of creation, diffusion and the dissipation of vorticity are not considered (H. Snel, 2003).

For low angles of attack when the flow is attached to the airfoil, the Euler calculation gives a reasonable pressure coefficient distribution, but the drag coefficients C_D tend to be underestimated due to the negligence of the viscous drag. Madsen (H. Madsen, 1988) evaluated the Euler equations for an axi-symmetrical case. A special solution of the Euler equations is the vortex wake method.

Recently, the free vortex wake method has been applied to wind turbines. It is more demanding than the BEM in terms of computational time. The flow field around the rotor, both upstream and downstream can be modelled by on viscous methods as long as the vorticity is accounted for (H. Snel, 2003). A practice is to apply this method for the study of the induction for yawed flow conditions. For more details concerning the wake method applied to wind turbines, the reader is referred to (H Snel, 1998) and application of the free vortex wake method can be found references (Bareiss, Guidati, & Wagner, 1997; Simoes & Graham, 1991).

An alternate to the wake method is the field method, where the Euler equations are solved with the addition of the vorticity created by the blade. In general, the CPU time needed for the resolution of the vortex wake methods is still high, so further simplifications have to be made. Because it is needed that the wake be extended to at least 2 rotor diameters behind the rotor plane, a hybrid method is used such as REVLM (Bareiss et al., 1997), that has reported a 75 % reduction in computer time with an error of 5%. This method assumes that for one rotor diameter downstream, the flow is treated as a free wake and the rest as a prescribed wake.

An additional Euler solver is the Asymptotic Acceleration Potential method formulated by the Delft University of Technology (Vanholten, 1977) for helicopters. It was extended by Bussel et al. (G. J. W. Van Bussel, 1995) for wind turbines. The method assumes small perturbations of the main flow, an assumption that holds for wind turbines and not for helicopters. This method much like the vortex wake methods, has been applied mainly to examine the flow fields in order to add improvements to the momentum method (G. van Bussel, 1996).

Above, the emphasis was made on the modeling of unsteady aerodynamics of the blade sections, but another vital area that needs consideration in wind energy modeling is the modeling of rotor wake. Wind turbine wakes have been a topic of evaluation since the 1970's when the interest in wind energy became more significant.

When regarding wind turbine wakes, a distinction is usually made between two types: near and far wakes. The near wake is taken at the area just behind the rotor. Vermeer et al. (Vermeer, Sørensen, & Crespo, 2003) considers the region of near wake extends up to one or two rotor diameters downstream. The far wake is the region beyond the near wake and attention is put on the influence on the wind turbines in the wind farm (up to 10 rotor diameters downstream). Hence the near wake is focused on the performance the process of power extraction from the kinetic energy in the incoming flow, whereas the far wake is more fixated on the mutual influence of wind turbines distributed in the farm. On the other hand, because of land and civil work costs, wind turbines tend to be built as closely as possible to one another.

Therefore, most interest has been focused on the study of far wakes. A guideline for wind turbine spacing can be found in (Builtjes & Smit, 1978).

Wind turbines mounted in large wind farms introduce two major issues: a reduction in power production due to wake velocity deficits and an increase in dynamic loads because of higher turbulence levels. According to Sanderse et al. (Sanderse, Pijl, & Koren, 2011), power loss of a downstream turbine can reach 40 % in full-wake conditions. Sheinman and Rosen (Sheinman & Rosen, 1992) showed that neglecting the effect of wake turbulence in the incoming flow can lead to an overestimation of turbine output by more than 10%. Power losses because of a lower incident wind speed in wind turbines grouped in wind farms have been reported in (R. Barthelmie et al., 2009; Rebecca J Barthelmie et al., 2008; Elliott, 1991; Neustadter & Spera, 1985; Sanderse et al., 2011; Sheinman & Rosen, 1992).

In an early approach (Bossanyi et al., 1980; Emeis & Frandsen, 1993; Frandsen, 1992; Milborrow, 1980), it was assumed that the turbines acted as distributed roughness elements modifying the ambient atmospheric flow. However, the most common approach is to consider each individual wind turbine wake and examine its interaction with and superposition on neighboring ones (Crespo, Hernandez, & Frandsen, 1999; S. Lissaman, 1979), thus calculating the detailed flow field and not the averaged distribution.

Crespo et al. (Crespo et al., 1999) surveyed the methods for wake modeling for both wind turbines and wind farms. Vermeer et al. (Vermeer, 2001; Vermeer et al., 2003) reviewed all previous experiments and analyses of the flow through the wind turbine rotor. It is clear from the review that only a few wind tunnel experiments on the wake flow behind the rotor have been pursued.

Sanderse et al. (Sanderse et al., 2011) presented an important review of the numerical calculation of wind turbine wake aerodynamics, examining the different turbulence models that are employed to study wake effects on wind turbines. Finally, modelling and measurements of wind turbine wakes in wind tunnels have been conducted using hot wire anemometry (HWA) or particle image velocimetry (PIV) in the following studies (Rebecca Jane Barthelmie et al., 2007; Chamorro & Porté-Agel, 2009; Ebert & Wood, 1997; Grant et al., 2000; Grant & Parkin, 2000; Grant, Parkin, & Wang, 1997; Grant, Smith, Liu, Infield, & Eich, 1991; Maeda, Kinpara, & Kakinaga, 2005; Mast, Vermeer, & van Bussel, 2004; Medici & Alfredsson, 2006; Vermeer, 2001; Whale, Anderson, Bareiss, & Wagner, 2000).

4.3 WIND TURBINE DESIGN NUMERICAL TOOLS

Many graphical user-friendly design tools have been developed for the purpose of airfoil preparation, rotor performance optimization and aero-elastic simulation of horizontal-axis wind turbines.

Below, we list the most relevant numerical tools for the design of HAWT's.

4.3.1 AIRFOIL PREPARATION CODES

In order to calculate the loads on the blade, the BEM methods requires the lift and drag coefficients of the airfoil distribution. AirfoilPrep (C. Hansen) is a design code developed by Windward Engineering & NREL that is used to generate airfoil data files from 2D data needed by aerodynamic softwares such as WT-Perf (Buhl, 2004) and AeroDyn (Moriarty & Hansen, 2005). A key feature of AirfoilPrep is the adjustment of 2D data for rotational augmentation: stall delay effect by Du-Selig (Du & Selig, 1998) and Eggers(Eggers et al., 2003) correction for drag. In addition, Viterna et Janetzke (Viterna & Janetzke, 1982) or flat plate theory is used to extrapolate the coefficients at high angle of attacks.

Several panel codes are used by designers in the design and analysis of airfoils. The Eppler code was used by Tangler and Somers (J. L. Tangler & Somers, 1995) to design the SERI/NREL S8xx-series. Nonetheless, the most standard code is the Xfoil developed by Drela (Drela, 1989). Similarly, Tangler and Kocurek (James Tangler & Kocurek, 2005) propose an extrapolation of post stall and is usually employed (Kenway & Martins, 2008). Xfoil is used in the optimization work of (Kenway & Martins, 2008).

An alternative to Xfoil is the Rfoil code (Van Rooij, 1996) that guarantees a better convergence around the max since different velocity profiles for the turbulent boundary layer. The Xfoil and Rfoil codes are used in studies (Clifton-Smith & Wood, 2007; Peter Fuglsang & Bak, 2004; Peter Fuglsang et al., 2004; Xuan et al., 2008) and (Bizzarrini et al., 2011; J. Chen et al., 2013; F. Grasso, 2011) respectively to calculate the pressure coefficient (***C_P***) for each blade section. According to the definition of the pressure coefficient, the pressure ***p*** can be computed.

$$C_p = \frac{\rho - \rho_\infty}{1/2\rho U^2} \qquad [4.1]$$

where ***ρ*** is the air density of 1.205 kg/m3; **C_P** is the pressure coefficient; ***ρ_∞*** is the standard atmospheric pressure; U is the relative velocity (combination of the axial velocity and the tangential velocity calculated from the BEM theory).

A similar code to XFOIL employed in (M. Grujicic et al., 2010), named Javafoil (Hepperle, 2011), a two- dimensional aerodynamic analysis computer code that solves the flow equations over an airfoil using the boundary integral method.

4.3.2 ROTOR PERFORMANCE MODELS

Giguère and Selig (Giguere & Selig, 2000) obtain their performance predictions from PROPID (P Giguère & Selig, 1997; Michael S Selig & Tangler, 1995); an inverse design method for HAWTs that is based on BEM theory. The airfoil data are modified in PROPID to include the three-dimensional effects using stall-delay models(Du & Selig, 1998; J. L. Tangler & Selig, 1997). WT-Perf (Buhl, 2004) is a software that computes a steady-state calculation (no dynamics), that computes the power, torque, thrust and blade-root bending moment that uses BEM theory. WT-Perf is incorporated in the optimization process of (Maki et al., 2012).

A second code by the name of HARP_Opt (Horizontal Axis Rotor Performance Optimization) developed by Sale (DC Sale, 2010) utilizes a multiple objective genetic algorithm and BEM theory to design HAWT and hydrokinetic rotors. The BEM theory of WT_Perf (Buhl, 2004) is used to predict the rotor performance metrics. In HARP_Opt the objective function can be single or multiple (the maximization of the AEP or /and the minimization of the blade mass). Since they are conflicting objectives, a set of Pareto optimal solutions are identified by HARP_Opt. This code is integrated into the optimization design process of (Maki et al., 2012). In (M. Grujicic et al., 2010), PROPID (M. Selig & Tangler, 1994) is utilized to compute the variation of the aerodynamic efficiency with the blade tip speed ratio.

In order to determine the overall sound pressure level, Xuan et al. (Xuan et al., 2008) use NAFNoise, Ramachandran et al. (Ramachandran et al., 2010) use AIBM (Yu, Zhou, & Zhuang, 2008) (similar to FW-H integral method (Williams & Hawkings, 1969)) combined with CFD to evaluate the aerodynamic and aeroacoustic performance of airfoil sections.

4.3.3 AERODYNAMIC LOADS SOLVERS

AeroDyn (Moriarty & Hansen, 2005) is another NREL software based from the work of Peters and He (Peters & He, 1991) that is used to compute the aerodynamic loads on the wind turbine blade as part of the aero-elastic solution. AeroDyn contains two models for the calculation of the effect of wind turbine wakes: BEM theory and the generalized dynamic-wake (GDW) theory. AeroDyn is integrated and used in the optimization procedure of the following references (G. Bir & Jonkman, 2007; Gallardo, 2011; Jeong et al., 2012; Lanzafame & Messina, 2007; A. Ning, 2013; DC Sale, 2010).

Kenway et Martins (Kenway & Martins, 2008) developed a BEM code by the name of pyBEM based on the theory of Hansen (M. O. Hansen, 2013). The code was extended for coned rotors using the model of Mikkelsen et al. (R Mikkelsen, Sørensen, & Shen, 2001).

Another blade element momentum method for analyzing the wind turbine performance is CCBlade developed by Ning (S. Ning, 2013) (which stands for **C**ontinuity and **C**onvergence). CCBlade integrates a new solution strategy that is robust with a better convergence based on (A. Ning, 2013) which allows the designers to apply CCBlade in gradient-based optimization applications. This code was added in the optimization design process of (A. Ning et al., 2013).

4.3.4 GEOMETRIC DESCRIPTION

One of the most important ingredients in numerical optimization is the choice of design variables and the parameterization of these variables. In order to reduce the number of necessary parameters to take to describe the airfoil's shape without losing information about the geometrical characteristics of the airfoil, several mathematical formulations are proposed. For instance, common parametric curves and analytical functions used in the geometry description in wind turbine optimization are:

- Bezier curve used in (Bizzarrini et al., 2011; X. Chen & Agarwal, 2010; X. Chen & R. Agarwal, 2012; X. M. Chen & R. Agarwal, 2012; F. Grasso, 2011; Francesco Grasso, 2012; Ju & Zhang, 2012; Kampolis & Giannakoglou, 2008; Karakasis, Giotis, & Giannakoglou, 2003; Liu et al., 2007; López et al., 2008; Peigin & Epstein, 2004; Vatandas & Özkol, 2008; L. Wang et al., 2011; Xuan et al., 2008)
- Splines description used in (Huyse et al., 2002)
- B-splines description used in (Duvigneau & Visonneau, 2004; F. Zhang, Chen, & Khalid, 2003)
- Hicks and Henne (H.-J. Kim, Sasaki, Obayashi, & Nakahashi, 2001; Yin, Xu, An, & Chen, 2008)
- Quadratic equations (Whitney et al., 2002)
- Combination of ellipses and splines (Rai & Madavan, 2000)

4.4 WIND TURBINE STRUCTURE DESIGN SOFTWARE

Very few commercial finite-elements based software's have been proven to be reliable tools for the structural analysis of wind turbines. Nevertheless, they fall into two major types of codes: static (time independent) and dynamic (time-dependent domains).

