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AIRFOIL SECTION OPTIMIZATION FOR USE IN SAILBOAT FOILS

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Abstract

In recent years we have been witnesses of an extraordinary development in sailing technology. All aspects of the sport have benefited from the advancement of computational tools. Computational fluid dynamics, finite element analysis of structures, and optimization tools can increasingly be found in the bag of tricks of designers. In this article we will present a methodology and a tool to treat the design of sailboat foils. The methodology is grounded in the adequate use of current technologies, scaling them when deemed necessary. The construction of a model that includes the treatment of geometrical and structural constrains at the same time using currently available tools will be described.

PRECISION MODELS

For years, the most used tools for foil design were based on panel codes. Those have the advantage of relative short running times with the computing power available today. Recent developments in CFD (computational fluid dynamics) technology have brought more precise predictive capacity. The downside is computational expense.

Today, it is possible to analyze a certain foil configuration or even several of them with CFD tools (RANS codes). If we want the added precision of more advance codes we would have to upgrade to LES (Large Edy Simulation) codes. These are still expensive from the computational time perspective. In terms of using them for an optimization that may involve tens or hundreds of evaluations is still prohibitive for most projects.

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The alternative is to use older models. A middle ground can be found though. Using a variety of technologies, namely neural networks and genetic algorithms it is possible to generate a model that mixes different models for use in optimization.

NEURAL NETWORKS

In general, the area of neural networks is based on our understanding of the workings of the human brain. NN (neural networks) work in a similar way to our brain, by learning. This is, in fact, their most significant property.

Neural computing concepts are mainly based on attempts to mimic the way our brain processes information in order to solve different kinds of problems. NN, obviously, have not even get close to model the complexity of the human brain but they have proven to be very efficient at problems that are easy for the human brain but difficult for traditional computers, such as pattern recognition.

The way to visualize the working of an ANN (artificial neural network) is to think of mathematical models of a biological neuron linked together on a network. This forms an information processing structure that has the ability to learn to perform certain tasks.

There are different kinds of neuron, different kinds of networks and different kinds of associated performance functions and learning algorithms.

Neuron models are mathematical models of the behaviour of a single neuron in a biological nervous system. These models receive information in the form of a set of numerical input signals. This information is then integrated with a set of free parameters to produce a message in the form of a single numerical output signal.

The kind of NN comes conditioned by the way its neurons are arranged to form a particular architecture. The architecture is defined by the number of neurons, their arrangement and their connectivity.

The performance function is in charge of defining the task the neural network is required to carry out and provides a measure of the quality of the representation that the network is required to learn. Each particular application requires a different performance function.

The missing piece in this puzzle is the learning algorithm. This is the procedure used to carry out the learning process. The learning (or training) algorithm is applied to the network in order to obtain a desired performance. There are different types of learning that are defined by the way the adjustment of the free parameters in the NN takes place.

In our case, we have used a neural network composed of perceptrons. This neuron model has been combined in what is known as a multilayer perceptron. The network is composed of an input layer for six inputs, sigmoid hidden layers, and an output layer.

GENETIC ALGORITHMS

According to [Heitkoetter, 1994]: *"Evolutionary algorithm is an umbrella term used to describe computer-based problem solving systems which use computational models of evolutionary processes as key elements in their design and implementation"*.

Genetic algorithms are based on an analogy with the laws of natural selection proposed by Darwin and its most famous principle of survival of the fittest. Genetic algorithms are multiple solution algorithms. They work on a *population* of solutions called *individuals*. Each individual is represented by its *genome*. A genome defines unequivocally a solution of the problem. The individuals strive for survival and for continuity of their genome (*reproduction*). The time is divided into discrete steps called generations. Depending on the type of genetic algorithm every individual (simple genetic algorithm) or some individuals (steady-state genetic algorithm) are born (created) each generation.

