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Efficient constraint multi-objective optimization with applications in ship design

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Citation

Winter, R. de. (2024, October 8). *Efficient constraint multi-objective optimization with applications in ship design*. Retrieved from <https://hdl.handle.net/1887/4094606>

Version: Publisher's Version

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Note: To cite this publication please use the final published version (if applicable).

Appendix B

Appendix

B.1 Expensive Single Objective Optimization

For the optimization of the two single objective ship design problems of Chapter 6 the Modular Adaptive Global Optimization Framework (MAGOF) is introduced. The objective from the two ship design problems were computationally expensive and the constraints are computationally inexpensive. To be ready for more different problem characteristics a modular adaptive framework is proposed. In this appendix a pseudocode and a detailed explanation is presented together with experiments and results on the well known constraint single objective G-Problem suite [93, 61].

B.2 Modular Optimization Framework

The pseudocode of the Modular Adaptive Global Optimization Framework (MAGOF) is presented in Algorithm 4. The evaluation method and strategy are described in more detail in Algorithm 5 and Section B.2.3. The input, the overall explanation of the pseudocode, and the working of the framework are described in more detail in the following subsections.

B.2.1 Input parameters

The input arguments for the modular framework are:

1. **Objective function** $f(\mathbf{x})$ that is to be minimized. The objective function is defined by the user as expensive $f_e(\mathbf{x})$, or inexpensive $f_c(\mathbf{x})$.

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2. **Constraint function(s)** $\mathbf{g}(\mathbf{x})$ that consist out of m separate constraint functions, where $m \geq 0$. The constraint function(s) are either defined by the user as expensive $\mathbf{g}_e(\mathbf{x})$, or inexpensive $\mathbf{g}_c(\mathbf{x})$. The constraint functions return the constraint violation, meaning that constraint values $g(\mathbf{x}) \leq 0$ are defined as feasible.
3. **Input space** $x \in \Omega \subset \mathbb{R}^d$ that is limited by the lower and the upper boundary $[\mathbf{x}_{lb}, \mathbf{x}_{ub}]$.
4. **Initial sample strategy and sample size** N_{init} and DoE define how many samples are evaluated in the design of experiments. This should at least be larger than $d + 1$.
5. **Evaluation budget** N_{max} defines how many expensive function evaluations are allowed to be evaluated.
6. **RBF strategy domain**, $\Phi = \{Cubic, Gaussian, Multiquadric, InverseQuadratic, InverseMultiquadric, ThinPlateSpline\} \times \{PLOG, standardized\}$. The RBF strategy domain defines the different surrogates that are used in every iteration to model the computationally expensive functions.
7. **Parallelism** p , is the number of solutions that can be evaluated in parallel. Note that parallelism is not a requirement as p can also be 1.
8. **Acquisition function** α that used to find promising solutions. The acquisition function uses the surrogates or the inexpensive functions directly to find p promising solutions for evaluation.
9. **Constraints first indicator** that defines if the constraints should all be satisfied before the objective function can be evaluated.

B.2.2 Design of Experiments

The framework in Algorithm 4 starts in line 2 by creating a Design of Experiments (DoE). The size and the strategy for the DoE can be chosen by the user and can be random, a latin hypercube sample, solutions on the boundaries, or a Halton sample. Each of these sample strategies has its strengths, however, an empirical comparison by Bossek et al. [23] showed that an as small as possible initial Halton sample [73] is in most cases the most efficient strategy. It is also possible to start with an initial sample that is already evaluated.

Algorithm 4: MAGOF.

Input: Objective function $f(\mathbf{x})$, that can be computationally expensive $f_e(\mathbf{x})$ or computationally inexpensive $f_c(\mathbf{x})$, constraint function(s) $\mathbf{g}(\mathbf{x})$, split where required into expensive constraint function(s) $\mathbf{g}_e(\mathbf{x})$, computationally inexpensive constraint function(s) $\mathbf{g}_c(\mathbf{x})$, decision parameters' lower and upper bounds $[\mathbf{x}_{lb}, \mathbf{x}_{ub}] \subset \mathbb{R}^d$, sampling strategy DoE, number of initial samples N_{init} , maximum evaluation budget N_{max} , RBF strategy domain consisting of 12 RBF strategies $\Phi = \{Cubic, Gaussian, Multiquadric, InverseQuadratic, InverseMultiquadric, ThinPlateSpline\} \times \{PLOG, standardized\}$, number of solutions that can be evaluated in parallel p , acquisition function α , constraint first indicator c_{first} .

Output: Evaluated solutions.

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1 Function MAGOF( $f, \mathbf{g}, \mathbf{x}_{lb}, \mathbf{x}_{ub}, \text{DoE}, N_{init}, N_{max}, \Phi, p, \alpha, c_{first}$ ):
2    $\mathbf{x}^* \leftarrow \{\mathbf{x}_1, \dots, \mathbf{x}_{N_{init}}\} \leftarrow \text{DoE}(\mathbf{x}_{lb}, \mathbf{x}_{ub}, N_{init})$  ▷ Generate DoE,  $\mathbf{X} \in \mathbb{R}^{d \times N_{init}}$ 
3    $\mathbf{F}, \mathbf{G}, \mathbf{X} \leftarrow \text{EVALUATE}(\mathbf{x}^*, f, \mathbf{g}, p, c_{first}, N_{init}, \mathbf{F} = [], \mathbf{G} = [], \mathbf{X} = [])$  ▷ Evaluate
   initial sample and initialize archives  $\mathbf{F}$ ,  $\mathbf{G}$  and  $\mathbf{X}$ 
4    $\mathbf{h} \leftarrow \{f_e \cup \mathbf{g}_e\}$  ▷ Union of expensive objective and constraint functions
5    $\varphi^* \leftarrow (\varphi_1, \dots, \varphi_{|\mathbf{h}|}) \leftarrow (Cubic, standardized)^{|\mathbf{h}|}$  ▷ Initialize RBF strategy for all
   expensive functions,  $\varphi^* \in \Phi$ 
6    $\mathbf{E}_{i,j} \leftarrow 0 \forall (i,j) \in \mathbf{h} \times \Phi$  ▷ Initialize RBF approximation errors for each
   possible RBF configuration( $\Phi$ ) for all expensive functions( $\mathbf{h}$ )
7    $j \leftarrow N_{init}$  ▷ Initialize expensive evaluation counter
8   while  $j < N_{max}$  do
9      $\mathbf{S}^\Phi \leftarrow (S_{h_1}^{\Phi_1}, \dots, S_{h_{|\mathbf{h}|}}^{\Phi_{|\mathbf{h}|}}) \leftarrow \{\text{FITRBF}(\mathbf{X}, h, \Phi, \mathbf{x}_{lb}, \mathbf{x}_{ub}) \mid \forall h \in \mathbf{h}\}$  ▷ Fit RBFs
     using all strategies( $\Phi$ ) for all expensive functions( $\mathbf{h}$ )
10     $\mathbf{S}^{\varphi^*} \leftarrow (S_1^{\varphi^*}, \dots, S_{|\mathbf{h}|}^{\varphi^*})$  ▷ Select best RBF strategy based on line 5 or 15
11     $\mathbf{x}_1^*, \dots, \mathbf{x}_p^* \leftarrow \text{MAX}(\alpha, p, \mathbf{S}^{\varphi^*}, f_c, \mathbf{g}_c)$  ▷ Get  $p$  new solutions based on
     acquisition function  $\alpha$ , use cheap functions  $f_c$  and  $\mathbf{g}_c$  directly
12     $j \leftarrow j + p$  ▷ Increase iteration counter to new matrix sizes
13     $\mathbf{X} \leftarrow [\mathbf{X}, \mathbf{x}_1^*, \dots, \mathbf{x}_p^*]$  ▷ Add  $p$  new solution vectors,  $\mathbf{X} \in \mathbb{R}^{d \times j}$ 
14     $\mathbf{F}, \mathbf{G}, \mathbf{X} \leftarrow \text{EVALUATE}(\mathbf{x}^*, f, \mathbf{g}, p, c_{first}, j, \mathbf{F}, \mathbf{G}, \mathbf{X})$  ▷ Evaluate new solutions
15     $\varphi^*, \mathbf{E} \leftarrow \text{SELECTBESTRBFSTRATEGY}(\mathbf{E}, \mathbf{S}^\Phi, \mathbf{F}, \mathbf{G}, \mathbf{X})$  ▷ Update RBF approximation
     errors  $\mathbf{E}$ , and new best RBF configuraiton  $\varphi^*$ 
16  end
17 return ( $\mathbf{F}, \mathbf{G}, \mathbf{X}$ )

```

B.2.3 Evaluation of the solutions

On lines 3 and 14 of Algorithm 4 the solutions that are proposed by the DoE, or after optimizing the acquisition function, are evaluated as described in the evaluate Algorithm 5. The approach is dependent on the inexpensiveness of the constraint and objective functions. There are 3 levels of expensiveness. (1) the function can be evaluated almost instantly and can therefore be evaluated millions of times (it must at least be faster than fitting and interpolating an RBF surrogate model). (2) the function

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requires a little bit of evaluation time and can therefore not be evaluated numerous times and evaluating them millions of times is too costly. Function evaluations of level 2 for example require a few seconds up to a few minutes and are significantly less costly compared to the most expensive evaluations. (3) the function is computationally expensive and the evaluation budget is very limited e.g. computational fluid dynamic simulations or finite element analysis that can take up to hours on a cluster to evaluate.

The inexpensive functions level 1 are used directly in the optimization algorithm, see Section B.2.5. If the constraints are inexpensive level 2, they are evaluated first before the computationally expensive functions. Only if the constraints are satisfied, the expensive functions (level 3) are evaluated. If the constraints are violated, a null is stored instead of the expensive outcome. This way, in the next iteration of MAGOF the RBF surrogates for the expensive functions remain the same as in the previous iteration while for the inexpensive functions level 2 the RBF surrogates are updated.

Algorithm 5: Evaluate.

Input: Solutions $\mathbf{x}^*$ to be evaluated, Objective function $f(\mathbf{x})$, that can be computationally expensive $f_e(\mathbf{x})$ or computationally inexpensive $f_c(\mathbf{x})$, constraint function(s) $\mathbf{g}(\mathbf{x})$, split where required into expensive constraint function(s) $\mathbf{g}_e(\mathbf{x})$, computationally inexpensive constraint function(s) $\mathbf{g}_c(\mathbf{x})$, number of solutions that can be evaluated in parallel p , constraint first indicator c_{first} , objective values of evaluated solutions $\mathbf{F}$, constraint values of evaluated solutions $\mathbf{G}$, evaluated solutions $\mathbf{X}$.

Output: Evaluated solutions.