4.4.1 STATIC TOOLS

Jureczko et al. (Jureczko et al., 2005) applied the MSC Patran commercial software to compute the shear centers, centroids, moments of inertia and sectionals areas.

Commercial finite element software such as ANSYS ("ANSYS,"), ABAQUS (Hibbitt, Karlsson, & Sorensen, 2001) and SolidWorks are used in (J. Chen et al., 2013; Jureczko et al., 2005; F. F. Song, Ni, & Tan, 2011; Zhu et al., 2012), (M. Grujicic et al., 2010) and (F. F. Song et al., 2011) respectively for the structural analysis of the wind turbine components.

A structural analysis tool named pBEAM (Polynomial Beam Element Analysis Module) was developed, which uses Euler-Bernoulli beam elements with 12 degrees of freedom (three translational and three rotational at each end of the element), see Yang (T. Yang, 1986) for more details. This code was used for the structural analysis of the wind turbine blade in the following references (A. Ning et al., 2013).

An in-house structural analysis code named pyFEA is utilized by Kenway and Martins (Kenway & Martins, 2008). It models the wind turbine blade internal spar using Timoshenko elements with 6 degrees-of-freedom. A similar code was built by Liao et al. (Liao et al., 2012) to verify the Prelayers code that compute the properties of the sectional layers using PreComp (Gunjit S Bir, 2006).

The authors of (Bottasso et al., 2010; A. Ning et al., 2013; Veers et al., 2003) used NuMAD (Laird, 2008); a FEM based software for the structural analysis of rotor blades. Also, two codes RotorOpt (Anonymous, 2007; L. Fuglsang, 2008) and FOCUS5 (Duineveld, 2008) were included as required environments and tools for optimization and wind turbine design in (Bottasso et al., 2010; A. Ning et al., 2013). The optimum results were tested by FOCUS5 in the following references (Bottasso et al., 2010; Liao et al., 2012; A. Ning et al., 2013).

PreComp (Gunjit S Bir, 2006) is a software developed by NREL that computes sectional properties of composite blades for beam types models. The inputs for PreComp are the external blade shape and internal lay-up of composite laminas and uses a modified laminate theory (CLT) with a shear flow approach. During the calculation of the stresses, all the loads and inertial properties are transferred to the elastic center and principal aces of each section. Some of its assumptions and limitations are: straight blades only, webs are assumed normal to the chord, thin-walled closed sections, no transverse shearing and no in-plane distortion. PreComp is incorporated in the design process of (Liao et al., 2012; Maki et al., 2012).

A recent program called BLADOPT (Bulder, Barhorst, Schepers, & Hagg, 2013), a successor of PVOPT (J. Schepers, 1996), is a numerical optimization computer program for the design of HAWT rotor blades. The chord and the twist are optimized as to minimize the cost of energy.

In order to compute the mode shapes and natural frequencies of the blade and the tower a software developed by NREL by the name of BModes (Gunjit S Bir, 2005). Using 15 degrees of freedom and a set of linearized equations, the mode shapes are derived under the following assumptions: straight blade, cantilevered blade root, isotropic material and no material couplings.

4.4.2 DYNAMIC TOOLS

The aeroelastic model that was used by Fuglsang et al.(Peter Fuglsang et al., 2002) is FLEX4 (Øye, 1996), a time domain solver of the loads based on blade element theory. Additional effects such as tower shadows, dynamic stall, wind shear and wind turbulence were included for a more efficient wind turbine design code. Hillmer et al. (Hillmer et al., 2007), generate the loading cases with the FLEX5 software.

Another aeroelastic computer-aided engineering tool for HAWT is FAST (Fatigue, Aerodynamics, Structures and Turbulence) (Jason M Jonkman & Buhl Jr, 2005) by NREL. The code models the wind turbine as a combination of flexible and rigid bodies (24 DOF for a 3-bladed wind turbine, 22 DOF for a 2-bladed turbine). The aerodynamic forces along the blade are generated by AeroDyn (Moriarty & Hansen, 2005). FAST is used in the following references (G. Bir & Jonkman, 2007; Jeong et al., 2012; Liao et al., 2012; Maki et al., 2012; Namik & Stol, 2010).

An additional design code to study the dynamics of the wind turbine is MSC. ADAMS (ADAMS, 2005) (stands for Automatic Dynamic Analysis of Mechanical Systems). An interface called MSC.ADAMS-to-AeroDyn (ADAMS2AD) (Laino & Hansen, 2001) was developed by NREL to analyze complex wind turbine dynamic models in MSC.ADAMS because ADAMS allows the user to create custom dynamic-link-libraries (DLLs) enabling a direct link between the program and the user's subroutines. Hence, complex dynamics can be analyzed in MSC. ADAMS while benefiting from the aerodynamics analysis capabilities of AeroDyn (Moriarty & Hansen, 2005). ADAMS2AD was incorporated in the following works (G. Bir & Jonkman, 2007).

4.5 CO-BLADE TOOL

Co-Blade is a tool that helps designers compute structural the properties of a wind turbine blade. It uses a combination of classical lamination theory (CLT) with an Euler-Bernoulli theory and shear flow theory applied to composite beams is used to perform its analysis. This approach allows for a direct computation of the structural properties of a given blade, within several seconds of execution.

In this section, we examine the main elements which were extracted from Co-Blade to build the winDesgin graphical tool.

4.5.1 CO-BLADE DESIGN TOOL

The fitness function that Co-Blade minimizes is the blade mass penalitized by the maximum stress, buckling, deflection and the natural frequency. The design variables are the chordwise width of the spar cap at the inboard and outboard locations, the thickness of the "blade-root" material, and the thicknesses of the laminas within the LEP, TEP, spar cap, and shear webs along the length of the blade. They are listed in Table XIII below.

At first, the blade is represented as a cantilever beam under flapwise and edgewise bendings, axial deflection, and elastic twist. Additional coupling between bending, extension, and torsion are accounted for, due to the offsets of between the beam shear center, tension center, and center of mass from the blade pitch axis (refer to **Error! Reference source not found.**). The beam cross sections are assumed thin-walled, closed, and single or multi-cellular and the periphery of each beam cross section is discretized as a connection of flat composite laminates.

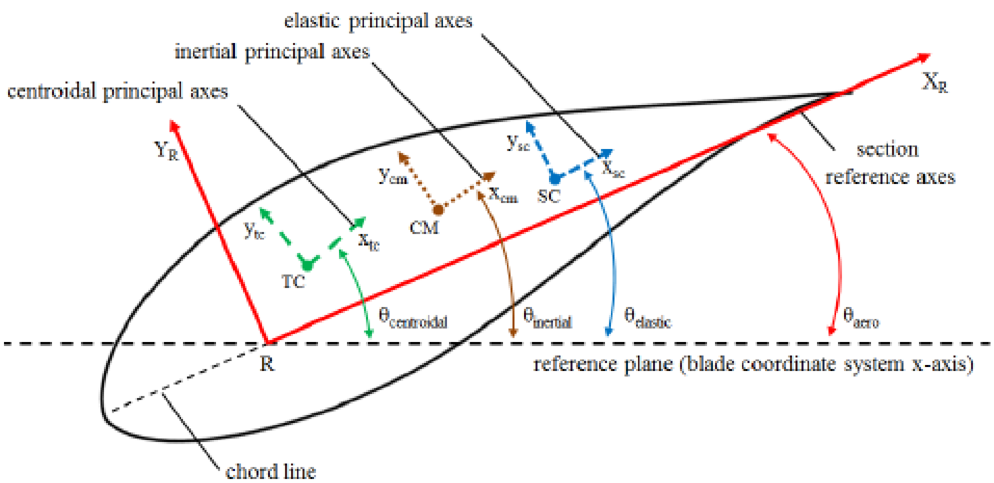

Figure 17 : Orientation of the blade axe systems (Danny Sale, 2012).

In regard to Euler-Bernoulli beam theory, the beam cross sections are considered as heterogeneous and each of the material properties depends on the location in each cross section. The structural analysis at each discrete portion of the composite beam characterizes effective mechanical properties computed via classical lamination theory. Each discrete portion of the cross section then contributes to the global section properties of the composite beam, (described further in (Allen & Haisler, 1985; Rivello, 1969)). Once the global cross sectional properties are calculated, the deflections and effective beam axial stress (σ_{zz}) and effective beam shear stress (τ_{zs}) can be now computed under the assumptions of an Euler-Bernoulli beam (refer to (Allen & Haisler, 1985; Bauchau & Craig, 2009; Rivello, 1969)).

Table 13 : Design variables for Co-Blade.

Parameters	Description
w_cap_inb, w_cap_oub	Width of the spar cap normalized by the chord length at the INB_STN and OUB_STN blade stations
t_blade_root	Thickness of the “blade-root” material at the INB_STN blade station
t_blade_skin1 …t_blade_skinN	Thickness of “blade-shell” material at control points 1 through NUM_CP. The control points are equally spaced along the blade between the TRAN_STN and OUB_STN blade stations
t_cap_uni1 …t_cap_uniN	Thickness of “spar-uni” material at control points 1 through NUM_CP
t_cap_core1 …t_cap_coreN	Thickness of “spar-core” material at control points 1 through NUM_CP
t_lep_core1 …t_lep_coreN	Thickness of “LEP-core” material at control points 1 through NUM_CP
t_tep_core1 …t_tep_coreN	Thickness of “TEP-core” material at control points 1 through NUM_CP
t_web_skin1, t_web_skin2	Thickness of “web-shell” material at the two control points located at INB_STN and OUB_STN
t_web_core1, t_web_core2	Thickness of “web-core” material at the two control points located at INB_STN and OUB_STN.
w_cap_inb, w_cap_oub	Width of the spar cap normalized by the chord length at the INB_STN and OUB_STN blade stations
t_blade_root	Thickness of the “blade-root” material at the INB_STN blade station
t_blade_skin1 …t_blade_skinN	Thickness of “blade-shell” material at control points 1 through NUM_CP. The control points are equally spaced along the blade between the TRAN_STN and OUB_STN blade stations
t_cap_uni1 …t_cap_uniN	Thickness of “spar-uni” material at control points 1 through NUM_CP
t_cap_core1 …t_cap_coreN	Thickness of “spar-core” material at control points 1 through NUM_CP
t_lep_core1 …t_lep_coreN	Thickness of “LEP-core” material at control points 1 through NUM_CP

The calculation of τ_{zs}, prediction of shear center and torsional stiffness are based on a shear flow approach, which is discussed in details in (Bauchau & Craig, 2009). Finally, by converting the distribution of effective beam stresses σ_{zz} and τ_{zs} into equivalent in-plane loads, the lamina-level strains and stresses in the principal fiber directions (ε_{11}, ε_{22}, γ_{12}, σ_{11}, σ_{22}, and τ_{12}) can be evaluated using CLT.

As mentioned earlier, Co-Blade applies a penalized blade mass defined as the following:

$$Minimize\ f(\vec{x}) = BladeMass \times \prod_{n=1}^{8} max(1, p_n)^2 \qquad [4.2]$$

$$p_1 = \frac{\sigma_{11,max}}{\sigma_{11,fT}} \qquad p_2 = \frac{\sigma_{11,min}}{\sigma_{11,fC}} \qquad p_3 = \frac{\sigma_{22,max}}{\sigma_{22,fT}} \qquad p_4 = \frac{\sigma_{22,min}}{\sigma_{22,fC}}$$

$$p_5 = \frac{|\tau_{12,max}|}{\tau_{12,y}} \qquad p_6 = (\frac{\sigma}{\sigma_{buckle}})^{\alpha} + (\frac{\tau}{\tau_{buckle}})^{\beta} \qquad p_7 = \frac{Tip\ Deflection}{Max\ Tip\ Deflection}$$

$$p_8 = max\left\{\frac{min\ allowable\ diff.between\ rotor\ freq.and\ the\ blade\ natural\ freq.}{|\omega_m - \omega_{rotor}|}\right\},$$

$$m = 1, \ldots Modes$$

Subject to:

$\overrightarrow{x_{LB}} \leq \vec{x} \leq \overrightarrow{x_{UB}}$ (lower and upper bounds)

$A\vec{x} \leq \vec{b}$ (linear constraints)

4.5.2 CLASSICAL LAMINATION THEORY

The classical lamination theory (CLT) is an extension of the classical plate theory for isotropic and homogeneous material initially proposed by Kirchhoff (Kirchhoff, 1850) and Love (Love, 2013). However, the extension of this theory to composite laminates requires some adjustments to consider the inhomogeneity in thickness direction. The assumptions made for classical lamination theory are given:

a) Perfectly bonded layers between laminates; no slip between adjacent layers. Therefore, the displacement components are continuous through the thickness layer. In-plane displacements are a linear function of the depth z.

b) The effective properties of each lamina are known.

c) Each lamina is in a state of plane stress.

d) The specific lamina can be isotropic, orthotropic or transversely isotropic.

e) The normal to the mid-plane remain straight and normal to the midplane after deformation.

f) The normal to the mid-plane do not change their dimensions.

g) Transverse shear strains and normal strain are negligible.

