Multi-Objective Optimisation Support for Co-Simulation

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19th Overture Workshop, Aarhus University / Online, Oct 2021

Overview

Multi-Objective Optimisation (MOO)
- Definition
- INTO-CPS integration

Case Study and Results
- Existing Robotti study
- Exhaustive and MOO results

Summary and Future Work

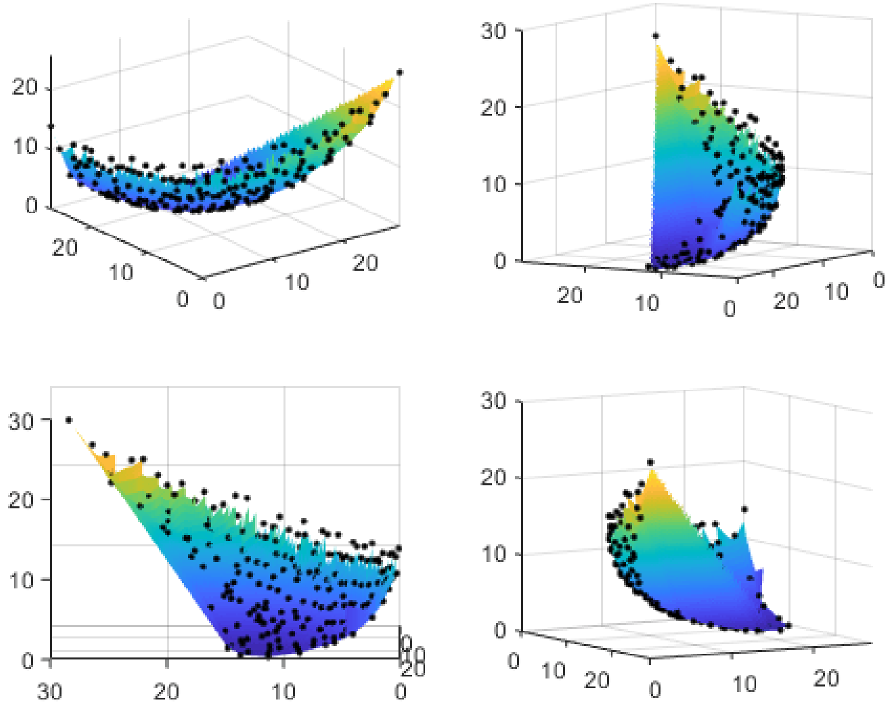
Multi-Objective Optimisation (MOO)

Definition

- Optimising a system according to multiple specific objective criteria
- Pareto optimality: no aspect of that solution can be improved without making another aspect of the solution worse

Types

- Commonly use Genetic Algorithms (GA)
  - Specialised fitness functions
  - Methods to promote solution diversity
- Other approaches: Simulated Annealing (SA) [probabilistic]
- Particle Swarm Optimisation (PSO) [biologically-inspired heuristic]



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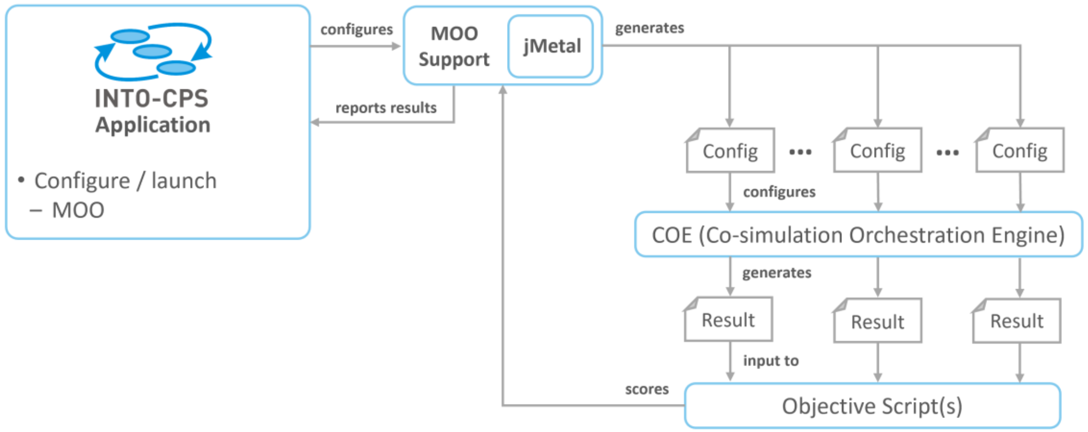
jMetal Integration

