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Intelligent computer-automated crane design using an online crane prototyping tool

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Papers:

- Bye, R.T., Osen, O.L., Pedersen, B.S. (2015). A computer-automated *design tool for intelligent virtual prototyping of offshore cranes. In: Proceedings of the 29th European Conference on Modeling and Simulation (ECMS'15)*, Albena, Bulgaria, pp. 147—156.
- Bye, R.T., Osen, O.L., Pedersen, B.S., Hameed, I.A. and Schaathun, H.G. (2016). A software framework for intelligent computer-automated product design. In: *Proceedings of the 30th European Conference on Modeling and Simulation (ECMS'16), Regensburg, Germany*.
- Hameed, I.A., Bye, R.T., Osen, O.L., Pedersen, B.S. and Schaathun, H.G. (2016). Intelligent computer-automated crane design using an online crane prototyping tool. In: *Proceedings of the 30th European Conference on Modeling and Simulation (ECMS'16), Regensburg, Germany*.
- Hameed, I.A., Bye, R.T. and Osen, O.L. (2016). A comparison between optimization algorithms applied to offshore crane design using an online crane prototyping tool. *Submitted to the 2nd International Conference on Advanced Intelligent Systems and Informatics (AISI2016), Cairo, Egypt*.

Outline

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Problem definition

- Offshore crane design requires the configuration of a large set of design parameters (ca. 120 parameters) in a way that meets customers' demands and operational requirements.
- Manual design is time consuming, tedious and expensive process.

Motivation

- Reduce time and cost involved in the design process using VP and optimization algorithms.

What is virtual prototyping?

- Virtual prototyping, VP, is a software-based engineering discipline which involves modeling a system, simulating and visualizing its behavior under real-world operating conditions, and refining its design through an iterative process.
- VP is used as a substitute for rapid prototyping.
- VP is used for simulation and visualization of physical systems.
- VP can be used to test anything from component parts to entire machines - without building relatively expensive physical prototypes.
- VP does not produce a physical object for testing and evaluation but, as its name suggests, carries out these tasks within a computer.

What is virtual prototyping?

- VP enables users to quickly explore multiple design variations, testing and refining them until system performance is optimized.
- This can help reduce the time and cost of new product development and significantly improving the quality of overall system designs.
- VP technology doesn't require hardware to physically make a prototype, as in rapid prototyping, and consequently involves less cost.
- The goal of using VP technology is to minimize time and cost, and maximize quality and efficiency

Optimization Algorithms

- Optimization is the selection of a best element (with regard to some criteria) from some set of available alternatives.
- Is used to replace the manual configuration process.
- Test and evaluate various alternatives of design parameters in a short time.

Optimization problem

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & f(x) \\ \text{subject to} \quad & g_i(x) \leq 0, \quad i = 1, \ldots, m \\ & h_i(x) = 0, \quad i = 1, \ldots, p \end{aligned}$$

