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PARAMETRIC OPTIMIZATION OF A SEMI-SUBMERSIBLE PLATFORM WITH HEAVE PLATES

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ABSTRACT
The hydrodynamic responses of a semi-submersible platform are driven by its mass properties and geometric parameters, e.g. column size, spacing, draft and pontoon size. The mooring system also influences the platform responses. Heave plates added to the base of each column have been proposed to enhanced stability of semi-submersible platforms, particularly in the lower payload range. Optimization of a platform typically involves a compromise among a large number of factors including the structural weight, vertical, horizontal motion and rotations in operating and extreme sea-states, airgap, mooring size, etc.

Optimization methods are reviewed. The complexity of the problem leads to the choice of a genetic algorithm presented herein. To allow systematic platform optimization assuming primary project parameters are given, i.e. payload, waterdepth, environmental conditions. A simplified hydrodynamic model is developed to capture the parametric sensitivity of the platform responses to primary design parameters.

KEYWORDS
Optimization, genetic algorithm, semi-submersible platform, Minifloat.

INTRODUCTION
Minifloat is a novel concept of semi-submersible platform developed to enable hydrocarbon production from marginal fields in deep and ultra-deepwater. The equipment is set on a triangular deck, which is supported by three rectangular columns, with a water-entrapment plate at the keel as shown in Figure 1. Several versions of the concept have been developed to cover a wide range of applications and payload: Minifloat II provides control and chemical injection features to subsea wells. It has limited power generation capabilities. Minifloat III is a larger version of the platform, expanded to provide large amounts of power for sea water-injection, multiphase pumping or subsea gas boosting. Finally, Minifloat IV is the largest version of the platform providing full process capabilities for up to 50,000 barrels of oil per day. This paper will focus primarily on the Minifloat III platform. The optimization method presented in this paper is applicable to other platform types and offshore systems in general.

Extensive hydrodynamic and structural design studies (Cermelli, 2004, Cermelli, 2005 and Aubault, 2006) have been performed to address the technical challenges. The design has been refined by multiple trial-and-error iterations aimed at enhancing the hydrodynamic performance of the platform while minimizing its cost. Various optimization studies have been conducted for several sets of functional requirements, and several locations in the Gulf of Mexico.

The optimization process involves a large number of design parameters interacting with each other through sometimes complicated relations. One such example is the platform maximum allowable rotation in roll and pitch which is based mainly on the functional requirements of the platform equipment and which depends on the platform mass distribution, the column size and spacing as well as the size of the water-entrapment plates.

Because of the number of parameters involved and their interdependence, it is difficult to perform optimizations in a systematic manner that ensures the lowest cost has been reached while satisfying all minimum requirements.

To assess quickly and efficiently the feasibility of the Minifloat in any location for a given set of functions, a fast optimization tool was developed and applied to cost optimization. Although the design of offshore platforms is driven by a multiple of criteria, minimizing the cost of design, fabrication and installation of the platform, also referred to as CAPEX (CAPital and EXpenditure cost) is the essential objective. The

cost of operation (OPerational EXpenditures or OPEX) has not been included in this analysis for simplicity.
A review of existing optimization methodologies was conducted. The applicability of so-called “genetic algorithm” is investigated in this paper.

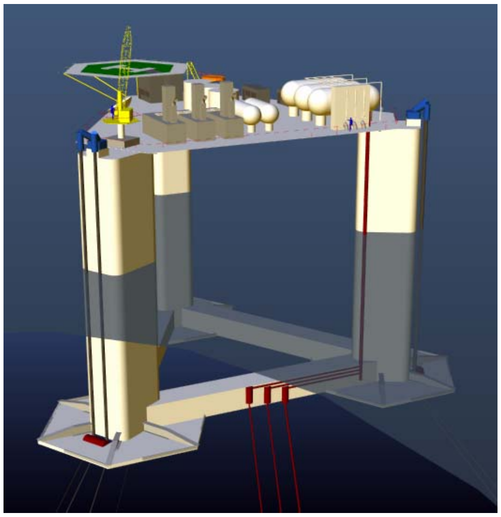

Figure 1: Minifloat III: a water-injection semi-submersible platform

PROBLEM DEFINITION

In this paper, a sea water injection facility for the Gulf of Mexico ultradeep water was considered to test the optimization process. The system under consideration is presented in the schematics of Figure 2. It includes the platform and water injection lines. The cost of the water injection wells is excluded because it is assumed that the performance of the platform will not affect the wells requirements. The production wells, flowline and production platforms are assumed to be existing and are not part of the system to be optimized.

