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MULTI-OBJECTIVE ROBUST CONCEPT EXPLORATION WITHIN THE MADE-TO-ORDER SECTOR

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1. Introduction

Concept exploration is an activity of fundamental importance when designing large, complex made-to-order engineering products. At the concept design stage of the design process, it is essential that many design alternatives are evaluated. In the case of large made-to-order products, the evaluation of a particular design can be both complicated and time consuming. Under these circumstances, designers often resort to the use of concept design models enabling both a reduction in complexity and time for evaluation. Stochastic optimisation methods are then typically used to explore the design space facilitating the selection of optimum or near optimum designs. These optimisation methods can however increase the concept exploration time considerably due to their often random search manner. The objective of this work is therefore to produce a generic framework that would enable a designer to efficiently explore the design space within the MTO domain facilitating the selection of robust designs.

2. Robust design methodology

A product's robustness is a measure of the variation in its utility experienced in a typical application. That is to say, the lower the sensitivity or variation in utility, the greater the robustness of the design. In this work, we consider robust design to be the process by which a design is produced in which changes in the selected parameters which define the optimum design have relatively little effect on the performance of the design, i.e. the behaviour of the selected design is insensitive to modest changes in the parameters.

Taguchi's robust design philosophy [1] was used as the basis of the robustness framework whilst state-of-the-art statistical techniques were incorporated to improve efficiency. The framework was broken down into a series of modules created to handle particular aspects of the robust design process. A graphical representation of the robustness framework can be seen in Fig. 1a. Concept exploration is undertaken via the use of simulation tools which are controlled by a tool management module. This module is responsible for ensuring that each simulation tool obtains the required information for execution. Design of Experiments (DOE) is utilised to enable the design space to be efficiently explored - Box et al [2].

The design and solution spaces are then defined using the DOE module by selecting the associated parameters and criteria. The DOE module enables the selection of the upper and lower bounds of the design space and the determination of the type of each parameter, i.e. control or noise. Each criterion can be selected as having either a minimisation, maximisation or a target value objective. The DOE module is finally responsible for designing the experiment to explore the design space. A point generator is incorporated within the DOE module which is capable of generating full and variable fractional factorial and Central Composite Designs (CCD). The full and fractional factorial designs are available for any order of problem, whereas the CCD is currently designed for second order problems only.

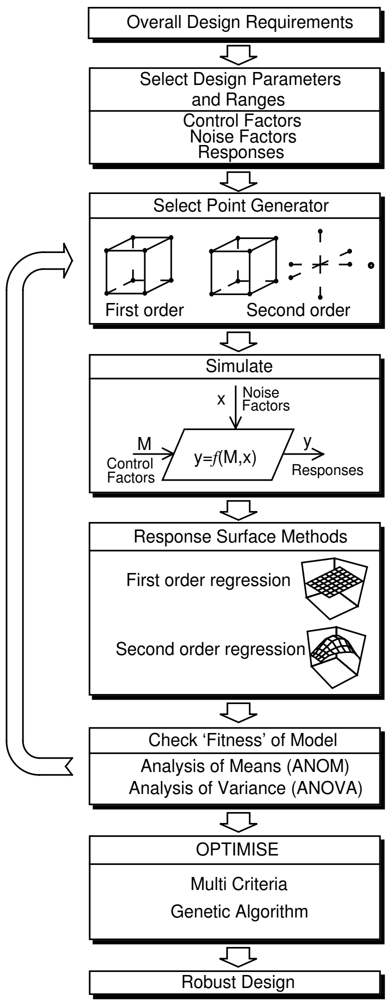

Fig. 1a. Robustness framework.