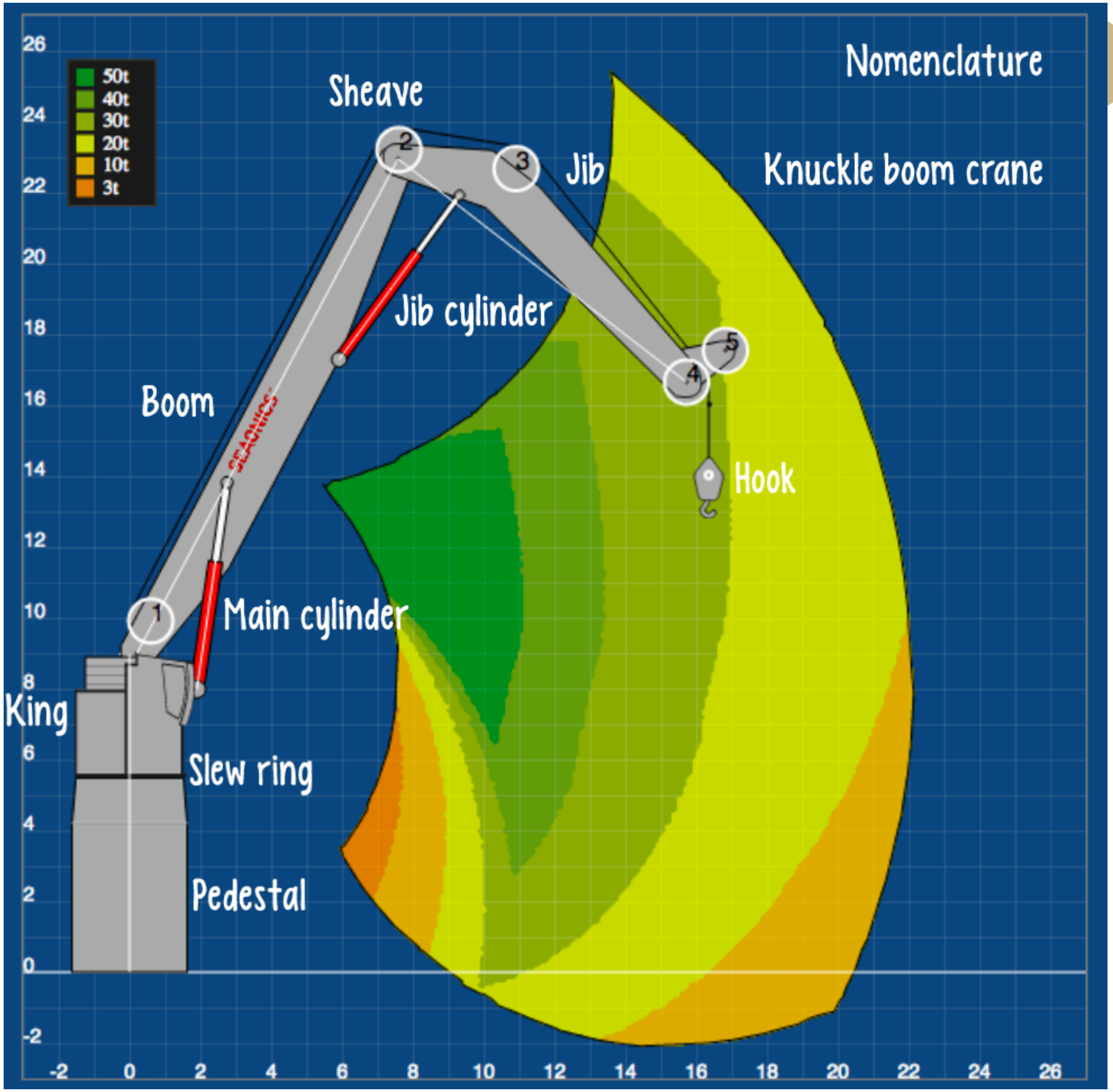
where

- $f(x) : \mathbb{R}^n \to \mathbb{R}$ is the **objective function** to be minimized over the variable x,
- $g_i(x) \leq 0$ are called **inequality constraints**, and
- $h_i(x) = 0$ are called **equality constraints**.