```

1 Function Evaluate( $\mathbf{x}^*, f, \mathbf{g}, p, c_{first}, j, \mathbf{F}, \mathbf{G}, \mathbf{X}$ ):
2    $\mathbf{G} \leftarrow [\mathbf{G}, \mathbf{g}_c(\mathbf{x}_1^*), \dots, \mathbf{g}_c(\mathbf{x}_p^*)]$   $\triangleright$  Add vectors of cheap constraints,  $\mathbf{G} \in \mathbb{R}^{m \times j}$ 
3   if not  $c_{first}$  then
4      $\triangleright$  If constraints do not need to be satisfied first then add
5      $\mathbf{F} \leftarrow [\mathbf{F}, f_e(\mathbf{x}_1^*), \dots, f_e(\mathbf{x}_p^*)]$   $\triangleright$  Vector of evaluated objectives,  $\mathbf{F} \in \mathbb{R}^j$ 
6      $\mathbf{G} \leftarrow [\mathbf{G}, \mathbf{g}_e(\mathbf{x}_1^*), \dots, \mathbf{g}_e(\mathbf{x}_p^*)]$   $\triangleright$  Vectors of evaluated constr  $\mathbf{G} \in \mathbb{R}^{m \times j}$ 
7   else
8     for  $\mathbf{x}_i \in \{\mathbf{x}_1^*, \dots, \mathbf{x}_p^*\}$  do
9       if  $\mathbf{g}_c(\mathbf{x}_i) \leq 0$  then
10         $\triangleright$  If constraints need to be satisfied first
11         $\mathbf{F} \leftarrow [\mathbf{F}, f_e(\mathbf{x}_i)]$   $\triangleright$  Only add objective value of feasible solutions
12         $\mathbf{G} \leftarrow [\mathbf{G}, \mathbf{g}_e(\mathbf{x}_i)]$   $\triangleright$  Only add constraint value of feasible solutions
13      else
14         $\triangleright$  If constraints are violated
15         $\mathbf{F} \leftarrow [\mathbf{F}, \text{null}]$   $\triangleright$  Don't evaluate and add null
16         $\mathbf{G} \leftarrow [\mathbf{G}, \text{null}]$   $\triangleright$  Don't evaluate and add null
17    end
18 return ( $\mathbf{F}, \mathbf{G}, \mathbf{X}$ )

```

B.2.4 Radial Basis Functions

In every iteration of MAGOF, surrogates are fitted to approximate the constraint and objective functions (line 9 of Algorithm 4). However, there are many kernel options and scaling techniques available when fitting RBF surrogates and each option can be good for different scenarios. Therefore, RBF surrogates are fitted with the following kernels: *Cubic*, *Gaussian*, *Multiquadric*, *InverseQuadratic*, *InverseMultiquadric*, *ThinPlateSpline* and two different scaling strategies are used to scale the constraint and objective values. The standardization method is used so that the uncertainty quantification method can be used for the RBFs. The PLOG transformation from Equation B.1 is selected so that the RBFs can better model steep slopes. For each combination of these kernels and transformation methods, a surrogate is fitted which results in a total 12 RBF surrogate models per expensive function. In every iteration, the RBF strategy with the smallest approximation error is selected (line 5 and 15 of Algorithm 4) and the RBF approximation errors are stored.

$$\text{PLOG}(y) = \begin{cases} +\ln(1+y), & \text{if } y \geq 0 \\ -\ln(1-y), & \text{if } y < 0 \end{cases} \quad (\text{B.1})$$

B.2.5 Acquisition Function Optimization

The acquisition functions integrated into the framework are: the expected improvement acquisition function [85], the generalized expected improvement acquisition function [119] for parallel evaluations when $p > 1$, and the purely exploitative acquisition function that predicts the objective value with the RBF surrogate without uncertainty. This acquisition function is optimized with the COBYLA algorithm [120]. COBYLA is a single objective optimization algorithm that optimizes an optimization problem with constraints by linearly approximating the acquisition function and the most violated constraint in a small trust region. COBYLA finds the most promising solution in this trust region, then checks the constraint and objective values, and iteratively adjusts the trust region until the trust region is so small and the local optimum is found.

For the functions with expensiveness levels 2 and 3, COBYLA is instructed to use the surrogate models when optimizing the acquisition function. The inexpensive functions (level 1) that can be calculated instantly, are directly used by COBYLA when optimizing the acquisition function. The usage of the inexpensive functions is beneficial because they don't make approximation errors that surrogate models make.

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Note that during the optimization of the acquisition function, the inexpensive functions (or surrogate for expensive functions) are evaluated many times.

Because COBYLA is a local optimizer, the COBYLA algorithm starts searching from multiple random locations. This makes it more likely that the global optimum is found.

B.3 Experiments

For this algorithm, four types of experiments are conducted. All experiments are conducted on the G-problem test suite [93, 61].

B.3.1 G-Problem experimental setup

The G-Problems (G1 to G11 from [93, 61]) are selected as an artificially created benchmark suite to validate the performance of MAGOF. A Python implementation of the G-Problems is taken from the CEC 2006 Special Session on Constrained Real-Parameter Optimization [63]. The G-problems considered have between 1 and 9 constraints and between 2 and 20 decision parameters, and all are to be minimized. The optimal solutions are known for all G-problems, some problems have active constraints at the optimum, while other optima are somewhere in the feasible region. The feasibility ratio of the G-Problems varies between less than 1% feasible and 99% feasible per test problem. More details regarding the G-Problems can be found in e.g. [13, 93, 61]. Evaluation of the constraint and the objective functions of the G-problems are computationally inexpensive. However, for the experiments, it is assumed that the objectives are computationally expensive to evaluate.

To test the functionality of the mixed expensiveness, four different configurations of MAGOF are tested with different infill criteria and different inexpensive function handling techniques.

1 Traditional The "traditional" configuration uses MAGOF without any special treatment and/or separation of expensive versus inexpensive functions. The objective and constraint methods are considered equally expensive which in MAGOF means that in every iteration the RBFs are fitted for the constraints and objective, the best RBF strategy is selected, and then the default acquisition function is optimized. The resulting solution is computed and evaluated with the constraints and the objectives.

2 Constraints First: The "constraints first" configuration of MAGOF utilizes the adjustment in the evaluation strategy as presented in Algorithm 5. In this con-

figuration it is assumed that the constraints evaluations are computationally way less expensive compared to the objective evaluation. In every iteration, the RBFs are fitted, the best RBF strategy is selected, and the default acquisition function is optimized using the surrogates. The solution that is proposed is now evaluated first on the constraints. In case any of the constraints are violated, the objective function is not evaluated and the next iteration starts. In case the constraints apply the objective function is evaluated.

