Complex System Configuration
Optimisation Using Machine Learning as a
Surrogate Model

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COMMERCIAL IN CONFIDENCE



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Testing and Evaluating

- Supporting in service and developing technologies
- Sites across the UK, Europe, and The World



Maritime and Land

- Working across a variety of vessels and technologies
- Supporting customers interests in the Land and Sea domain



Noise and Vibration

- Based in Rosyth, Scotland
- Supporting acoustic stealth of maritime platforms
- Experienced Personnel



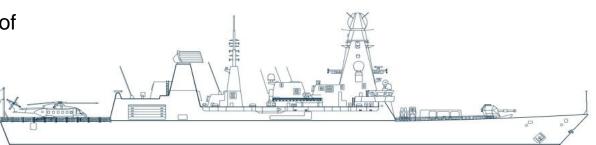


Introducing the Problem



The Problem

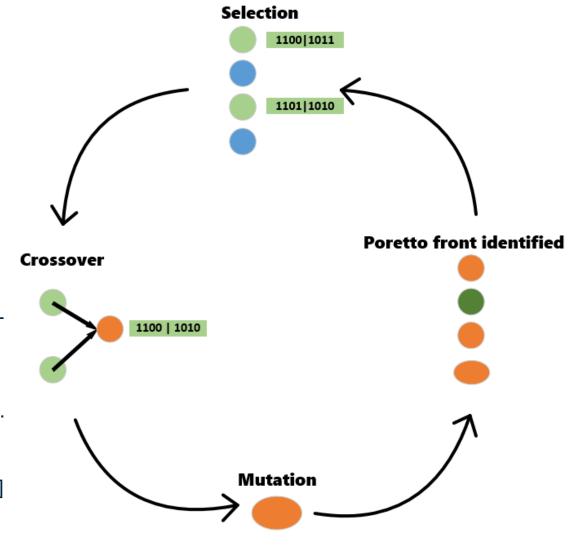
- Ship Systems are complex and layered:
- A ships mechanical systems are made up of hundreds of pumps, motors, and fans
- Redundancy through duplicate systems.
- Balancing Stealth and Mission Priorities
- Stealth is an important weapon in a ships arsenal and improves survivability
- Shutting down systems increases stealth but potentially inhibits operability and redundancy.
- This presents a challenge
- Many possible machine combinations creates challenges around system interactions
- Many un-observed line ups.





Our Proposed Solution

- Use a Multi-objective optimiser:
- NSGA-II Genetic Algorithm;
- Minimise hull vibrations while maintaining core operability;
- Investigate the design space efficiently;
- Use real measured operational data:
 - Every combination of running machines cannot be measured.
- Use an ML model as a surrogate
- Where a line-up has not previously been observed / measured, use ML prediction.
- Down selection of 66 machines
 - Optimise across a single OTO frequency band over 2 compartments.
- Machine Line-Up vector example:







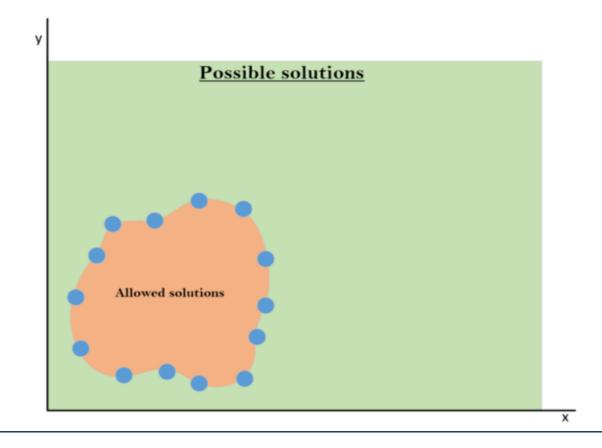


Objective Function

Evaluates machine line-ups by their vibration level.

Objective Function constraints

- In theory, the best acoustic line up is to switch everything off;
- The objective function constraints define the goal of balancing acoustic performance with functionality of the vessel:
 - e.g. firefighting pumps always required
- In this study 22 constraints were used based on experienced personnel advice.



Defines the set of allowed solutions from all possible solutions

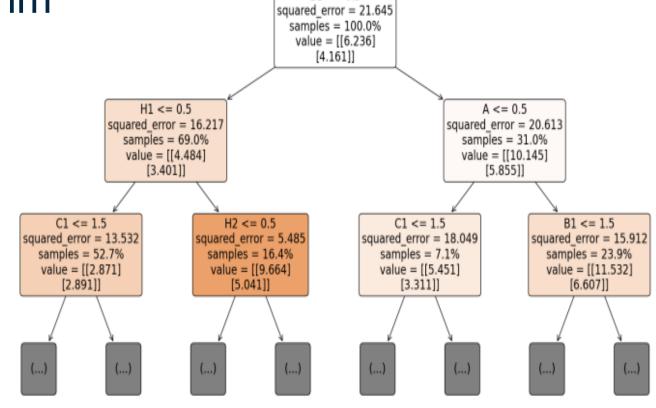


Machine Learning Algorithm

Training Data

80% Used to create decision tree 20% Used to test tree

Unobserved line-ups are fed into the decision tree, to be characterised. An estimated vibration level is given for that system configuration.