The analogy of the environment for a genetic algorithm is the evaluation function. This function assigns a fitness value to each individual. The goal of the algorithm is to find the individual best fitted to the environment, thus maximizing the evaluation function.

GAs (Genetic Algorithms) differ from classical optimization strategies in several respects:

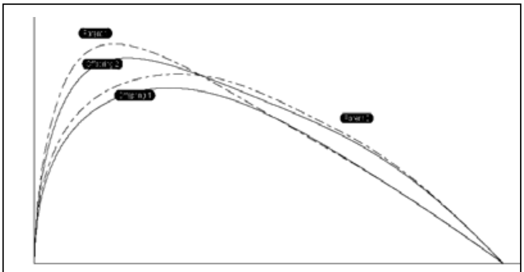
— GAs operate simultaneously on a population of potential solutions not on a single instance that gets iterated to find the optimum.

— GAs use directly the objective function and do not need to calculate derivatives or other auxiliary knowledge.

— GAs are stochastic methods, not deterministic. They are frequently found more robust in some cases. This is especially true in the case of non differentiable, multi-modal or convex functions.

— GAs have a greater potential to explore the whole search space.

The way a genetic algorithm works is by evolving the population to find the best individual (best solution to the problem). To accomplish that, three genetic operators are applied to the population: selection, crossover and mutation. Each individual can either survive, reproduce or die according to their fitness value which is related to the value of the cost functional.



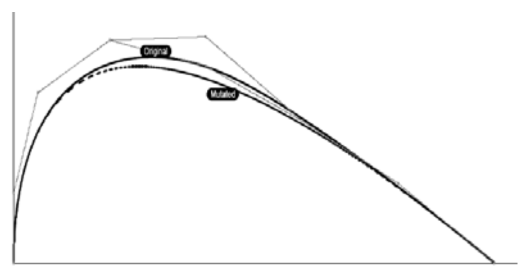
Crossover Example

The selection operator decides if an individual reproduces, survives or dies. There are two basic types of selection, roulette wheel and tournament. The most popular tournament is the two-point tournament. In this case, two individuals are drafted at random from the population and compared, the best one is stored and both are reintroduced in the population. The procedure is repeated until a new population of adequate size is reached.

Since selection does not create new individuals, crossover is need to increase diversity among the population. It is applied with a probability close to one. The operator selects at random a position in the chromosome and from that position it switches the information in the chromosome.

Another key ingredient is the mutator operator. This operator is applied because important genetic information may be lost as a result of crossovers. It is applied with a small probability and introduces random values to the chromosome.

If we describe in pseudo code a genetic algorithm we would have something similar to:



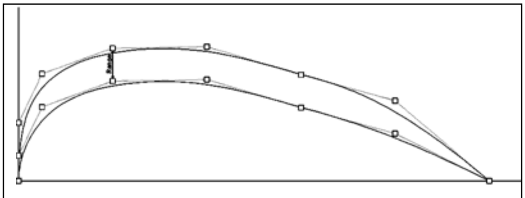
Mutation Example

```
begin
   initiate population P
   evaluate population P
   repeat
        select parents in P
        recombine parents
        mutate
        evaluate
        select
   until (termination condition)
end
```

In our case we have used a steady state genetic algorithm with two point crossover. The genome described seven parameters that represented the y coordinate of a fifth degree B-spline and a scaling factor.

GEOMETRICAL REPRESENTATION

In the way the section has been set up it is defined by the position of the control polygon of a fifth degree B-spline. These points are allowed to vary trough a definite range around the starting section. In order to cover a wider design space an scaling factor is also used that multiplies the height of all the control points.


Range

This way of representing the section allows for great variation of the shape while preserving a certain degree of smoothness.