3 Constraints Integrated: The "constraint integrated" configuration in MAGOF is not conventional as instead of fitting RBFs for the constraints, the constraints are directly used when optimizing the acquisition function because it is assumed that the constraint function evaluations are computationally cheaper than fitting an RBF and making predictions with RBFs. The RBFs are now only used to model the objective function since the objective function evaluation is assumed to remain computationally expensive.

4 Parallel: The "parallel" configuration of MAGOF does not assume inexpensive constraints or objectives and therefore uses RBF models to model the assumed expensive constraint and objective functions. After the RBF models are fitted, the best RBF approximation is selected, and the generalized expected improvement acquisition function is optimized. The hyperparameter (g_{EI}) of the acquisition function is set in such a way that one solution proposed by the algorithm is purely exploitative ($g_{EI} = 0$), one is explorative and would be most similar to solutions proposed by the expected improvement acquisition function ($g_{EI} = 6$), and one solution is a balance between exploitative and explorative ($g_{EI} = 3$). This way, the generalized expected improvement acquisition function can be used to propose 3 different solutions. After the solutions are proposed, they are evaluated in parallel with both the objective and constraint functions.

All configurations start with an as small as possible initial Halton sample as a DoE. After the DoE the first 3 configurations are allowed to do a total of $300 - |\text{DOE}|$ iterations for the non-parallel configurations. The configuration that proposes 3 solutions per iteration was allowed to do an additional 100 iterations. This way each algorithm configuration has in theory the possibility to do 300 objective function evaluations. Note that the configuration with constraint first, does not necessarily use all these 300 objective evaluations since in the 300 iterations, this configuration also sometimes proposes infeasible solutions. The constraints integrated configuration uses a lot more constraint function evaluations since when optimizing the acquisition function, the constraints are evaluated many more times.

B.4. Results

B.4 Results

In Table B.1 the results are presented for the G-problem test suite. In this table, the mean smallest objective scores of the feasible solutions are presented after 10 independent runs of MAGOF with the four different options. Besides the mean objective score, the number of required function evaluations is reported that was required to reach the minimum. Please refer to [63] for the complete set of minima for all functions. A red cross (x) indicates that the optimum was not found within 300 evaluations.

Function		Traditional	Constraint First	Constraint Integrated	Parallel P=3
G01	fv	−15.00	−15.00	− 15.00	−13.54
	fe	28	24	22	x
G02	fv	−0.304	−0.304	− 0.383	−0.304
	fe	x	x	x	x
G03	fv	−0.000	− 0.089	−0.006	−0.000
	fe	x	x	x	x
G04	fv	−30665	−30665	− 30665	−30665
	fe	26	19	11	111
G05	fv	5126.5	5126.5	5126.5	5126.5
	fe	41	12	10	x
G06	fv	−6957	− 6959	− 6959	−6956
	fe	x	x	x	x
G07	fv	24.306	24.306	24.306	35.479
	fe	34	22	21	x
G08	fv	− 0.096	−0.096	−0.096	−0.096
	fe	13	30	28	100
G09	fv	680.63	1186.8	680.64	1597.8
	fe	240	x	89	x
G10	fv	7114.3	7088.6	7049.3	9233.1
	fe	x	x	65	x
G11	fv	0.7500	0.7500	0.7500	0.7500
	fe	7	5	5	12

Table B.1: The mean minimum encountered objective score of feasible solutions (fv), and the mean objective function evaluations (fe) required to find the optimal value (a x indicates the known optimal value was not reached in 300 iterations). Four different approaches are compared, the traditional optimization technique, the constraint first approach, the constraints integrated into the acquisition function optimization process, and the approach with the generalized expected improvement acquisition function that proposes 3 solutions in parallel. The best combination of fv and fe are marked in **bold** per G-problem. All G-problems are optimized in 10 independent optimization runs.

Inspection of the results shows that in the majority of the problems using the cheap

constraints directly in the optimization algorithm when optimizing the acquisition function is beneficial in terms of execution time and convergence. The other option where the constraints are first evaluated to check for feasibility before the objective function is evaluated also shows better results compared to the conventional approach where the objective is evaluated together with the constraints. The option to propose 3 solutions in parallel with the generalized expected improvement acquisition function does not show good results. It was expected upfront that when proposing multiple solutions for parallel evaluation (and this way save computation time), the number of iterations of the algorithm could be reduced. However, the number of required iterations and therefore also the number of function evaluations is higher compared to the other approaches.

On the G08 test problem, the traditional approach finds the optimum in less required objective evaluations compared to the other approaches. It is assumed that the reason for this quick convergence is that the information gathered from the evaluated infeasible solutions is of great value for this optimization problem. The information from the infeasible evaluated solutions is missing when the constraint first configuration or constraints integrated configuration is used in MAGOF.

B.5 Conclusion and Future Work

Specifically for the optimization of the two single objective ship design problems from Chapter 6, the Modular Adaptive Global Optimization Framework (MAGOF) is introduced. MAGOF can solve constraint single objective problems with a mix of computationally expensive and computationally inexpensive constraint and objective functions. MAGOF uses RBF surrogates for expensive functions, the inexpensive functions can directly be used when searching for promising solutions with an acquisition function. Besides this, a strategy is added to MAGOF that enforces the feasibility of the inexpensive constraints before computationally expensive objective and/or computationally expensive constraints are evaluated. MAGOF with the inexpensive constraints used directly when optimizing the acquisition function showed to be the most promising option when optimizing the G-Problem test suite.

In the future, more research is required on how to effectively propose multiple solutions in parallel with other batch acquisition functions described in e.g. [67, 171, 8]. Secondly, more research is required on setting up the parameterization of optimization problems.

B.5. Conclusion and Future Work

Bibliography

- [1] Hamid Afshari, Warren Hare, and Solomon Tesfamariam. Constrained multi-objective optimization algorithms: Review and comparison with application in reinforced concrete structures. *Applied Soft Computing*, 83:105631, 2019.
- [2] AISHub. Ais data sharing and vessel tracking by aishub, 2024. accessed: 10-01-2023, <https://www.aishub.net/>.
- [3] Taimoor Akhtar and Christine A Shoemaker. Efficient multi-objective optimization through population-based parallel surrogate search, 2019.
- [4] Richard Allmendinger and Joshua Knowles. Heterogeneous objectives: state-of-the-art and future research. *arXiv preprint arXiv:2103.15546*, 2021.
- [5] Juan J Alonso, Patrick LeGresley, and Víctor Pereyra. Aircraft design optimization. *Mathematics and Computers in Simulation*, 79(6):1948–1958, 2009.
