Course: Natural Computing

8. Applications of Metaheuristic Algorithms

J. Michael Herrmann
School of Informatics, University of Edinburgh
michael.herrmann@ed.ac.uk, +44 131 6 517177

Applications of MHO algorithms

- Application areas
- Pros and Cons in applying MHO algorithms
- What algorithm fits where?
- Case studies

"Nature has evolved over millions of years under a variety of challenging environments and can thus provide a rich source of inspiration for designing algorithms and approaches to tackle challenging problems in real-world applications."

(Patnaik, Yang, Takamatsu, 2017)

Application Areas (Examples from Wikipedia)

- Combinatorial optimisation
  - Determining the optimal way to deliver packages
  - Job allocation: Deciding which taxis in a fleet to route to pick up fares, working out the best allocation of jobs to people, job-shop scheduling, cutting stock problem, knapsack problem
- Design problems in engineering
  - Form finding, e.g. in truss structures for pylons, bridges, roofs
  - Behavior finding
  - Logistics, supply chain optimization, reverse logistics
  - Developing the best airline network of spokes and destinations
  - Designing water distribution networks, reservoir flow-rates

"new applications will emerge in the future."

(Xin-She Yang, Scholarpedia, 2011)

MOO Applications

- Flight scheduling (cost, flight duration, total travel time, CO_2, number of changes, time of day, extras)
- Load balancing in telecommunication networks (performance, persistence, respecting interdependencies, using segregation, dynamics, fault tolerance, scalability, risk, DDoS behaviour)
- Wind farm layout (cost, nominal power, power variation, maintenance, environmental impact (movement, cables)

Application Areas (selection)

Lists of MHO applications, such as,

"..., telecommunications, aircraft design, software engineering, network and computer security, civil engineering, ad-hoc networks, design of mechanical and robotics systems, mechanical components, process optimisation in chemical engineering, production planning and scheduling, signal and image processing, fishery, finance, design of political campaigns, logistics, ..."

require a critical assessment

What is an application?

Self-reported success needs to be critically assessed

- × Applied successfully to challenging benchmark problems (e.g. CEC functions)

Benchmarking is a good start, but the path to application is long:

1. Can solve idealised examples of problems that also occur in real applications (e.g. TSP)
2. Proven to outperform other methods (beyond MHO) in real application problems
3. Enables success in new domains or in domains where human labour would be the only alternative
4. Practice tests/pilot studies/prototypes exist
5. Actually adopted and used in industry and society

Pros and Cons of MHO in practice

Pros

- Little background knowledge required
- Multiple solutions (Multiobjective Opt.)
- Simple solutions may be explainable (GP)
- Any-time behaviour

Cons

- Fitness evaluations are costly. (How to avoid redundancy?)
- Out-of-the-box algorithms are rarely efficient
- *Heuristic* may serve case better
- Relatively few successful application cases

What is an *application* (in the real world)?

- Technological readiness level
  - does the algorithm create value (or make money) or
  - is the research merely *inspired* by potential applications?
- How well is the problem specified? How is success evaluated?
- How are other aspects of optimality considered or discussed? (certainty, robustness, compatibility with other objectives)
- Can the complexity and specificity of the problem be captured by a model or is it due to the difference of the model from the real world?
- Is it an existing problem?
  - if so, how does the new solution compare to previous attempts?
  - if not, is it a new application enabled by an MHO algorithm?