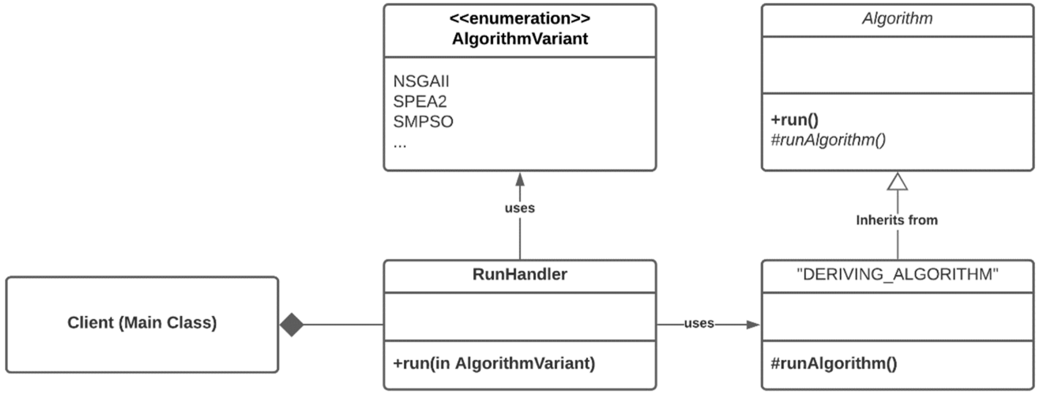
jMetal

- **Met**aheuristic **Al**gorithms in **J**ava
- Fifth major release in 2015
- 22 multi-objective algorithms, 5 single-objective optimisations

Implementation

- `Problem` represents the MOO problem to be solved (multi-model)
- `Solution` represents possible solution (multi-model parameters)
- Generate co-simulation configurations for `Solution` instances
- Evaluate the `Problem` using the COE and objective scripts

