Automated Multidisciplinary Design Optimization Method for Multi-hull Vessels

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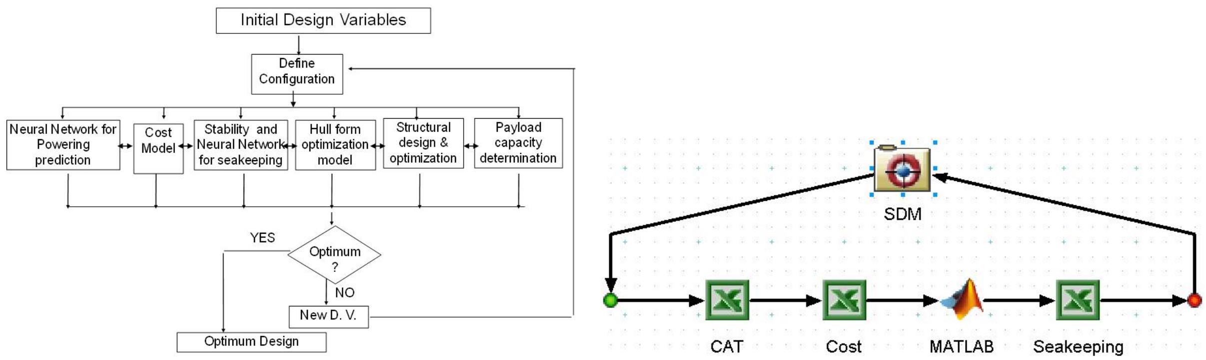
1 Abstract

The purpose of this project is to extend a previously developed synthesis level multidisciplinary design and optimization (MDO) method for a trimaran and apply it to preliminary design stage of a catamaran vessel concept. The synthesis method integrates stability, powering, structural weights, payload, ship cost and hydrodynamic performance of a ship concept into a single design tool. The MDO method itself consists of various "models" to evaluate powering, cost, stability, etc. The seakeeping model is represented by a set of 40 Neural Networks (NN) trained with an algorithm developed at California State University, Long Beach (CSULB) based on cascade correlation. The MDO optimization seeks to minimize three objectives: displacement to resistance boost ratio (DTRBR), dead weight to displacement ratio (DWTDR) and price subject to several constraints including seakeeping. Three single objective optimizations (Multi-Island Genetic Algorithm, MIGA) are first run and those results are used in the initial population of a Neighborhood Cultivation Genetic Algorithm (NCGA). Within this report, pareto results for different configurations are compared without the integration of the NN within the design tool.

2 Introduction

Catamaran hull form vessels can offer several favorable characteristics over comparable monohulls, including the possibility of superior motions and seakeeping characteristics in rough weather. In the preliminary design stage, the MDO program combined with an artificial neural networks is being developed to determine overall dimensions and hull configurations. Figure 1(a) shows a schematic of the MDO process.

The heart of the optimization process is "managed" by iSIGHT-FD [2]. iSIGHT-FD is an optimization software that is used to integrate the different modules defining the catamaran. It combines models such as catamaran performance (weights, cargo capacity, powering, etc), cost and seakeeping 1(b) and maps these components together in a desired data flow. An optimization can then be chosen in iSIGHT-FD to minimize or maximize one or several objective sets in the model. In this research program, it is my responsibility to train the NN and implement the network along with the other modules in iSIGHT-FD.



(a) Schematic description of the synthesis level MDO process

(b) iSIGHT Workflow

Figure 1: Design Overview

3 Concept and Methodology

The goal of the synthesis level optimization is to define the optimum overall system architecture [1], in terms of a limited number (10-20) of design parameters. The first step it to integrate modules into a work flow, define objective functions, constraints and input variables. Then, for each objective function, an initial population for NCGA is determined using single MIGA. Finally, the initial population is migrated and optimized with NCGA. The result is a pareto optimal solution.

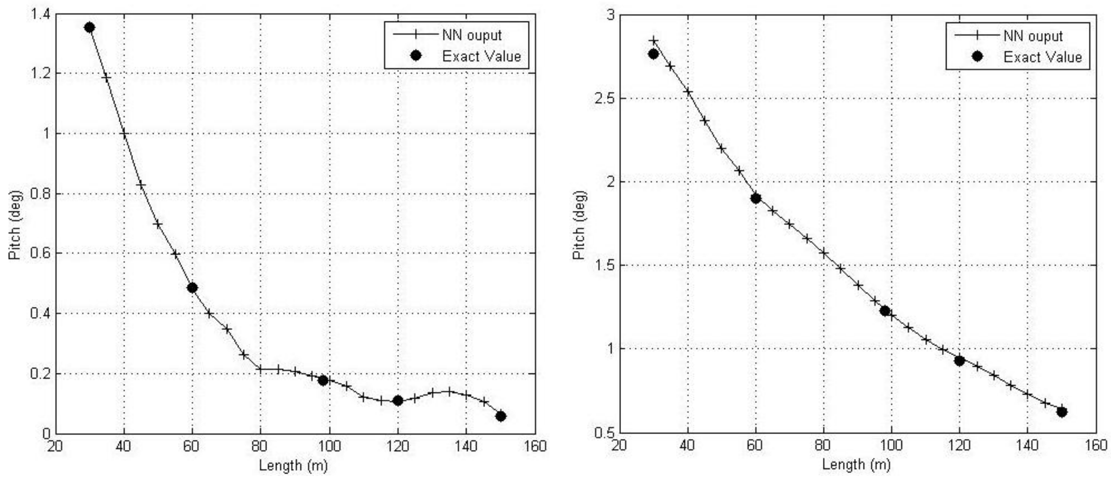
In particular, variables for these optimization include catamaran length, draft, depth, beam and various coefficients. Three objectives are identified: DTRBR, DWTDR and price. The calculated price includes factors such a construction and schedule risk but does not include profit. These functions are to be minimized. The MIGA runs have a sub-population size of

10, 5 islands and 100 generations which results in 5000 iterations. The goal is to pick 30 to 35 points at different locations of the optimization. The underlying idea is to produce several feasible ships spanning the computational domain to have a diverse population to start the NCGA optimization. Finally, the points are used as initial population for the NCGA optimization.