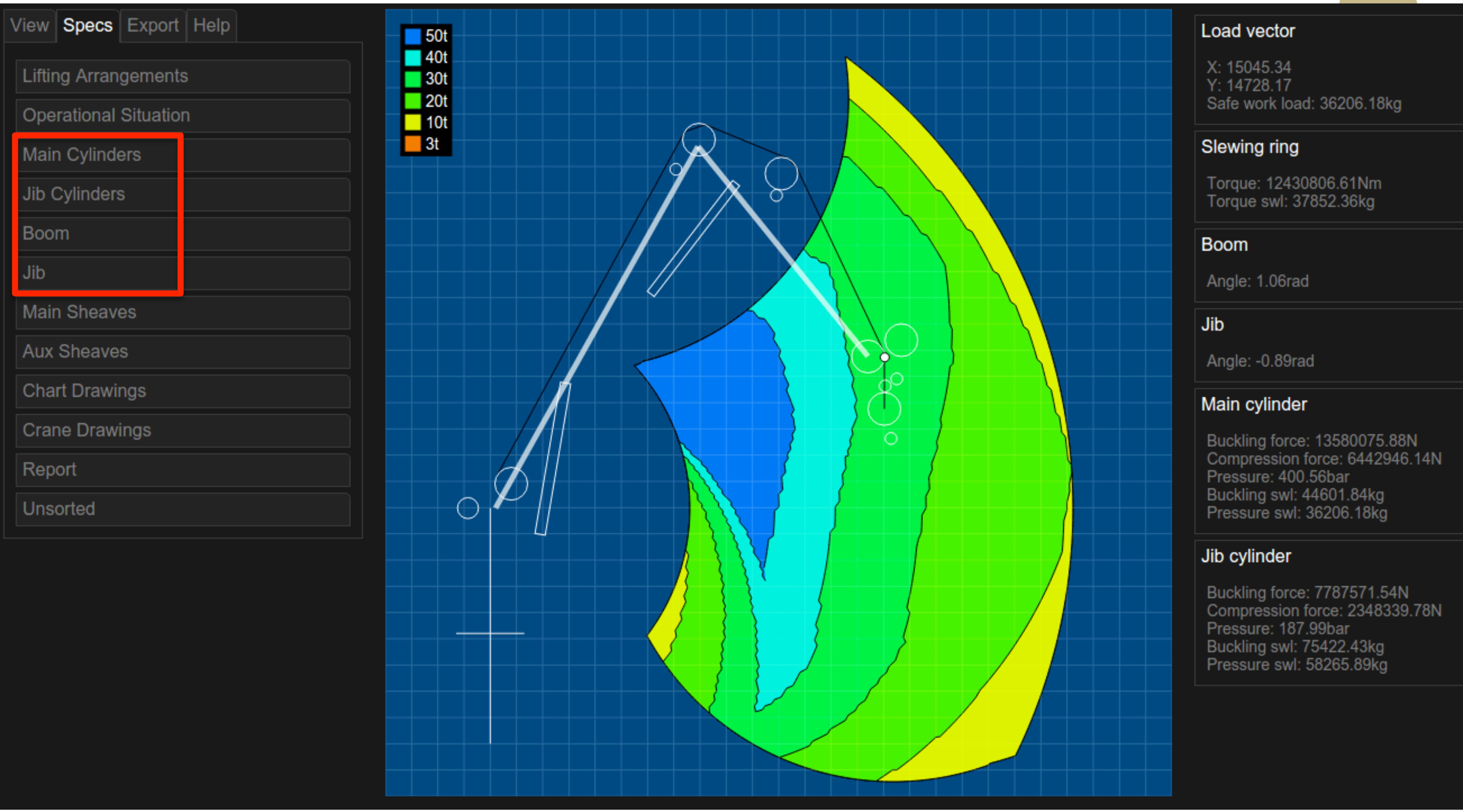
- A maximization problem can be treated by negating the objective function.
- Multi-objective functions can be combined into single objective function

Case study: an off-shore knuckleboom crane designed by Seaonics AS

Main components of the crane and its 2D load chart



CPT GUI


View
Specs
Export
Help
Lifting Arrangements
Operational Situation
Main Cylinders
Jib Cylinders
Boom
Jib
Main Sheaves
Aux Sheaves
Chart Drawings
Crane Drawings
Report
Unsorted
50t
40t
30t
20t
10t
3t
Load vector
X: 15045.34
Y: 14728.17
Safe work load: 36206.18kg
Slewing ring
Torque: 12430806.61Nm
Torque swl: 37852.36kg
Boom
Angle: 1.06rad
Jib
Angle: -0.89rad
Main cylinder
Buckling force: 13580075.88N
Compression force: 6442946.14N
Pressure: 400.56bar
Buckling swl: 44601.84kg
Pressure swl: 36206.18kg
Jib cylinder
Buckling force: 7787571.54N
Compression force: 2348339.78N
Pressure: 187.99bar
Buckling swl: 75422.43kg
Pressure swl: 58265.89kg

Choice of optimization variables

Main Cylinders

Abilities

Expanding time [sec]	4000
House weight [kg]	664
Max. length [mm]	6450
Max. pressure [bar]	315
Min. length [mm]	3925
Weight [kg]	2624

House

Outer diameter [mm]	394
Cylinder house length [mm]	3642
House wall thickness [mm]	37
Piston guide clearance [mm]	0,17

Other

Eye bearing friction coefficient	0,19
Eye bearing radii [mm]	80
No. of cylinders	2

Position

Height to boom hinge [mm]	-1000
Dist. to boom line [mm]	0
Distance along boom line [mm]	1700
Distance along jib line [mm]	5469

Rod

Rod diameter [mm]	230

Jib Cylinders

Abilities

Expanding time [sec]	4000
Max. length [mm]	6680
Max. pressure [bar]	215
Min. length [mm]	4000
Weight [kg]	1609

House

Outer diameter [mm]	326
Cylinder house length [mm]	3758
House wall thickness [mm]	22
House weight [kg]	409
Piston guide clearance [mm]	0,17

Other

Eye bearing friction coefficient	0,19
Eye bearing radii [mm]	70
No. of cylinders	2

Position

Dist. to boom line [mm]	-1175
Distance along boom line [mm]	5783
Distance along jib line [mm]	2001
Dist. to jib line [mm]	250