Although it may be tempting to simplify the problem by only considering the platform, a whole system optimization is preferable, since lowering the cost of the platform only may result in detrimental effects on the risers, which may in turn lead to a higher total system cost.

A set of functional requirements are first established; in the selected test case, the following functions must be performed:

1. ability to support sea-water treatment (deox) and injection capabilities for 30,000 barrels of water per day in two injection wells
2. ability to operate the equipment in all weather conditions up to a 10 year winter storm; it is assumed that equipment breakdown is taken into account by providing proper amount of spares and redundancy, therefore the only time when the platform shuts down is when the 10 year winter storm criteria is exceeded.
3. ability to remain on location and sustain only minimal damage in a 100 year hurricane
4. ability to accommodate platform operators for overnight stay, and helicopter landing and take-off during one year winter-storm.

In addition, it is assumed that the platform must meet the minimum requirements for ABS certification for Floating Production Systems

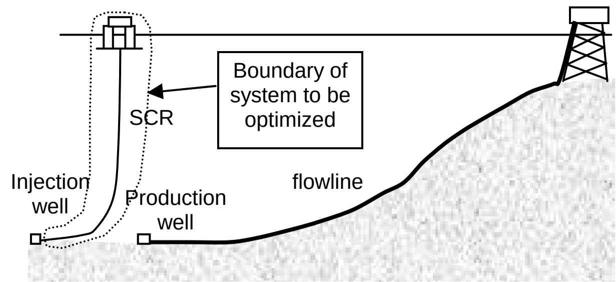

Figure 2: Representation of the offshore system the optimization process focuses on

A minimal set of input parameters must be defined for the algorithm, such as environmental conditions and waterdepth. Clearly, this analysis is not meant to replace a detail engineering phase in which all relevant parameters, including directionality of the environment, soil conditions, bathymetry, etc would be considered. The above requirements are converted to a set of design criteria which depend on the project input parameters.

It is assumed for this problem that the general shape of the platform is already known but dimensions must be adjusted. In a first phase, the design variables are selected: they are a set of geometric parameters for instance airgap, draft, column spacing, water-entrapment plate size, etc. These may be defined as a vector **λ** of n variables also referred to herein as “strings”.
The objective of this work is to minimize the CAPEX, also referred to as objective function herein. The objective function is defined as:

$$CAPEX = f(\lambda) \qquad (1)$$

Fixed costs, such as engineering of the platform, are neglected in the formulation of the objective function. The main contribution to the cost function can be split in four subsets:

- Hull and deck fabrication
- Mooring manufacturing
- Riser fabrication
- Installation

The hull and deck related costs are expressed as a sum over its individual parts of the estimated cost density c_i of the part

times its mass M_i. The mass is a function of **λ**. The installation costs are treated as a function of the size of the platform and vary with location. Proper cost modeling of risers and mooring needs to take into account the hydrodynamic performance of the platform. Since this paper focuses on implementation of the optimization method, the mooring, riser and installation costs are not included here for simplicity.
The optimization problem is formulated as follows:

$$\underset{\lambda}{Min}\left\{\sum_i c_i \mathrm{M}_i + C_{moor} + C_{riser} + C_{install}\right\}, \qquad (2)$$

where *i* the parts of the platform (columns, pontoons, plates, deck, equipment).

The minimization is subject to physical constraints. These constraints include the requirement to balance weight and platform displacement:

i. $\rho\nabla = \sum_i M_i + M_{ballast}$, where $\rho\nabla$ is the displacement in operation, and $M_{ballast}$ is the weight of ballast.

Additionally, this payload constraint must be verified with no ballast at the transit draft. The maximum allowable transit draft depends on the integration yard.
The optimization is also constrained by stability considerations. Both intact and damaged stability should be verified. Only the former is considered in the present paper. The solution should result in a stable structure during the towing phase as well as in operation.

ii. $GM \geq \beta$, where β is the minimum metacentric height.

