Barge Design Optimization

Anonymous MIT Students

Abstract— In this project, three members of the Armed Forces tested the multi-disciplinary system design optimization approach to concept evaluation on a simplified platform, a barge. A barge is a non-self propelled vessel that incorporates the basic disciplines of ship building: hydrodynamics, hydrostatics, and structural mechanics. Using four bounded design variables, we attempt to optimize the payload, in tons, that a barge could carry within the physical constraints. We conduct a design of experiments to select an initial design to further optimize. Sequential quadratic programming (SQP) was used to solve the non-linear program (NLP) in computer software MATLAB. The NLP was also solved using the genertic algorithm (GA) heurisitic. SQP converged quickly and found the optimal solution. The problem was expanded to include another objective, structural weight. The multi-objective problem was solved to create a Pareto front to show the trade-offs for each objective. The results of the study show this approach is feasible for these types of platforms and allow the opportubnity for expansion of included disciplines as well as increased fidelity of the model used. Thus, eventually, a warship or some other such complex system could be designed with this approach.

Index Terms—Barge, MDO, SQP, Genetic Algorithm

1 Introduction

A barge is a typically non-self propelled, flat-bottomed vessel used initially for river or canal transportation of heavy goods. Although other means of transportation have been developed since their introduction, barges are still used all over the world as a low-cost solution for carrying either low-value or heavy and bulky items.

Although a barge is very simplistic compared to most of its waterborne brethren, it still presents ample opportunity to experiment with balanced designs. A customer may desire to carry as much payload as possible to gain effeciencies in their transportation costs, but maximizing these payloads must be balanced by engineers to operate within the laws of physics (including stability, buoyancy, powering, resistance, structures, etc.) and balanced by financiers to operate within a customer's allowable limits of cost. These two very obvious considerations alone can create quite a complex balancing act, since these forces - requirements, feasibility, cost - tend to oppose each other.

2 Motivation

The team's interest and background in many associated disciplines has primarily motivated this project. During the team's tenure at Massachusetts Institute of Technology, they have taken a range of courses including Marine Hydrodynamics, Design Principles for Ocean Vehicles, Principles of Naval Architecture, Power and Propulsion, Structural Mechanics, Plates and Shells, Ship Structural Analysis and Design, and Ship Design and Construction. Each of these courses had one of two approaches. Either the course examined a particular discipline of ship design and mentioned that a designer should not forget other disciplines, or the course examined the design as a process and recognized the many disciplines but encouraged an iterative, "throw-it-over-the-wall" approach to converge to a point design. To further emphasize, even the courses that recognized the multi-disciplinary aspects of ship design only designed for convergence to any feasible design within the space, not necessarily an optimal design.

Thus, the team wished to explore the possibility of an optimal design amongst each of the disciplines. We wanted to create an optimal design from a multi-disciplinary standpoint and understand the associated trade-offs within the design vector. Meanwhile, we wanted to acquire knowledge and skills by using the methods and tools of this new trade.

The team knew, however, that using these tools to design any standard sea-going vessel would provide diminishing returns due to the incredibly complex and coupled nature of the entire set of design variables. Thus, the team used a simplified, low-fidelity model on a simple vessel – a barge – to demonstrate the benefit of these tools within the marine design environment. The understanding was that the design vector could grow and the fidelity of the model could increase modularly to accommodate increasingly complex designs for more typical ocean platforms. Indeed, two team members have the task of performing a clean slate design of a warship for the next year, so, should they incorporate these tools in the design process, the design vector will grow and the

- *Student A is pursuing a Naval Engineer's Degree and an MS in Engineering Management through the Systems Design and Management program, both at the Massachussetts Institute of Technology in Cambridge, MA 02139.*
- *Student B is pursuing a Naval Engineer's Degree and an MS in Engineering Management through the Systems Design and Management program, both at the Massachussetts Institute of Technology in Cambridge, MA 02139.*
- *Student C is pursuing an MS in Operational Research at Massachusetts Institute of Technology in Cambridge, MA 02139.*

fidelity and computational expense of the model will increase very quickly. This project proved a good proof of concept for the team members to grow and add variables, parameters, constraints, and fidelity to at a later date.