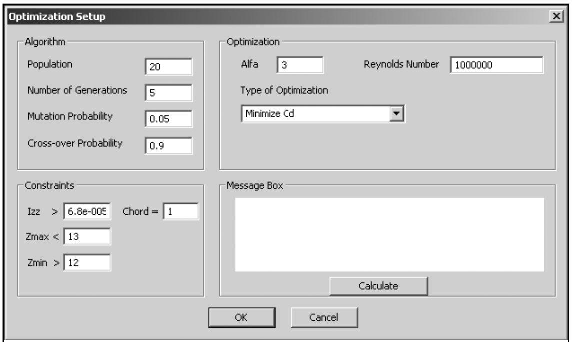
COMPUTATIONAL TOOLS

For the calculations necessary to carry out the optimization we have used varied tools. From the aerodynamic perspective we have used two distinct tools.

Firstly, we used the well know airfoil analysis code Xfoil. This is a panel code with a strongly coupled boundary layer solution. The code has been widely used in foil design for some time and is considered sufficiently accurate for the application we were after.

We have also used a graphical user interface that has been created to make the used of Xfoil more user friendly. This gui is called XFLR5. To this gui, a option to control the optimization has been added.

On the other side, we also used a CFD code, Tdyn. In this case, the code is a multi-physics finite element code. This code can be easily used from within a pre-post processing software, GiD. This software can be called in batch mode witch therefore facilitates the integration in the flow of the optimization.



Optimization Options

The structural part is considered from two different fronts. First, we take into consideration geometric constraints for the generation of individuals in the population. These constraints have a significant structural meaning. In particular, they are the maximum thickness of a section (that has to be within certain values) and the sectional inertia that can be set up either as a constraint or in a multi objective optimization.

The other structural consideration is based on the finite element analysis of the structure of the whole keel. To accomplish that, we have used the parameterization capabilities of modern modeling software. In particular, the coordinates of the control points drive the creation of the geometry in Catia. This software allows the creation of a complete parametric model that would change with each input of different coordinates. Associated to the geometric capabilities, Catia also has an integrated finite element analysis module. Once the geometry is created, with its topology defined, the finite element solver is automatically called upon to mesh the new geometry and solve the case when the geometry gets updated.

Other tools that have been used include programming libraries for neural networks and for genetic algorithms. These libraries, for example GAlib, are available as open source in C++.

GLOBAL MODEL

The different tools have been scaled with respect to their performance and quality to create a global model. The model scales each tool to use it with the part of the population that seems more adequate for it. In that context, we distinguished 3 types of solutions: those coming from the neural network, those from the panel code, and those from the CFD code.

The way this works is the following. The first step was to train the neural network. This was carried out by generating a first population of randomly generated individuals. These individuals were calculated using the panel code. This data set serves as the base training set for the NN. At this point the NN is capable of predicting aerodynamic properties from the genes of an individual.

For each subsequent generation, the neural network makes a prediction of the fitness of the individuals. The best half of the population is then evaluated with the panel code to improve the quality of the results. This method has the drawback of possibly missing good individuals that are badly predicted by the NN. This is partially avoided by the calculation of a large part of the population (half of it) with the more reliable prediction method. In order to establish another failsafe, a small number of individuals draw at random are also evaluated even if they do not belong to the top 50%.

These calculations are also used to improve the quality of the prediction by adding them to the training set.

In order to refine the search even further, it was proposed to evaluate the top 10% with the CFD code. This has the drawback of multiplying the computational effort required. Looking for ways to save computing time it was decided to evaluate these sections only at regular interval and not in every generation. This way, scores for the chosen genes are corrected once out of several generations (depending on the general number of generations). These scores are also used to improve the training set.

In the same way, these individuals that are found best fitted are used as the definition of the geometry within Catia. Simple put, another row with the coordinates of the control points is added to the table that defines the different configurations. That row is selected as the actual configuration for that particular part. With this done, the part is updated and the new mechanical properties are measured. This also calls for an update to the structural calculation. Since the topology of the part has not changed, this can all be done automatically.