4.5.2.1 LAMINATED BEAMS IN PURE BENDING

For simplicity, let us assume that the beam has a geometrical and property symmetry about the middle axis. Figure 18 shows a beam element of length *dx* subjected to a moment *M*, therefore having a radius of curvature *ρ* and an angle between the normals to the beam *dθ*. From the assumptions made, an expression for the longitudinal strain at a distance *z* from the middle axis is:

$$\epsilon_x = \frac{(\rho + z)d\theta - \rho d\theta}{\rho d\theta} = \frac{z}{\rho} \qquad [4.3]$$

The longitudinal stress at a distance *z* from the middle axis becomes:

$$\sigma_x = E_x \frac{z}{\rho} \qquad [4.4]$$

The static equilibrium gives the following expression for the bending moment:

$$M = \int_{-h/2}^{h/2} \sigma_x . b . z . dz \qquad [4.5]$$

By taking into account the stress σ_x^k and elasticity modulus E_x^k in each layer k, we obtain:

$$M = \sum_{k=1}^{N} \int_{z_{k-1}}^{z_k} E_x^k . \frac{b . z^2}{\rho} dz = \frac{b}{3\rho} \sum_{k=1}^{N} E_x^k . (z_{k-1}^3 - z_k^3) \qquad [4.6]$$

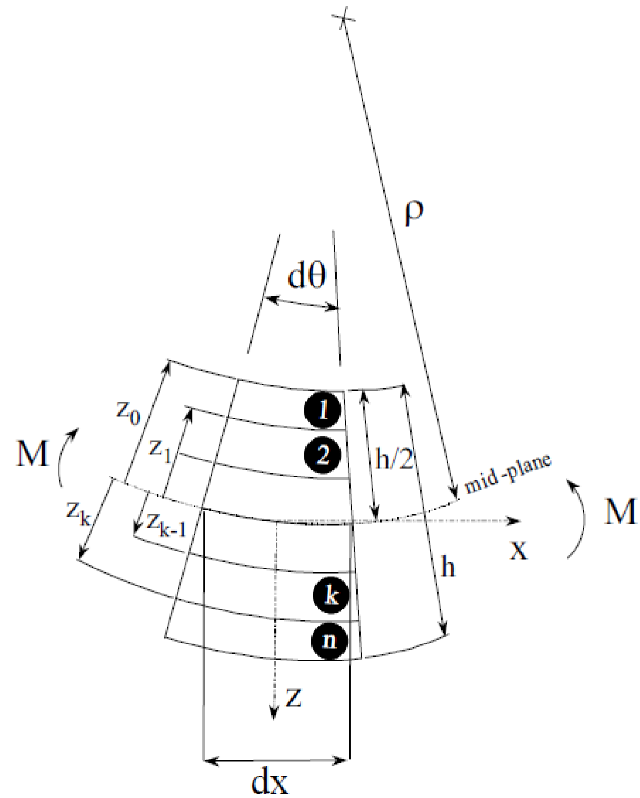

Figure 18 : Composite beam bending with layer numbering.

The bending moment can also be expressed as a function of the elasticity modulus of the laminated beam E_x^l:

$$M = \frac{E_x^l . I_y}{\rho} \ with \ I_y = b \int z^2 dz \qquad [4.7]$$

An expression for the elasticity modulus of the beam can be obtained:

$$E_x^l = \frac{b}{3I_y} \sum_{k=1}^{N} E_x^k . (z_{k-1}^3 - z_k^3) \qquad [4.8]$$

Using this expression, the stress in the k[th] layer σ_x^kcan be expressed as:

$$\sigma_x^k = \frac{M.z}{I_y} \left(\frac{E_x^k}{E_x^l} \right) \qquad [4.9]$$

This relation for the stress is similar to the expression used for isotropic beams, corrected by the dimensionless term in bracket. The stress is therefore a discontinuous function of the beam depth, in contrast to the stress in an isotropic beam.

4.5.2.2 THEORY OF LAMINATED PLATES

A more general case of a laminated plate under plane stress condition was analysed and incorporated in the *winDesign* tool. In-plane loading (axial and shear) as well as moments (bending and torsion) will be considered as loadings. The layers are assumed perfectly bonded together.

Coupling effects that result in a complex combination of extensional, flexural and torsional deformations are taken into consideration. The different notations and associated coordinate systems are defined in Figure 19.

The position of the layers in the normal direction is defined with the mid-plane as a reference and not the neutral plane. According to assumption (a), the in-plane displacements can be expressed with the displacement in the middle surface (u^0 and v^0) as:

$$\begin{aligned} u &= u^0(x,y) + z.f_u(x,y) \\ v &= v^0(x,y) + z.f_v(x,y) \\ w &= w^0(x,y) = w(x,y) \end{aligned} \qquad [4.10]$$

Using the expressions for the in-plane displacements, the in-plane strains are:

$$\begin{aligned} \epsilon_1^* &= \frac{\partial u}{\partial x} = \epsilon_x^0 - z\frac{\partial^2 w}{\partial x^2} \\ \epsilon_2^* &= \frac{\partial v}{\partial y} = \epsilon_y^0 - z\frac{\partial^2 w}{\partial y^2} \\ \epsilon_6^* &= \frac{\partial u}{\partial y} + \frac{\partial v}{\partial x} = \gamma_{xy}^0 - 2z\frac{\partial^2 w}{\partial x \partial y} \end{aligned} \qquad [4.11]$$

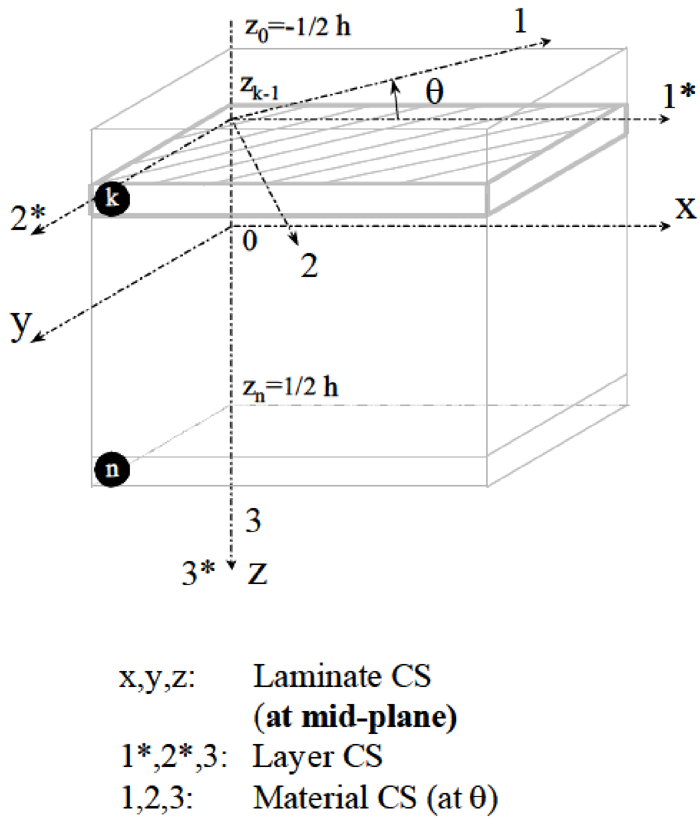

Figure 19 : Coordinate systems used in the laminated plate theory.

An expression for the stress in the k^{th} layer as a function of the mid-plane strain and the plate curvature is obtained from eq. 4.10 in matrix form:

$$\{\sigma^*\}_k = [C^*]_k.\{\epsilon^0\} + z[C^*]_k.\{\kappa\} \quad [4.12]$$

The external loads acting on a laminated plate can be related to the stress in the layer, and then to the laminate deformation. For example, the axial forces N_x per unit width can be obtained by summing the axial stresses σ_x acting on each layer:

$$N_x = \sum_{k=1}^{N}\left(\int_{z_{k-1}}^{z_k} (\sigma_1)_k.dz\right) \quad [4.13]$$

where $(\sigma_1)_k$ is the stress in the k^{th} layer in the (Selim & Alsultan) direction in the layer coordinate system. Similarly, an expression for the normal force in the y-direction as well as the in-plane shear force N_{xy}. Substituting eq. 4.12 in the force resultants gives the general matrix form:

$$\{N\} = \sum_{k=1}^{N}\left(\int_{z_{k-1}}^{z_k}([C^*]_k.\{\epsilon^0\} + z[C^*]_k.\{\kappa\})dz\right)$$

$$\{N\} = \left(\sum_{k=1}^{N}[C^*]_k(z_k - z_{k-1})\right)\{\epsilon^0\} + \left(\frac{1}{2}\sum_{k=1}^{N}[C^*]_k(z_k^2 - z_{k-1}^2)\right)\{\kappa\} \tag{4.14}$$

This is mostly rewritten in the following way:

$$\begin{Bmatrix} N_x \\ N_y \\ N_{xy} \end{Bmatrix} = \begin{bmatrix} A_{11} & A_{12} & A_{16} \\ & A_{22} & A_{26} \\ sym & & A_{66} \end{bmatrix} . \begin{Bmatrix} \epsilon_x^0 \\ \epsilon_y^0 \\ \gamma_{xy}^0 \end{Bmatrix} + \begin{bmatrix} B_{11} & B_{12} & B_{16} \\ & B_{22} & B_{26} \\ sym & & B_{66} \end{bmatrix} . \begin{Bmatrix} \kappa_x \\ \kappa_y \\ \kappa_{xy} \end{Bmatrix} \tag{4.15}$$

The A-matrix is symmetric and is called the laminate extensional stiffness matrix, its components are defined as:

$$A_{ij} = \sum_{k=1}^{N}\left(C_{ij}^*\right)_k(z_k - z_{k-1}) \tag{4.16}$$

The B-matrix is also symmetric and is referred to the laminate coupling stiffness matrix, its components are defined as:

$$B_{ij} = \frac{1}{2}\sum_{k=1}^{N}\left(C_{ij}^*\right)_k(z_k^2 - z_{k-1}^2) \tag{4.17}$$

Similarly, the moment resultants expression can be computed, and the result is the following relation:

$$\begin{Bmatrix} M_x \\ M_y \\ M_{xy} \end{Bmatrix} = \begin{bmatrix} B_{11} & B_{12} & B_{16} \\ & B_{22} & B_{26} \\ sym & & B_{66} \end{bmatrix} . \begin{Bmatrix} \epsilon_x^0 \\ \epsilon_y^0 \\ \gamma_{xy}^0 \end{Bmatrix} + \begin{bmatrix} D_{11} & D_{12} & D_{16} \\ & D_{22} & D_{26} \\ sym & & D_{66} \end{bmatrix} . \begin{Bmatrix} \kappa_x \\ \kappa_y \\ \kappa_{xy} \end{Bmatrix} \tag{4.18}$$

The D-matrix is called the laminate bending stiffness matrix and its components are defined as:

$$D_{ij} = \frac{1}{3}\sum_{k=1}^{N}\left(C_{ij}^{*}\right)_k \left(z_k^3 - z_{k-1}^3\right) \quad [4.19]$$

The relations from equations 4.14 and 4.16 are often written in partition form as:

$$\begin{Bmatrix} N \\ M \end{Bmatrix} = \begin{bmatrix} A & B \\ B & D \end{bmatrix} \begin{Bmatrix} \epsilon^0 \\ \kappa \end{Bmatrix} \quad [4.20]$$

Since loading is mostly expressed “per unit width”, the force resultants *N* in N/m and moments *M* in N), the *A*-components in N/m, the *B*-components in N and the *D*-components in N.m.

4.6 SUMMARY

Many graphical user-friendly design tools have been developed for the purpose of airfoil preparation, rotor performance optimization and aero-elastic simulation of horizontal-axis wind turbines. In this chapter, we examined the state-of-art wind turbine flow solvers, numerical tools and design software. A numerical tool named Co-Blade which uses a combination of classical lamination theory (CLT) with an Euler-Bernoulli theory and shear flow theory applied to composite beams served as a foundation for *winDesign*. The latte will be the topic of discussion in the following chapter.