3 Problem Formulation

As with any vessel operating in the marine environment, the designer has to deal with stability, seakeeping and structural strength issues – to name a few - all of which come from different disciplines: hydrostatics, hydrodynamics, and structural mechanics. The team used the methods and tools of multi-disciplinary system design optimization to optimize the design of a barge with respect these disciplines. The primary design objective was to maximize the payload (i.e. the cargo capacity) that the barge can effectively carry. Eventually, this project also balanced that optimization against the cost of the vessel, represented by the barge's weight.

To start, the team utilized a MATLAB® code implemented to model a barge's seakeeping behavior (the hydrodynamics of the vessel) during a Design Principles of Ocean Vehicles term project. The code was limited to non-self-propelled vehicles, and only evaluated heave and pitch motions. The original code also only studied one particular hull shape with a particular beam to draft ratio. Out of a desire to eliminate discrete variables, the hydrodynamic properties represented in the code for each beam to draft ratio were first fitted to curves in order to allow for a continuous design space exploration instead of limiting the beam to be either 2-, 4-, or 8- times the draft of the barge.

Additionally, the team modeled the hydrostatics and structural strength of the barge. The hydrostatics requirements and implementation were derived from Principles of Naval Architecture, and provided the basic requirements that the barge float (buoyancy equals weight) and that it floats upright (positive metacentric height). The structural mechanics module was derived from the American Buereau of Shipping (ABS) rules for steel vessels assuming mild steel as the type of material.

Originally, the team designated 8 design variables to be changed during the exporation of the design space. These variables were length, beam, draft, depth, vertical center of gravity (VCG), speed, cross-sectional area coefficient, and displacement. However, cross-sectional area coefficient was a result of beam and draft, so it was eliminated and only used as an intermediate variable. Also, displacement and VCG were a result of length, beam, draft, and the payload – our objective – so they were eliminated as design variables, also, and only used as an intermediate variables. Because draft was also a result of payload, it was eliminated as a design variable. Finally, speed was removed as a design variable because it only affected the hydrodynamics, not the hydrostatics or structural mechanics, so the team thought it uninteresting to explore at this time, besides the fact that typically a speed is designated as a requirement by a customer.

Thus, the remaining design variables for this project were:

- The length (L)
- The beam (B)
- The depth (D)
- The thickness of the steel plates (t)

The bounds for our design variables are typical of barges.

Design Variables		Lower Bound	Upper Bound	Unit
L	Length	90	140	m
B	Beam	20	35	m
D	Depth	4	9	m
t	Plate Thickness	12	28	mm

3-1: Design Variables and Bounds

Additionally, implementation of the code required several other inputs that the team considered fixed for the purposes of this exploration. These parameters were required by one or more modules to adequately model the appropriate responses of the modules to the design vector. These design parameters were:

Design Parameters		Value	Unit
v	Speed	10	knots
kg	Payload vertical center of gravity	1.2D	
lcg	Payload longitudinal center of gravity	0.5L	
ω	Peak spectral frequency	0.7	rad/sec
H	Significant wave height	2.5	m
ρ	Sea water density	1025	kg/m³
ρ_{str}	Material thickness	7850	kg/m³

3-2: Design Parameters and Values

- The significant wave height of the assumed ocean conditions (H)
- Peak spectral frequency of the assumed ocean conditions (ω)
- Mild steel material density (ρ)
- Young's Modulus of mild steel (E)
- The longitudinal position of the center of gravity (LCG)
- Sea-water density (ρ_{sw})
- Fresh water density (ρ_{fw})

Like any typical engineering problem, the team recognized there would be constraints that limited our potential solution set. Steel beams and plates cannot extend to infinite without buckling under their own weight at some point, let alone sustain added pressure from a payload without buckling. Other physical constrainsts were accounted for. There were also assumed customer constraints, for instance the frequency that the customer would allow the cargo to get wet given the assumed sea state. The team did their best to account for several physical and customer constraints on this problem, finally ending with:

Inequality constraints:

Inequality Constraints	
N<60	Number of occurences of green water on deck per hour
T<6m	Draft
GM>0.15m	Metacentric height
B<30m	Beam <30m to fit through Panama Canal
$\sigma_{k,sag}$<250MPa	Keel stress at sagging wave
$\sigma_{k,hog}$<250MPa	Keel stress at hogging wave
$\sigma_{d,sag}$<250MPa	Deck stress at sagging wave
$\sigma_{d,hog}$<250MPa	Deck stress at hogging wave

3-3: Inequality Constraints

- The maximum allowable stresses for the deck and the keel in sagging, hogging and calm water conditions must be less than or equal to the critical stress of mild steel
- Initial metacentric height greater than 0.15m for initial stability (Limit set by American Bureau of Shipbuilding (ABS) rules)
- Occurrences of green water on deck less than or equal to one every minute
- The draft must be less than 6m, a reasonable depth for a dredged channel or river
- The width must be less than 35m in order to fit in certain locks along seaways

Equality constraints were:

- Buoyancy must equal the weight (floating condition)

Because the model was greatly simplified, the Design Structure Matrix (DSM) representation of each of the parameters and variables within each of the modules was also rather simple to see. We were able to remove iterations and loops using only one iteration through the DSM, as noted from Figure 1 to Figure 2 below.

Design Vector	Const Vector	Hydrodynamics	Hydrostatics	Structural Mechanics
		1-6,8	1-5,8	1-5
		20,21,25,26,27	23,25-27	22-24
		7		7

Figure 1: Initial DSM

Design Vector	Const Vector	Hydrostatics	Hydrodynamics	Structural Mechanics
		1-5,8	1-6,8	1-5
		23,25-27	20,21,25,26,27	22-24
			7	7

Figure 2: Final DSM

The analysis routines include the evaluation of the three disciplines modules. The hydrostatic module comprises calculations for determining the position of the barge's center of gravity in its loading condition. This is then used to determine the vertical metacentric height (GM), which is the most representative stability index. This implementation evaluates GM that has to be greater than 0.15m according to the ABS rules.

The structural analysis module evaluates ABS-derived parametric equations to determine the maximum stresses in hogging and sagging wave conditions. This assumes a uniform longitudinal weight distribution, which is not expected to be always true in real-case scenarios but is a reasonable assumption within the scope of this project. Maximum bending moment stresses are experienced in the deck and keel edges and these particular values are evaluated against the stress limit for mild steel, which is our material choice.

The hydrodynamic module evaluates the seakeeping behavior of the barge. Seakeeping analysis is limited in the coupled heave and pitch responses and the output is the number of occurrences of green water on deck per hour. For this project we have set the constraint to be less than sixty. Pitch and heave motions are calculated based on 2D strip theory and are evaluated against head seas. The local hydrodynamics properties are based on experimental measurements from Lewis form theory. The necessary curve fitting is implemented to allow for a continuous design space exploration. Seakeeping is evaluated for the Bretschneider spectrum with a significant wave height of 3m and peak spectral frequency of 0.7rad/sec. This choice of spectrum may not be ideal for a barge project design since it is most applied for fully developed seas but still is adequate for the purpose of this project.

The basic input/output diagram is depicted below in Figure 3. There are several intermediate variables and parameters, as mentioned, but this simple diagram captures the design variables, the outputs of the modules, and the subsequent calculation of our objectives using those outputs.

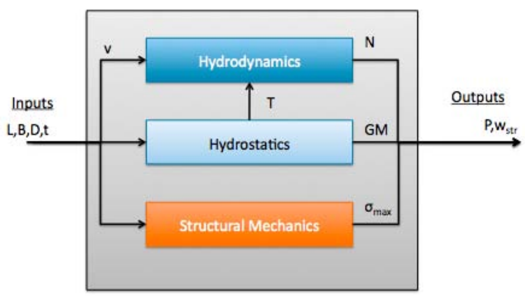

Figure 3: Input/Output Diagram with Modules

The program starts from zero payload and performs iterations until the maximum payload is achieved for a specific design vector without violating any constraint in a Multi-disciplinary Feasible (MDF) aproach. At the same time the structural weight necessary to implement this design is calculated, this value can be used as a surrogate result for the cost of the vessel.