Rod

Rod diameter [mm]	180
Rod length [mm]	3770
Rod weight [kg]	1226

Boom

Size

Length [mm]	15800
Side area [mm?]	14000000
Top area [mm?]	12960000

Center of gravity

X [mm]	6880
Y [mm]	-500
Weight [kg]	14250

Hinge

Max hinge force [N]	1
Hinge width [mm]	2040
Boom hinge X [mm]	200
Boom hinge Y [mm]	8980

Jib

Size

Length [mm]	10300
Side area [mm?]	11520000
Top area [mm?]	6786000

Center of gravity

X [mm]	5334
Y [mm]	0
Weight [kg]	8500

Hinge

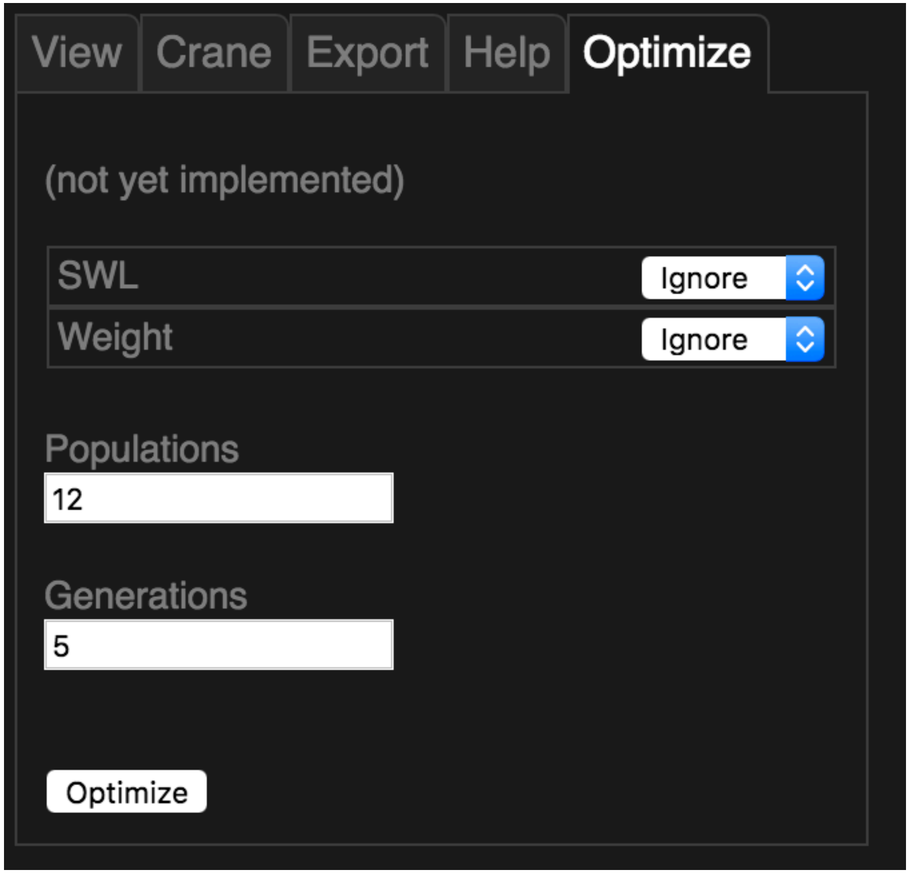
Max. hinge force [N]	2
Hinge width [mm]	800

Choice of optimization variables

- Among the 120 different design parameters, four design parameters that greatly affect both SWLmax and W were chosen as decision variables, namely:
  - the boom length L_{boom};
  - the jib length L_{jib};
  - the maximum pressure of the boom cylinder $P_{max,boom}$; and
  - the maximum pressure of the jib cylinder $P_{max,jib}$.
- All other design parameters were identical to those of the nominal crane.