How to tell which MHO algorithm fits where

- With no prior knowledge, all algorithms are equally good (NFL)
- Prior or initial knowledge, such as
  - discrete or continuous or mixed, dimensionality
  - size of search space, desired precision, desired quality
  - fitness function(s), cost of fitness evaluations, budget
  - time scales; periodicity: once, episodic, ongoing
- Application-related knowledge, such as
  - previous applications of other MHOAs in the target domain
  - previous applications of the same MHOA in a similar domain
  - previously or currently applied (working) solutions (e.g. how a human operator solves the task; existing models etc.)
- Experiences with the algorithm in the domain, such as
  - properties of fitness landscape, quality of random solutions
  - rate of innovations, rate of failure
  - deceptiveness of the problem
  - parameter values, initialisation
  - local search, hybridisations, ensembles, hyperheuristics

Guidelines for applications of MHO

- Design fitness functions
  - expressing the main goal(s, if multi-objective)
  - smooth with few local optima
  - stepping stones
- Find good representation (search space)
  - trade-off between complexity (or constraints) and dimensions
  - compatible with the fitness function(s)
  - compatible with algorithm (see e.g. schema theorem)
- Find a good algorithm
  - check compatibility (see above)
  - check prior knowledge (see previous slide)
  - test scenarios

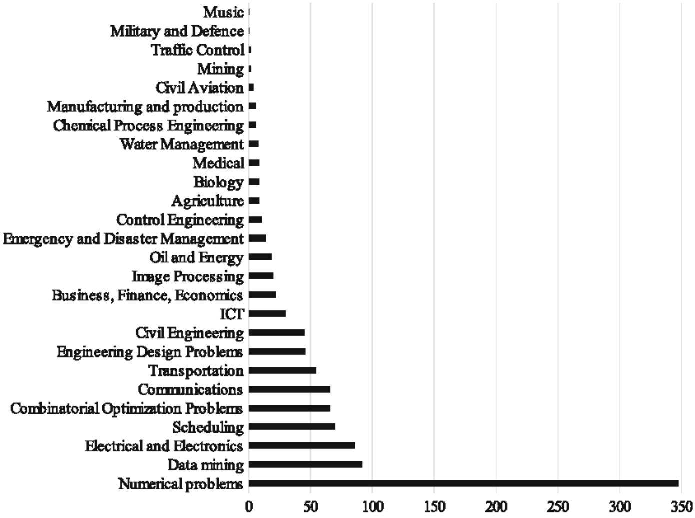
Current state

Reviewing about 250 algorithms:

- "benchmark problems of real world applications" such as
  - Tension/compression spring design (engineering design)
  - Economic load dispatch (energy)
  - Portfolio optimisation (finance)
  - Vehicle routing problem or TSP (operational research)
- $\approx$ 50% of algorithms have been applied a real problem in the initial work. There are more applicable algorithms now than 10 years ago, and also the fraction increased.
- $\approx$ 30% of algorithms have not been applied in any problem since proposed.
- New techniques are often either PSO-like approaches or variations of other existing nature-inspired algorithms.

adopted from Tzanetos & Dounias, 2020

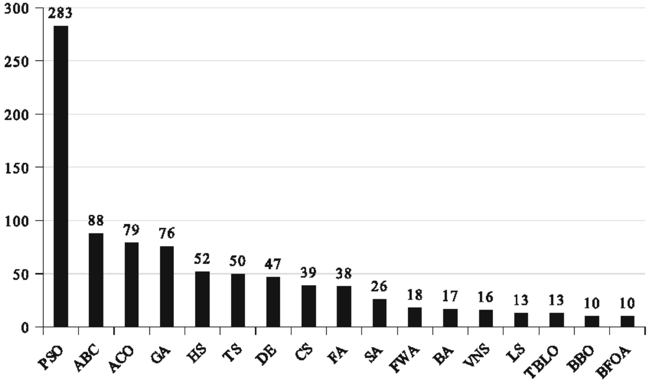
Domains of metaheuristic applications



1222 publications from year 1983 to 2016

Hussain, Kashif et al. Metaheuristic research: A comprehensive survey. *AI Review* **52**:4 (2019) 2191.

Number of publications per algorithm



GP?

Hussain, Kashif et al. Metaheuristic research: A comprehensive survey. *AI Review* **52**:4 (2019) 2191.
See also Kaveh & Mesgari (2023) Application of Meta-Heuristic Algorithms for Training NN and DLA. NPL **55**, 4510.