CHAPTER 5

PROPOSED WIND TURBINE BLADE DESIGN TOOL – 'WINDESIGN'

5.1 INTRODUCTION

In the previous chapters, we observed that the primary objective of wind turbine design tools is to maximize the aerodynamic, or power extracted from the wind. However, this objective should be met by satisfying mechanical strength and environmental aspects. Since wind turbine rotor blades are a high-technology product that must be produced at moderate cost for the resulting energy to be competitive in price, a fast and reliable preliminary design tool was the core objective of our doctoral studies. In this chapter, we will focus on the newly proposed: *winDesign*, graphical tool which incorporates the novel VCH and KGA techniques.

5.2 WIND TURBINE MULTIOBJECTIVE OPTIMIZATION

5.2.1 INTRODUCTION

Many authors carried a multi-disciplinary study (Benini & Toffolo, 2002; Bottasso et al., 2010; Deb, 2001; Giguere & Selig, 2000; Philippe Giguère et al., 1999; M. Grujicic et al., 2010; Ju & Zhang, 2012; Kusiak et al., 2010; M. S. Selig & Coverstone-Carroll, 1996; L. Wang et al., 2011), where many objectives are considered in the design of wind turbines. The most common technique to combine conflicting functions (such as annual energy production and cost of energy) is by means of an appropriate set of weights. The variations that exist among these contradictory functions are essential for designers and therefore pursue to sketch the Pareto fronts.

It can be easily seen from Figure 20 that the number of studies conducted on the topic of MOEA has increased well over the last two decades. In less than 10 years, the number of year-wise publications has tripled, and it can be expected that the growth will continue as new studies, books, surveys, research papers and dissertations will be published.

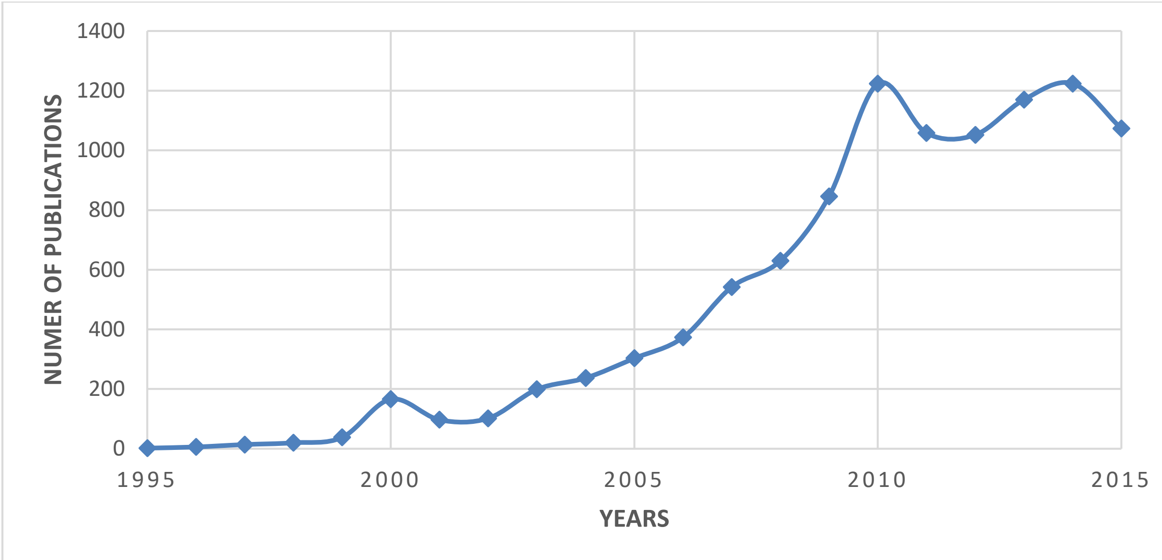

Figure 20 : Number of published documents on multi-objective evolutionary algorithms.

The term optimization refers to the finding of one or more feasible solutions which correspond to extreme values of one or multiple objectives. Optimization methods are important in scientific experiments, particularly in engineering design and decision making. When the problem is to find the optimal solution of one objective, the task is called *single-objective optimization*.

There exist many algorithms that are gradient-based and heuristic-based that solves single-objective optimization problems. Beside deterministic search techniques, the field of optimization has evolved by the introduction of stochastic search algorithms that seek to find the global optimal solution with more ease. Among them, *evolutionary algorithms* (EA) mimic nature's evolutionary principles and are now emerging as popular algorithms to solve complex optimization problems.

In engineering optimization, the designers are sometimes interested in finding one or more optimum solutions when dealing with two or more objective functions. This is known as *multi-objective optimization* and in fact, most real-world optimization problems involve multiple objectives. In this case, different solutions produce trade-offs or conflicting situations among the different objectives. Not enough emphasis is usually given to multi-objective optimization and there is a reasonable explanation for that. The majority of the methods that solve multi-objective optimization problems (MOOP) transform multiple objectives into a single function. Therefore, most of the effort has been invested in improving the single-objective optimization algorithms. The studies concentrate on the conversion of multi-objective into single-objective problems, the convergence, constraint-handling approaches and speed of these single-objective techniques.

Let us discuss the fundamental difference between single and multi-objective optimization by taking two conflicting objective functions as an example. Obviously, each objective function possesses a unique and different optimal solution. For instance, if one is interested in buying a house, the decision-making has to take into consideration the cost and the comfort. If the buyer is willing to sacrifice comfort, they will get a house with the lowest price. However, if money is not an issue, the buyer is able to afford a house with the best comfort. Between these two extremes, there exist many house choices at various costs and comfort. Now the big question is among these trade-offs, which solution is the best with respect to both objectives? Ironically, no house among the trade-off choices is the best with respect to both cost and comfort. Without any further information about these solutions (in our case example the houses), no solution from the set of trade-offs can be said to be better than any other. This is the fundamental difference between a multi-objective and a single-objective optimization problem. From a practical standpoint, after a set of trade-off solutions are found, the user will use higher-level information to determine the convenient solution.

5.2.2 MATHEMATICAL FORMULATION

In order to undertake the design of a horizontal wind turbine under multi-objective optimization, there are numerous issues to be considered. The motif of this section is to present the results of a case study on a multi-objective optimization wind turbine design problem using *winDesign*.

A multi-objective optimization problem is composed of a number of objective functions which are to be maximized or minimized. Similarly, to single-objective problems, the MOOP is subjected to a set of design constraints which any optimal solution must satisfy. We can state the general form of a multi-objective optimization problem as:

Minimize or *Maximize*	$f_m(\vec{\boldsymbol{x}})$,	m = 1, 2… M	[5.1]
Subject to	$g_j(\vec{\boldsymbol{x}}) \geq 0$	*j* = 1, 2 … J	
	$h_k(\vec{\boldsymbol{x}}) = 0$	*k* = 1, 2 … K	
	$\vec{\boldsymbol{x}}_i^L \leq \vec{\boldsymbol{x}}_i \leq \vec{\boldsymbol{x}}_i^U$	*i* = 1, 2 … N	

The solution $\vec{\boldsymbol{x}}$ is a vector of *n* variables $\vec{\boldsymbol{x}} = (x_1, x_2, \dots x_n)^{\mathrm{T}}$. Often, the user will restrict the design variables between lower and upper bounds $\vec{\boldsymbol{x}}_i^L$ and $\vec{\boldsymbol{x}}_i^U$ respectively. In the above problem, there is J inequality and K equality constraints that can be linear and/or nonlinear functions. A solution $\vec{\boldsymbol{x}}$ is said to be *feasible* when *all* the constraints (J + K + 2N) are satisfied. Because of the presence of M objective functions that need to be minimized and/or maximized, it is regularly convenient to apply the duality principle. The latter suggests that we can convert a maximization problem into a minimization one by multiplying the objective function by -1. This is a practical method because many optimization algorithms are developed to solve one type e.g. minimization problems. A major difficulty arises when any of the objective or constraint functions are nonlinear; the resulting MOOP becomes a nonlinear multi-objective problem. Until now, the techniques to solve such problems do not have convergence proofs. Unfortunately, most real-world MOOP are nonlinear in nature, and thus creates a major challenge for scholars.

As stated earlier, the task in multi-objective optimization problems is to find a set of solution called the Pareto-optimal solution set, in which any two solutions must be non-dominated with respect to each other. In addition, any solution in the search space must be dominated by at least one point in the Pareto-set. Therefore, the ultimate goal in multi-objection optimization is to find a set of solutions as close as possible to the Pareto-optimal front and as diverse as possible. The concept of domination is used in most MOOP algorithms. Without going into deep details, a solution $\vec{\boldsymbol{x}}_1$ is said to dominate $\vec{\boldsymbol{x}}_2$ if both conditions are satisfied:

1. The solution $\vec{\boldsymbol{x}}_1$ is no worse than $\vec{\boldsymbol{x}}_2$ in all objectives,
2. The solution $\vec{\boldsymbol{x}}_1$ is strictly better than $\vec{\boldsymbol{x}}_2$ in at least one objective.

To gain more knowledge on the procedures to find the non-dominated set in a given set P of size N, the reader is referred to Deb 2001 (Deb, 2001).

5.2.3 MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS

The classical way to solve multi-objective problems is to scalarize multiples objectives with a relative preference vector. Since only a single optimized solution can be found in one simulation, evolutionary algorithms shined as interesting methods to solve MOOP. The main reason is unlike classical methods, EA's use a population of solutions in each iteration and therefore the outcome of an EA is a population of solutions. This ability to find multiple solutions in one single run made EA's an ideal approach to solve multi-objective optimization problems.

According to the available literature, the first real application of evolutionary algorithms in the determination of trade-off solutions for a MOOP was proposed in the doctoral dissertation of David Schaffer (Schaffer, 1985). He developed the vector-evaluated genetic algorithm (VEGA) which demonstrated the ability of genetic algorithm to capture multiple trade-off solutions. Not much attention was given until another half a decade when David E. Goldberg published his book in 1989 (David E. Goldberg, 1989) on a multi-objective evolutionary algorithm (MOEA) using the concept of dominance.

From the latter derived many MOEA's such as Srinivas and Deb's non-dominated sorting (NSGA) (Srinivas & Deb, 1994) and the niched Pareto-GA by Horn et al. (Horn et al., 1994). Other techniques different than the domination-based MOEA's where proposed by Kursawe in

1990 (Kursawe's diploidy approach (Kursawe, 1990)) and Hajela and Lin's weighted-based approach (Hajela & Lin, 1992) just to name a few.

5.3 WINDESIGN – GENERAL STRUCTURE

5.3.1 MONOOBJECTIVE OPTIMIZATION – WINDESIGN

The reader is referred to our publication published in the Transactions of the Canadian Society for Mechanical Engineering (Chehouri, Younes, Ilinca, Perron, & Lakiss, 2015). The fitness function expressed in Eq. 4.3 is composed of the product of all 8 penalties with the blade mass. In other words, their blade mass minimization problem is "tampered" by the exceeded constraints, making the objective function linearly depend on them. If we take a look at the constraints p_1 to p_5, we notice that they are based on the "maximum stress failure envelope". Failure is predicted in a lamina, if any of the normal or shear stresses in the local axes of a lamina is equal to or exceeds the corresponding ultimate strengths of the unidirectional lamina therefore this criterion ignores the interaction of stresses. For this reason, our motive in this section is to introduce a quadratic failure criterion such as the Tsai-Wu failure criteria (Eq. 5.1) for anisotropic materials (Tsai & Wu, 1971) in our proposed optimization scheme.

$$f_1\sigma_1 + f_2\sigma_2 + f_{11}{\sigma_1}^2 + f_{22}{\sigma_2}^2 + f_{66}{\tau_6}^2 + 2f_{12}\sigma_1\sigma_2 = 1 \qquad [5.1]$$

with $\boldsymbol{f_{ij}}$ and $\boldsymbol{f_i}$ are constants that can be evaluated at boundary conditions. Their expressions can be found in detail in (Tsai & Wu, 1971).