OPTIMIZATION PROBLEM

In a general way, the example problem would be to find the best profile for a keel taking into account structural constraints. The keel subject to optimization is destined for a GP 42. This is a racing sailboat rule of the type known as box rules.

The GP 42 rule has been created with the target of

"...to promote the conception and construction of boats fun to sail, seaworthy and with considerable longevity."

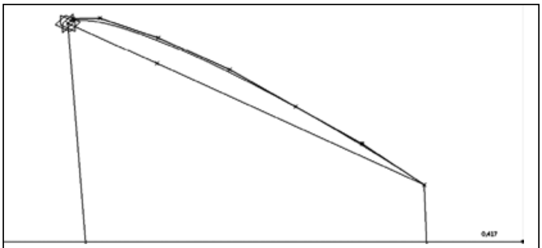
It is in this environment that the proposed problem is framed. The idea is to used the previously exposed methodology to optimize a baseline keel for its use in a GP 42.

In a very brief way, the rule sets a few limits on properties of the keels. These limits are the keel weight, and thickness measurement at three different points of the span. Of course, there is also a limit in draft for the whole boat that affects the keel span. The following table presents the measures that have to be considered:

Keel Measurements	
Keel Maximum weight.	2300 kg.
Keel Thickness 100 mm. Below hull.	0.090 m.
Keel Thickness mid-span.	0.080 m.
Keel Thickness 100 mm. Above bulb.	0.070 m.

Based on these measurements, the keel maximum thickness distribution is set. A key aspect to consider here is that the weight represents the weight of the whole keel assembly. Therefore, the parallel consideration of the structural aspect is of prime importance. A lighter keel blade that can support the same or more weight will allow for a bigger bulb.

The baseline keel was designed using a previously develop section. With respect to the plan form, it was fixed once the required blade area was determined from the sail plan.



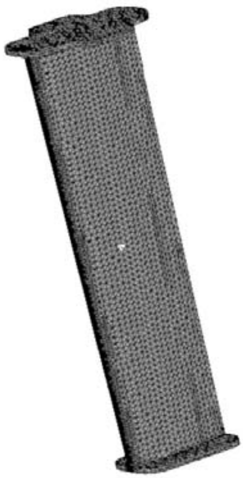
Control Points for Catia Model

These geometric restrictions were parameterized on a Catia model. For the connection to the aerodynamic part of the optimization the control points of the section are updated from the ones send by the optimizer. This way, the same genome defines the shape used for the aerodynamic calculations and for the structural calculations.

Once the model is parameterized, linking different features is possible. For example, important properties such as weight can be linked. Thus, the weight of the bulb can be changed in a way that keeps the total weight of the keel constant.

Furthermore, in the structural part, meshing properties only have to be defined once. Since the topology of the geometry does not change, only the geometry trough its control points does, the meshing can be accomplish automatically after setup of the baseline model. The load conditions for the calculation are also parameterized. Since the bulb weight changes as a function of the section so does the load.

This set up allows considering some of the downstream effects that choosing a certain section has.



Meshed Baseline Model

A very similar procedure is used to pass information to the CFD. In this case, the geometry of the baseline section is set up. This includes the meshing definition (how fine or coarse) and the boundary conditions. The pre-processing software GiD associates this definitions to geometry and passes them to the mesh just before the problem is run. By changing the geometry instead of creating a new one, all conditions are kept in the same entities. Once in place, GiD and Tdyn can be run in batch mode. The optimizer changes the geometric definition (in fact, just moves the control points) and the problem is meshed and run.

The fact that the geometry is unequivocally defined by the same genome allows the interplay of different pieces of software than can be run in batches. With this structure in place the problem is set up to run.

Geometry Definition in GiD

OPTIMIZATION FUNCTION

What needs to be optimize to improve the performance of a sailboat appendix is not always clear. The variety of operating conditions that the boat is expected to find makes it hard to decide what needs to be optimized. In this case, to test the procedure, we decided to start with a simple optimization and to progress from there.