Application Areas (what works quite well)

- Number of variables, equations, constraints (etc.) not known apriorily: Design
- Problems with some creative leeway: Interior design, ad placement
- Specialist areas with little competition: Theater lighting, professional sports training equipment, construction of facial composites of suspects by eyewitnesses in forensic science
- Small data problems: Specialist queries
- Heterogeneous search spaces
- Data are soon outdated: Finance, politics
- Internet of Things (IoT)*

*Sharma & Tripathi (2022) A systematic review of meta-heuristic algorithms in IoT based application. *Array* 14, 100164

Successful applications (my personal view)

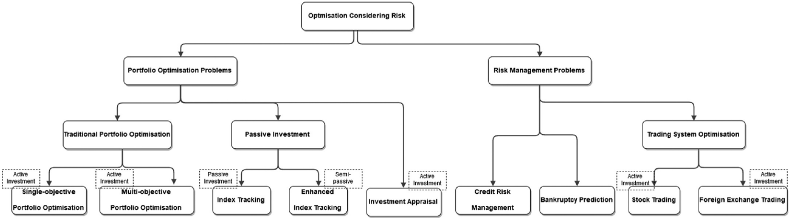
- Recommendation systems
- Artificial creativity
- Design and re-design of electronic circuits
- Symbolic regression
- Multiple sequence alignment
- Optimization of truss structures
- Geometric placement (e.g. of wind turbines)
- Feature selection for Machine Learning
- Robot design and modelling (Lipson & Pollack, 2000; Ghafil & Jármai, 2020)
- Data mining, explainability, fairness (possibly)
- Prospectively: Combination with other methods, e.g. optimisation, neural networks (Hitoshi Iba, 2018)

Financial Applications

- Metaheuristics in portfolio optimisation, index tracking, enhanced indexation, credit risk, stock investments, financial project scheduling, option pricing, feature selection, bankruptcy and financial distress prediction, and credit risk assessment.
- MHO interesting because of uncertainty, dynamism, diversity, multi-periodicity, complexity (similarly to other worthwhile applications of MHO)
- Mostly portfolio optimisation or credit-risk management
- Usually population-based metaheuristics of standard types, but increasingly MOO

Amparo Soler-Dominguez, Angel A. Juan, Renatas Kizys (2017)
A Survey on Financial Applications of Metaheuristics

Portfolio optimisation and risk management



Doering, J., Kizys, R., Juan, A.A., Fitó, À. and Polat, O., 2019. Metaheuristics for rich portfolio optimisation and risk management: Current state and future trends. Operations Research Perspectives, 6, p.100121.

Conclusions

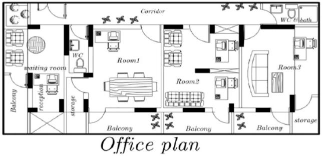
- "Application" often merely means a specific fitness function (see NFL theorem)
- Actual applications suggest that MHO approaches require some effort to set-up the algorithm
- Among the indicators for MHO are
  - Data-driven approaches
  - Multi-objective decision-making problems
  - Problems with ephemeral, fuzzy, eclectic information
  - Problems with relatively high cost for modelling, such as non-stationary systems without a model of the non-stationarity
  - Structural optimisation and design

Now: A closer look at a few actual MHO applications

Design of prefabricated wall-floor building systems

Optimal layout for free and irregular wall arrangements, structural performance, architectural parameters, easy fabrication, cost, minimum efforts

Simultaneous TSP, hubs-location, spanning tree. Solution: PSO



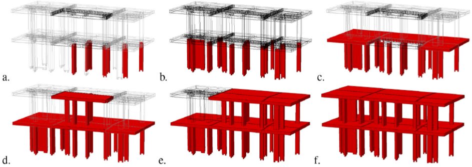
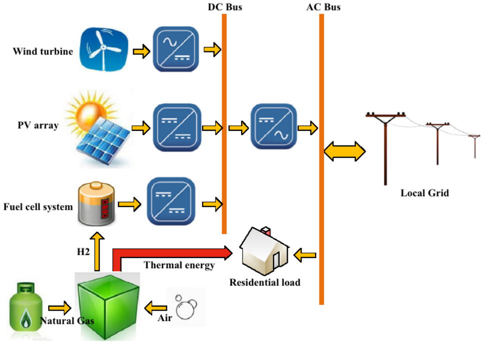


Fig. 8. Wall-Floor building assembly stages (a to f).