We define our main objective as the minimization of the blade mass solely. However, the Tsai-Wu failure criterion is dependent of the principal stresses, hence, the failure criteria in our case the Tsai-Wu failure criterion is a nonlinear constraint and the formulation of such minimization problem can now be described in (Eq. 5.2):

$$Minimize\ f(\vec{x}) = BladeMass \qquad [5.2]$$

$$\text{Tsai-Wu}\ (\vec{x})\ -1 \leq 0 \qquad \left(\frac{\sigma}{\sigma_{buckle}}\right)^{\alpha} + \left(\frac{\tau}{\tau_{buckle}}\right)^{\beta} - 1 \leq 0 \qquad \frac{Tip\ Deflection}{Max\ Tip\ Deflection} - 1 \leq 0$$

$$max\left\{\frac{min\ allowable\ diff.\ between\ rotor\ freq.\ and\ the\ blade\ natural\ freq.}{|\omega_m - \omega_{rotor}|}\right\} - 1 \leq 0$$

Subject to:

$\overrightarrow{x_{LB}} \leq \vec{x} \leq \overrightarrow{x_{UB}}$ (lower and upper bounds)

$A\vec{x} \leq \vec{b}$ (linear constraints)

From the first optimization problem as per Eq. 4.3, after 17 iterations with 1017 evaluations, a blade mass of 44186 kg is obtained. If we consider our optimization problem introduced in (Eq. 5.2), after 45 iterations with 2700 evaluations, we obtain a total blade mass of 72348 kg. A much more realistic blade mass (30 % more than the first mass) is obtained, according to the predicted blade mass for SNL-100 as per Jackson and al. (Jackson et al., 2005). The Tsai-Wu failure criterion written in (Eq. 5.1) permits the evaluation of a “static failure” variable ***f***. The value of ***f*** can be greater or less than one. If its value exceeds one, it indicates that the composite component has reached static failure.

In the two previous simulation results, a comparison between two different objective function formulations was made. However, an additional study can be carried out to show the effectiveness of our minimization formulation under the quadratic failure constraint in contrast of that written in (Eq. 4.3) under the maximum stress theory, particularly with the advantage in stating the failure limits as nonlinear constraints rather than linearly depend. To show the difference between both interpretations, we modify the optimization problem of (Eq. 5.2), by substituting the penalties to nonlinear constraints of the form $c(x) - 1 < 0$. The mathematical formulation is presented in Eq. 5.3.

After 44 iterations with 2730 evaluations we obtain a blade mass of 55528.7 kg. This means that a larger blade mass in comparison with (Eq. 4.3) is obtained, however it is remarkably smaller than the blade mass from the optimization formulation under the quadratic failure constraint of (Eq. 5.2). In summary, we can reproduce the results for the optimizations under failure constraints in Table XIV.

Table 14 : Blade mass for different optimization formulations.

Optimization formulation	Objective function f(x)= BladeMass	Nonlinear constraints?	Tsai-Wu criterion?	BladeMass (kg)
(4.3)	NO	NO	NO	44 186
(5.2)	YES	YES	NO	55 528
(5.3)	YES	YES	YES	72 348
Sandia 100 m Baseline Blade	NA	NA	NA	114,172

$$Minimize\ f(\vec{x}) = BladeMass \qquad [5.3]$$

$$p_1 = \frac{\sigma_{11,max}}{\sigma_{11,fT}} - 1 < 0 \quad p_2 = \frac{\sigma_{11,min}}{\sigma_{11,fC}} - 1 < 0 \quad p_3 = \frac{\sigma_{22,max}}{\sigma_{22,fT}} - 1 < 0 \quad p_4 = \frac{\sigma_{22,min}}{\sigma_{22,fC}} - 1 < 0$$

$$p_5 = \frac{|\tau_{12,max}|}{\tau_{12,y}} - 1 < 0 \quad p_6 = (\frac{\sigma}{\sigma_{buckle}})^{\alpha} + (\frac{\tau}{\tau_{buckle}})^{\beta} - 1 < 0 \quad p_7 = \frac{Tip\ Deflection}{Max\ Tip\ Deflection} - 1 < 0$$

$$max\left\{\frac{min\ allowable\ diff.between\ rotor\ freq.and\ the\ blade\ natural\ freq.}{|\omega_m - \omega_{rotor}|}\right\} - 1 \leq 0$$

Subject to:

$\overrightarrow{x_{LB}} \leq \vec{x} \leq \overrightarrow{x_{UB}}$ (lower and upper bounds)

$A\vec{x} \leq \vec{b}$ (linear constraints)

5.3.2 MULTIOBJECTIVE OPTIMIZATION – WINDESIGN

In this section, we solve a numerical example for the design of a wind turbine blade using *winDesign*.

The two conflicting objective functions are the blade mass and the annual energy. Solving such MOOP can be achieved by the method of scalarizing. It consists of formulating a single-objective optimization problem such that optimal solutions to the single-objective optimization problem are Pareto optimal solutions to the MOOP. A general formulation for a scalarization of a multiobjective optimization is given as:

$$\min \sum_{i=1}^{M} w_i f_i(\boldsymbol{\vec{x}}) \qquad [5.4]$$

where the weights of the objectives $w_i > 0$ are the parameters of the scalarization.

We propose to use the following fitness function to minimize the mass and maximize the annual energy production:

$$\min\left(\alpha\frac{M(\vec{\boldsymbol{x}})}{M_0}+(\alpha-1)\frac{AEP(\vec{\boldsymbol{x}})}{AEP_0}\right) \qquad [5.5]$$

For a value of alpha near zero, the mass ratio is eliminated, and the fitness function becomes $\min\left((\alpha-1)\frac{AEP(\vec{x})}{AEP_0}\right)$, which translates into the maximization of the normalized energy. Likely, for an alpha value close to 1, the energy ratio disappears, and the problem is now a minimization of the mass. If we run the optimization problem for different values of alpha between 0 and 1, we can find Pareto optimal solution to the MOOP. The reference mass and energy are taken respectively from the case study of alpha equals 0.

Let us consider the following mechanical properties during the structural analysis. In our study, these properties are derived from Sandia 100 m blade SNL-100 (Griffith & Ashwill, 2011). Table A.1 is a list the mechanical properties utilized in the structural design of the blade. Likewise, in Table A.2, we list the configurations (input, model, turbine data and algorithm) for the input file needed by the WT-Perf solver. The general flowchart of multi-objective optimization algorithm can be summarized in Figure 22. The complete inputs for the multi-objective optimization algorithm are listed in Table A.3.

The objective is maximum AEP and minimum mass, and the winDesign algorithm provides the Pareto optimal front solutions as displayed in Figure 21. The blade mass increases obviously with the increase of AEP. Three blades of the Pareto set are chosen to conduct a comparison with the reference blade. It can be seen that AEP increases by 5.19% for blade 2, while the mass is reduced by 13.45%.

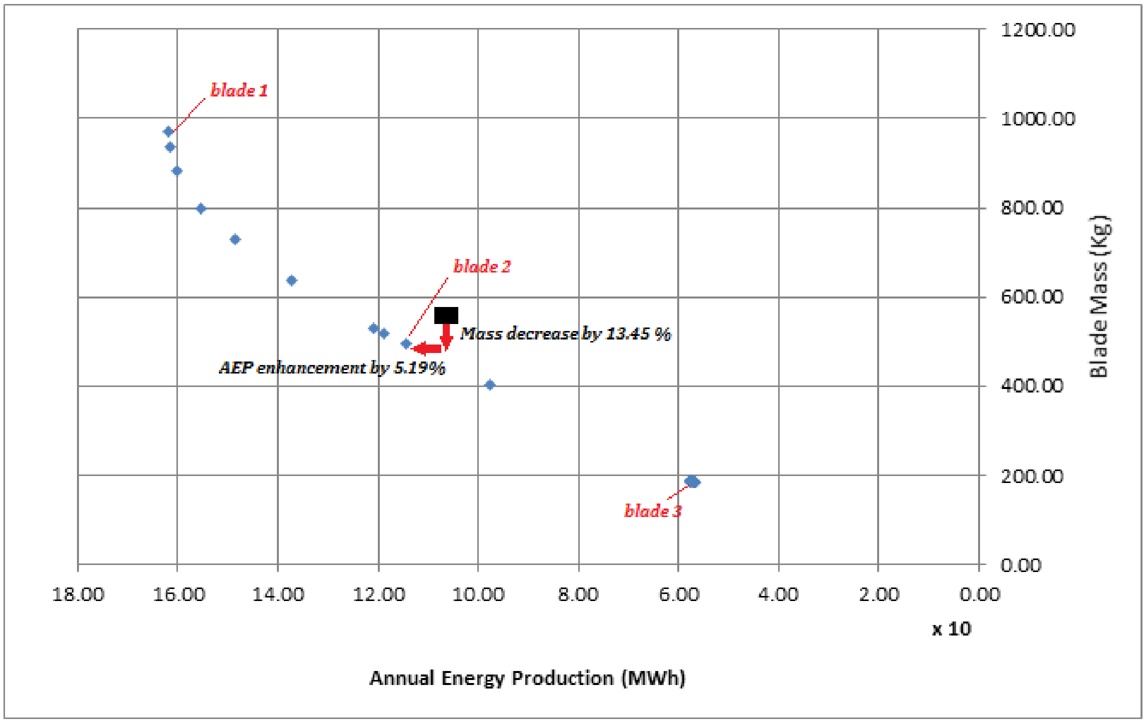

Figure 21 : Pareto-front for the given numerical example (Annex A, Eq. 5.5)

5.4 SUMMARY

In this chapter, we were able to present the fundamental principles of multi-objective optimization in wind turbine design. We briefly discussed the fundamentals and terminology of wind turbine multi-objective optimization. The most common optimization algorithms used to solve multi-objective wind turbine optimization problems were presented.

The developed *winDesign* numerical tool is capable of provide the following benefits for wind turbine blade designers in a preliminary stage:

- Design and simulation of composite wind turbine blades under various turbine configurations (Figure B.1), environmental properties (Figure B.2), optimization objectives (Figure B.3), analysis options (Figure B.4), and design constraints.

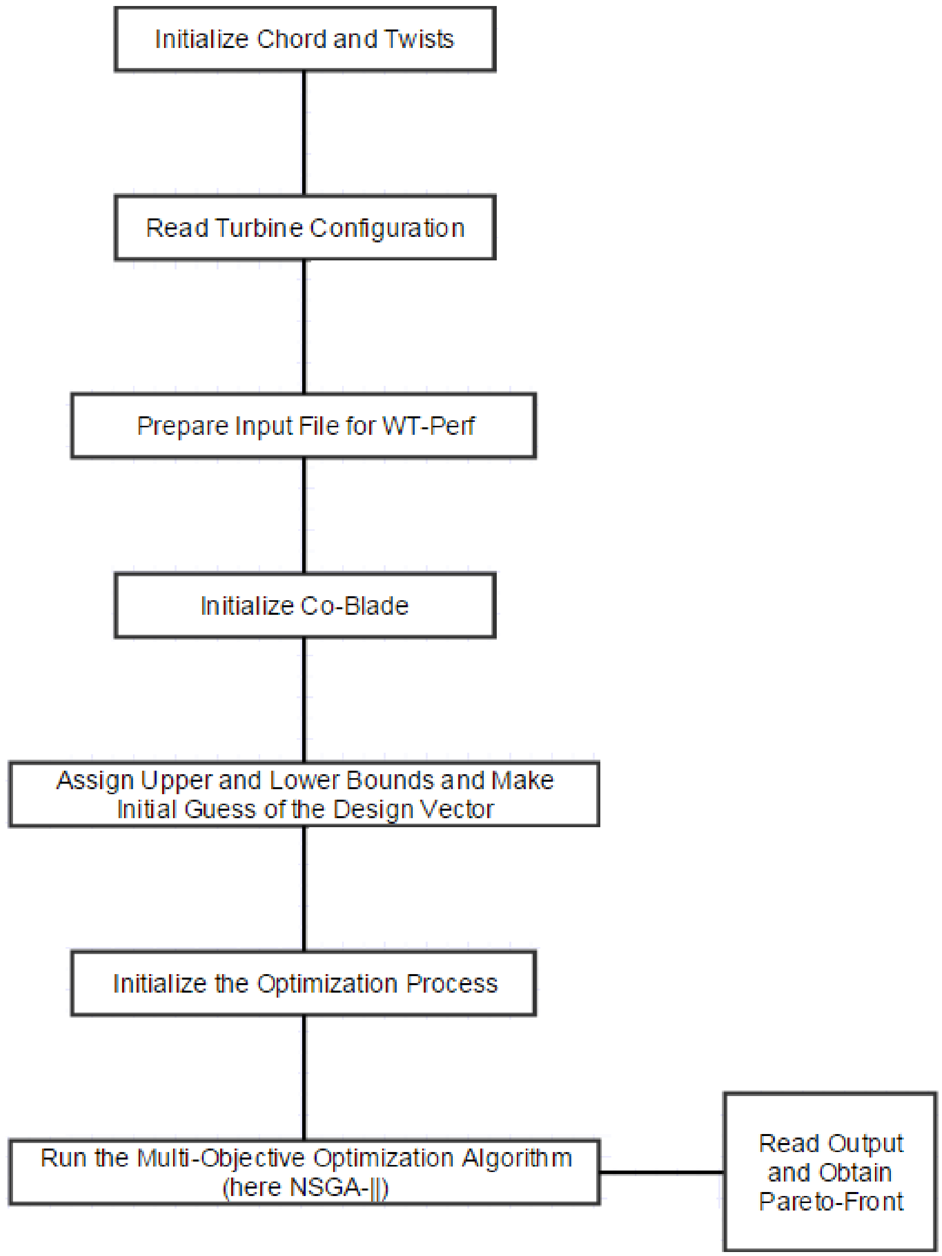

Figure 22 : Flowchart of the multi-objective optimization algorithm.