The hydrodynamic behavior of the platform is considered by monitoring the period of resonance of the system in heave. A more detailed hydrodynamic modeling, based on the maximum response in a design sea state, was also investigated.

iii. $T_{heave} \geq \gamma$, where γ is the minimum heave period

Other constraints may be included in the analysis to reach a physically reliable solution. The tension in the mooring lines for instance should be limited in conditions of operation:

iv. $a \leq h(T, MBL) \leq b$, where MBL is the Maximum Breaking Load of a given segment of mooring, T the tension which should be carefully estimated.

As noted above, constraints and costs related to mooring, risers and installation are left aside in this study, to focus on the implementation and validation of the optimization algorithm.

All equality and inequality constraints above can be summarized respectively as:

$$h(\lambda) = 0 \text{ or } g(\lambda) \geq 0 \qquad (3)$$

OPTIMIZATION WITH A GENETIC ALGORITHM

The optimization problem defined above is fully non-linear. A classical approach to such non-linear problems involves the use of conjugate gradient methods. Such methods require the objective function to be differentiable. Since this work aims at taking in account all contributions to the cost of the platform, including the installation cost, it is expected that the cost function may not be a continuous function of the geometric parameters of the platform. Also, the potentially large number of design variables yields a complex problem, best handled with methods that rely on the direct computation of the objective function.
Genetic algorithms (GAs), a probabilistic procedure of optimization using parallel computation and evolutionary parameters, use this approach. Onwubiko (2000) also points out the robustness of GAs in finding an optimum solution to a variety of problems.

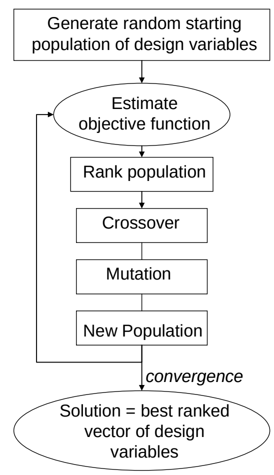

Figure 3: Structure of the genetic algorithm

Genetic algorithms are based on the convergence of a random "population" to the solution, through "reproduction" or "crossover". The objective is to outperform a purely arbitrary search tool by combining probabilistic rules with the information from previous generations of tested design variables to converge to a solution. Initially, a number M of design variables **λ** are randomly generated. This "population" is tested: the objective function is evaluated and the design variables are ranked according to their ability to solve the problem, i.e. to minimize the cost function and to satisfy the constraints. The best sets of design variables are retained. "Reproduction" aims to produce a set of N combinations of design variables to be considered for the next iteration. In this phase, the method described by Zodhi and Wriggers (2003) has the advantage of mixing random generation and preservation of the good design variables. At every iteration, the new "population" is computed as follows:

- M vectors (or strings) **λ** are kept from the previous iteration: they gave the most promising results, i.e. the lowest value of the objective function.
- M vectors **λ** are created by combination of two **λ** from the group above: they are the "children". In some problems,

the combination method can have a large impact on how fast the algorithm converges toward an acceptable solution. In the case of the Minifloat III cost optimization, no difference in convergence was observed whether an arithmetic crossover of parents or a geometric crossover was used. The former was kept to obtain results.

- N-2M vectors **λ** are generated randomly. They are important especially at the beginning of the process, to keep bringing more diversity to the population and converge faster towards acceptable solutions

To ensure the convergence of the algorithm, it is important to retain diversity in the set of strings that carry on from one generation to the other as well as to avoid disrupting the convergence of the optimization process. Diversity of the tested strings prevents the algorithm from early convergence toward a local minimum. This is achieved by bringing in new random combinations, but also, as recommended by Eshelman and Schaffer (1991) by forbidding similar parents to mate, to prevent the population from becoming uniform. Keeping the best parents and using them to create modified versions encourages local convergences. If this local minimum is also the global minimum, the mating scheme will help converging. If the global minimum is located elsewhere, it is essential to leave the opportunity for the algorithm to come out of the local minimum it has found.
To enable the algorithm to come out of potential local minima, another feature is added to the genetic algorithm: the best parents **λ** are randomly picked up to undergo a mutation. The mutation consists in a random modification of a given number of the variables of **λ**. The impact of the mutation may be function of the iteration number as described in Michalewicz and Shoenauer (1996). The probability of mutation, or mutation rate, is set to a large value. Figure 4 illustrates the efficiency of mutation, even in the simple case of the unconstrained problem: the convergence to the solution is faster when the probability of mutation of the parents and children in the population grows. With a probability of 10%, one notices that the search stagnates during 5 iterations in the same local solution.