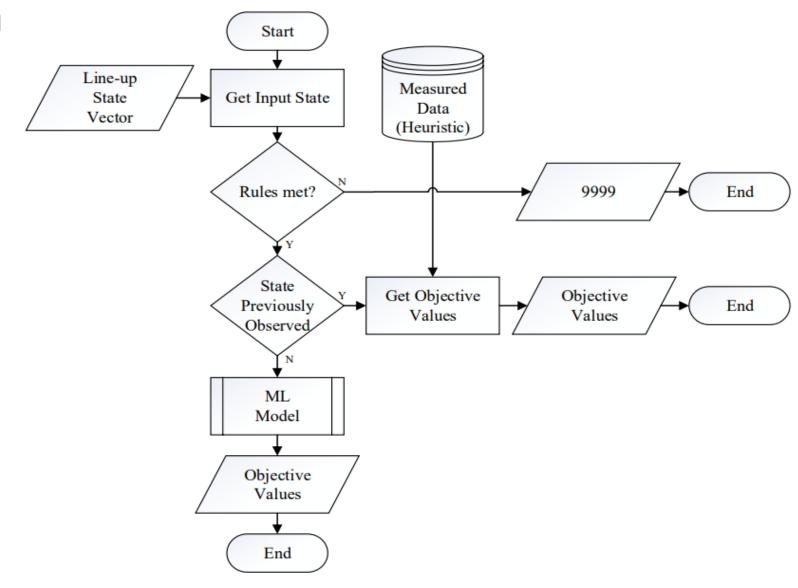


 $B1 \le 0.5$

observed machine line-ups use a statistical model to output vibration values, as they have been seen and measured before.



Full System



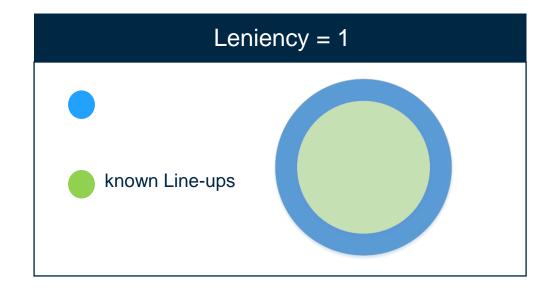


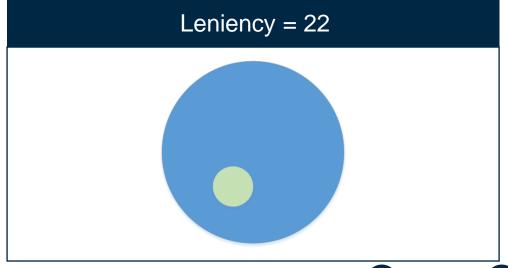




Leniency Variable

- The Leniency variable was introduced to counter a problem discovered during development of the optimiser;
- If the initial population of machine line-ups (which was randomly generated) did not contain any observed machine line-ups, it was unlikely it would uncover any during the optimisation process;
- The leniency value allows for a level of control of the starting population, and how many of them are observed machine line ups;
- By passing the initial starting population through the objective function constraints, it increases the probability that known and feasible solutions are found but limits the optimisers' ability to fully explore the design space for novel solutions.





Test Procedure

Test ID	Population	Generations	Constraints	Leniency
1	500	20	None	1
2	500	20	None	22
3	500	20	All	22
4	500	25	All	22

- Testing was done first with a single measurement location, then two hull locations;
- The initial population was kept consistent at 500 for all tests, this was largely to do with computational costs; and
- Constraints were swapped between NONE and ALL to test the impact they would have on the results.



Test Results

Test ID	Population	Generations	Constraints	Leniency
1	500	20	None	1
2	500	20	None	22
3	500	20	All	22
4	500	25	All	22

Single Objective

Test ID	Pareto Front/ Unique Solutions	Baseline Comparison
1	500	-2.1dB
2	500	-1.1dB
3	12	-1.5dB
4	197	-1.7dB



Test Results

Test ID	Population	Generations	Constraints	Leniency
1	500	20	None	1
2	500	20	None	22
3	500	20	All	22
4	500	25	All	22

Multi-Objective

Test ID	Pareto Front/ Unique Solutions	Baseline Comparison
1	25	-1.8dB, -1.4dB
2	24	-1.8dB, -1.1dB
3	8	-1.0dB, -1.2dB
4	5	-0.6dB, -1.2dB



Future Work

Whole vessel optimisation

- Different compartments across a vessel could have different machine line-up requirements;
- The goal would be to optimise across all vessel compartments;
- Investigate holistic optimisation.

Larger data set

- To improve on accuracy, more data can be gathered across a wider variety of vessels;
- This will also improve the size of the statistical model that is called when a known line-up is seen.

Neural Network

- Different methods of ML modelling, such as a neural network, should be investigated and compared;
- Neural networks are better suited to dealing with complex non-linear relationships in data and may provide a better understanding of machine line-ups.



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