- Ability to present the fundamental principles of multi-objective optimization in wind turbine design. The proposed *winDesign* tool can perform a Pareto optimization where optimal decisions need to be taken in the presence of trade-offs between two conflicting objectives: AEP and the weight of the blade.

- Structural analysis and design of composite blades for wind turbines in order to accelerate the preliminary design phase.

- A large variety of 2D & 3D visualizations through a graphical user interface to provide instant visual feedback inspired from Co-Blade.

- For a given external blade shape, the design load is computed by means of WT-Perf, *winDesign* can determine an optimal composite layup, chord and twist distributions which either minimizes blade mass or maximizes the annual energy production while simultaneously satisfying constraints on maximum stress, buckling, tip deflection and natural frequencies.

CHAPTER 6

CONCLUSION & FUTURE WORKS

6.1 VCH METHOD: CHALLENGES AHEAD & UPCOMING SUCCESS

The diversity and popularity of evolutionary algorithms does not imply that there are no problems that need urgent attention. From one point of view, these optimization algorithms are very good at obtaining optimal solutions in a practical time. On the other, they still lack in balance of accuracy, computational efforts, global convergence and the tuning and control of their parameters. Nature has evolved over millions of years, providing a rich source of inspiration for researchers to develop diverse algorithms with different degrees of success and popularity. Such diversity and accomplishment does not signify that we should focus solely on developing more algorithms for the sake of algorithm development, or even worse for the sake of publication. This attitude distracts from the search for solutions for more challenging and truly important problems in optimization and new algorithms may be proposed only if they:

- deliver truly novel ideas
- demonstrate to be efficient techniques that solve challenging optimization problems (that are not solved by existing methods)
- verify to the “3-self” (self-adaptive, self-evolving and self-organizing algorithms)

It is vital to state that during the development of this technique, several other versions of the same approach were examined without much success. For example, different reproduction probabilities (crossover and mutation) were tested. The authors avoided a high mutation rate to prevent the method of becoming a random search but choose to keep it at 0.05 for a more robust global search and exploration. More than a few other crossover techniques were examined but the objective of this study was not to present a comparative study on their performance but rather present the parameter-free constraint-handling technique using the violation factor. It is still unclear how to achieve optimal balance of exploitation and exploration by proper parameter tuning of the evolutionary operators of GA in general and in the VCH algorithm specifically. The crossover operator ensured an efficient exploitation in the local search within a subspace and can provide good convergence in local subspace. The selection and mutation operators enabled the GA to have a higher ability for exploration. It could be argued that the VCH technique is competent because it does not require any fine-tuning of the GA, which is normally performed by trial and error and is time consuming.

It is worth mentioning that for many of them, it is unclear if the authors implemented a stopping criterion or not. In our study however, a severe criterion was introduced based on the minimum relative error of the design variables. Moreover, the user–defined tolerance has to be respected for a number of generations before the execution is terminated.

The main challenges that still require further examination are: The proof of convergence of some EA, control and tuning of parameters, the solution of large scale applications (e.g., the traveling salesman problem) and finally tackling Nondeterministic Polynomial (NP)-hard problems. Solving these issues is becoming more imperative than ever before. Among these matters is the open question of constraint-handling in GA specifically to solve engineering optimization problems. The insights gained by the proposed VCH technique should have an impact on the manner constrained problems are solved.

Lastly, the authors suggest in the upcoming work, further numerical simulations could be investigated for more complex optimization problems. It would be motivating to explore the integration of VCH technique in other EA's such as Particle Swarm Optimization (PSO), ant Colony Optimization (ACO), Bee Colony Optimization (BCO) and Differential Evolution (DE). Parameter tuning of the evolutionary operators in GA is an active area of research and could be examined in future work. Present work is aimed at introducing the proposed constraint-handling technique in a multi objective platform for the optimization of the composite lay-out of wind turbine blades using a genetic algorithm as discussed in (Chehouri, Younes, Ilinca, & Perron, 2015)

The VCH method is a penalty-free constraint-handling method that only uses the violation factor to perform the sorting of the population with both feasible and infeasible individuals. In the proposed VCH method, at a given iteration, the individuals of the population are never compared in terms of both objective function value and constraint violation information. Essentially, the main motif is to keep the fitness function equivalent to the designer's objective function and therefore the conversion of the constrained problem into an unconstrained one is no longer required.

Genetic algorithms try to mimic the principle of the survival of the fittest, where newer generations are evolved in attempt to produce descendants with a better 'fitness'. Because at all times the fitness function is equal to the objective function to be minimized, our proposed VCH technique is more conforming with the biological fundamentals of genetic algorithms. A major drawback of many techniques in the literature is that the constraint handling method requires a feasible initial population. For some problems, finding a feasible solution is NP-hard, and even impossible for the problems with conflicting constraints. In the VCH approach, it is not required to have a feasible initial population. There are available techniques that ensure feasibility of the population when dealing with linear constraints such as [53, 54] by means of mathematical programming.

Compared to other constraint-handling techniques based on penalty functions, the VCH method was able to provide a consistent performance and demonstrated to be simpler, faster and delivered reliable optimal solutions without any violation of the constraints. As the population evolves, the VCH method will lead the search to reach faster feasible regions. This was revealed in Figure 13, with the convergence of the average constraint violation of the elites towards zero (no violation) as the population evolves.

The VCH method allows the closest solutions to the feasible region in favorable areas of the search space to remain in the population. Specific methods such as the reduced gradient method, cutting plane method and the gradient projection method are appropriate. However, they are only fitting either to problems having convex feasible regions or with few design variables. Furthermore, the overall results suggest that the proposed approach is highly competitive and was even able to contest (some cases improve) the results produced by other methods, some of which are more difficult constraint-handling techniques applied to genetic algorithms. The VCH algorithm was tested on several benchmark examples and demonstrated its ability to solve problems with a large number of constraints.

6.2 KGA TECHNIQUE: FEASIBLE SCIENTIFC IMPACT

The fields of optimization and computational intelligence have grown rapidly in the past few decades. Classical methods are not efficient in solving current problems in engineering and management. The development of optimization algorithms can be mainly divided into deterministic and stochastic approaches.

Most conventional algorithms are deterministic, such as gradient-based algorithms that use the function values and their derivatives. These methods work extremely well for smooth unimodal problems, but in the case of some discontinuities, non-gradient algorithms are preferred (X.-S. Yang, 2014). Nelder-Mead downhill simplex (Nelder & Mead, 1965) and Hooke-Jeeves pattern search technique (Hooke & Jeeves, 1961) are a few examples of deterministic gradient-free algorithms. For stochastic algorithms, we have two types: heuristic and meta-heuristic. Although there is no agreed definition of each type in the literature, the aim of stochastic methods is to find feasible solutions in a satisfactory timescale. There is no guarantee that the best solutions can be found, however it is expected that the algorithm will provide nearly optimal solutions most of the time.

Evolutionary algorithms (EA's) are stochastic optimization algorithms based on the principle of natural selection and biological evolution. They are population-based meta-heuristic optimization algorithms that make use of biological evolution operators such as selection, recombination and mutation.

In our doctoral studies, we only dealt with genetic algorithms (GA's). They were originally proposed by Holland (Holland, 1975), inspired by the principle of natural selection of biological systems or 'Darwinian evolution'. GA's have demonstrated their capability to solve a wide range of optimization problems such as revenue management, optimal engineering system designs, scheduling applications, image processing, quality control etc. John Holland essentially formed the foundation of modern evolutionary computing by fundamentally defining three key genetic operators: crossover, mutation, and selection. These evolutionary operators provide a way to generate offspring from parent solutions.

In the last few years, evolutionary algorithms have been applied to clustering problems, due to their ability to solve different problems with little changes. These algorithms are able to manage constraints of any type (linear/nonlinear and equality/inequality) in an efficient way. In this study, a new selection process for genetic algorithms called K-means genetic algorithm selection (KGA) process has been introduced. Two different versions of the KGA technique are presented: using a fixed number of clusters K (KGA_f) and via an optimal number K_{opt} (KGA_o). In the latter, the optimal number of clusters is determined using two validity indexes: silhouette and Davies-Bouldin. The KGA techniques are composed of 4 stages: clustering, membership phase, fitness scaling and selection. Clustering the population aids the search algorithm to preserve a constant selection pressure throughout the evolution. A membership probability number is assigned to each individual following the k-mean clustering phase. Fitness scaling converts the membership scores in a range suitable for the selection function which selects the parents of the next generation. The performance of each KGA technique (KGA_o-S, KGA_o-DB and KGA_f) is tested on 7 benchmark problems for two separate dimensions of the search spaces D = 10 and 20. The computational results reveal that the proposed selection process is superior or competitive with the standard genetic algorithm for the problems considered.

The current study was limited to single-objective optimization problems. Future research could test the performance of KGA techniques in solving constrained optimization problems and/or multiobjective formulations (Chehouri, Younes, Perron, & Ilinca, 2016). Also, the stability of the novel selection processes should also be considered in future work. It would be compelling to integrate the KGA processes in further population-based optimization algorithms such as particle swarm optimization (PSO) (Kennedy, 2011), ant colony optimization (ACO) (Dorigo, Birattari, & Stutzle, 2006) and firefly algorithm (FA) (X.-S. Yang, 2010). Lastly, larger scale examples should be tested and further research on the impact of GA parameters (such as population size, probabilities of crossover and mutation) on the KGA process will be examined.

6.3 WINDESIGN TOOL: MOVING TOWARDS WINDESIGN 2.0

6.3.1 AIM & FOCUS

Within the last 20 years, wind energy conversion systems have reached maturity. The obvious growing world-wide wind energy market will culminate to further improvements. The continuous effort for the advancement in horizontal wind turbine performance strategies and techniques will result to additional cost reductions. The ultimate aim of any wind turbine manufacture is to design a wind turbine able to compete with fossil fuel. The numbers of publications that apply optimization techniques in the attempt to reach an optimal blade design have demonstrated a significant increase in the recent decade alone.

Despite the fact that a minimal cost of energy was chosen as the single main objective in most of the research publications, many have argued that it is more stimulating to evaluate the wind turbine design as an optimization problem consisting of more than one objective. Using multi-objective optimization algorithms, the designer is able to identify a trade-off curve called Pareto-front that reveals the weaknesses, anomalies and rewards of certain targets.

We can anticipate that future optimization problems will be set as multi-disciplinary formulations. Consequently, solving such difficult optimization problem will require further developments in the optimization algorithm itself. Since traditional optimization techniques cannot overcome many of their drawbacks such as rapid divergence and sensitivity to the initial solution, population based, and nature-inspired algorithms will continue to emerge as worthy alternatives.

To include the significance of the aerodynamic load, the cost of energy is mostly evaluated because a shape optimization does not imply a minimum cost of energy but rather care must be taken in choosing a proper cost model with a high fidelity to prevent the loads on wind turbine components to become extreme.

Furthermore, in order that the metric of minimum cost of energy be appropriate and suitable in severe operation conditions e.g. Nordic regions, additional requirements such as high gust and icing conditions need to be included. For this reason, it is crucial to perform the optimization under uncertainty due to the stochastic behavior of stochastic environment inputs like gust. In this case, an appropriate design method would be a robust design optimization (RDO) where in addition to the minimum or maximum objects (e.g. minimum cost of energy) the sensitivity of the objectives to the uncertainties of the design variables is minimized.

Another reason why the contemporary tendency is to construct a robust optimization technique is due to the nature of the wind turbine optimization problem. In the case of performance optimization of wind turbine, there are both continuous (e.g. chord, twist, pitch, yaw etc.) and discontinuous (number of blades, airfoil family etc.). Likewise, the design variables are interdependent; implicating that they have competing objectives within the metric of cost of energy. As a result, to ensure that the algorithm converges, a gradient method approach is inadequate.