The algorithm was tested on a Minifloat III, with column side, pontoon side, water entrapment plate edge, draft, airgap and column spacing as variables. The optimization was focused on the cost of the platform, but no physical constraint was considered. The fixed cost of equipment is not included, and the final price of the hull is null, which is consistent with the fact that excluding all constraints, the cheapest platform is no platform!

A reliable convergence criterion is difficult to determine for a genetic algorithm, as it could easily lead to a local solution or it could stagnate for a number of iterations before undergoing further improvement toward a lower cost solution. To ensure that convergence is attained, sensitivities are performed on the number of iteration and the series of pseudo-random numbers that are used. This is discussed more thoroughly in the next sections.

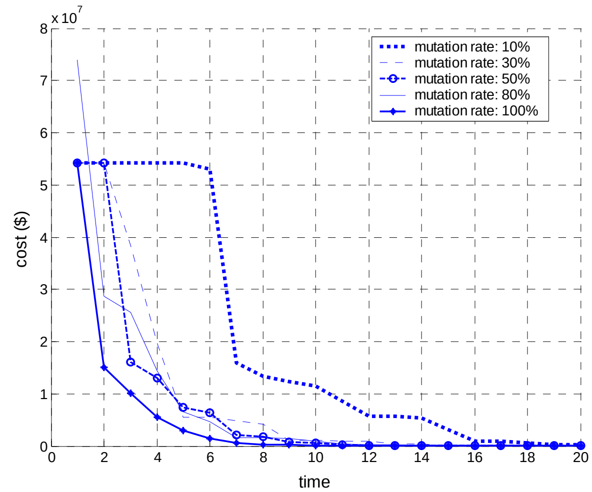

Figure 4: Comparison of Speed of Convergence for Several Mutation Rates

CONSTRAINED OPTMIZATION

Constrained optimization may be approached in two different ways. Some methods evaluate the constraints at each stage of iteration of the optimization method and discard solutions that do not fulfill all constraints. This approach may lead to inefficient programming in case of complex constraints. A popular method, the introduction of global penalty functions is used to alter the objective function and account for the constraints i to iv. The final problem to solve is unconstrained:

$$\underset{\lambda}{Min}\left\{f(\lambda)+\phi(R,g(\lambda))+\varphi(R',h(\lambda))\right\} \qquad (4)$$

Where g is the inequality constraint function and h the equality constraint function of equation (3); R and R' are the penalty parameters and Φ and φ are the penalty functions, which increase with R. They are defined as follows:

$$\phi=\begin{cases} 0 \; if \;\; g(\lambda)\geq 0 \\ u(R,g(\lambda)) \; otherwise \end{cases} \quad \text{and} \quad \varphi=\begin{cases} 0 \; if \;\; |h(\lambda)|\leq\varepsilon \\ u(R,h(\lambda)) \; otherwise \end{cases}$$

Michalewicz and Shoenauer (1996) reviewed definitions of the penalty function u. For this paper, the approach chosen by Joines and Houck (1994), where the penalty parameter increases with the iteration number, was selected. Such a variation reduces the drawbacks of a small R that would allow unfeasible designs and of a too large R that would initially shrink the design space:

$$u(R,g(\lambda)) = Rn\times\left|g(\lambda)\right|^2$$, with n the iteration number

The search is allowed at first to increase the range of possible strings by allowing more unfeasible combinations of design variables, and, as the iteration number increases, the solution converges towards a feasible one.