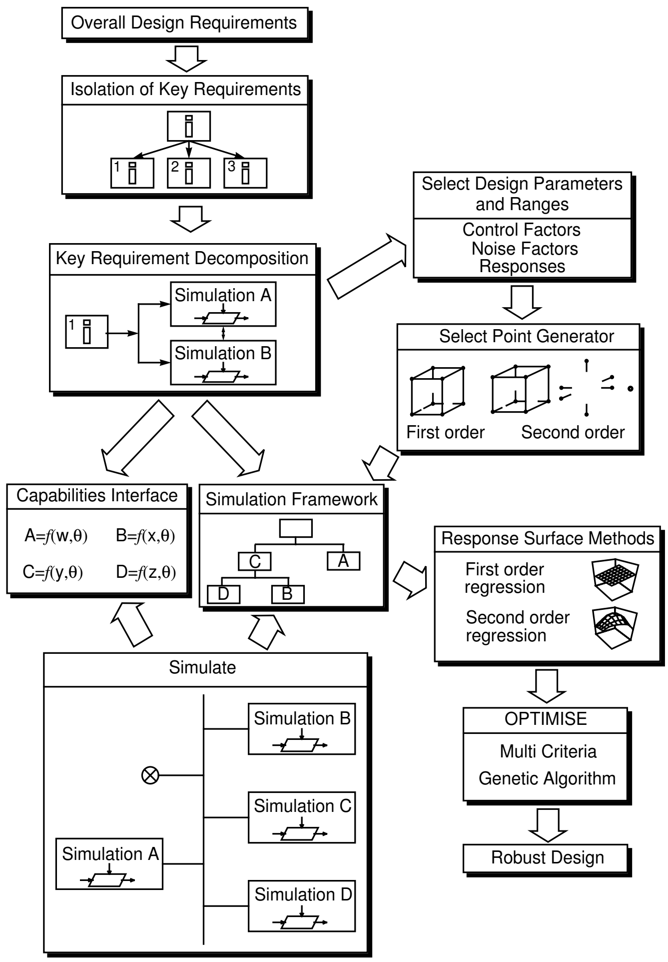

Fig. 1b. Design coordination system.

The tool management module then evaluates the potential design concepts generated by the DOE module. Design concepts are evaluated sequentially, however research is currently being undertaken to enable the integration of the robustness framework with a design coordination system to considerably reduce the time taken for concept exploration - Coates et al [3], Fig. 1b.

Upon completion of the concept exploration stage, the response surface module uses the information obtained from the DOE module to produce a set of normal equations. If a criterion is dependent on a noise parameter the response surface module will produce two measurements for the criterion, one for the mean value, and one for the standard deviation. The objective for the standard deviation criterion will be automatically set to minimisation. The GA module then uses the response surfaces to quickly explore the design space and produce a Pareto-optimal set of solutions. The solutions are represented by a design concept with associated evaluations for the criteria. The designer can then select from the Pareto-optimal set the design that most closely satisfies the overall requirements.

3. Description of the design problem

The design problem incorporates a single simulation tool which is capable of giving a number of measurements for the seakeeping of a catamaran. The objective of the work is to explore the design space for the catamaran and select a concept which is most robust with respect to the selected seakeeping quantities for any particular waveheading. The design space for the catamaran problem was defined by six control parameters and one noise parameter:

Control Parameters (Primary):	Hull length	L,
	Breadth to draft ratio	B/T,
	Distance between demihull centres	Hs,
Control Parameters (Secondary):	Longitudinal centre of buoyancy	LCB,
	Coefficient of waterplane	Cwp,
	Longitudinal centre of flotation	LCF,
Noise Parameter:	Waveheading	ϕ.

The seakeeping quantities available are the peak values of heave (s_3), roll(s_4), pitch(s_5) and the relative motion at the bow of each demihull (s_r).

$$s_r = s_3 + y \cdot s_4 - x \cdot s_5 - \zeta_{x,\,y} \tag{1}$$

Criteria:	Maximum heave amplitude,	$\lvert s_3 \rvert_{max}$
	Maximum roll amplitude,	$\lvert s_4 \rvert_{max}$
	Maximum pitch amplitude,	$\lvert s_5 \rvert_{max}$
	Maximum relative bow motion, RBM.	$\lvert s_r \rvert_{max}$

A diagrammatic representation of the design parameters and criteria for the catamaran design problem can be seen in Fig. 2.