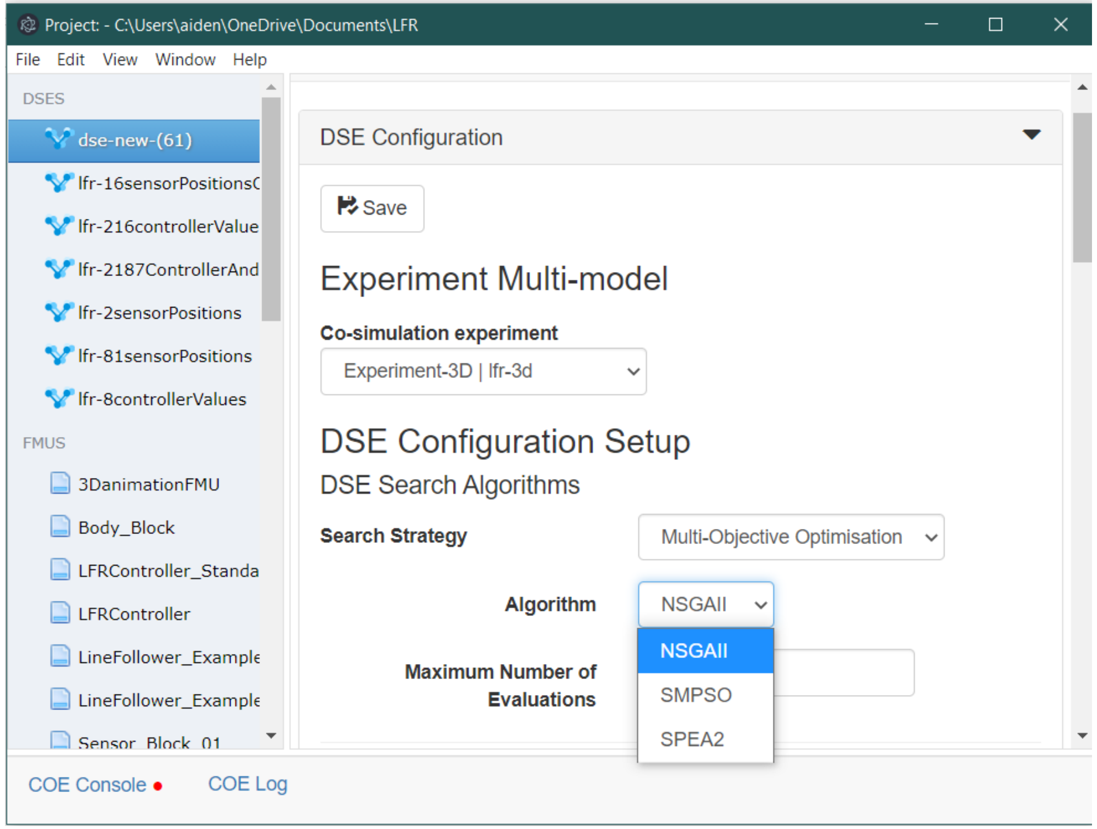




INTO-CPS Application

Expanded DSE Configuration Pane

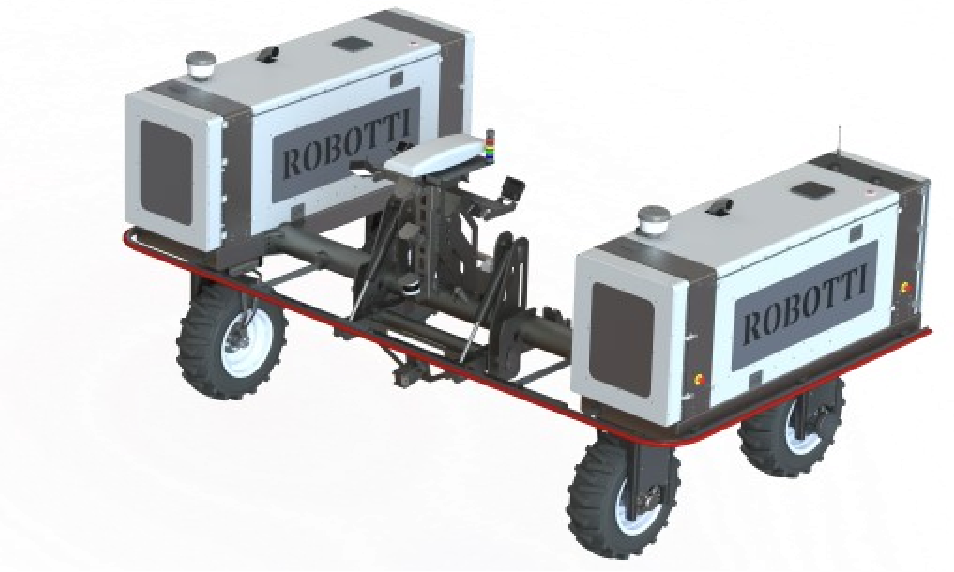
- Initial support for NSGA-II, SMPSO, SPEA2
- JSON configuration
  - Path to the COE
  - Path to base co-simulation configuration JSON
  - Length of the simulation in seconds
  - Algorithm to use
  - Path to the COE
  - Path to the COE
  - Array of multi-model parameters of the design space:
    - Parameter identifier
    - Upper bound
    - Lower bound
  - An array objectives:
    - Type ("SCRIPT" or "PARAMETER")
    - Identifier (path to script, or parameter identifier)
    - A Boolean value indicating maximisation / minimisation



Case Study

Robotti

- Pilot study assessing the viability of DSE for improving model fidelity
- Data from field trials of under four scenarios with a total of 27 runs
  - **Speed step**: Wheel speed increased incrementally in lock step
  - **Speed ramp**: Wheel speed increased smoothly.
  - **Turn ramp**: Right wheel speed increased smoothly, left wheel constant
  - **Sin**: Left and right wheel is increased and decreased sinusoidally