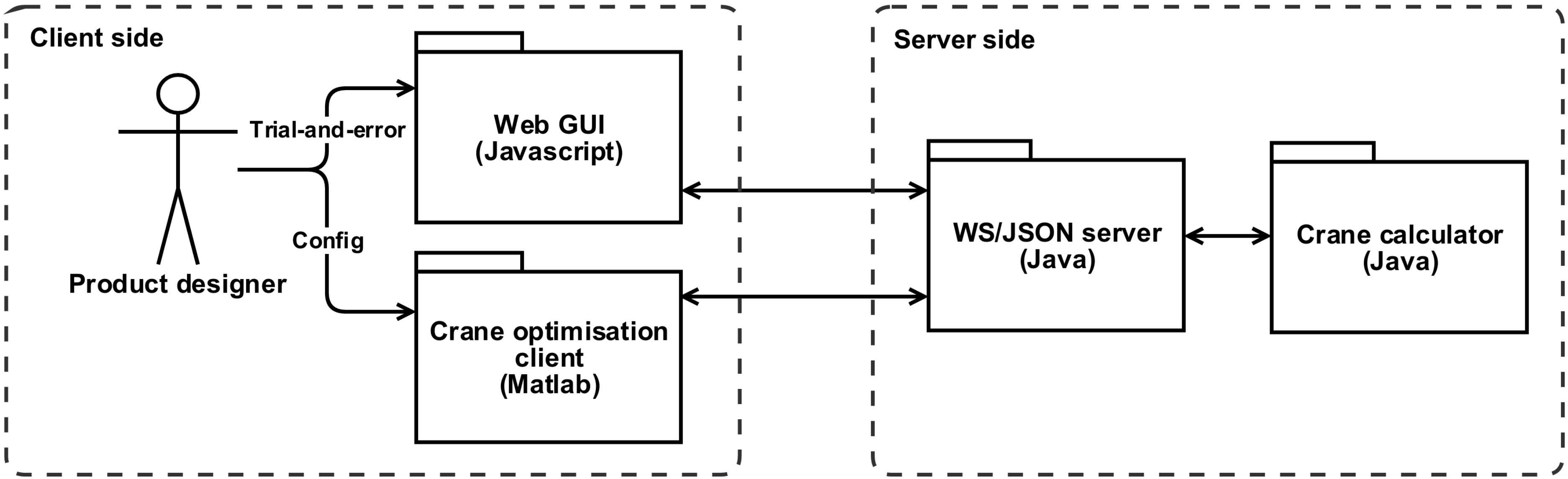
Objective functions

- SWL: safe working load (ton) (🡅)
- Weight: total crane weight (ton) (🡇)



Software architecture for Matlab optimizer

Crane is modeled and simulated as a black box



Use Matlab WebSocket (WS) and JavaScript Object Notation (JSON)

Standard GA & Obj. Functions

- Continues GA
- Single objective function
- Minimization
- Problem formulation:

$$\min_{x \in X} f(x) = \min_{x \in \left\{ \begin{array}{l} L_{boom}, \\ L_{jib}, \\ P_{max,boom}, \\ P_{max,jib} \end{array} \right\}} \sum_{i=1}^{2} \omega_i f_i(x)$$

$$\begin{aligned} such\,that\ 12000 &\le L_{boom} \le 26000, \\ 6000 &\le L_{jib} \le 16000, \\ 100 &\le P_{max,boom} \le 400, \\ 50 &\le P_{max,jib} \le 300, \end{aligned}$$

$Obj.Functions:$

$$f_1(x) = W / SWL$$

$$f_2(x) = \omega_1 / SWL + \omega_2 W$$

$$f_3(x) = \omega_1 / SWL + \omega_2 |W_n - W|$$

$$f_4(x) = \omega_1 |SWLn - SWL| + \omega_2 W$$

measure	units	nominal	(min, max)
L_{boom}	mm	15800	(12000, 26000)
L_{jib}	mm	10300	(6000, 16000)
$P_{\text{max,boom}}$	bar	315	(100, 400)
$P_{\text{max,jib}}$	bar	215	(50, 300)
SWL_{max}	tonne	99.978	-
W	tonne	50.856	-