6.3.2 CURRENT TRENDS & FUTURE CHALLENGES

Nevertheless, there are two major issues in the optimization of wind turbine blade construction that have not yet been satisfactorily resolved:

1. Complete load calculation
2. Composite structural optimization

Load Calculation: As we have reviewed, there are two methods to compute the loads on a wind turbine blade. The basic method is to translate the aerodynamic load into a concentrated force for numerical simulation using classical momentum blade element theory. Since it is incapable of revealing the pressure distribution of the blade surface, some researchers have chosen to substitute the inverse design tool with computational fluid dynamics software and to load the distribution into a finite element solver to investigate the mechanical strength. The focal difficulty that the researchers have reported with the latter technique is that incorporating it in the optimization scheme will dramatically increase the computational time of the optimization process. Advancements in computational simulations and optimization algorithms such as heuristic, Pareto-optimization techniques and parallel techniques are a promising area of research that will facilitate the complete load calculation on wind turbine components.

Composite Structural Optimization: Few researchers have taken the weight (blade mass) as an objective function; the main reason is that the parameterization for the finite element model of the wind turbine blade is not wholly established. The uses of composite materials in the manufacture of wind turbine blade have become more popular with the increasing size of wind turbine blades. The popularity arises from its lower weight, high stiffness and good resistance to loads. However, the concern with the use of traditional 2D laminates are its low through-thickness properties (stiffness, strength and fatigue performance), the failure to withstand high interlaminar shear stresses and its poor interlaminar fracture toughness making it difficult to conceive a new generation of wind turbine blades. While these properties can be improved by the use of tougher resins or fibres, these alternatives are expensive and not reliable that is why over the past 40 years considerable attention has been given to the development of reinforced 3D composite textile architectures essentially woven, braided, stitched and knitted composites.

The importance of composite materials is well recognized in the recent years and its applications continue to surge (El Hage, Younes, Aboura, Benzeggagh, & Zoaeter, 2009; Ali Hallal, Rafic Younes, & Farouk Fardoun, 2013; Hallal, Younes, Fardoun, & Nehme, 2012;

Hallal, Younes, Nehme, & Fardoun, 2011; Nehme et al., 2011; Younes, Hallal, Fardoun, & Chehade, 2012). We can predict that the development of new weaving architectures will continue to expand the scope of these materials. The multitude of complex architectures in terms of geometric designs pose on the one hand the problem of the mechanical behavior of the new materials and on the other hand, the choice of the geometric parameters of the weaving patterns that will provide the best compromise between cost, performance and mass. Wind turbine blades are an important application for this problem for the sake of producing clean energy with maximum efficiency and reduced mass of materials. Initially, we noted that the focus was on the reduction in weight of the composite relative to those of metals and its alloys. Therefore, the optimization studies were oriented towards the compromise between design and weight. Later, there was the birth of design over cost. The main purpose of the cost approach was and will continue to be to achieve a reduction in total cost during the life cycle of a structure.

The tendency to reduce the weight of wind turbine blades for a given airfoil shape is essential for the production of clean sustainable wind energy. Given the global trend towards renewable energy, saw the beginning of a development of local industries for the manufacturing of these blades, it becomes important to follow international trends in the integration of 3D textiles composites (Ali Hallal et al., 2013; A. Hallal, R. Younes, & F. Fardoun, 2013). The advantage of composite materials in the manufacturing of wind blades is to enable the realization of all shapes and sizes, as well as get the exact mechanical and elastic properties. For example, one can vary the amount of material layup along the blade e.g. a profile having very thin skin near the tip to become a solid profile at the blade root. That's why one way of achieving cost reduction is going to be threw the examination and development of new composite textiles with new manufacturing techniques - another promising research area.

In addition, classical failure mechanisms and linear buckling models are no longer sufficient. Current optimization tools require the introduction of new criterions in the optimization structure to assess complex effects such as cross sectional shear distortion and large deformations (J. Yang, Peng, Xiao, Zeng, & Yuan, 2012) from the bending moment (crushing pressure due to Brazier effect (Brøndsted & Nijssen, 2013)). The prominence of composite materials has led to the use of unidirectional laminate in the spar cap, bi-axial laminates in the webs and tri-axial laminates at the root of the blade.

Currently turbine manufacturers are seeking greater cost effectiveness through increased turbine size rather than minor increases through enhanced blade efficiency. This is likely to change as larger models become difficult to construct, transport and assemble Therefore, it is probable that the general shape will remain the same and will continue to increase in length-size until a physical plateau is reached. Minor changes to the external blade shape may then occur as manufacturers integrate new aerofoils, tip designs and materials.

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ANNEX

ANNEX A: INPUTS FOR WINDESIGN

Table A 1. Mechanical properties derived from Sandia SNL-100

E_{11} (Pa)	E_{22} (Pa)	G_{12} (Pa)	υ_{12} (-)	ρ (kg/m^3)	Material Name (-)
2.80E+10	1.40E+10	7.00E+09	0.4	1850	(blade-root)
2.80E+10	1.40E+10	7.00E+09	0.4	1850	(blade-shell)
4.20E+10	1.40E+10	3.00E+09	0.28	1920	(spar-uni)
2.60E+08	2.60E+08	2.00E+07	0.3	200	(spar-core)
2.60E+08	2.60E+08	2.00E+07	0.3	200	(LEP-core)
2.60E+08	2.60E+08	2.00E+07	0.3	200	(TEP-core)
1.40E+10	1.40E+10	1.20E+10	0.5	1780	(web-shell)
2.60E+08	2.60E+08	2.00E+07	0.3	200	(web-core)

Table A 2. Input file for aerodynamic solver

Input Configuration		
False	Echo:	Echo input parameters to "<rootname>.ech"?
True	DimenInp:	Turbine parameters are dimensional?
True	Metric:	Turbine parameters are Metric (MKS vs FPS)?
Model Configuration		
1	NumSect:	Number of circumferential sectors.
1000	MaxIter:	Max number of iterations for induction factor.
1.00E+06	ATol:	Error tolerance for induction iteration.
1.00E+06	SWTol:	Error tolerance for skewed-wake iteration.
Algorithm Configuration		
True	TipLoss:	Use the Prandtl tip-loss model?
True	HubLoss:	Use the Prandtl hub-loss model?
True	Swirl:	Include Swirl effects?
True	SkewWake:	Apply skewed-wake correction?

True	AdvBrake:	Use the advanced brake-state model?
True	IndProp:	Use PROP-PC instead of PROPX induction algorithm?
True	AIDrag:	Use the drag term in the axial induction calculation?
True	TIDrag:	Use the drag term in the tangential induction calculation?
Turbine Data		
3	NumBlade:	Number of blades.
10	RotorRad:	Rotor radius [length].
0.5	HubRad:	Hub radius [length or div by radius].
0	PreCone:	Precone angle, positive downstream [deg].
0	Tilt:	Shaft tilt [deg].
0	Yaw:	Yaw error [deg].
30	HubHt:	Hub height [length or div by radius].
30	NumSeg:	Number of blade segments (entire rotor radius).

Table A 3. Input file for the Multi-Objective Algorithm

WT-Perf Settings		
1000	MaxIter:	Max number of iterations for induction factor.
1.00E-06	ATol:	Error tolerance for induction iteration.
1.00E-06	SWTol:	Error tolerance for skewed-wake iteration.
True	TipLoss:	Use the Prandtl tip-loss model?
True	HubLoss:	Use the Prandtl hub-loss model?
True	Swirl:	Include Swirl effects?
True	SkewWake:	Apply skewed-wake correction?
True	AdvBrake:	Use the advanced brake-state model?
True	IndProp:	Use PROP-PC instead of PROPX induction algorithm?
True	AIDrag:	Use the drag term in the axial induction calculation?
True	TIDrag:	Use the drag term in the tangential induction calculation?
3	NumBlade:	Number of blades.
0	Yaw:	Yaw error [deg].
30	HubHt:	Hub height [length or div by radius].

0.00001464	KinVisc:	Kinematic air viscosity
0	ShearExp:	Wind shear exponent (1/7 law = 0.143).
False	UseCm:	Are Cm data included in the airfoil tables?
True	TabDel:	Make output tab-delimited (fixed-width otherwise).
True	KFact:	Output dimensional parameters in K (e.g., kN instead on N)
True	WriteBED:	Write out blade element data to "<rootname>.bed"?
True	InputTSR:	Input speeds as TSRs?
"mps"	SpdUnits:	Wind-speed units (mps, fps, mph)
0	NumCases:	Number of cases to run. Enter zero for parametric analysis.
WS or TSR	RotSpd Pitch	Remove following block of lines if NumCases is zero.
3	ParRow:	Row parameter (1-rpm, 2-pitch, 3-tsr/speed).
1	ParCol:	Column parameter (1-rpm, 2-pitch, 3-tsr/speed).
2	ParTab:	Table parameter (1-rpm, 2-pitch, 3-tsr/speed).
True	OutPwr:	Request output of rotor power?
True	OutCp:	Request output of Cp?
True	OutTrq:	Request output of shaft torque?
True	OutFlp:	Request output of flap bending moment?
True	OutThr:	Request output of rotor thrust?
0.0 0.0 0.0	PitSt, PitEnd, PitDel:	First, last, delta blade pitch (deg).
80 80 0.00	OmgSt, OmgEnd, OmgDel:	First, last, delta rotor speed (rpm).

Analysis Options

t	SELF_WEIGHT:	Include self-weight as a body force?
t	BUOYANCY:	Include buoyancy as a body force?
true	CENTRIF:	Include centrifugal force as a body force?
true	DISP_CF:	Apply correction factors to the beam displacements?
0	N_MODES:	Number of modes to be computed
50	N_ELEMS:	Number of blade finite elements to be used in the modal analysis

Optimization Options

t	OPTIMIZE:	Perform optimization of composite layup?
GS	OPT_METHOD:	Optimization algorithm for the optimization of composite layup
false	OPT_PITAXIS:	Optimize the pitch axis?

0.375	PITAXIS_VAL:	Pitch axis value outboard of max chord (ignored if OPT_PITAXIS = false)
3	INB_STN:	Inboard station where the leading and trailing edge panels, spar caps, and shear webs begin
8	TRAN_STN:	Station where the root transition ends
28	OUB_STN:	Outboard station where the leading and trailing edge panels, spar caps, and shear webs end
4	NUM_CP:	Number of control points between INB_STN and OUB_STN
false	READ_INITX:	Read the initial values for the design variables from INITX_FILE?
none	INITX_FILE:	Input file for the intitial values of the design variables.
false	WRITE_STR:	Write structural input files at each function evaluation?
f	WRIT E_F_ALL:	Write the fitness value and penalty factors at each function evaluation?
f	WRIT E_X_ALL:	Write the design variables at each function evaluation?
f	WRITE_X_ITER:	Write the design variables at each iteration?
100	NumGens	Max number of generations for GA iterations
100	PopSize	Number of individuals per generation
1	EliteCount	Number of elite individuals per generation
0.5	CrossFrc	Fraction of individuals created by crossover
1.00E-06	GATol	Error tolerance for the GA fitness value
	Environmental Data	
1.225	FLUID_DEN:	Fluid density (kg/m^3)
9.81	GRAV:	Gravitational acceleration (m/s^2)
6.03	U_mean:	Long term mean flow (m/s)
1.91	Weib_k:	Shape factor
6.8	Weib_c:	Scale factor
	Blade Data	
30	NUM_SEC:	Number of blade cross sections
10	BLD_LENGTH:	Blade length (m)
0.5	HUB_RAD:	Hub radius (m)
0	SHAFT_TILT:	Shaft tilt angle (deg)
0	PRE_CONE:	Pre-cone angle (deg)
180	AZIM:	Azimuth angle (deg)

100	MAX_ROT	Maximum rotational speed (rpm)
10	MIN_ROT	Minimum rotational speed (rpm)
cosine	INTERP_AF:	Interpolate airfoil coordinates? (choose "none", "cosine", or
1	ElmSpc	Blade element radial spacing (0 equal, 1 cosinus)
60	N_AF:	Number of points in interpolated airfoil coordinates (ignored
mats-Wind.inp	MATS_FILE:	Input file for material properties
0.13	RootTranSt	Start of root transition region
3	RootTranSt_index	Index of start of root transition region
0.288	RootTranEnd	End of root transition region
8	RootTranEnd_index	Index of end of root transition region
3 9 19 26 30	CP_Index	Index of control points (Chord and Twist)