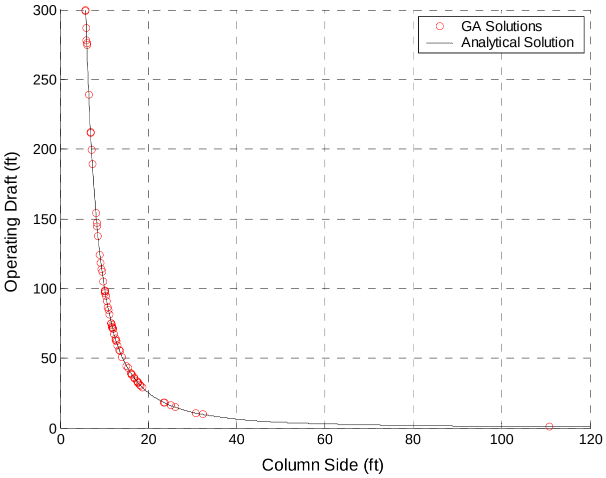

Figure 5: Comparison of results from genetic algorithm with 70 different starting populations (red circles) with the analytical solution (black curve) for a payload of 850 s.t., assuming a column mass density of 8lb/ft3

The implementation of the penalty function method was validated on the cost minimization problem with six variables, subjected to one equality constraint, i.e. a solution is feasible if the total displacement of the structure is equal to its total mass. The solution to this problem may be obtained analytically for given payload, water density and column, pontoon and heave plate mass densities. Assuming the mass of the deck depends linearly on column spacing, the optimized solution yields a structure with no deck, no water entrapment plate, and no pontoon. The cost of this 3-column structure is minimized when the volume of a column is defined by:

$$V_{column} = c^2 T = \frac{M_{equipment}}{3(\rho_{water} - \rho_{column})}, \qquad (5)$$

where c is the side of a square column, T the draft of the structure, and ρ the mass density.
The analytical function that defines all possible solutions is plotted on Figure 5: the cost is minimal for all combinations of draft and column side on the curve, given an 850-ton payload. The genetic algorithm is run with different starting populations of 50 vectors each. All variables but the column cross section and draft converge to 0. Figure 5 displays the mapping of results for the operating draft T and column side length c. Each starting population yields one converged combination of draft and length. All results have converged to the same cost and the design variables are randomly distributed on the curve of possible combinations of draft and column side length. Hence, the design variables from the GA verify the analytical solution.

The convergence of the objective function and the cost function for one of these populations is represented in a logarithmic scale on Figure 6. The difference between the objective function and the cost function corresponds to the penalty. One notices that the decrease of the cost function is not monotonous, unlike in the unconstrained case. At iteration 19, for instance, the cost function increases. In the meantime, the objective value gets smaller, because the penalty has been reduced. This means that the constraints are better verified. Convergence to the solution involves both minimizing the cost and verifying the constraints. The problem has converged to a feasible state when the cost function and the objective function are equal: all constraints are satisfied. Convergence to a global solution is reached if different initial populations yield similar results.

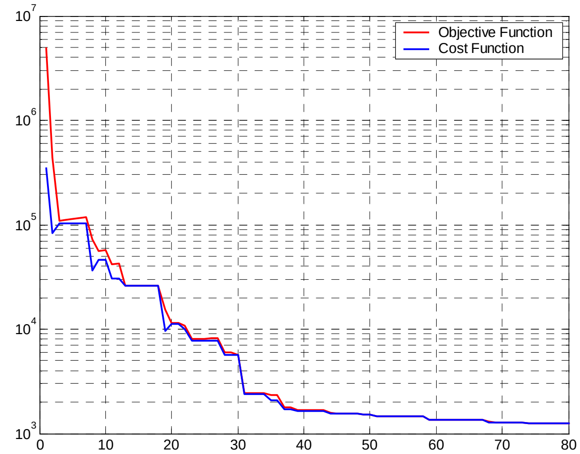

Figure 6: Evolution of the cost function and the objective function (cost + penalty) of the best vector vs the number of iteration, for the cost optimization problem subject to one buoyancy constraint, with 850 s.t. payload. The cost is plotted in a logarithmic scale.

Although it appears to be very efficient on simplified problems, the inclusion of the constraints as penalties to the objective function raises several difficulties. Michalewicz mentions the limits of this approach, as the penalty may be too large and drive the search towards local minima. A solution to this issue is to carefully adjust the weight of each constraint with respect to the others and to the cost function. This method was used to solve the overall minimization problem, including stability considerations in towing and operation and a hydrodynamic modeling. But on complex problems, with a number of non-linear constraints, as Reeves and Rowe (2003) point out, the direct inclusion of penalty functions in the objective function is difficult to achieve successfully. Recent works explore the robustness of algorithms where the penalty function and the objective function are separated.
Results in the present paper were obtained with a set of penalty functions that were scaled with respect of each other, as Onwubiko (2000) recommends in his review of constrained optimization. The constraints were first non-dimensionalized, and then multiplied by a constant, so that their relative weight was similar. It was considered for instance that a difference of

40 tons between the displacement of the structure and its weight was equivalent to a drop or increase of about 1ft in airgap, assuming a column section of approximately 400ft^2. The constraints were scaled so that such a difference of 1ft in airgap would be penalized to the same extent as a drop of 1ft of GM.