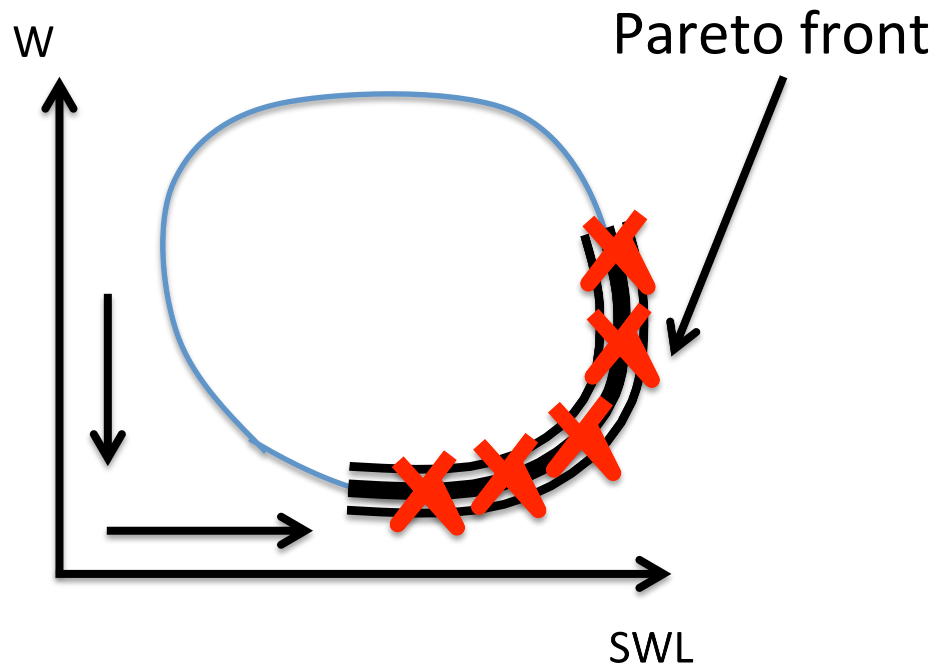
Multi-Objective Optimization (MOO)

- In MOO, optimal decision need to be taken in the presence of trade-offs between two or more conflicting objectives (competing obj. functions)
- The two KPIs SWL and W were used as two individual objective functions.
- Matlab MOOGA Solver is used to maximize SWL and minimize W.
- f_1=1/SWL, and f_2=W
- The optimal solution is provided as a set of Pareto-optimal solutions for values of the design parameters.
- Each of these solutions results in a crane design with SWLmax = 140.95 tones and W = 43.88 tones.

Bio-objective optimization problem

L_{boom}	L_{jib}	$P_{max,boom}$	$P_{max,jib}$
12000.9	6000.95	331.309	67.1085
12000.8	6000.50	331.183	75.4687
12000.9	6000.39	332.326	88.6125
12000.9	6000.60	332.32	71.5644
12000.6	6000.95	331.309	67.1085
12000.6	6000.49	332.241	80.8655
12001.0	6000.69	332.101	72.0046
12000.9	6000.88	331.984	68.08
12000.9	6000.61	332.333	83.6164
12000.9	6000.98	331.788	74.0161
12001.0	6000.99	331.876	75.4702
12000.8	6000.95	331.309	67.1554
12000.9	6000.74	332.816	66.7924
12000.9	6000.55	331.308	75.4687
12000.7	6000.92	332.344	82.1006
12000.8	6000.61	332.227	82.379
12000.8	6000.82	332.414	66.8399
12000.5	6000.97	331.109	72.9711
12000.7	6000.79	331.142	87.5899
12000.6	6000.99	332.633	81.1601
12000.6	6000.95	331.151	84.4106
12000.8	6000.93	332.252	89.7784
12000.9	6000.86	331.048	82.0198
12000.6	6000.81	331.017	80.539
12000.9	6000.51	332.668	68.4269
12000.7	6000.98	331.41	79.5427
12000.9	6000.91	331.983	68.8521
12000.7	6000.99	331.75	81.9171
12000.7	6000.66	332.401	82.9699
12000.8	6000.82	331.325	72.0107
12000.9	6000.95	331.246	67.1085
12000.7	6000.49	332.264	80.928
12000.9	6000.93	331.261	68.3642
12000.8	6000.63	332.088	78.7431
12000.9	6000.51	332.668	68.4269

Table 3: Pareto set of optimised cranes using MOO that all have $SWL_{max} = 140.95$ and $W = 43.88$.



Maximize SWL and minimize W

GA and MOO results

objective function	$\mathrm{SWL}_{\mathrm{max}}$	W	T (min)
f_1	142.14	44.01	98.4
f_2, $w_1 = w_2 = 1$	140.63	44.22	115.21
f_2, $w_1 = 1$, $w_2 = 5000$	140.59	44.22	89.39
f_2, $w_1 = 10$, $w_2 = 5000$	140.02	44.22	106.19
f_2, $w_1 = 0.1$, $w_2 = 5000$	143.37	43.88	66.36
f_3, $w_1 = w_2 = 1$	112.54	50.81	125.82
f_4, $w_1 = w_2 = 1$	99.94	47.1	90.97
MOO	140.95	43.88	182.83
mean	132.52	45.29	109.40
standard deviation	16.60	2.47	34.68
nominal	99.98	50.86	-
difference of mean with nominal	32.54	-5.56	-

Table 2: Processing time T in minutes and optimal values of $\mathrm{SWL}_{\mathrm{max}}$ and W for the set of objective functions, their mean and standard deviation, and the difference of the means from the nominal crane.