4 Validation

The code was used in analysis mode to validate its results against a known barge, the MARMAC 400, found with Macdonough Marine Service. This benchmarking gave good confidence in the model and the results. Our design vector was:

- 122m length
- 30m beam
- 6.1m depth
- 16mm thickness

The analysis code gave the results of:

- 4.35m loadline draft
- 14,670MT payload

These results compare very well with the MARMAC 400. The characteristics of this existing barge are:

- 121.92m length
- 30.4m beam
- 6.1m depth
- 4.34m loadline draft
- 11,453.9MT payload

Initially, there was concern that the team's result for payload was significantly higher (28% higher) than this existing barge. However, upon further inspection of the characteristics of the MARMAC 400, there are differences that can explain a good portion of this difference. For instance, the modeled barge was an exact square box with an inner bottom for added structural strength. The MARMAC 400 is not a perfect box; it has shaped bow and edges. This decreases the volume of the MARMAC 400 compared to the model.

Additionally, the MARMAC 400 does not have an inner bottom for added strength. The team postulates that the MARMAC 400 could be limited in the capacity it can carry due to its structural members; the shell might buckle earlier and thus have hogging or sagging stresses in the deck or keel as a limiting factor, whereas the active constraint of the model was the number of occurances of water on deck. Additionally, the MARMAC 400 likely has more structural members in the form of plate stiffeners and girders that likely increase the structural weight of that vessel compared to ours, which will also increase the hogging and saggin moments of that vessel compared to ours, which in trun decrease the payload.

Lastly, the payload characteristic of the MARMAC 400 is based on operations, where the segmentation of the stores on the MARMAC 400 limits its capacity. Operators could overcome this limitation by stacking cargo higher, but then would run into the metacentric height constraint for stability. Contrastingly, the model has no segmentation, and assumes a uniformly distributed load both longitudinally and athwartship throughout the vessel (uniformly distributed dirt, or sugar cane, or concrete, for instance). This aspect allows the model to fit more payload in the vessel with a lower metacentric height of the vessel-payload system.

Thus, with these considerations in mind, the team considered the model adequate enough for evaluation purposes. Additionally, the team recognized that these differences and real world constraints would scale with the barge, so that any optimal solution would remain the optimal solution with the above considerations, even though the payload may not be exact.

5 Initial Design Space Exploration

An initial exploration of the design space was carried out using a fractional factorial design. We discretized the remaining four continuous design variables to three levels – high, medium, and low. For simplicity, the team chose the high values to be the upper bounds of each of the design variables, the low values to be the lower bounds of the variables, and the medium values to be the midpoint of the bounds. A full factorial design would mean 3^4=81 experiments. At the time, the team was only interested in the main effects and two-way interactions, so a fractional factorial design was selected instead.

Thus, the team completed 48 runs. Sixteen of these runs returned infeasible results, and were eliminated, leaving 32 runs to analyze. The results of these 32 runs were used in JMP® statistical software to determine the main effects. The results, in Figure 4 below, conclude that the beam had the most significant effect on the payload, and length and depth had about half as much affect. The values for length and beam had very high confidence levels, while the draft was quite widely distributed. This gave the team good confidence in the model, but, more importantly, gave a good starting point for the numerical optimizations.

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-25816.74	1781.269	-14.49	<.0001
L	220.82255	11.14172	19.82	<.0001
B	444.69651	34.35048	12.95	<.0001
D	218.94769	126.6491	1.73	0.0953
t	-50.15281	39.0948	-1.28	0.2104

Figure 4: Design Variable Estimates from JMP®

Specifically, the starting point used during optimization, based on the results of the DOE, was:

- 140m length
- 30m beam
- 9m depth
- 20mm plate thickness

6 Optimization Algorithms

6.1 Gradient-based Optimization: SQP

We selected Sequential Quadratic Programming (SQP) for our gradient-based optimizer. MATLAB uses this algorithm in the function "fmincon." The barge model uses a multi disciplinary feasible (MDF) approach that builds the equality and inequality constraints into the subsystem modules. Subsequently, no constraints are handled by the optimization algorithm at the system level.