Bogomolov, S., Fitzgerald, J., Foldager, F.F., Gamble, C., Larsen, P.G., Pierce, K., Stankaitis, P., Wooding, B.: Tuning Robotti: the machine-assisted exploration of parameter spaces in multi-models of a cyber-physical system. John Fitzgerald, Tomohiro Oda, and Hugo Daniel Macedo (eds) p. 50 (2021)

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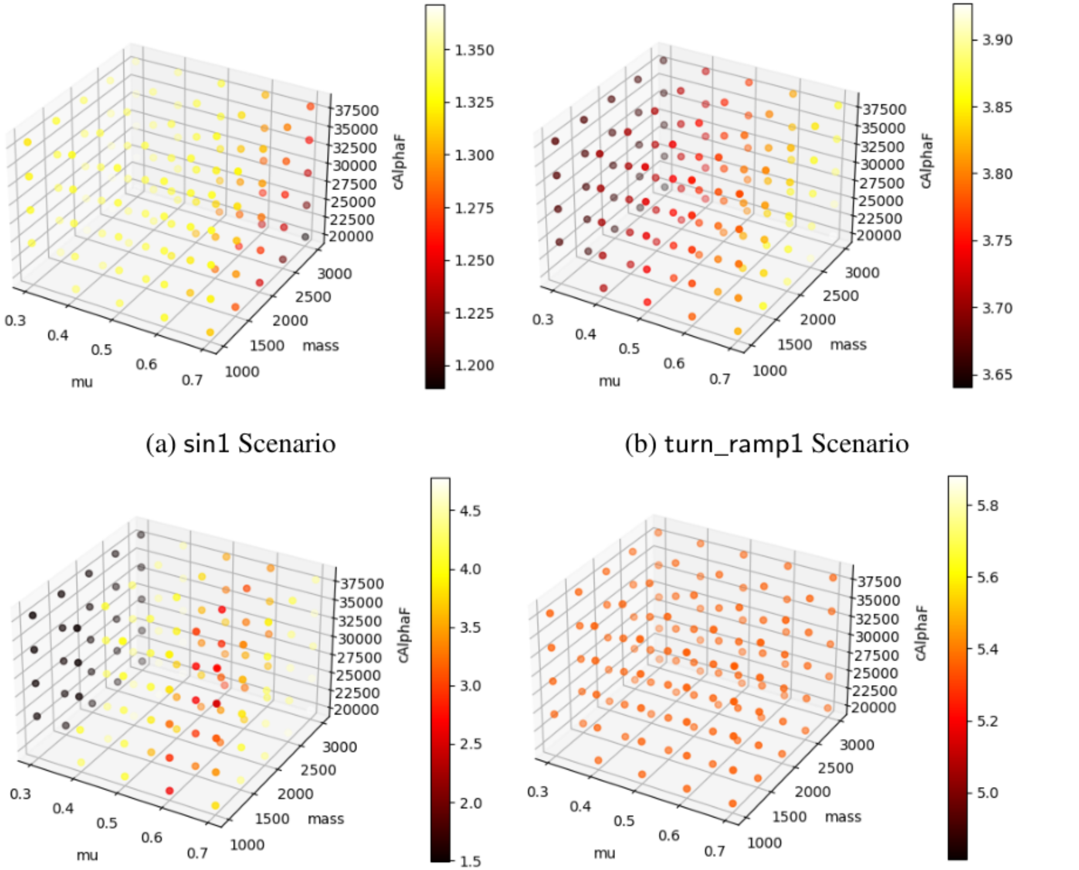
Results

Exhaustive

- Parameters for friction (mu), mass and turn co-efficient (cAlphaF)
- **Sin1**: optimal has highest friction, mass and turn co-efficient
- **Turn_ramp1**: low-friction dominates
- **Speed_ramp1**: low-friction dominates, plus medium-friction region
- **Speed_step1**: no overall effect