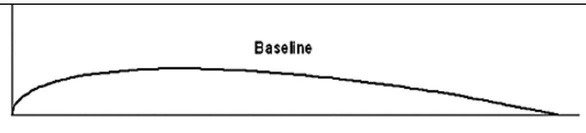
The optimization conditions where all set up at a Reynolds number of 3000000. This was considered a good starting point for the performance optimization of the vessel when we consider that in this phase only a single point of sail is treat at any one calculation.

The first optimization is designed to model the behavior of the keel on a dead run. It is probably unrealistic to set up the section at an angle of attack of zero degrees but it seems adequate to check the methodology. It could be argued, besides, that canting keels and similar could be designed to operate at or very close to zero angle of attack. It does not seem very likely that such is the case but it something that has been sometime heard.

MINIMUM DRAG SECTION

The optimization goal in this case is to find the minimum drag coefficient for a section operating at zero degrees angle of attack and at a Reynolds number of 3000000.

In these conditions, the performance of the baseline section and keel is:



Geometry of Baseline Section

Baseline Keel	
C_d	0.00548
Maximum Thickness	0.090 m.
Inertia	$1.834e^{-5}$ m^4.
Blade Weight	725 kg.
Bulb Weight	1575 kg.
Max. Von Misses Stress	76.98 MPa
Maximum Displacement	15.69 mm.
Factor of Safety (Yield stress 700 Mpa)	9.09

From this keel, an optimization is carried over. In this optimization the score of each individual is develop simply by calculating the inverse of the drag coefficient. This is done in such a way because it permits configuring any optimization as a maximization problem.

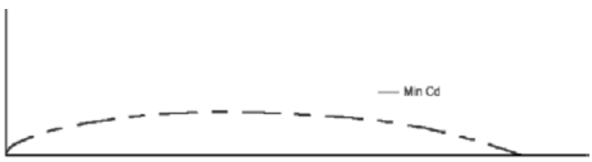
$$Score = \frac{1}{C_d}$$

The restrictions applied to the problem are:

Restrictions	
Minimum Thickness	0.09 m
Minimum Inertia	$1.834e^{-5}$ m^4.

The inertia is used as a restriction here to try not to be in a worse position structurally than with the baseline design.

The restrictions are imposed as "*soft*" barriers. This means that a violating genome (one that lays outside the genotype) is not directly given a score of 0. Instead, other criteria are applied to allow for solution that are very close to the restrictions. For example, if a genome violates the minimum thickness criteria it is given a score inversely proportional to its distance to that constraint.



Geometry of Minimum Drag Section

Thus, the population naturally evolves towards genes that are inside of the constraints.

In addition, the top five sections are analyzed using finite elements and their scores corrected. The results obtained are reflected in the following table.

Minimum C_d Keel	
C_d	0.00317
Maximum Thickness	0.090 m.
Inertia	1.995 e^{-5} m^4.
Blade Weight	760 kg.
Bulb Weight	1540 kg.
Max. Von Misses Stress	68.74 MPa
Maximum Displacement	14.25 mm.
Factor of Safety (Yield stress 700 Mpa)	10.18

In this case, the drag coefficient is reduced notably. The trade off, however is present on the weight of the blade that has increase. Therefore, the vertical weight distribution has changed as the bulb has to be made lighter. An added benefit is the increase in factor of safety for this geometry.

MAXIMUM Cl/Cd

As mentioned before, considering the keel operating at zero angle of attack is not very realistic. A modern design such as this will almost never sail dead downwind. For this reason, the objective of the optimization was changed to maximizing the ratio of lift over drag. The operating point used in this case was 3 degrees angle of attack at a Reynolds number of 3 million.

In these conditions, the performance characteristics of the baseline keel are a little different with respect to lift and drag. The lift in this case is C_l = 0.283 while the drag is C_d = 0.586.