The bounds on the design variables make the optimization process challenging using an unconstrained algorithm. MATLAB's "fminsearch" and "fminunc" functions were available to use Steepest Descent, Quasi-Newton, or Newton's method but would require a formulation to penalize the objective function when the design variables fell outside of the feasible region (outside of the design variable bounds). Introducing penalties for bounds violation would introduce complexity in the optimization algorithm. Consequently, the team selected "fmincon" as the most effective and elegant way to input bounds for the design variables and optimize the model.

6.2 Single Objective Optimization: Payload

Payload was selected as the single objective function to be optimized. Between payload and structural weight, we believe that the process of optimizing the payload will provide better insights for the design process. Moreover, payload seems to be more directly coupled with all constraints.

Convergence of the algorithm was achieved only after the convergence tolerance on the model was significantly reduced. High convergence tolerance initially caused the optimization algorithm to finite difference noise and fail. When we specified a smaller convergence tolerance, the optimization algorithm yielded the local optimum in the order of 20-25 iterations with a random starting point.

Starting from $x_0 = \begin{bmatrix} 140 \\ 35 \\ 9 \\ 20 \end{bmatrix}$ where the DOE found the best solution. After 16 iterations the algorithm yielded:

$$x^* = \begin{bmatrix} 140 \\ 35 \\ 8.2 \\ 15.78 \end{bmatrix}$$

as the optimal solution, resulting in a payload of 24,358 tons. Compared to the initial starting point payload of 23,757 tons, the optimal had an increase in 601 tons.

The optimal barge maintains the maximum length and beam, but is 0.7 meters less deep, and 4.22 mm less plate thickness. The DOE showed, and we expected, the largest boat in length and beam to provide the largest payload possible. The solver confirmed that and did not move from the upper bound on length and beam. The decrease in the last two variables, depth and plate thickness, produced a more efficient ship, mainly because of structural considerations. Reducing plate thickness applies to the entire barge so even a small reduction brings down overall barge weight. Any lessening in hull thickness needs to maintain the structural constraints, such as maximum allowable stresses at a hogging wave, but will also reduce the weight that goes into the hydrostatic constraints. The solver found the thinner hall, with a reduced depth, was still feasible and reduced the barge weight allowing for additional payload.

The algorithm yielded a moderate improvement. Taking into account that our starting point was the best estimation from the DOE, the small amount of improvement seems reasonable.

6.3 Sensitivity Analysis

The gradient of the objective function at the optimal solution was:

$$\nabla J = \begin{bmatrix} 1.62 * 10^6 \\ 717 \\ 16 \\ -140 \end{bmatrix}$$

Figure 5 shows the normalized sensitivities for each design variable after normalization around the optimal solution.

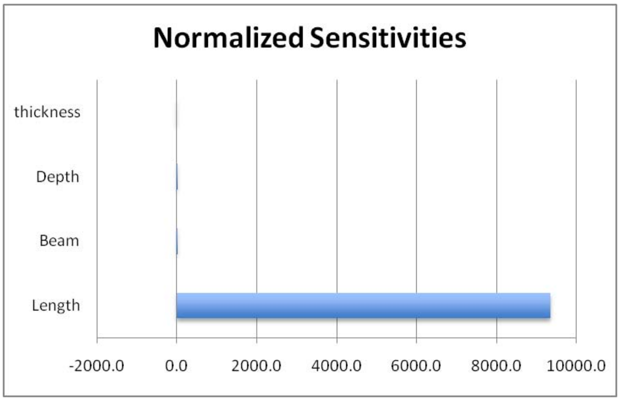

Figure 5: Normalized Sensitivites for Design Variables

The length (L) has the significant effect. This agrees with intuition; the size of the barge has a significant effect on the payload capacity of the barge. This finding strengthens our notion that SQP found the optimal solution. Any increase in length has a large impact on improving the objective; the SQP solution was the upper bound of length. As long as constraints are not violated, the most length will be used. We expected to experience similar results with beam, but found that it had little impact.