Particle Swarm Optimization (PSO)

- PSO is inspired by the observation that groups of individuals work together to improve not only their collective performance on some task, but also their individual performance.
- Performance in PSO is improved based on these basic ideas:
  - **inertia**, where individuals tend to stick to the old ways that have been proven successful in the past,
  - **influence by society**, where individuals try to emulate the approaches of successful stories of others, and
  - **influence by neighbours**, where individuals learn the most from those who are personally close to them rather than their societies.
- A simple PSO is initialized with a group of random particles (solutions) moving in the search space with the same velocity, searching for optimum solution by updating generations.

Simulated Annealing (SA)

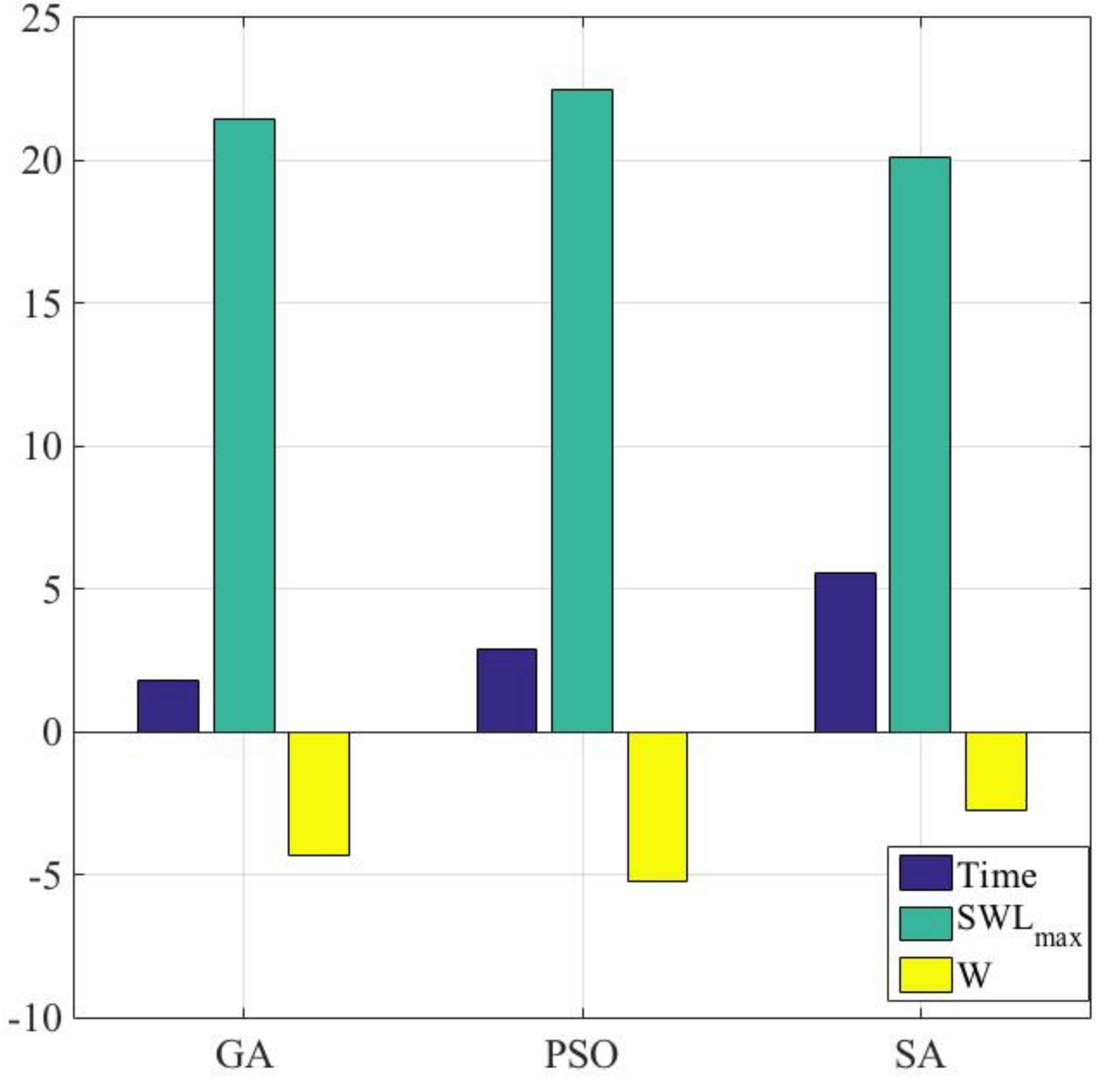
- SA is an optimization algorithm that is emulating the cooling and crystallizing behavior of chemical substances.
- Since annealing in nature results in low-energy configurations of crystals, it can be simulated in an algorithm to minimize cost functions.