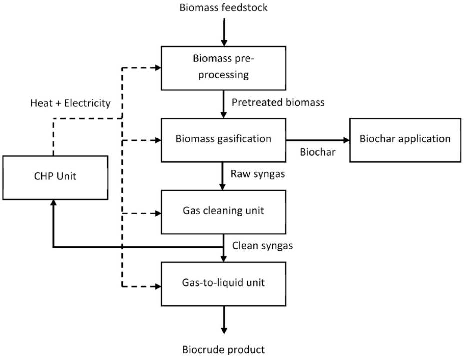
Baghdadi, A., Heristchian, M. and Kloft, H., 2020. Design of prefabricated wall-floor building systems using meta-heuristic optimization algorithms. *Automation in Construction* **114**, p.103156.

Optimization of a hybrid solar-wind-hydrogen system



Maleki, A., Hafeznia, H., Rosen, M.A. and Pourfayaz, F., 2017. Optimization of a grid-connected hybrid solar-wind-hydrogen CHP [combined heat and power] system for residential applications by efficient metaheuristic approaches. *Applied Thermal Engineering* **123**, pp.1263-1277.

Optimization models for bio-refinery



Tan, R.R., Aviso, K.B. and Ng, D.K.S., 2019. Optimization models for financing innovations in green energy technologies. *Renewable and Sustainable Energy Reviews* **113**, p.109258.

Picture relates to a second case study in the paper not mentioned in the title.

Diagnosis of chronic disorders

- Comprehensive comparison, but largely only among (*insect-based*) MHO algorithms.
- Noisy data and many subcases increase the chance of an algorithm in a competition.
- Focus is on diagnosis of diabetes and cancer (Rare diseases would be a more challenging problem)

Gautam, R., Kaur, P. and Sharma, M., 2019. A comprehensive review on nature inspired computing algorithms for the diagnosis of chronic disorders in human beings. *Progress in Artificial Intelligence* **8**(4), pp.401-424.

Optimisation of flight connections

- Variants of TSP: time-dependent, asymmetric, soft constraints
- Data from Kiwi.com
- Operators: Swap, Change airport, Insert, Reverse
- Yields sub-optimal preferable routes, complementing well-defined criteria with experience

Alrasheed, M., Mohammed, W., Pylyavskyy, Y. and Kheiri, A., 2019, September. Local search heuristic for the optimisation of flight connections. *International Conference on Computer, Control, Electrical, and Electronics Engineering* (ICCCEEE) (pp. 1-4). IEEE.

Energy resource scheduling hyperheuristics

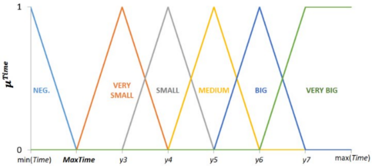


Fig. 1. Membership function of efficiency

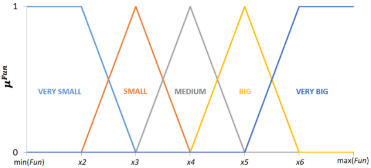


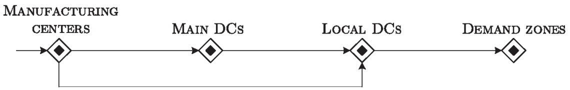
Fig. 2. Membership function of effectiveness

A case-based reasoning methodology considers previous cases of execution of different optimization approaches for different problems. The computational complexity is conveniently reduced by fuzzy encoding.