PRELIMINARY RESULTS

The genetic algorithm was run with all towing and operating constraints, as well as the constraint on heave period of resonance. Eight design variables were considered, assuming square sections for columns and pontoons: the length of the column side, of the pontoon side, the edge of a hexagonal water-entrapment plate, the operating draft and towing draft, the airgap, the distance between column centers, or column-spacing and the amount of operating ballast. A solution is searched within given boundaries.

Table 1: Summary of results for 30 runs of genetic algorithm with 850-ton payload

	Average Solution	Standard deviation (ft)	Standard deviation (%)	Best Solution
Column Side	18.8	0.56	2.97	18.3
Pontoon Side	12.6	0.11	0.84	12.6
Water Entrapment Plate Edge	33.7	0.86	2.56	32.7
Operating Draft	15.1	1.03	6.82	13.8
Towing Draft	14.0	0.67	4.81	13.1
Airgap	50.4	0.52	1.02	50.1
Column Spacing	173.0	2.57	1.49	174.7

The program is run with 30 different starting populations. The structure should be able to carry an 850-ton payload. GM should be greater than 10ft in operation and 3ft in towing phase. Assuming a design sea-state with Tp=14sec, the period of resonance of the structure should be higher than 20sec. The minimum airgap is fixed at 50ft.

Results are summarized in Table 1. The lowest final cost does not include fixed costs, such as equipment costs. Results for this best solution are given in the last column of Table 1.

The genetic algorithm aims at narrowing down the dimensions of a platform, in a primary phase of design. The precision needed for the values of design variables is sufficient if it is of the order of about 1ft.

On Figure 7, the results are plotted for all runs. The optimized combinations of variables are similar for all runs and usually meet the 1ft precision with the exception of the draft which exhibits more scatter. The standard deviation of the "converged" values of draft is indeed higher than other design variables. To overcome this issue, the next runs will be performed with 10 different starting populations and the best one will be kept. It has proven more efficient to ensure convergence this way rather than to keep running the algorithm for a large number of iterations.

In Figure 8, the displacement of the Minifloat III structure was plotted for various amounts of payload. For converged results, it is equal to the mass of the platform without ballast to a half ton precision. The displacement increases linearly with the amount of payload on the platform.

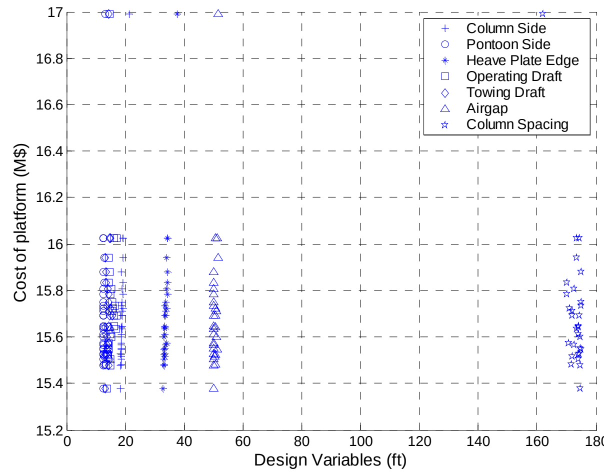

Figure 7: Values of Design Variables for 30 runs of genetic algorithm, with 850-ton payload

The search of an optimized design for the Minifloat III with a genetic algorithm seems to give converged results for the simplified model described above. But, although the solution verifies all physical constraints of stability, buoyancy and period of resonance, it is not a physically viable solution yet. Indeed, the operating draft is kept to very small values and so is the operating ballast. With such shallow drafts, the RAO in heave will tend to be very large. The optimization process is lacking a more restrictive hydrodynamic constraint.