The plate thickness (t) slightly decreases the payload as it increases. This also follows intuition. Any additional thickness of the hull will increase the barge weight, and will not allow the same amount of payload to meet structural constraints.

Two of the constraints were active at the optimal solution, the number of occurrences of green water on deck per hour (N) and deck stress at hogging wave ($\sigma_{d,hog}$).

We manually extracted the parameter sensitivity. The output arguments of the optimization algorithm could not provide this because we used an MDF implementation -- all constraints were handled within the model. This is a disadvantage of MDF implementation of the model.

The manually extracted parameter sensitivity showed us the impact of speed, v, as seen in the Figure 6. The constraint of green water on deck is highly dependent on speed. The increase of speed will cause more green water on deck and violate the constraint. The violation of the constraint because of faster spped could be remedied by decreasing the payload or the size of the barge (which would also decrease the payload).

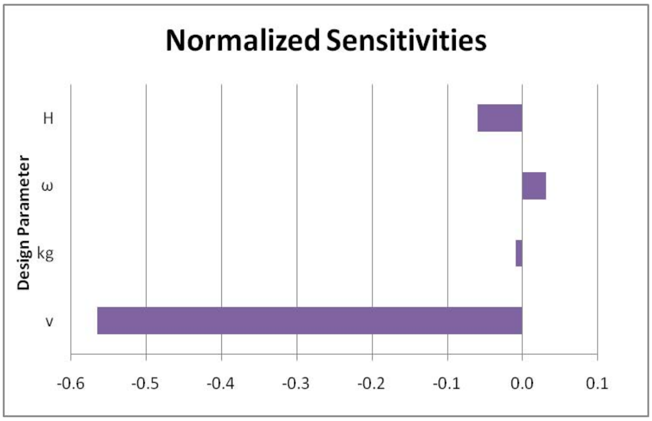

Figure 6: Normalized Sensitivites of Design Parameters

The parameters payload vertical center of gravity (kg) and significant wave height (H) also had negative impact on the overall payload. An increase in either parameter would also impact the number of green waves on deck, but not as significantly as speed.

6.4 Heuristic Optimization

We used a Genetic Algorithm on maximize barge payload. The team expected the GA to be easiest heuristic to understand and implement. Moreover, the fitness function implementation was straightforward for our maximization problem and without necessity to include any constraints. Finally, the bounds of the design variables can be set within the algorithm.

Although the GA was expected to be computationally expensive, we decided to leverage the probabilistic transition rules it uses for a more robust design space exploration.

Our first attempt to implement the GA yielded results comparable to the gradient-based SQP we used in the previously. Specifically, the best fitness occurred at:

$$x^*_{ga} = \begin{bmatrix} 138.7 \\ 34.6 \\ 8.9 \\ 25.1 \end{bmatrix}$$

resulting to P = 22,468 tons compared to 24,358 tons at

$$x^*_{SQP} = \begin{bmatrix} 140 \\ 35 \\ 8.7 \\ 14.2 \end{bmatrix}$$

from the gradient-based SQP.

The GA appeared to stop near a local optimal that was much thicker than the SQP solution (10.9 mm greater). The thicker hull probably required a smaller boat so the length and beam were reduced. This plate thickness was actually greater than the 20 mm we used from the DOE.

This GA implementation used crossover rate of 1, mutation rate of 0.03 and 16 bit encoding for all design variables. This encoding corresponds to a precision higher than 10^{-2} for all design variables based on

$\Delta x = \dfrac{x_{UB} - x_{LB}}{2^{bits}}$ and drives the population size.