Faia, R., Pinto, T., Sousa, T., Vale, Z. and Corchado Rodríguez, J., 2017. Automatic selection of optimization algorithms for energy resource scheduling using a case-based reasoning system. *25th International Conference on Case-Based Reasoning* (ICCBR) 2017.

Sustainable-resilient pharmaceutical supply chain

- Strategic (location) and tactical (allocation) decisions in a pharmaceutical network design
- Resiliency and sustainability as objectives
- Coping (fuzzy stochastic) with the inherent uncertainty of input parameters
- Lower bound to evaluate the performance



Zahiri, B., Zhuang, J. and Mohammadi, M., 2017. Toward an integrated sustainable-resilient supply chain: A pharmaceutical case study. *Transportation Research Part E*: Logistics and Transportation Review **103**, pp.109-142.

Mixed-integer problems in computational biology

Reverse engineer large dynamic models of complex biological pathways (100s of continuous, 10s of binary variables)

- efficient mixed-integer local solver for sequential quadratic programming
- a novel self-adaption mechanism to avoid convergence stagnation
- the injection of extra diversity during the adaptation steps
- restarting most of reference set of the reconfigured processes
- additional local mixed-integer nonlinear programming solvers (work in progress)
- hyper-heuristic for coordinate them (work in progress)

New possibilities for other mixed-integer dynamic optimization problems in the life sciences such as metabolic engineering, synthetic biology, drug scheduling.

Penas, D.R., Henriques, D., González, P., Doallo, R., Saez-Rodriguez, J. and Banga, J.R., 2017. A parallel metaheuristic for large mixed-integer dynamic optimization problems, with applications in computational biology. *PloS one* **12**(8), p.e0182186.

Covid-19 pandemics

- Prediction (Khalilpourazari and Doulabi, 2021)
- Supply chain design for personal protection (Mosallanezhad et al., 2021)
- Modelling and controlling of coronavirus distribution process (Hosseini et al., 2020)
- Sustainable-resilience healthcare network (Goodarzian et al., 2021)
- Optimal control strategy for vaccine administration (Libotte et al., 2020)
- Social network contact tracing (Al-Shaikh et al., 2021)

- F. Martínez-Álvarez et al. (2020) Coronavirus optimization algorithm. *Big Data* **8**:4, 308-322.
- Emami, H. (2022) Anti-coronavirus optimization algorithm. *Soft Computing* **26**:11, 4991-5023.

Dynamic optimisation*

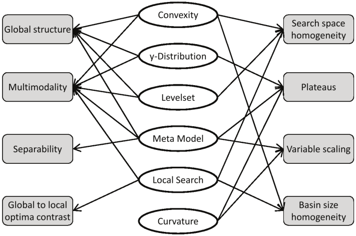
For dynamic problems there a generally two options

- Accept some level of lag or imprecision: Keep exploration active
- Anticipate direction of change: Several populations, hierarchical approach

Michalis Mavrovouniotis, Changhe Li, Shengxiang Yang (2017) A survey of swarm intelligence for dynamic optimization: Algorithms and applications.

Automatic Selection of MHOA: Classification of problems

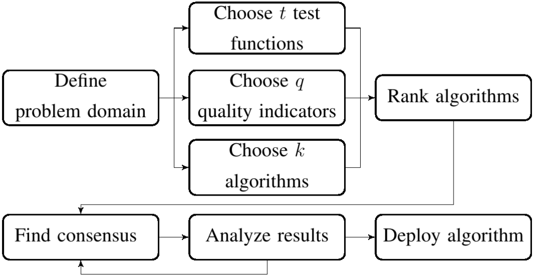
- Exploratory landscape analysis [Mersmann, 2011]⟶
- Classification of problems to be optimized [Stegherr, 2020; Talbi, 2021]
- Problem is implied by a fitness function $f : X \to \mathbb{R}$