Therefore, the score function used in the optimization becomes:

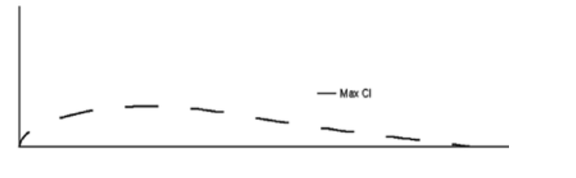
$$Score = \frac{C_l}{C_d}$$

In turn, the performance of the optimized keel is:

Maximum C_l/C_d Keel	
C_d	0.00467
C_l	0.34019
Maximum Thickness	0.102 m.
Inertia	2.497 e^{-5} m^4.
Blade Weight	775 kg.
Bulb Weight	1525 kg.
Max. Von Misses Stress	62.49 MPa
Maximum Displacement	11.58 mm.
Factor of Safety(Yield stress 700 Mpa)	11.20

After the optimization, the section thickness has increase. This, however, has not come associated to an increase in drag from the baseline keel. In fact, the drag has come down from 0.00548 to 0.00468. The draw back in this case is the increase in weight of the blade that comes associated to a thicker section. Of course, on the up side, there is an improvement in safety factor for this keel as compared with the baseline.

MAXIMUM LIFT



Geometry of Maximum Cl

A very desirable characteristic for a foil is its ability to produce a great amount of lift. This is a requirement most often look after in rudder sections than in keel sections, although for a rudder is ultimate lift what one is usually after. However, modern race boat plan forms that have little surface may be required at times (out of a tack or at the start) to produce a high amount of lift. From that perspective, it seemed interesting to find what the optimum section would be for a keel producing high lift at low angles of attack.

With that in mind, an optimization was carried over for the keel at 3º angle of attack and for the same Reynolds number. The score function used in the optimization process is setup directly from the lift coefficient.

$$Score = \frac{C_l}{C_{l_0}}$$

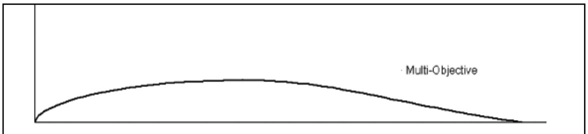
The result is summarized in the following table:

Maximum C_l Keel	
C_d	0.00592
C_l	0.3454
Maximum Thickness	0.097 m.
Inertia	1.21 e^{-5} m^4.
Blade Weight	679 kg.
Bulb Weight	1621 kg.
Max. Von Misses Stress	83.79 MPa
Maximum Displacement	17.01 mm.
Factor of Safety (Yield stress 700 Mpa)	8.35

In this case, the price to pay for a high lift coefficient is a high drag. On the other hand, the weight of the blade is notably reduced. This allows for a bigger bulb at the cost of a reduced safety factor.

MULTI-OBJECTIVE

As was to be expected, the mixed requirements that are asked from a modern keel calls for a more refined optimization that the mere consideration of one characteristic. To accomplish that, it was decided to carry out a multi-objective optimization.



Geometry of Multi-objective Optimization

A classical way of dealing with multi-objective optimization is by weighting the different objectives that are to be optimized. It is a somehow simplistic approach but it is quick to set up. The function that we want to optimize should include, as we have seen, drag coefficient, lift coefficient, and measures of structural performance.

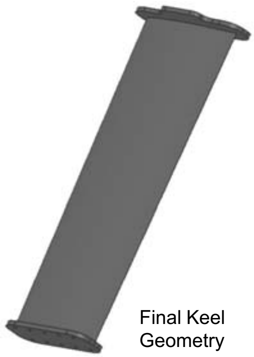
In that light, we introduce two other objectives, sectional area and inertia with respect to the chord axis. These become objectives and not restrictions. The restriction of minimal section thickness is kept due to the limitations of the rule.