Results

Table 1. Optimization results for various objective functions compared to benchmar nominal crane design f_n.

	measure	f_n	$f_1 - f_n$	$f_2 - f_n$	$f_3 - f_n$	$f_4 - f_n$	mean	median
GA	L_{boom}	15800	-3763	-3533	3666	-2356	-1497	-2945
	L_{jib}	10300	-4176	-4179	-4015	-1971	-3585	-4096
	$P_{\text{max,boom}}$	315,0	68,0	25,9	77,1	-41,6	32,4	47,0
	$P_{\text{max,jib}}$	215,0	47,0	51,8	79,7	-114,0	16,1	49,4
	fitness	-	1,26	40,66	0,02	50,89	23,21	20,96
	SWL_{max}	100,0	42,2	40,7	3,0	-0,0	21,4	21,8
	W	50,7	-6,8	-6,6	-0,0	-3,8	-4,3	-5,2
	T	-	1,64	2,30	1,73	1,52	1,80	1,69
	iterations	-	26	31	23	22	25,5	24,5
PSO	L_{boom}	15800	-3800	-3800	3940	-3789	-1862	-3795
	L_{jib}	10300	-4300	-4300	-4300	-4297	-4299	-4300
	$P_{\text{max,boom}}$	315,0	45,6	45,6	66,5	-87,7	17,5	45,6
	$P_{\text{max,jib}}$	215,0	85,0	85,0	13,8	-65,4	29,6	49,4
	fitness	-	1,30	28,29	0,01	50,86	20,12	14,80
	SWL_{max}	100,0	43,4	43,4	3,2	0,0	22,5	23,3
	W	50,9	-7,0	-7,0	0,0	-7,0	-5,2	-7,0
	T	-	1,50	1,67	4,04	4,37	2,89	2,85
	iterations	-	21	21	61	66	42,25	41
SA	L_{boom}	15800	-3799	-3793	-220	-92	-1976	-2006
	L_{jib}	10300	-1445	-3364	246	-219	-1195	-832
	$P_{\text{max,boom}}$	315,0	22,5	44,1	65,7	-0,5	33,0	33,3
	$P_{\text{max,jib}}$	215,0	-41,5	61,0	2,6	-59,8	-9,5	-19,5
	fitness	-	1,00	25,92	0,01	50,86	19.45	13,46
	SWL_{max}	100,0	37,0	40,0	4,0	0,0	20,1	20,5
	W	50,9	-4,6	-6,2	0,0	-0,3	-2,8	-2,4
	T	-	8,14	8,13	4,44	1,54	5,56	6,29
	iterations	-	11708	11708	6418	2198	8008	9063

Comparison



Conclusions

- PSO outperforms GA and SA algorithms in terms of resultant KPIs' values.
- PSO provided the highest possible maximum safe working load, SWLmax, and the lowest possible crane weight, W, compared to GA and SA.
- GA converges faster than PSO, however, it requires tedious and time consuming human involvement in setting up various parameters before using it or re-tuning.
- In addition to its implementation simplicity and the less number of parameters required to be tuned, PSO can be considered as a multi-population EAs and therefore it is believed that it outperforms both GA and SA.

Conclusions

- The results also showed that SA has the slowest performance compared to GA and PSO and this is because SA does not have a population of candidate solution and instead use a single candidate solution each generation.

Future work

- The solution proposed in this paper is not limited to crane design but can easily be extended and applied to the design of various other products or complex systems.
- Various optimization algorithms should be tested.
- Other KPIs should be investigated.
- Optimization or decision variables should be extended to include other design variables (up to 120 parameters)
- How the load-chart can be optimized requires more investigation.

Acknowledgment

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- SoftICE Lab members NTNU in Ålesund http://blog.hials.no/softice/
- Seaonics AS http://www.seaonics.com/

references

- A full list of reference is provided in the paper version.
- For correspondence: ibib@ntnu.no

Thanks for your attention …

Questions?