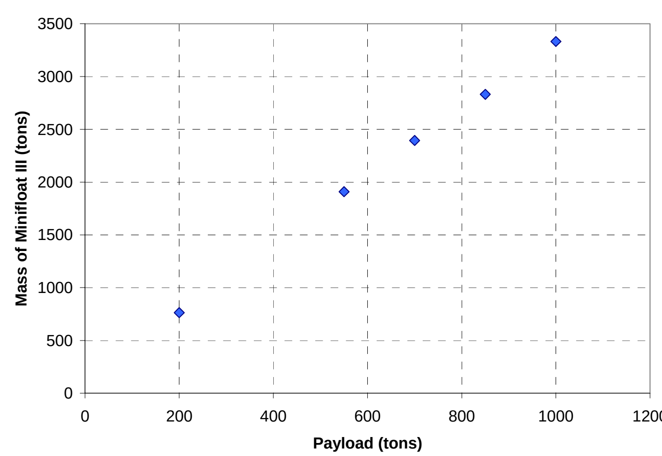

Figure 8: Dimensions of the Minifloat III versus payload

HYDRODYNAMIC MODELING

The hydrodynamic behavior of the Minifloat III in heave was controlled so far by a constraint on the heave period of resonance. It is derived from a model of harmonic oscillator and defined as:

$T_{heave} = 2\pi\sqrt{\dfrac{M+\mu}{K}}$, where μ is the added mass in heave including the contribution of the heave plates, M the mass of the system, and K the hydrostatic stiffness based on the column section.

But the control of the period of resonance does not guarantee a reasonable amplitude of motion at a given sea state. The amplitude of motion at any wave period is represented by the RAO (Response Amplitude Operator) of the structure. These may be calculated by the diffraction-radiation analysis tool WAMIT®. The amplitude of motion in heave is limited by restricting the value of the response for the design sea state, i.e. a significant wave height H_s and period Tp. The design criterion is determined by estimation of the RMS of the waves and the RAO yields the amplitude of motion. Birk and Clauss (1999) have used WAMIT to perform shape optimization of semi-submersible platforms. But direct determination of the RAO for each string of design variables would be strenuous in the case of a genetic algorithm, due to the large number of strings. It was not investigated at this stage of development of the algorithm. Instead, simplified formulations for the hydrodynamic constraint were explored.

A simple hydrodynamic model assumes that the heave RAO depends exponentially on depth:

$$RAO(T) = e^{-kz} f(T') \qquad (6)$$

k is the wave number in deep water and $\dfrac{T}{T'} = \sqrt{\dfrac{d}{d'}}$ using Froude scaling based on column spacing, with d and d' the column spacing of the tested design and of a base case design. The function f(T) is based on WAMIT results obtained for previous Minifloat III studies, with column spacing d'=150ft. Previous research by Cermelli and Roddier (2004) has demonstrated that heave motion is primarily controlled by the water entrapment plate located at the bottom of the columns.

In Figure 9, an example of the RAO scaling is shown. The original WAMIT results, for a draft of 85ft and column spacing of 150ft are plotted with the scaled RAO, assuming a design sea state of 14sec, column spacing 175ft and draft 60ft. For each set of design variables, at a given sea state, the RAO is calculated and its value is compared to the target. The algorithm is run several times for a specified number of iterations, until all constraints are satisfied. The target RAO is achieved within 5% and the dependence of the RAO on draft is clearly visible in Figure 10.