- [6] Hanan Alsouly, Michael Kirley, and Mario Andrés Muñoz. An instance space analysis of constrained multi-objective optimization problems. *IEEE Transactions on Evolutionary Computation*, 2022.
- [7] DJ Andrews. A comprehensive methodology for the design of ships (and other complex systems). *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, 454(1968):187–211, 1998.
- [8] Javad Azimi, Alan Fern, and Xiaoli Fern. Batch bayesian optimization via simulation matching. *Advances in neural information processing systems*, 23:109–117, 2010.
- [9] Thomas Bäck. *Evolutionary algorithms in theory and practice: evolution strategies, evolutionary programming, genetic algorithms*. Oxford university press, 1996.
- [10] Thomas Bäck, Anna V Kononova, Bas van Stein, Hao Wang, Kirill Antonov, Roman Kalkreuth, Jacob de Nobel, Diederick Vermetten, **Roy de Winter**, and Furong Ye. Evolutionary algorithms for parameter optimization—thirty years later. *Evolutionary Computation*, 31(2):81–122, 2023.

Bibliography

- [11] Samineh Bagheri, Wolfgang Konen, and Thomas Bäck. Online selection of surrogate models for constrained black-box optimization. In *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, pages 1–8. IEEE, 2016.
- [12] Samineh Bagheri, Wolfgang Konen, and Thomas Bäck. Comparing kriging and radial basis function surrogates. In F. Hoffmann, E. Hüllermeier, and R. Mikut, editors, *Proc. 27. Workshop Computational Intelligence*, pages 243–259. Universitätsverlag Karlsruhe, 2017.
- [13] Samineh Bagheri, Wolfgang Konen, Michael Emmerich, and Thomas Bäck. Self-adjusting parameter control for surrogate-assisted constrained optimization under limited budgets. *Applied Soft Computing*, 61:377–393, 2017.
- [14] Sunith Bandaru, Amos HC Ng, and Kalyanmoy Deb. Data mining methods for knowledge discovery in multi-objective optimization: Part A-Survey. *Expert Systems with Applications*, 70:139–159, 2017.
- [15] Slim Bechikh, Lamjed Ben Said, and Khaled Ghedira. Estimating nadir point in multi-objective optimization using mobile reference points. In *IEEE Congress on Evolutionary Computation (CEC)*, pages 1–9. IEEE, 2010.
- [16] Robert Beck, Arthur Reed, Paul Sclavounos, and Bruce L Hutchison. Modern computational methods for ships in a seaway. *Transactions-Society of Naval Architects and Marine Engineers*, 109:1–51, 2001.
- [17] David Berengut. Statistics for experimenters: Design, innovation, and discovery. *The American Statistician*, 60:341–342, 2006.
- [18] Nicola Beume, Boris Naujoks, and Michael Emmerich. SMS-EMOA: Multiobjective selection based on dominated hypervolume. *European Journal of Operational Research*, 181(3):1653–1669, 2007.
- [19] Julian Blank and Kalyanmoy Deb. Constrained bi-objective surrogate-assisted optimization of problems with heterogeneous evaluation times: Expensive objectives and inexpensive constraints. In Hisao Ishibuchi, Qingfu Zhang, Ran Cheng, Ke Li, Hui Li, Handing Wang, and Aimin Zhou, editors, *International Conference on Evolutionary Multi-Criterion Optimization (EMO)*, pages 257–269. Springer, 2021.
- [20] Julian Blank and Kalyanmoy Deb. pysamoo: Surrogate-assisted multi-objective optimization in python, 2022.
- [21] Julian Blank, Kalyanmoy Deb, Yashesh Dhebar, Sunith Bandaru, and Haitham Seada. Generating well-spaced points on a unit simplex for evolutionary many-objective optimization. *IEEE Transactions on Evolutionary Computation*, 25(1):48–60, 2021.

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- [22] Torsten Bosse, Nicolas R. Gauger, Andreas Griewank, Stefanie Günther, and Volker Schulz. One-shot approaches to design optimization. In Günter Leugering, Peter Benner, Sebastian Engell, Andreas Griewank, Helmut Harbrecht, Michael Hinze, Rolf Rannacher, and Stefan Ulbrich, editors, *Trends in PDE Constrained Optimization*, pages 43–66, Cham, 2014. Springer International Publishing.
- [23] Jakob Bossek, Carola Doerr, and Pascal Kerschke. Initial design strategies and their effects on sequential model-based optimization: an exploratory case study based on BBOB. In *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO)*, pages 778–786, 2020.
- [24] Jakob Bossek, Carola Doerr, Pascal Kerschke, Aneta Neumann, and Frank Neumann. Evolving sampling strategies for one-shot optimization tasks. In Thomas Bäck, Mike Preuss, André Deutz, Hao Wang, Carola Doerr, Michael Emmerich, and Heike Trautmann, editors, *Parallel Problem Solving from Nature – PPSN XVI*, volume 12269, pages 111–124, Cham, 2020. Springer International Publishing.
- [25] Leo Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.
- [26] BRL Shipping Consultants. Brl active fleet vessels, 2024. accessed: 20-12-2023, <http://www.brldata.net/Pages/AFV.aspx>.
- [27] Philip Bronkhorst, **Roy de Winter**, Thijs Velner, and Austin A Kana. Enhancing offshore service vessel concept design by involving seakeeping-developing a framework to efficiently design high-performance offshore service vessel concepts. In Volker Bertram, editor, *22nd Conference on Computer and IT Applications in the Maritime Industries (COMPIT)*, pages 273–287. Hamburg University of Technology, Schriftenreihe Schiffbau, 2022.
- [28] Philip D.H. Bronkhorst. Enhancing offshore service vessel concept design by involving seakeeping. Master’s thesis, Delft University of Technology, 2021. <http://resolver.tudelft.nl/uuid:f674236b-c71c-4335-8b37-22f1a53d5a3d>.
- [29] Martin D Buhmann. *Radial basis functions: theory and implementations*. Cambridge University Press, 2003.
- [30] C-Job Naval Architects. Wind feeder vessel – solution for us offshore wind, 2022. Accessed 20-12-2023, <https://c-job.com/wind-feeder-vessel-solution-for-us-offshore-wind/>.
- [31] C-Job Naval Architects. Saronic ferries, 2023. Accessed: 20-12-2023, <https://c-job.com/projects/saronic-ferries/>.
- [32] C-Job Naval Architects. Saronic ferries partners with c-job naval architects for the design of the first fully-electric ro-pax ferry in greece, 2023. Accessed 20-12-2023, <https://c-job.com/press/saronic-ferries-partners-with-c-job-naval-architects-for-the-design-of-the-first-fully-electric-ro-pax-ferry-in-greece/>.

Bibliography

- [33] Yu Cai, Dushhyanth Rajaram, and Dimitri N Mavris. Multi-mission multi-objective optimization in commercial aircraft conceptual design. In *AIAA Aviation 2019 Forum*, page 3577, 2019.
- [34] Yu Cai, Dushhyanth Rajaram, and Dimitri N Mavris. Simultaneous aircraft sizing and multi-objective optimization considering off-design mission performance during early design. *Aerospace Science and Technology*, 126:107662, 2022.
- [35] CN Calvano, O Jons, and RG Keane. Systems engineering in naval ship design. *Naval engineers journal*, 112(4):45–57, 2000.
- [36] Tian-You Chai. Challenges of optimal control for plant-wide production processes in terms of control and optimization theories. *Acta automatica sinica*, 35(6):641–649, 2009.
- [37] Nikoleta Dimitra Charisi, Hans Hopman, Austin Kana, Nikos Papapanagiotou, and Thijs Muller. Parametric modelling method based on knowledge based engineering: The lng bunkering vessel case. In *Proceedings of the 12th Symposium on High-Performance Marine Vehicles, HIPER’20*. Technische Universität Hamburg-Harburg, 2020.