4 Seakeeping Model

Seakeeping capability of the ship is calculated by a set of 40 Neural Networks [3] modeled in a MATLAB code. The Office of Naval Research generated the initial Catamaran points using a seakeeping panel code (WASIM code) method. The NNs are trained for a specific heading angle (0, 45, 90, 135 and 180 degrees) and for a specific output: pitch, roll, vertical acceleration, transverse acceleration, bending moment, shear force and two motion sickness coefficients. The inputs are length, spacing, sea state, and Froude number. For each ship configuration calculated, the seakeeping module evaluates the eight outputs for sea states three to six, headings 0 to 180, speeds 15, 25, 35 and calculates a seakeeping index using the excel spreadsheet model. This index is then used in the NCGA optimization.

Figure 2 plots the respective pitch output compared to the training points for a fixed sea state, spacing and Froude as the length of the ship is varied. Plot 2(a) shows pitch vs length at a heading of $0\,^{\circ}$, figure 2(b) shows the same plot with a heading of $45\,^{\circ}$. As expected, pitch decreases on both graphs as the length of the vessel is increasing. The network smoothly interpolates the underlying points at larger pitch values, while it shows some oscillatory motion at pitch values below 0.2. A possible solution is to train the network on denser data in these problematic regions. Notice that the pitch range on figure 2(b) has about twice the range of figure 2(a), which means that the former figure actually displays a much more detailed look of the behavior of the vessel.



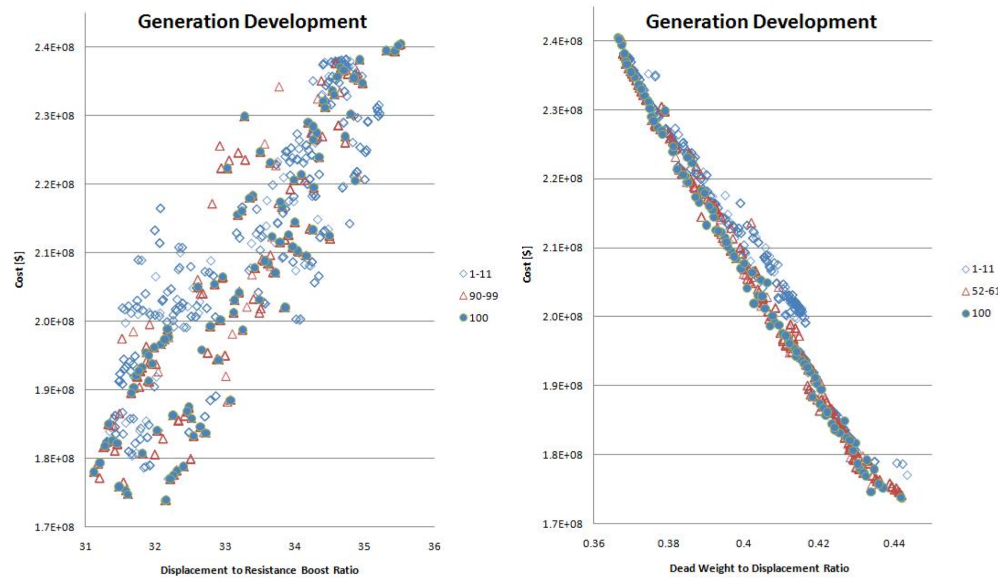
(a) Pitch vs Length at 0 degree (b) Pitch vs Length at 45 degrees

Figure 2: Pitch vs Length for two Networks

5 Results

The initial population plays an important role in the various multi-objective optimizations in order to obtain a meaningful pareto optimal solution. These specified initialization points significantly influence the range of results obtained in the multi-objective optimization. In particular, the optimum results obtained from the MIGA must be included in the initial population to obtain a pareto set that extends though the possible range of the three objective functions.

The pareto set of the final results are presented as a 2D graph considering the objective functions (e.g. Cost vs DTRB). These results, which extend between the two single objective optimized solutions, allow the designer to "trade off" various objectives if necessary. Example results are shown in figure 3. Both graphs display selected pareto sets (i.e. 100 points corresponding to an NCGA optimization with a population of 100 run for 100 iterations). The designer can also choose from any of the pareto set points, different optimum vessels, depending on overall requirements and design constraints.



(a) Cost vs DTRBR

(b) Cost vs DWTDR

Figure 3: Preliminary Results

5.1 Results with Seakeeping

The first optimization runs have been conducted without the seakeeping model. These runs are primarily being carried out to test the model, the software and the procedure employed. Preliminary results shown in figure 3 indicated that the model is working where results already outperform previous research conducted. Work is being accomplished to implement the neural network into the iSIGHT-FD optimization procedure. Results are expected in the near future. This will add an additional layer of optimization and will produce a more stable and manoeuvrable vessel.

6 Acknowledgement

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