Level of classification

- Instances or templates (or sets) of instances (SAT, TSP, ...)
- Types of prior knowledge (see figure from [Mersmann, 2011])
- Amount of available knowledge and respective costs
- Generating or evolving of additional problem instances

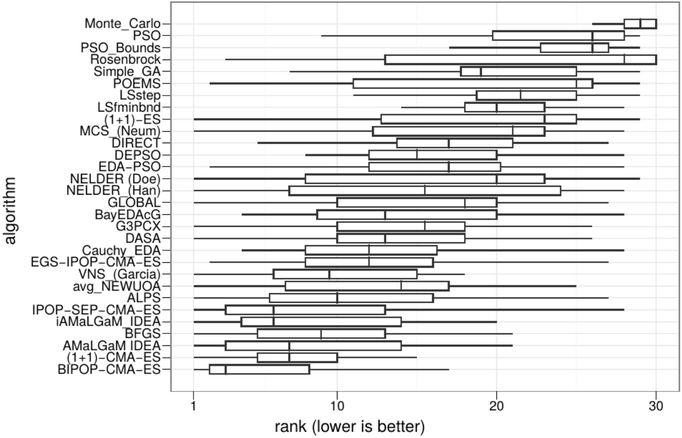
Exploratory Landscape Analysis



- ELA aims at finding a relation between problems (fitness functions) and algorithms based on landscape features which can be extracted by suitable methods
- There may be more direct or comprehensive ways to identify *alignement* (see NFL theorem) between algorithms and problems.

O. Mersmann ea. (2010) Benchmarking evolutionary algorithms: Towards exploratory landscape analysis.

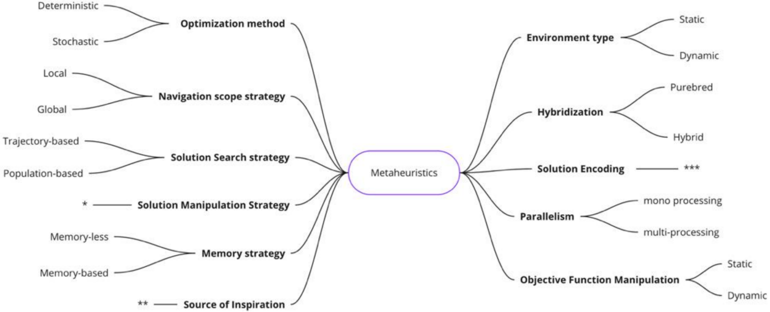
Ranking



Search in 5, 10, 20 dimensions averaged over 24 benchmark functions

O. Mersmann ea. (2010) Benchmarking evolutionary algorithms: Towards exploratory landscape analysis.

Classification of algorithms



* Solution manipulation refers to algorithm details: Best suited for classification.
** The source of inspiration may be irrelevant and is often not even unique.
*** Encoding is crucial in practical applications; this may help for re-use of algorithms.

Peres, F. and Castelli, M.: Combinatorial Optimization Problems and Metaheuristics: Review, Challenges, Design, and Development. *Applied Sciences* 11:14 (2021) 6449.

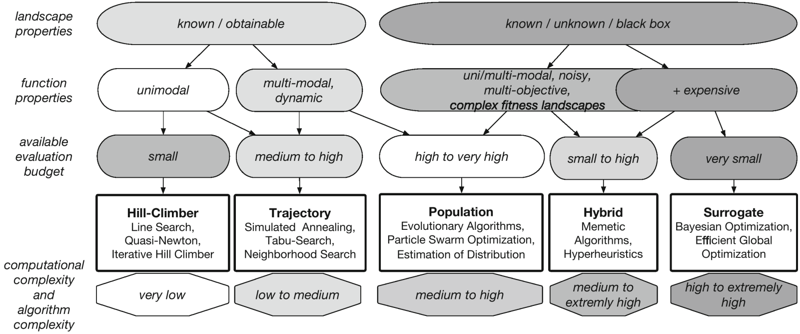
Matching of algorithms and problems

- Ideally: Alignment (see NFL theorem)
- Hyperheuristic algorithms (ibid.)
- Algorithm selection (next slides)