- [38] Tinkle Chugh, Karthik Sindhya, Jussi Hakanen, and Kaisa Miettinen. A survey on handling computationally expensive multiobjective optimization problems with evolutionary algorithms. *Soft Computing*, 23(9):3137–3166, 2019.
- [39] Tinkle Chugh, Karthik Sindhya, Kaisa Miettinen, Jussi Hakanen, and Yaochu Jin. On constraint handling in surrogate-assisted evolutionary many-objective optimization. In *Parallel Problem Solving from Nature–PPSN XIV: 14th International Conference, Edinburgh, UK, September 17–21, 2016, Proceedings 14*, pages 214–224. Springer, 2016.
- [40] Clarksons Research. World fleet register, 2024. accessed: 20-12-2023, <https://www.clarksons.net/wfr/>.
- [41] Carlos A Coello Coello, Gary B Lamont, David A van Veldhuizen, et al. *Evolutionary algorithms for solving multi-objective problems*. Springer, 2007.
- [42] Carlos A Coello Coello. Constraint-handling using an evolutionary multiobjective optimization technique. *Civil Engineering Systems*, 17(4):319–346, 2000.
- [43] Sabine Coquillart. Extended free-form deformation: A sculpturing tool for 3d geometric modeling. In *Proceedings of the 17th annual conference on Computer graphics and interactive techniques*, pages 187–196, 1990.
- [44] Rituparna Datta and Rommel G Regis. A surrogate-assisted evolution strategy for constrained multi-objective optimization. *Expert Systems with Applications*, 57:270–284, 2016.
- [45] GM Watson David. *Practical ship design*. Elsevier Ocean Engineering Series Editor, 1998.

-
- [46] Kalyanmoy Deb. *Multi-objective optimization using evolutionary algorithms*. John Wiley & Sons, 2001.
- [47] Kalyanmoy Deb and Samir Agrawal. A niched-penalty approach for constraint handling in genetic algorithms. In Andrej Dobnikar, Nigel C. Steele, David W. Pearson, and Rudolf F. Albrecht, editors, *Artificial neural nets and genetic algorithms*, pages 235–243. Springer Vienna, 1999.
- [48] Kalyanmoy Deb and Himanshu Jain. An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part i: Solving problems with box constraints. *IEEE Trans. Evolutionary Computation*, 18(4):577–601, 2014.
- [49] Kalyanmoy Deb, Amrit Pratap, Sameer Agarwal, and Thirunavukarasu Meyarivan. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2):182–197, 2002.
- [50] Kalyanmoy Deb, Amrit Pratap, and T Meyarivan. Constrained test problems for multi-objective evolutionary optimization. In Eckart Zitzler, Lothar Thiele, Kalyanmoy Deb, Carlos Artemio Coello Coello, and David Corne, editors, *International conference on evolutionary multi-criterion optimization (EMO)*, pages 284–298. Springer, 2001.
- [51] Audrey Delévacq, Pierre Delisle, Marc Gravel, and Michaël Krajecki. Parallel ant colony optimization on graphics processing units. *Journal of Parallel and Distributed Computing*, 73(1):52–61, 2013.
- [52] Det Norske Veritas. *Recommended Practice. Environmental Conditions and Environmental Loads*. DNV RP C205, 2010.
- [53] Mike Diessner, Joseph O’Connor, Andrew Wynn, Sylvain Laizet, Yu Guan, Kevin Wilson, and Richard D Whalley. Investigating bayesian optimization for expensive-to-evaluate black box functions: Application in fluid dynamics. *Frontiers in Applied Mathematics and Statistics*, 8:1076296, 2022.
- [54] EAE Duchateau. *Interactive evolutionary concept exploration in preliminary ship design*. PhD thesis, Delft University of Technology, 2016.
- [55] J. d’Almeida. *Arquitectura Naval – O Dimensionamento do Navio*. Prime Books, 2009.
- [56] Agoston E. Eiben and James E. Smith. *Introduction to evolutionary computing*. Natural Computing Series. Springer, Berlin, 2003.
- [57] Khairy Elsayed, Dean Vucinic, Roberto Dippolito, and Christian Lacor. Comparison between rbf and kriging surrogates in design optimization of high dimensional problems. In *3rd International Conference on Engineering Optimization*, 2012.

Bibliography

- [58] J Harvey Evans. Basic design concepts. *Journal of the American Society for Naval Engineers*, 71(4):671–678, 1959.
- [59] Zhun Fan, Yi Fang, Wenji Li, Jiewei Lu, Xinye Cai, and Caimin Wei. A comparative study of constrained multi-objective evolutionary algorithms on constrained multi-objective optimization problems. In *2017 IEEE congress on evolutionary computation (CEC)*, pages 209–216. IEEE, 2017.
- [60] Vinicius Sousa Fazio and Mauro Roisenberg. Spatial interpolation: an analytical comparison between kriging and rbf networks. In *Proceedings of the 28th Annual ACM Symposium on Applied Computing*, pages 2–7, 2013.
- [61] Christodoulos A Floudas and Panos M Pardalos. *A collection of test problems for constrained global optimization algorithms*. Springer, 1990.
- [62] Alexander Forrester, Andras Sobester, and Andy Keane. *Engineering design via surrogate modelling: a practical guide*. John Wiley & Sons, 2008.
- [63] Manolis Georgioudakis. PyDE, 2017.
- [64] Gerard Petersen. *Powerful Ship Hull Design in Rhino with Rapid Hull Modeling Methodology*. Rhino Centre, 2015. <http://rhinocentre.blogspot.com/2009/11/rhino-rapid-hull-modeling-methodology.html>.
- [65] David Ginsbourger, Rodolphe Le Riche, and Laurent Carraro. Kriging is well-suited to parallelize optimization. In *Computational intelligence in expensive optimization problems*, pages 131–162. Springer, 2010.
- [66] Wenyin Gong, Zhihua Cai, and Li Zhu. An efficient multiobjective differential evolution algorithm for engineering design. *Structural and Multidisciplinary Optimization*, 38(2):137–157, 2009.
- [67] Javier González, Zhenwen Dai, Philipp Hennig, and Neil Lawrence. Batch bayesian optimization via local penalization. In *Artificial intelligence and statistics*, pages 648–657. PMLR, 2016.
- [68] David Goodfriend and Alan J Brown. Exploration of system vulnerability in naval ship concept design. *Journal of Ship Production and Design*, 34(01):42–58, 2018.
- [69] Tim Gourlay, Alexander von Graefe, Vladimir Shigunov, and Evert Lataire. Comparison of aqwa, gl rankine, moses, octopus, pdstrip and wamit with model test results for cargo ship wave-induced motions in shallow water. In *International Conference on Offshore Mechanics and Arctic Engineering*, volume 56598, page V011T12A006. American Society of Mechanical Engineers, 2015.
- [70] Steven Gustafson and Edmund K Burke. The speciating island model: An alternative parallel evolutionary algorithm. *Journal of Parallel and Distributed Computing*, 66(8):1025–1036, 2006.

-
- [71] M Gutsch, S Steen, and F Sprenger. Operability robustness index as seakeeping performance criterion for offshore vessels. *Ocean Engineering*, 217:107931, 2020.
- [72] Raphael T. Haftka, Diane Villanueva, and Anirban Chaudhuri. Parallel surrogate-assisted global optimization with expensive functions - a survey. *Structural and Multidisciplinary Optimization*, 54(1):3–13, 2016.
- [73] John H Halton. On the efficiency of certain quasi-random sequences of points in evaluating multi-dimensional integrals. *Numerische Mathematik*, 2(1):84–90, 1960.
- [74] Zhonghua Han, Fei Liu, Chenzhou Xu, Keshi Zhang, and Qingfu Zhang. Efficient multi-objective evolutionary algorithm for constrained global optimization of expensive functions. In *IEEE Congress on Evolutionary Computation (CEC)*, pages 2026–2033. IEEE, 2019.
- [75] Gideon Hanse, **Roy de Winter**, Bas van Stein, and Thomas Bäck. Optimally weighted ensembles for efficient multi-objective optimization. In *International Conference on Machine Learning, Optimization, and Data Science*, pages 144–156. Springer, 2021.