A second attempt was made by at 0.02 mutation rate. The results were comparable to the first GA implementation but did not reach the gradient-based SQP implementation.Namely, the best fitness occurred at

$$x^*_{ga} = \begin{bmatrix} 139.77 \\ 34.97 \\ 8.99 \\ 24.29 \end{bmatrix}$$ with P = 23,060 tons.

Both GA runs exceeded 10 hours to evaluate 100 generations. The noticeable difference between GA and SQP was the plate thickness (t). Both GA implementations pointed higher thicknesses but the lower thickness found from the SQP yields higher payload and follows intuition as explained previously. Additional GA tuning was seen unnecessary.

6.5 Global Optimum

Running the optimization with different starting points resulted in different optimum solutions. This reveals that our design space is non-linear. Although, after leveraging the DOE results, we expected SQP to have found the global optimum, we were cautious since SQP is inherently incapable of dealing with local optima and we had indications that there may be many in this design problem. GA implementation pointed towards this direction even though it did not succeed in reaching the optimum with good accuracy.

The global optimum is thus estimated at:

$$x^*_{SQP} = \begin{bmatrix} 140 \\ 35 \\ 8.7 \\ 14.2 \end{bmatrix}$$

where P = 24,358 tons.

7 Post-optimality Analysis

The calculated Hessian matrix using second order finite differencing for a stesize of 10^{-4} at the optimal solution was

$[2.4473\text{x}10^{12} \quad 2.44731\text{x}10^{12} \quad 2.44695\text{x}10^{12} \quad 2.44695\text{x}10^{12}]$

Altough these entries were very high, they still were of the same order and subsequent attempt to scale the design variables did not provide any improved results. This was expected as the convergence history was fairly straightforward as depicted in Figure 7. The function approaches convergence at the sixth iteration of the algorithm.

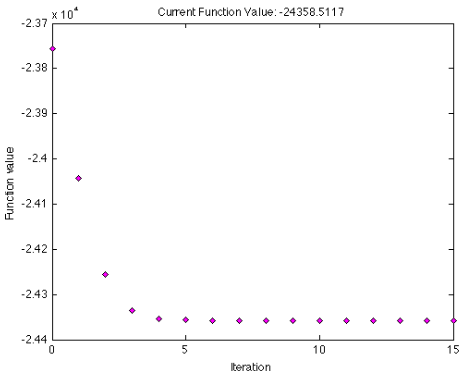

Figure 7: Convergence

8 Multi-objective Optimization

The two objective functions are:

- Payload [tons] representing the cargo capacity of the barge (maximize).
- Structural Weight [tons] representing the material cost of mild steel needed to construct the barge (minimize).

Since these two objectives were decoupled in the model we were able to optimize the structural weight for different values of feasible payload.

As can be depicted from the Pareto front in Figure 8, these two objectives are opposing. Function evaluations of barge designs have typically shown that larger payloads were achieved by increasing the principal dimensions, which entails increased structural weight.

The initial linear behavior is probably dictated by the principal dimensions' lower bounds. Afterwards, the limitations seem to be imposed by the various non-linear constraints.

The upper right corner is the single objective optimal solution for payload represented by the red circle.

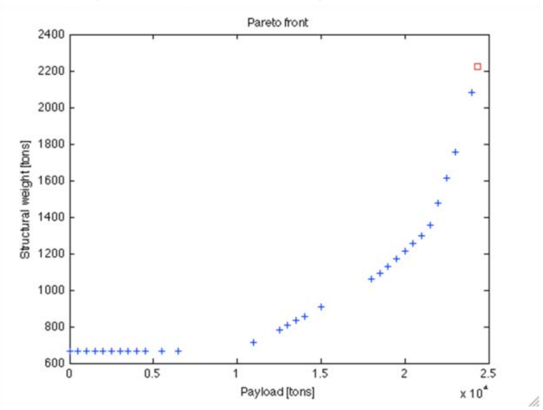

Figure 8: Pareto

We conducted a trade off analysis at our single objective optimal point. We found one extra ton of payload required 326 kg of structural weight.

Acknowledgment

None.

References

[1] ABS Rules, Steel Vessels 2007