The score function thus becomes:

$$Score = \frac{C_l}{C_{l_0}} + \frac{C_{d_0}}{C_d} + \frac{Area_0}{Area} + \frac{I}{I_0}$$

The sub 0 values come from the baseline section. Thus, all values are normalized with the original section. Usually, weighting factors are given to each variable to reflect what features are sough after. In this case, we did not use any differentiation between optimization objectives. The results from this optimization are reflected in the following table.

Multi-Objective Optimization Keel	
C_d	0.00461
C_l	0.3428
Maximum Thickness	0.091 m.
Inertia	1.748 e^{-5} m^4.
Blade Weight	693 kg.
Bulb Weight	1607 kg.
Max. Von Misses Stress	82.8 MPa
Maximum Displacement	16.89 mm.
Factor of Safety (Yield stress 700 Mpa)	8.45



Final Keel Geometry

With this optimization we have develop a section with a lower drag and better lifting potential than the baseline. The blade is also lighter therefore we can make the bulb bigger also. The only draw back is the reduction on safety factor. This comes to be expected as we have reduced quite a bit the amount of supporting material in the keel. However, the righting moment has increased considerably.

CONCLUSION

We have presented a methodology for the systematic optimization of foil sections. This optimization has been carried out for a keel section for a GP 42 racing sailboat. A first baseline keel was created to evaluate performance gains over it. Different objectives have been evaluated and finally integrated into a multi-objective optimization. The optimization did not only include aerodynamic characteristics but also took consideration of structural features both as optimization variables and as restrictions.

The final section found presents good characteristics for the presumed use. It has lower drag than the baseline model, higher lift and a lower weight for the structure. It can be argued that the margin of safety for the keel, although considerable, has been reduced. An alternative approach could be to use righting moment as the characteristic to maintain constant. This way, the reduced weight of the blade would come associated to a reduced weight of the bulb. The complete keel assembly would be lighter but the righting moment would be the same. At the same time, the lighter bulb would help keeping safety factors contained.

Summary Table (% change from base at 3º)
bold italics mean improvement

	Min C_d	Max C_l/C_d	Max C_l	Multi-O
C_d	**-20.14**	**-20.31**	1.02	**-21.33**
C_l	-67.61	**20.42**	**22.01**	**21.09**
Blade Weight	4.83	7.03	**-6.34**	**-4.41**
Bulb Weight	-2.22	-3.24	**2.92**	**2.03**
Max. Stress	**-8.51**	**-16.82**	11.53	10.21
Max. Displ.	**-10.71**	**-27.45**	6.52	5.8
S.F.	**9.30**	**20.23**	-10.34	-9.26

FUTURE WORK

There are some other things to consider when it comes to the optimization of sailboat appendices. Two things jump quickly to mind. The first is the fact that our real measure of merit should be the speed of the boat and not directly characteristic of any of its parts. Second, a classical approach to multi-objective optimization does not give enough insight into the trade-offs present in the problem, more flexible optimization schemes are needed.

A logical next step will be to link the optimization process to a velocity prediction program. This would allow us to better grasp what the real improvements can be and help us make a more educated choice.

From the optimization point of view it seems logical to do the optimization looking for non-dominated solutions. Therefore, we will be looking after obtaining the pareto front of solutions. This would improve the value of the solution by helping the designer make choices that adjust better to the requirements while not damaging much other characteristics.