- [76] Nikolaus Hansen, Anne Auger, Raymond Ros, Olaf Mersmann, Tea Tušar, and Dimo Brockhoff. Coco: A platform for comparing continuous optimizers in a black-box setting. *Optimization Methods and Software*, 36(1):114–144, 2021.
- [77] DP Hardin and EB Saff. Minimal riesz energy point configurations for rectifiable d-dimensional manifolds. *Advances in Mathematics*, 193(1):174–204, 2005.
- [78] Julian Heinrich and Daniel Weiskopf. State of the art of parallel coordinates. In *Eurographics (STARs)*, pages 95–116, 2013.
- [79] J Holtrop, GGJ Mennen, et al. An approximate power prediction method. *International Shipbuilding Progress*, 29(335):166–170, 1982.
- [80] Qi Huang, **Roy de Winter**, Bas van Stein, Thomas Bäck, and Anna V Kononova. Multi-surrogate assisted efficient global optimization for discrete problems. In *2022 IEEE Symposium Series on Computational Intelligence (SSCI)*, pages 1650–1658. IEEE, 2022.
- [81] IMO. Chapter II-1 - Construction - Structure, subdivision and stability, machinery and electrical installations, Part B - Subdivision and stability, 2020.
- [82] Hisao Ishibuchi, Hiroyuki Masuda, Yuki Tanigaki, and Yusuke Nojima. Modified distance calculation in generational distance and inverted generational distance. In *Evolutionary Multi-Criterion Optimization: 8th International Conference, EMO 2015, Guimarães, Portugal, March 29–April 1, 2015. Proceedings, Part II* 8, pages 110–125. Springer, 2015.

Bibliography

- [83] Himanshu Jain and Kalyanmoy Deb. An evolutionary many-objective optimization algorithm using reference-point based nondominated sorting approach, part II: Handling constraints and extending to an adaptive approach. *IEEE Transactions on Evolutionary Computation*, 18(4):602–622, 2014.
- [84] Yaochu Jin. Surrogate-assisted evolutionary computation: Recent advances and future challenges. *Swarm and Evolutionary Computation*, 1(2):61–70, 2011.
- [85] Donald R Jones, Matthias Schonlau, and William J Welch. Efficient global optimization of expensive black-box functions. *Journal of Global optimization*, 13(4):455–492, 1998.
- [86] Shahroz Khan, Kosa Goucher-Lambert, Konstantinos Kostas, and Panagiotis Kaklis. Shiphullgan: A generic parametric modeller for ship hull design using deep convolutional generative model. *Computer Methods in Applied Mechanics and Engineering*, 411:116051, 2023.
- [87] Bhuvan Khoshoo, Julian Blank, Thang Q. Pham, Kalyanmoy Deb, and Shanelle N. Foster. Optimal design of electric machine with efficient handling of constraints and surrogate assistance. *Engineering Optimization*, pages 1–19, 2023.
- [88] Joshua Knowles. ParEGO: a hybrid algorithm with on-line landscape approximation for expensive multiobjective optimization problems. *IEEE Transactions on Evolutionary Computation*, 10(1):50–66, 2006.
- [89] Alexander Kossiakoff, William N Sweet, et al. *Systems engineering: Principles and practices*. Wiley Online Library, 2003.
- [90] Rémi Lam, Matthias Poloczek, Peter Frazier, and Karen E Willcox. Advances in bayesian optimization with applications in aerospace engineering. In *2018 AIAA Non-Deterministic Approaches Conference*, page 1656, 2018.
- [91] Sangmin Lee and Seoung Bum Kim. Parallel simulated annealing with a greedy algorithm for bayesian network structure learning. *IEEE Transactions on Knowledge and Data Engineering*, 32(6):1157–1166, 2019.
- [92] Jian-Yu Li, Zhi-Hui Zhan, and Jun Zhang. Evolutionary computation for expensive optimization: A survey. *International Journal of Automation and Computing*, 18:1–21, October 2021.
- [93] Jing J Liang, Thomas Philip Runarsson, Efren Mezura-Montes, Maurice Clerc, Ponnuthurai Nagaratnam Suganthan, CA Coello Coello, and Kalyanmoy Deb. Problem definitions and evaluation criteria for the cec 2006 special session on constrained real-parameter optimization. *Journal of Applied Mechanics*, 41(8):8–31, 2006.
- [94] Fei Tony Liu, Kai Ming Ting, and Zhi-Hua Zhou. Isolation forest. In *2008 eighth ieee international conference on data mining*, pages 413–422. IEEE, 2008.

-
- [95] Nasrulloh Loka, Ivo Couckuyt, Federico Garbuglia, Domenico Spina, Inneke van Nieuwenhuijse, and Tom Dhaene. Bi-objective bayesian optimization of engineering problems with cheap and expensive cost functions. *Engineering with Computers*, 39(3):1923–1933, 2023.
- [96] Manuel López-Ibáñez, Luís Paquete, and Thomas Stützle. Exploratory analysis of stochastic local search algorithms in biobjective optimization. In homas Bartz-Beielstein, Marco Chiarandini, Luís Paquete, and Mike Preuss, editors, *Experimental methods for the analysis of optimization algorithms*, pages 209–222. Springer, 2010.
- [97] Zhongwei Ma and Yong Wang. Evolutionary constrained multiobjective optimization: Test suite construction and performance comparisons. *IEEE Transactions on Evolutionary Computation*, 23(6):972–986, 2019.
- [98] Marine Traffic. Vessels, 2024. accessed: 20-12-2023, https://www.marinetraffic.com/en/data/?asset_type=vessels.
- [99] R Timothy Marler and Jasbir S Arora. The weighted sum method for multi-objective optimization: new insights. *Structural and multidisciplinary optimization*, 41:853–862, 2010.
- [100] J Marzi, A Papanikolaou, P Corrigan, G Zaraphonitis, and S Harries. Holistic ship design for future waterborne transport. *Proceedings of the 7th Transport Research Arena TRA*, 2018.
- [101] Charles A Micchelli. Interpolation of scattered data: distance matrices and conditionally positive definite functions. *Constructive approximation*, 2(1):11–22, 1986.
- [102] Bas Milatz. Multi-level optimisation and global sensitivity analysis of the probabilistic damage stability method for single hold ships. Master’s thesis, Delft University of Technology, 2022. <http://resolver.tudelft.nl/uuid:24b94160-8804-4d9a-887f-24e3c68ae89c>.
- [103] Bas Milatz, **Roy de Winter**, Jelle DJ van de Ridder, Martijn van Engeland, Francesco Mauro, and Austin A Kana. Parameter space exploration for the probabilistic damage stability method for dry cargo ships. *International Journal of Naval Architecture and Ocean Engineering*, page 100549, 2023.
- [104] Jeremy Miles. R squared, adjusted r squared. *Wiley StatsRef: Statistics Reference Online*, 2014.
- [105] Seyedali Mirjalili, Pradeep Jangir, and Shahrzad Saremi. Multi-objective ant lion optimizer: a multi-objective optimization algorithm for solving engineering problems. *Applied Intelligence*, 46(1):79–95, 2017.
- [106] Farrokh Mistree, WF Smith, B Bras, JK Allen, D Muster, et al. Decision-based design: a contemporary paradigm for ship design. *Transactions, Society of Naval Architects and Marine Engineers*, 98(1990):565–597, 1990.

Bibliography

- [107] Jonas Močkus. On Bayesian methods for seeking the extremum. In Josef Stoer, editor, *Optimization techniques IFIP technical conference*, pages 400–404. Springer, 1975.
- [108] Anthony F Molland. *The maritime engineering reference book: a guide to ship design, construction and operation*. Elsevier, 2011.
- [109] Yew Soon Ong, PB Nair, AJ Keane, and KW Wong. Surrogate-assisted evolutionary optimization frameworks for high-fidelity engineering design problems. In Yoachu Jin, editor, *Knowledge Incorporation in Evolutionary Computation*, pages 307–331. Springer, 2005.