ANNEX B: WINDESIGN LAYOUT

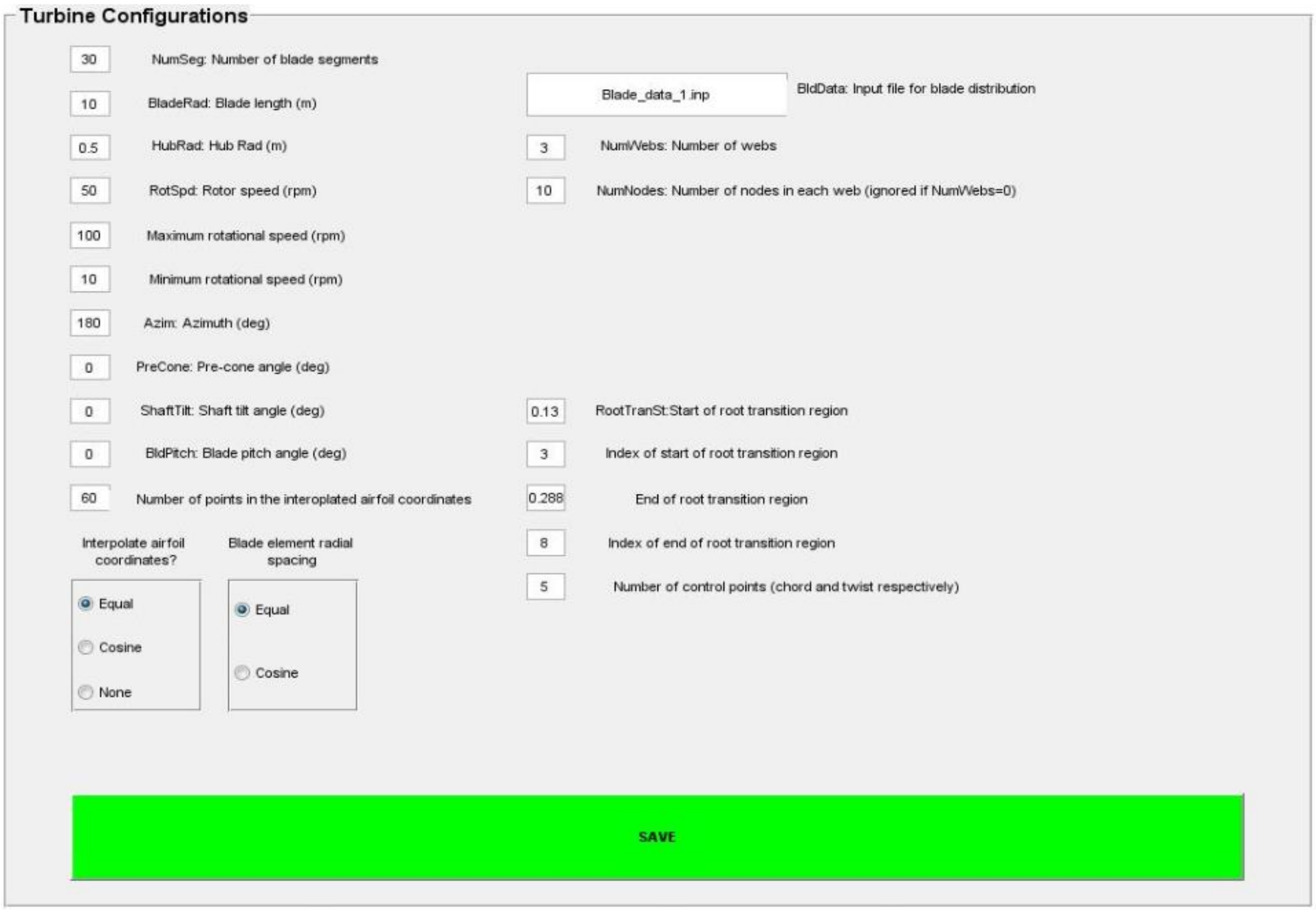

Figure B 1. winDesign turbine configurations input window.

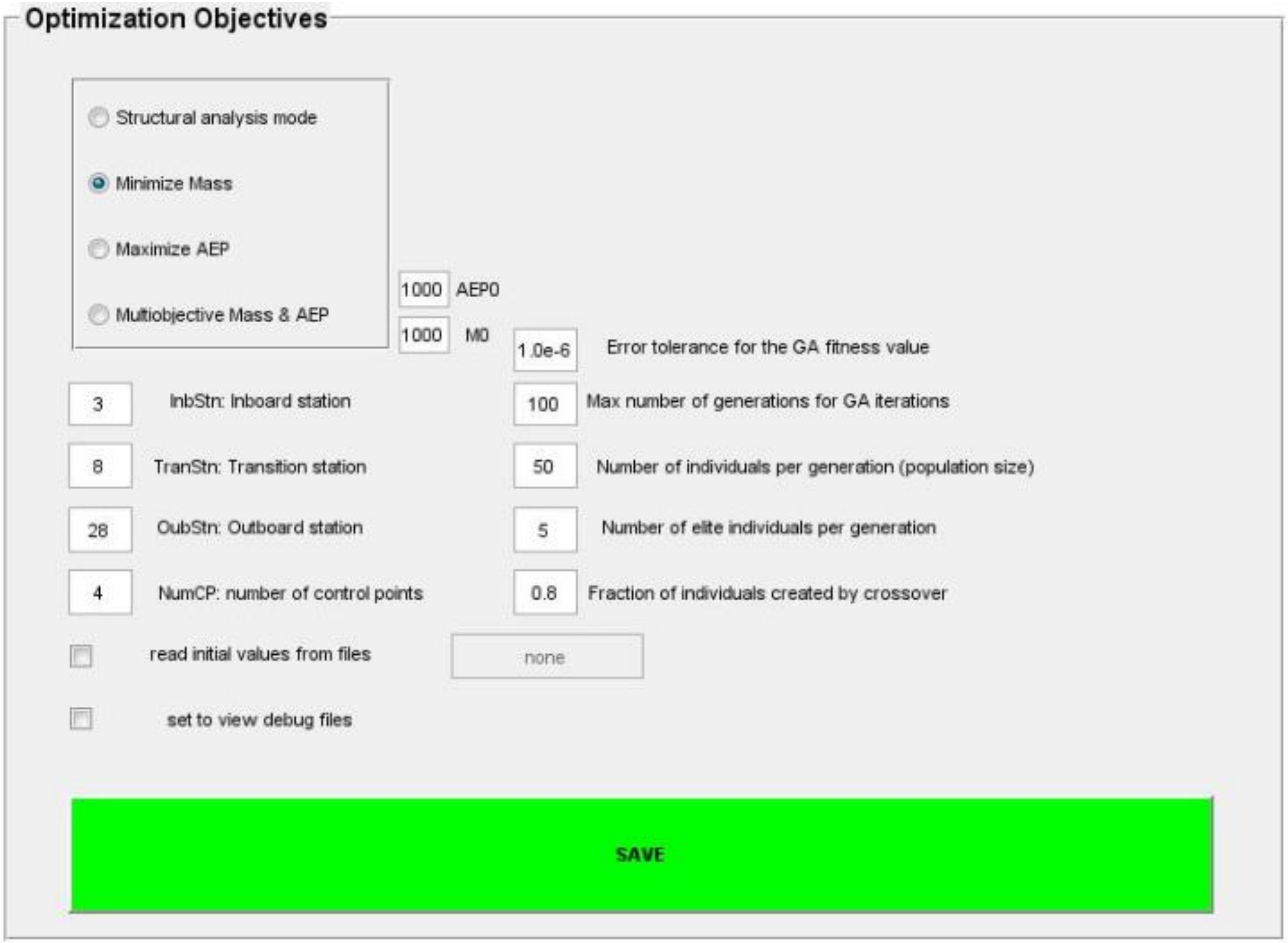

Figure B 2. winDesign optimization objectives input window.

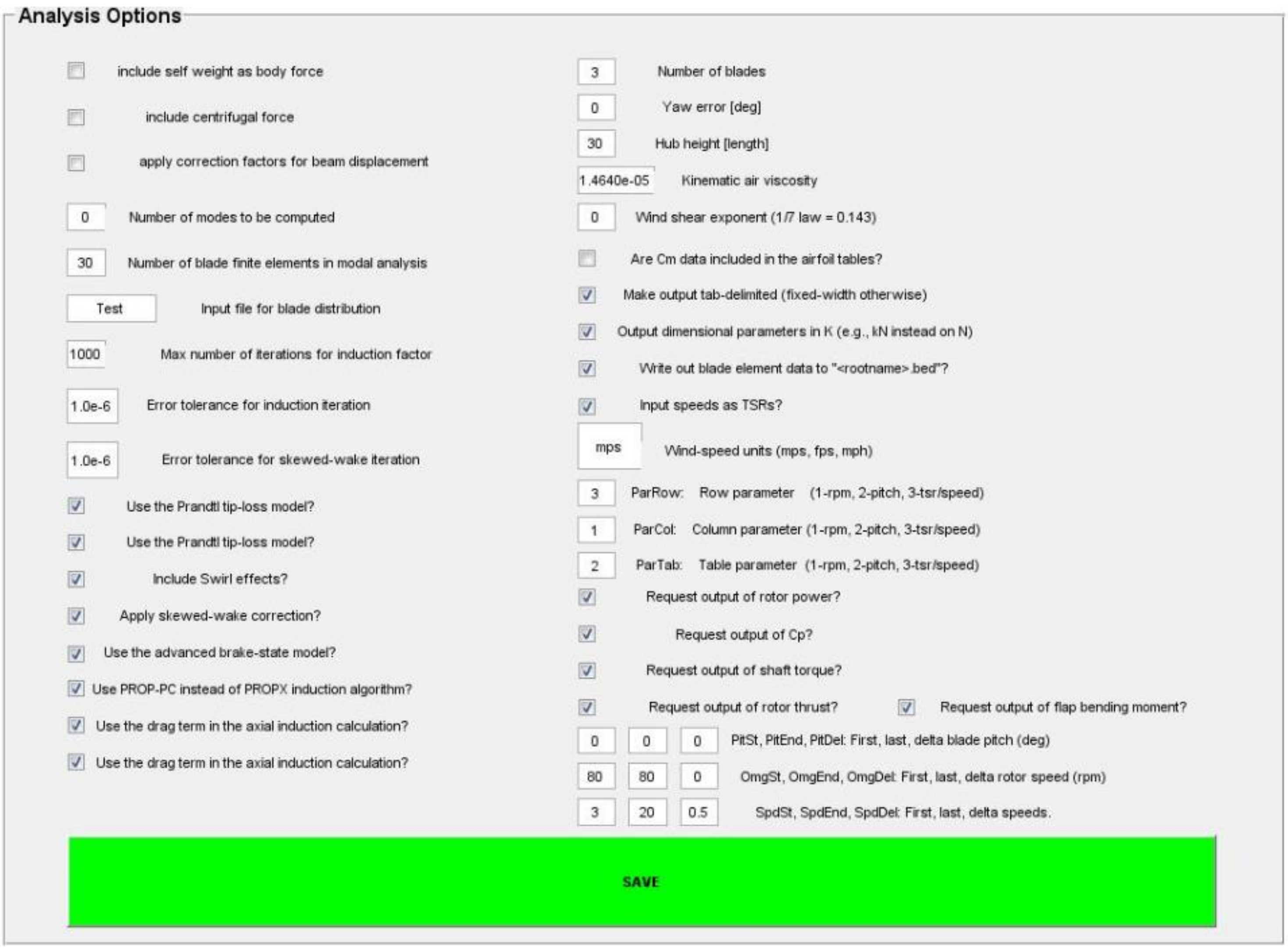

Figure B 3. winDesign analysis options input window.

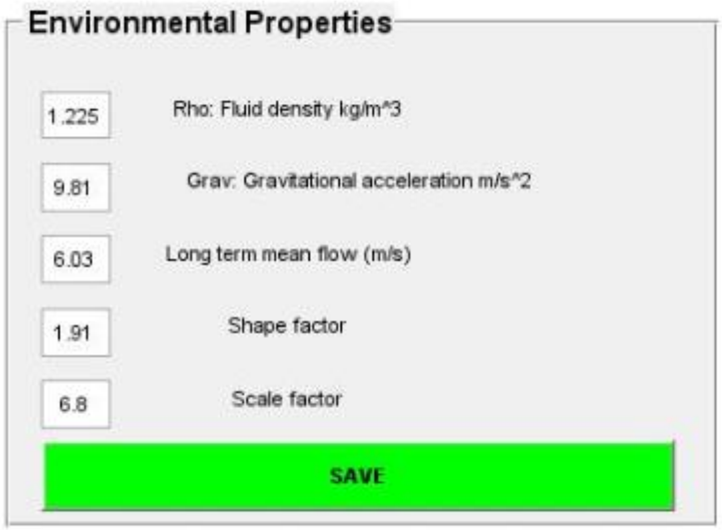

Figure B 4. winDesign environmental properties input window.