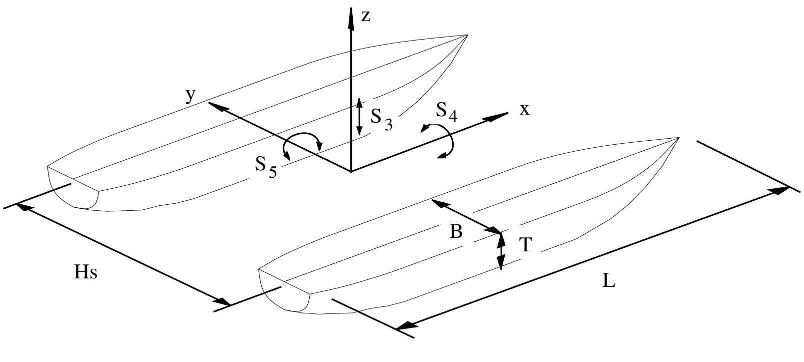

Fig. 2. Design parameters and criteria for catamaran.

Given this particular problem, the response space would have eight dimensions; a mean and a standard deviation component for each of the criteria, and would subsequently prevent the illustration of the results obtained from the optimisation process. For illustrative purposes, an example was chosen which demonstrates the application of the methodology with respect to the roll criterion only. A complete analysis, however, can be seen in Whitfield et al [4]. The design space was explored relative to a parent design and was expressed as a percentage change for the primary and secondary design parameters and in absolute terms for the noise parameter as shown in Table 1.

Table 1: Design Space for Catamaran Problem

Parameter	Type	Parent	Lower Bound	Mid Point	Upper Bound
ϕ	Noise		90	135	180
L	Control	104.0 m	-9%	+1%	+11%
B/T	Control	2.0	-9%	+1%	+11%
Hs	Control	31.0 m	-9%	+1%	+11%
LCB	Control	45.408	-0.9%	+0.1%	+1.1%
Cwp	Control	0.758	-0.9%	+0.1%	+1.1%
LCF	Control	43.306	-0.9%	+0.1%	+1.1%

4. Results and Discussion

The DOE module is capable of selecting a number of different DOE methods to enable the efficient exploration of the design space. In this particular example, the DOE module designed 79 experimental runs to be undertaken using the CCD method to enable an efficient exploration of the design space such that a quadratic response surface could be generated.

The tool management module was then requested to execute the design algorithms to evaluate the design concepts. The design space as defined by the DOE module was subsequently explored in approximately 10 minutes using a Sun UltraSparc 10 workstation. The results from the concept exploration stage were then used by the response surface module to construct the regression equation. A set of normal equations were produced using the method of least squares based upon the information generated from the concept exploration. These normal equations were then solved using Cholesky LU factorisation producing the following regression equation for the roll criterion as a function of the seven design parameters.

$$
\begin{aligned}
Y = &-6.5458 + 0.0595x_1 - 1.3781x_2 + 1.2068x_3 - 0.2762x_4 - 8.5906x_5 + 0.4558x_6 \\
&+ 5.9358x_7 - 0.0001x_1^2 - 0.0044x_1x_2 - 0.0059x_1x_3 + 0.0019x_1x_4 + 0.0892x_1x_5 \\
&- 0.0055x_1x_6 - 0.0514x_1x_7 - 0.0024x_2^2 - 0.0071x_2x_3 + 0.0007x_2x_4 - 0.0439x_2x_5 \\
&- 0.0016x_2x_6 + 0.0419x_2x_7 + 0.0012x_3^2 - 0.0008x_3x_4 - 0.0526x_3x_5 - 0.0026x_3x_6 \\
&+ 0.0667x_3x_7 + 0.0024x_4^2 - 0.0016x_4x_5 - 0.0111x_4x_6 + 0.0151x_4x_7 + 1.2537x_5^2 \\
&- 0.1066x_5x_6 - 1.0257x_5x_7 + 0.2874x_6^2 + 0.9469x_6x_7 + 2.1161x_7^2 \qquad (2)
\end{aligned}
$$

The GA module conducted an evaluation of the regression equation for a number of different waveheadings and produced estimates for the mean and standard deviation of the roll criterion. These two criteria were then used to guide the GA to facilitate the selection of a Pareto-optimal set of designs. The Pareto-optimal designs can be seen within Fig. 3. For a full description of the GA used within this framework see Todd et al [5].

Fig. 3 represents 54 design concepts covering the range of values for the minimisation of both the mean (μ) and standard deviation (σ) estimates for the roll criterion. It represents a range of designs having a low value of σ indicating a relatively flat region of the response surface, to designs having a high σ indicating a spiked region. Trade-offs can then be made between the designs to suit the characteristics required. Fig. 3 indicates that the majority of the designs have a mean reduction in roll of approximately 27%, however there is a sharp increase in the values for the standard deviation component of the roll criterion. Two designs were chosen for further investigation indicated by the points within Fig. 3 and can be seen within Table 2.