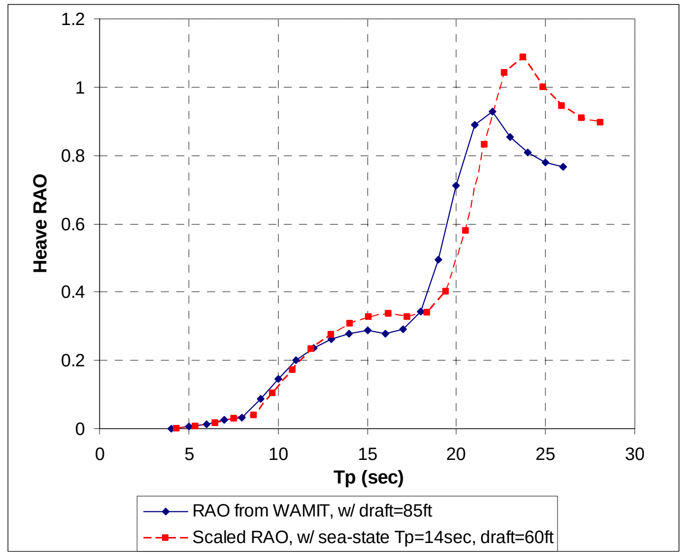

Figure 9: RAO scaling for hydrodynamic modeling of heave motion

Once the acceptable minimum draft is determined by the hydrodynamic constraint, the genetic algorithm offers a good estimate of design variables. Assuming an 850 ton payload, a design sea state Tp=14sec, and a target RAO of 0.3, the minimum cost is K$18,800. This optimum is achieved with a column side length of 25.8ft, a pontoon height of 6.8ft and a heave plate edge equal to 29.9ft. The operating draft is 73.3ft, which, with a column spacing of 175ft corresponds to an achieved RAO of 0.305 at Tp=14sec. The towing draft is 40ft and airgap 50ft. Note that further consideration of structural integrity of the structure will probably result in reduced column spacing.

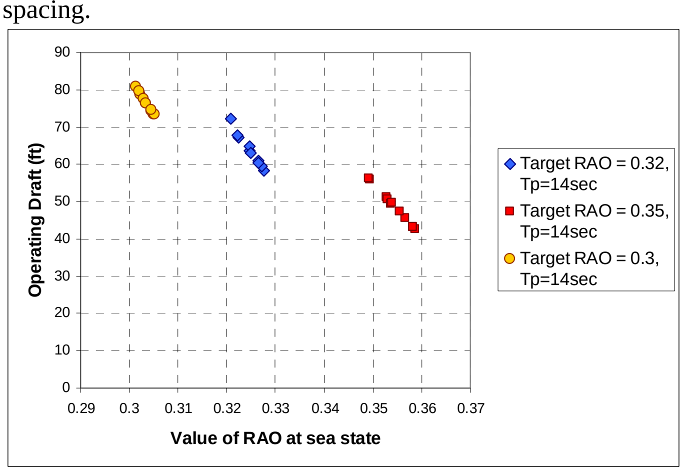

Figure 10: Operating Draft of Optimized Designs for different sea-states

Future research to enhance the robustness of the genetic algorithm with all constraints will be key to precisely identify the optimized solution. Although the algorithm converges quickly at first, the convergence slows down when the region of a minimum is reached. Hence solutions obtained with different starting populations tend to be scattered. This is believed to be due to issues in scaling of penalty function. It may also be related to a lack of local convergence in the search: when the algorithm reaches the region of the solution, there is not enough incentive to test the values nearby to reach the true minimum and the precision of the optimized design is low, which results in a scattering of the solutions from different runs. It is therefore less expensive in computation to generate several solutions and keep the best.

CONCLUSION

To perform cost optimization of platforms such as the Minifloat-III, a method capable of handling complex non-linear multi-variable problems is necessary. Genetic algorithms provide the design engineers with an efficient tool to estimate the dimensions of an offshore structure subject to physical requirements. But constrained optimization raises complex numerical issues. Its implementation with penalty functions as mentioned above may result in a lack of robustness if the constraints are not properly scaled with respect to each other. As a result, it may be challenging to increase the number of physical constraints to the cost optimization problem. Other approaches to constrained optimization will be the subject of future work. An optimized design solution, function of a few physical parameters, was found for a simple problem, with no risers nor mooring, and simplified hydrodynamic considerations. These results encourage future development of the algorithm, with a more complete set of physical constraints to reach an acceptable design for the industry.

Preliminary results, with static constraints, show a linear relation between payload and the platform displacement. But, since the need for a sizeable draft is mostly driven by hydrodynamic considerations, the optimization process resulted in a shallow operating draft. The genetic algorithm is able to produce more meaningful results, using a simple hydrodynamic model based on previous Minifloat III work using the WAMIT hydrodynamic software. A comprehensive hydrodynamic model will be explored, including a more systematic use of WAMIT simulations.

Furthermore, the genetic algorithm should eventually include missing physical considerations, such as structural integrity, and estimate the cost effectiveness of the system as a whole with riser and mooring contributions and installation costs.

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