(a) sin1 Scenario

(b) turn_ramp1 Scenario

(c) speed_ramp1 Scenario

(d) speed_step1 Scenario

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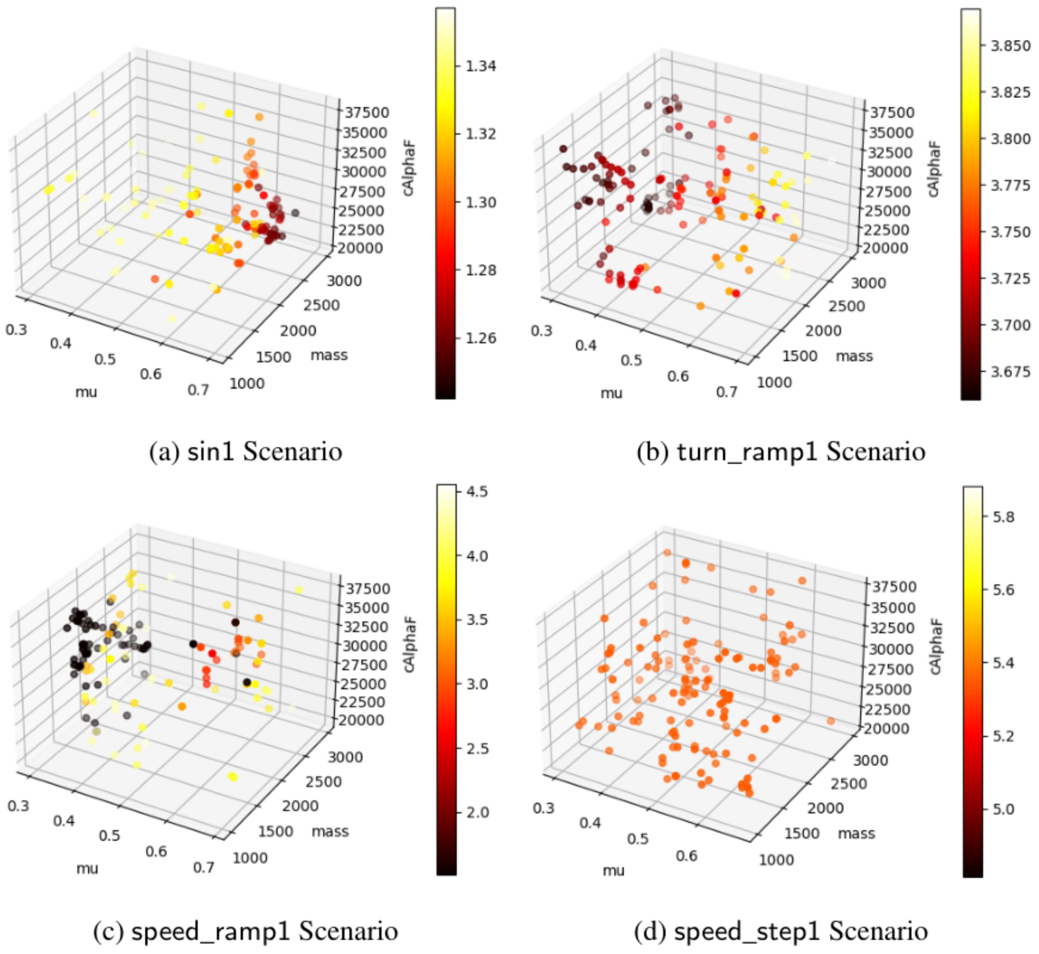
Results

NSGA-II Limited to 125 Iterations

- Initial MOO tests with the same 125 co-simulations as exhaustive search
- MOO identified trends as with the exhaustive
- Optimal solutions not identified with limited runs

Robotti Case Study Not a True Multi-Objective Problem

- Wanted to understand relation to existing DSE functionality
- MOO is not a replacement for DSE
- Need for new multi-objective multi-model example



(a) sin1 Scenario (b) turn_ramp1 Scenario

(c) speed_ramp1 Scenario (d) speed_step1 Scenario

Results of a NSGA-II results for the four scenarios limited to 125 co simulations