Decisions based on performance measures

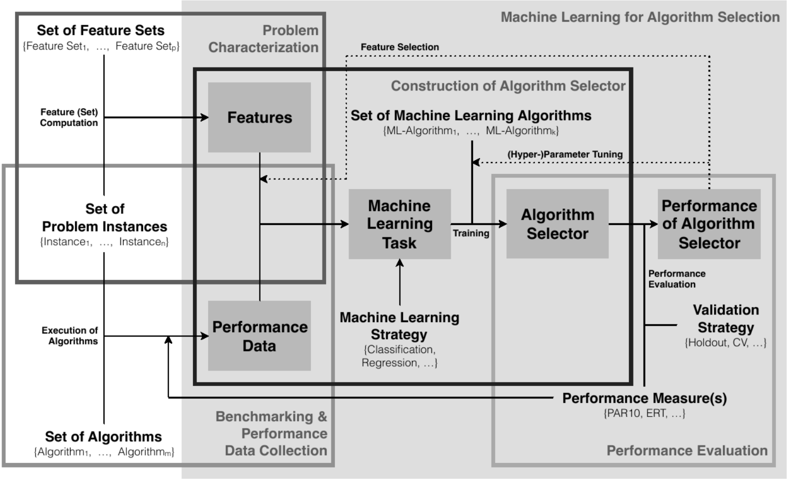
- Resources or runtime needed for given solution quality
- Solution quality obtainable by given budget
- Robustness (stochasticity of the algorithm's search behaviour, complexity of fitness landscape, problem noise)
- Performance relative to problem class
- Time course of performance (e.g. slower for hyperheuristics)
- Deviation of fitness from estimate by a surrogate model

Algorithm selection guideline



Stork e.a.: A new taxonomy of global optimization algorithms. *Natural Computing* (2020) 1-24.

Automated algorithm selection



Kerschke e.a.: Automated algorithm selection: Survey and perspectives. *Evol. Comp.* **27**:1 (2019) 3-45.

Remarks: Automated algorithm selection

- Algorithm selection (AS) for portfolio selection
  - Specialised: SATzilla [Xu, 2008]
  - More general: AutoFolio [Lindauer, 2015] for speed-up
  - Algorithm schedules [Lindauer 2014, 2016]
  - Machine learning: Bag of landscape features [Shirakawa & Nagao, 2016]
  - See review [Kerschke e.a., 2019]
- No clear winner: AS for AS or hyper-hyperheuristics?
- Background knowledge on problem instance or problem class can be more useful than automated AS

DIY

- moPLOT landscape explorer: Visualizing Multi-Objective Optimization Problems
- ParadisEO: Heuristic Optimization Framework (S. Cahon (2004) Paradiseo: A framework for the reusable design of parallel and distributed metaheuristics. *Journal of Heuristics* **10**:3 ,357-380)
- irace: Automated algorithm configuration tool (M. López-Ibáñez et al. (2016) The *irace* package: Iterated racing for automatic algorithm configuration. *Operations Research Perspectives* **3**, 43-58)
- IOHprofiler: Experimental platform (C. Doerr et al. (2018) IOHprofiler: A benchmarking and profiling tool for iterative optimization heuristics. arXiv:1810.05281)

Eneko Osaba e.a. (2021) A Tutorial On the design, experimentation and application of metaheuristic algorithms to real-World optimization problems. [sic!] *Swarm and Evolutionary Computation* **64**, 100888 (see in particular Table 2)

Conclusions

- Landscape analysis is suggestive, but perhaps not easier than optimisation itself.
- Other attempts with huge numbers of features have been made.
- AAS is an advanced form of hyperheuristics.
- Evolved into automatic algorithm composition based on neural networks