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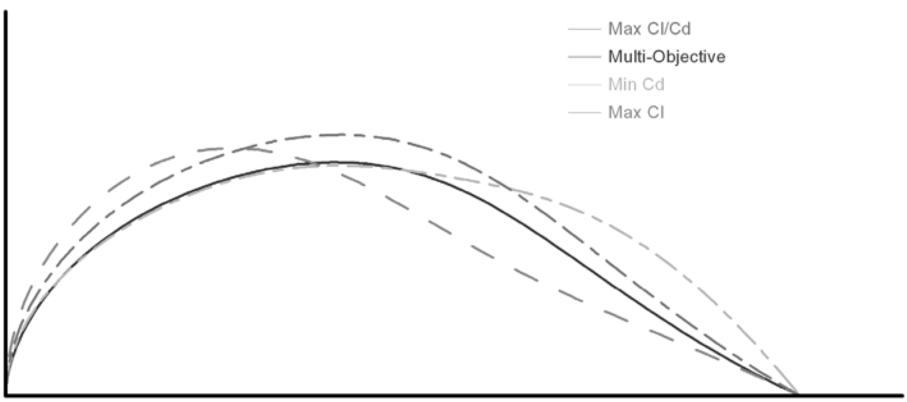
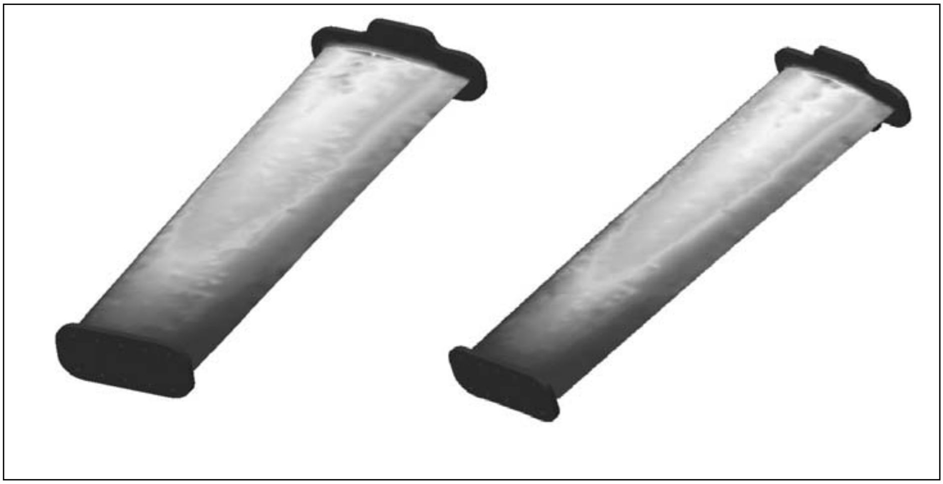
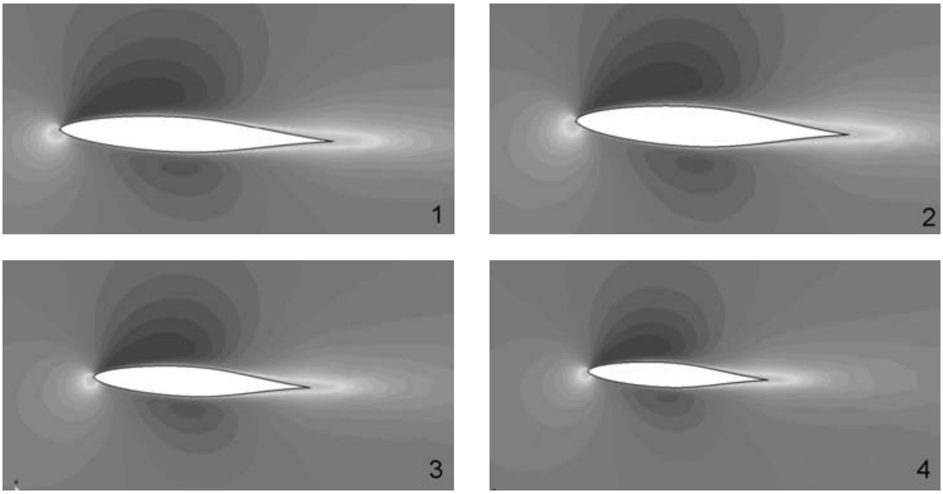
APENDIX



Best Sections for each Optimization



Stress on Baseline Keel and on Multi-Objective Optimization Keel



Velocity Distribution of Best Four Sections for Multi-Objective Optimization