- [110] IMO International Maritime Organization. International convention for the safety of life at sea (solas), 1974, 2023.
- [111] Emre Özkaya and Nicolas R Gauger. Single-step one-shot aerodynamic shape optimization. In *Optimal control of coupled systems of partial differential equations*, pages 191–204. Springer, 2009.
- [112] A Papanikolaou, S Harries, M Wilken, and G Zaraphonitis. Integrated design and multiobjective optimization approach to ship design. In *Proceedings of the 15th International Conference on Computer Applications in Shipbuilding, IC-CASAt: Trieste*, 2011.
- [113] Apostolos Papanikolaou. Holistic ship design optimization. *Computer-Aided Design*, 42(11):1028–1044, 2010.
- [114] Apostolos Papanikolaou. *A Holistic Approach to Ship Design*. Springer, 2019.
- [115] Apostolos Papanikolaou, George Zaraphonitis, Markus Jokinen, Adrien Aubert, Stephan Harries, Jochen Marzi, George Mermiris, and Rachmat Gunawan. Holistic ship design for green shipping. In *SNAME Maritime Convention*. OnePetro, 2022.
- [116] Sung-Wook Park, Jae-Hoon Choi, and Byung-Chai Lee. Multi-objective optimization of an automotive body component with fiber-reinforced composites. *Structural and Multidisciplinary Optimization*, 58:2203–2217, 2018.
- [117] Michael G Parsons and Randall L Scott. Formulation of multicriterion design optimization problems for solution with scalar numerical optimization methods. *Journal of Ship Research*, 48(1):61–76, 2004.
- [118] Wolfgang Ponweiser, Tobias Wagner, Dirk Biermann, and Markus Vincze. Multiobjective optimization on a limited budget of evaluations using model-assisted $\mathcal{S}$ -metric selection. In Günter Rudolph, Thomas Jansen, Nicola Beume, Simon Lucas, and Carlo Poloni, editors, *International Conference on Parallel Problem Solving from Nature (PPSN)*, pages 784–794. Springer, 2008.

-
- [119] Wolfgang Ponweiser, Tobias Wagner, and Markus Vincze. Clustered multiple generalized expected improvement: A novel infill sampling criterion for surrogate models. In *2008 IEEE congress on evolutionary computation (IEEE world congress on computational intelligence)*, pages 3515–3522. IEEE, IEEE, 2008.
- [120] M. J. D. Powell. A direct search optimization method that models the objective and constraint functions by linear interpolation. In Susana Gomez and Jean-Pierre Hennart, editors, *Advances in Optimization and Numerical Analysis*, pages 51–67. Springer Netherlands, 1994.
- [121] Alexandros Priftis, Apostolos Papanikolaou, and Timoleon Plessas. Parametric design and multiobjective optimization of containerships. *Journal of Ship Production and Design*, 32(3):1–14, 2016.
- [122] Hoyte Christiaan Raven. *A solution method for the nonlinear ship wave resistance problem*. Phd thesis, Delft University of Technology, 1998.
- [123] Rommel G Regis. Constrained optimization by radial basis function interpolation for high-dimensional expensive black-box problems with infeasible initial points. *Engineering Optimization*, 46(2):218–243, 2014.
- [124] Rommel G Regis. A survey of surrogate approaches for expensive constrained black-box optimization. In Hoai An Le Thi, Hoai Minh Le, and Tao Pham Dinh, editors, *World Congress on Global Optimization*, pages 37–47. Springer, 2019.
- [125] Rommel G Regis and Christine A Shoemaker. A quasi-multistart framework for global optimization of expensive functions using response surface models. *Journal of Global Optimization*, 56(4):1719–1753, 2013.
- [126] Frederik Rehbach, Martin Zaefferer, Boris Naujoks, and Thomas Bartz-Beielstein. Expected improvement versus predicted value in surrogate-based optimization. In *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO)*, GECCO ’20, page 868–876, New York, NY, USA, 2020. Association for Computing Machinery.
- [127] Carl Fredrik Rehn. *Ship design under uncertainty*. PhD thesis, Norwegian University of Science and Technology, 2018.
- [128] Nery Riquelme, Christian Von Lücken, and Benjamin Baran. Performance metrics in multi-objective optimization. In *2015 Latin American computing conference (CLEI)*, pages 1–11. IEEE, 2015.
- [129] Herbert Schneekluth and Volker Bertram. *Ship design for efficiency and economy*, volume 218. Butterworth-Heinemann Oxford, 1998.
- [130] Thomas P Scholcz, Tomasz Gornicz, and Christian Veldhuis. Multi-objective hull-form optimization using kriging on noisy computer experiments. In *MARINE VI: proceedings of the VI International Conference on Computational Methods in Marine Engineering*, pages 1064–1077. CIMNE, CIMNE, 2015.

Bibliography

- [131] Lei Shi, RJ Yang, and Ping Zhu. A method for selecting surrogate models in crashworthiness optimization. *Structural and Multidisciplinary Optimization*, 46(2):159–170, 2012.
- [132] Daniel Sieger, Stefan Menzel, Mario Botsch, et al. A comprehensive comparison of shape deformation methods in evolutionary design optimization. In *Proceedings of the International Conference on Engineering Optimization*, pages 1–5. Citeseer, 2012.
- [133] Prashant Singh, Ivo Couckuyt, Francesco Ferranti, and Tom Dhaene. A constrained multi-objective surrogate-based optimization algorithm. In *2014 IEEE Congress on Evolutionary Computation (CEC)*. IEEE, 2014.
- [134] I.M Sobol. On the distribution of points in a cube and the approximate evaluation of integrals. *USSR Computational Mathematics and Mathematical Physics*, 7(4):86–112, 1967.
- [135] Siemens Digital Industries Software. Simcenter STAR-CCM+ User Guide, version 2021.1. In *Adaptive Mesh Refinement for Overset Meshes*, pages 3067–3070. Siemens, 2021.
- [136] S&P Market Intelligence. Sea-web ships, 2024. accessed: 20-12-2023, <https://www.spglobal.com/marketintelligence/en/mi/products/sea-web-vessel-search.html>.
- [137] Bas van Stein, Hao Wang, and Thomas Bäck. Automatic configuration of deep neural networks with parallel efficient global optimization. In *2019 International Joint Conference on Neural Networks (IJCNN)*, pages 1–7. IEEE, 2019.
- [138] Michael Stein. Large sample properties of simulations using latin hypercube sampling. *Technometrics*, 29(2):143–151, 1987.
- [139] Robert Taggart. *Ship design and construction*. Society of Naval Architects & Marine Engineers, 1980.
- [140] Yusuke Tahara, F Stern, and Y Himeno. Computational fluid dynamics-based optimization of a surface combatant. *Journal of ship Research*, 48(04):273–287, 2004.
- [141] Ryoji Tanabe and Akira Oyama. A note on constrained multi-objective optimization benchmark problems. In *IEEE Congress on Evolutionary Computation (CEC)*, pages 1127–1134. IEEE, 2017.
- [142] **Roy de Winter**. Designing ships using constrained multi-objective efficient global optimization, 2018. Available at <https://theses.liacs.nl/pdf/2017-2018-WinterRoyde.pdf>.
- [143] **Roy de Winter**. RoydeZomer/SAMO-COBRA: Release with new experiments, November 2020. <https://doi.org/10.5281/zenodo.5105636>.

-
- [144] **Roy de Winter**. Roy de winter/multi-point-samo-cobra: Release1, February 2022. <https://doi.org/10.5281/zenodo.6461614>.
- [145] **Roy de Winter**. IOC-SAMO-COBRA: Release 1.1.1 for Swarm and Evolutionary Computation, July 2023. <https://doi.org/10.5281/zenodo.8112883>.
- [146] **Roy de Winter**. Parallel constrained multi-objective optimization for ship design damage stability problem with (in)expensive function evaluations. In *Marine 2023*, page 1. Marine 2023, Scipedia, 2023.