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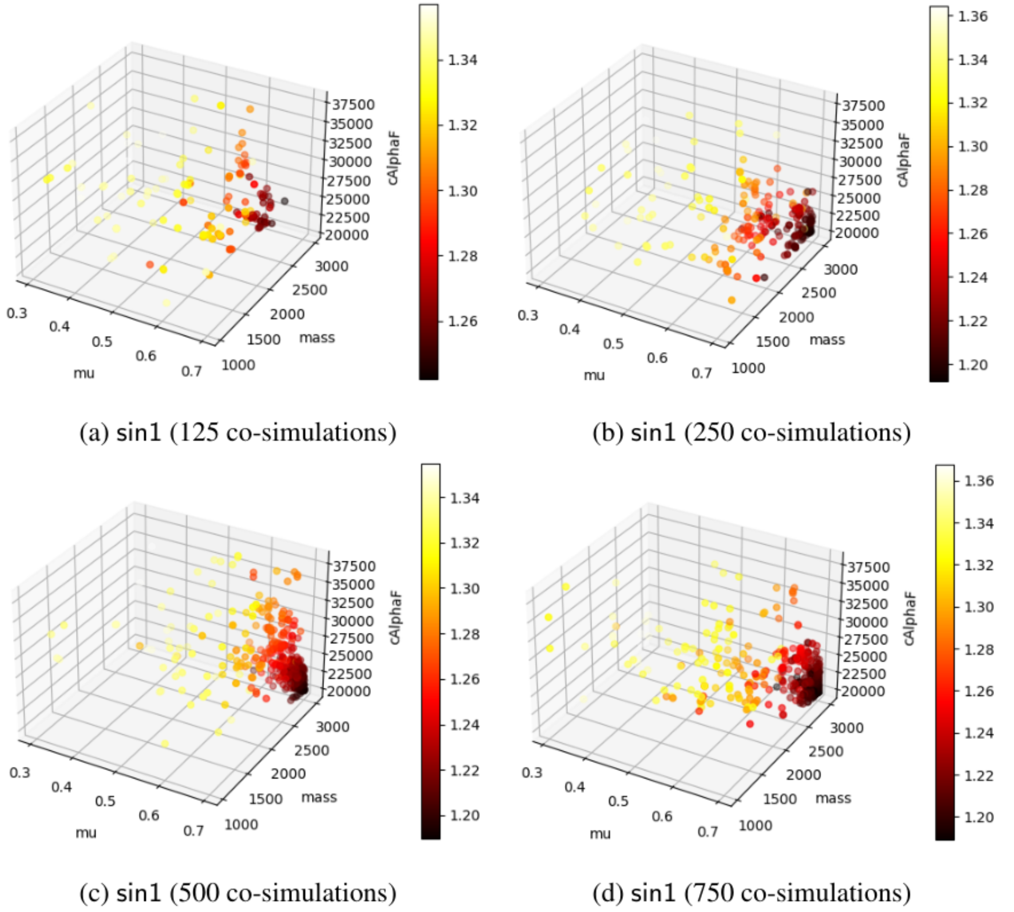
Results

NSGA-II Increasing Limits

- Scenarios re-run with increasing number of co-simulations
- Overall trends found as seen in exhaustive
- Needed ~750 to consistently find the same results

Scenario	Algorithm	Mean Time / Evaluation (s)	Mean Total (s)
sin1	NSGA-II (6 threads)	2.2	280
sin1	NSGA-II (1 thread)	6.1	771
sin1	Exhaustive (1 thread)	5.3	664
turn_ramp1	NSGA-II (6 threads)	3.8	480
turn_ramp1	NSGA-II (1 thread)	10.9	1365
turn_ramp1	Exhaustive (1 thread)	9.1	1141
speed_ramp1	NSGA-II (6 threads)	3.9	488
speed_ramp1	NSGA-II (1 thread)	11.8	1485
speed_ramp1	Exhaustive (1 thread)	10.4	1296
speed_step1	NSGA-II (6 threads)	4.6	584
speed_step1	NSGA-II (1 thread)	12.3	1540
speed_step1	Exhaustive (1 thread)	10.8	1350



Results of NSGA-II on sin1 with increasing numbers of co-simulations

Summary and Future Work

Summary

- Produced a MOO plugin for INTO-CPS
- Demonstrated the implementation on existing Robotti case study

Future work

- Apply MOO in other existing examples
- Develop a true MOO multi-model example to demonstrate benefits and drawbacks of MOO vs. DSE vs. exhaustive

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