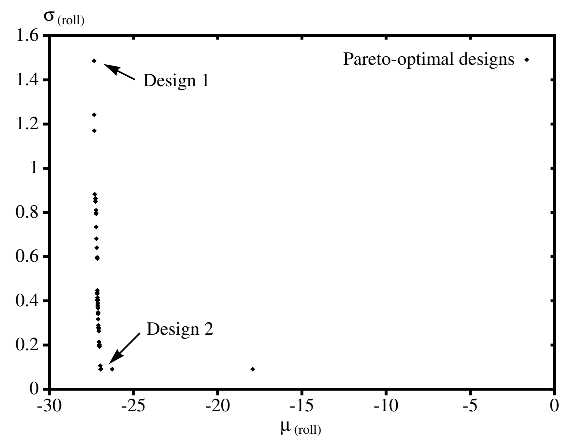

Fig. 3. Pareto-optimal designs.

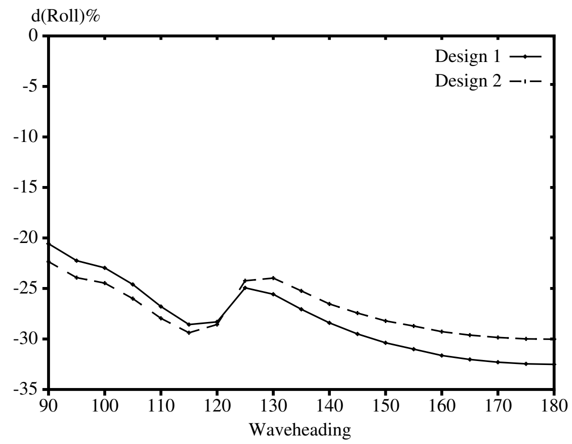

Fig. 4. Variation in roll with waveheading.

The simulation tool was subsequently used to evaluate the two designs with respect to the roll criterion by varying the waveheading between 90° and 180° and can be seen in Fig. 4. The values of the roll criterion were obtained with respect to the parent design, hence increasing negative values indicate increasing desirability. Fig. 3 would suggest that design 2 is more robust than design 1 since it has a lower standard deviation component whilst having a similar mean component. This can also be seen within Fig. 4, with design 2 having a lower variation in *d(Roll)* indicating that this design is on a flatter region of the response surface.

Table 2: Designs selected for analysis.

Design	d(*L*)%	d(*B/T*)%	d(*Hs*)%	d(*LCB*)%*L*	d(*Cwp*)	d(*LCF*)%*L*	$\mu_{(RBM)}$	$\sigma_{(RBM)}$
1	10.99	-9.0	1.36	0.85 forward	0.47	0.04 forward	-12.96	9.89
2	11.00	-8.99	9.28	0.81 forward	0.82	0.41 forward	-9.00	5.38

The advantages of using this methodology are that the designer is faced with a set of Pareto-optimal designs which can be used within the selection process when further information is required regarding customer requirements. Trade-offs can subsequently be made within later stages of the design process whilst ensuring that the chosen design has optimal criteria.

5. Conclusions

The methodology demonstrates the use of robust design techniques, integrated with a multi-objective genetic algorithm to enable the exploration and selection of robust design concepts. DOE techniques were used to quickly explore the design space for the catamaran, facilitating the generation of a regression equation representing the roll seakeeping criterion. The regression equation was subsequently used to generate estimates for the mean and standard deviation components by evaluating the roll criterion over a number of different waveheadings. The GA then used these estimates to guide the search process, enabling the production of a Pareto-optimal set of solutions.

The framework enabled these robust design concepts to be produced in approximately 10 minutes using a Sun UltraSparc 10 platform. Average reductions of approximately 27% for the roll criterion were achieved across the waveheadings.

The framework can be applied to problems incorporating multiple criteria - Whitfield [4], such as the selection of design parameters that would provide suitable seakeeping quantities whilst maximising the cargo carrying capacity and cruise speed.

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