- [147] **Roy de Winter**, Thomas Bäck, and Niki van Stein. Modular optimization framework for mixed expensive and inexpensive real-world problems. In *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO)*, 2024.
- [148] **Roy de Winter**, Philip Bronkhorst, Bas van Stein, and Thomas Bäck. Constrained multi-objective optimization with a limited budget of function evaluations. *Memetic Computing*, 14:151–164, 2022.
- [149] **Roy de Winter**, Jan Furustam, Thomas Bäck, and Thijs Muller. Optimizing ships using the holistic accelerated concept design methodology. In Tetsuo Okada, Katsuyuki Suzuki, and Yasumi Kawamura, editors, *Practical Design of Ships and Other Floating Structures (PRADS)*, pages 38–50, Singapore, 2021. Springer.
- [150] **Roy de Winter**, Fu Xing Long, Andre Thomaser, Niki van Stein, de, Thomas Bäck, and Anna V Kononova. Landscape analysis based vs. domain-specific optimization algorithm selection for engineering design applications: A clear case. In *2024 IEEE Conference on Artificial Intelligence (CAI)*. IEEE, 2023.
- [151] **Roy de Winter**, Bas Milatz, Julian Blank, Niki van Stein, Thomas Bäck, and Kalyanmoy Deb. Hot off the press: Parallel multi-objective optimization for expensive and inexpensive objectives and constraints. In *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO)*, 2024.
- [152] **Roy de Winter**, Bas Milatz, Julian Blank, Niki van Stein, Thomas Bäck, and Kalyanmoy Deb. Parallel multi-objective optimization for expensive and inexpensive objectives and constraints. *Swarm and Evolutionary Computation*, 86:101508, 2024.
- [153] **Roy de Winter**, Bas van Stein, and Thomas Bäck. SAMO-COBRA: A fast surrogate assisted constrained multi-objective optimization algorithm. In Hisao Ishibuchi, Qingfu Zhang, Ran Cheng, Ke Li, Hui Li, Handing Wang, and Aimin Zhou, editors, *International Conference on Evolutionary Multi-Criterion Optimization (EMO)*, pages 270–282. Springer, 2021.
- [154] **Roy de Winter**, Bas van Stein, Matthys Dijkman, and Thomas Bäck. Designing ships using constrained multi-objective efficient global optimization. In

Bibliography

- Giuseppe Nicosia, Panos Pardalos, Giovanni Giuffrida, Renato Umeton, and Vincenzo Sciacca, editors, *International Conference on Machine Learning, Optimization, and Data Science*, pages 191–203. Springer, 2018.
- [155] **Roy de Winter**, Bas van Stein, and Thomas Bäck. Ship design performance and cost optimization with machine learning. In *20st Conference on Computer and IT Applications in the Maritime Industries (COMPIT)*, pages 185–196. Hamburg University of Technology, 2020.
- [156] **Roy de Winter**, Bas van Stein, and Thomas Bäck. Multi-point acquisition function for constraint parallel efficient multi-objective optimization. In *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO)*, pages 511–519, 2022.
- [157] André Thomaser, Anna V Kononova, Marc-Eric Vogt, and Thomas Bäck. One-shot optimization for vehicle dynamics control systems: towards benchmarking and exploratory landscape analysis. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, pages 2036–2045, 2022.
- [158] Ye Tian, Ran Cheng, Xingyi Zhang, Miqing Li, and Yaochu Jin. Diversity assessment of multi-objective evolutionary algorithms: Performance metric and benchmark problems. *IEEE Computational Intelligence Magazine*, 14(3):61–74, 2019.
- [159] Magnus Urquhart, Emil Ljungskog, and Simone Sebben. Surrogate-based optimisation using adaptively scaled radial basis functions. *Applied Soft Computing*, 88:106050, 2020.
- [160] Magnus Urquhart, Emil Ljungskog, and Simone Sebben. Surrogate-based optimisation using adaptively scaled radial basis functions. *Applied Soft Computing*, 88:106050, 2020.
- [161] Koen van der Blom, Timo M Deist, Vanessa Volz, Mariapia Marchi, Yusuke Nojima, Boris Naujoks, Akira Oyama, and Tea Tušar. Identifying properties of real-world optimisation problems through a questionnaire. In *Many-Criteria Optimization and Decision Analysis: State-of-the-Art, Present Challenges, and Future Perspectives*, pages 59–80. Springer, 2023.
- [162] Lucas Van Rooij, **Roy de Winter**, Anna V Kononova, and Bas van Stein. Explainable AI for ship design analysis with AIS and static ship data. In *15th International Symposium on Practical Design of Ships and Other Floating Structures (PRADS)*, pages 1521–1535, 2022.
- [163] Niki van Stein, de **Roy de Winter**, Thomas Bäck, and Anna V Kononova. AI for Expensive Optimization Problems in Industry. In *2023 IEEE Conference on Artificial Intelligence (CAI)*, pages 251–254. IEEE, 2023.
- [164] Takashi Wada and Hideitsu Hino. Bayesian optimization for multi-objective optimization and multi-point search, 2019.

-
- [165] Hao Wang, Bas van Stein, Michael Emmerich, and Thomas Bäck. A new acquisition function for bayesian optimization based on the moment-generating function. In *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 507–512. IEEE, IEEE, 2017.
- [166] Hao Wang, Diederick Vermetten, Furong Ye, Carola Doerr, and Thomas Bäck. IOHanalyzer: Detailed performance analyses for iterative optimization heuristics. *ACM Transactions on Evolutionary Learning and Optimization*, 2(1), apr 2022.
- [167] Jolan Wauters, Andy Keane, and Joris Degroote. Development of an adaptive infill criterion for constrained multi-objective asynchronous surrogate-based optimization. *Journal of Global Optimization*, 78(1):137–160, 2020.
- [168] Henry G Weller, Gavin Tabor, Hrvoje Jasak, and Christer Fureby. A tensorial approach to computational continuum mechanics using object-oriented techniques. *Computers in physics*, 12(6):620–631, 1998.
- [169] Thomas Wortmann, Christoph Waibel, Giacomo Nannicini, Ralph Evins, Thomas Schroepfer, and Jan Carmeliet. Are genetic algorithms really the best choice for building energy optimization? In Michela Turrin, Brady Peters, William O’Brien, Rudi Stouffs, and Timur Dogan, editors, *Proceedings of the Symposium on Simulation for Architecture and Urban Design*, pages 51–58, 2017.
- [170] Haofeng Wu, Jinliang Ding, and Qingda Chen. Gaussian process-assisted evolutionary algorithm for constrained expensive multi-objective optimization. In *Asian Control Conference (ASCC)*, pages 1027–1032. IEEE, 2022.
- [171] Jian Wu and Peter Frazier. The parallel knowledge gradient method for batch bayesian optimization. *Advances in neural information processing systems*, 29:3126–3134, 2016.
- [172] Yongkuan Yang, Jianchang Liu, and Shubin Tan. A multi-objective evolutionary algorithm for steady-state constrained multi-objective optimization problems. *Applied Soft Computing*, 101(107042), 2021.
- [173] Yiming Yao and Xudong Yang. Efficient global multi-objective aerodynamic optimization using combined multi-point infilling strategy and surrogate models. In *IEEE Congress on Evolutionary Computation (CEC)*, pages 1537–1542. IEEE, 2021.
- [174] Eckart Zitzler, Marco Laumanns, and Lothar Thiele. SPEA2: Improving the strength pareto evolutionary algorithm. *TIK-report*, 103, 2001.
- [175] Eckart Zitzler and Lothar Thiele. Multiobjective optimization using evolutionary algorithms—a comparative case study. In Agoston E. Eiben, Thomas Bäck, Marc Schoenauer, and Hans-Paul Schwefel, editors, *International conference on parallel problem solving from nature (PPSN)*, pages 292–301. Springer, 1998.