Next Generation of Multi-Objective Evolutionary Optimization and Decision-Making Algorithms

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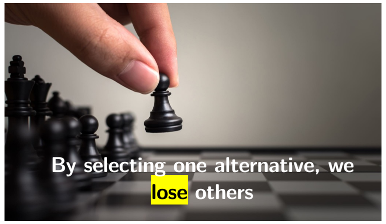
Decision Science

Why is decision-making so hard?



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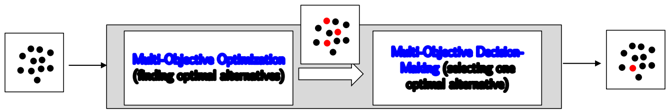
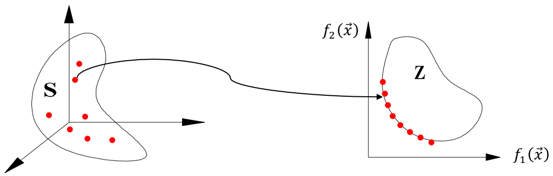
Decision Science

Decision-Making is a two-step problem (each step is a challenge on its own):





Minimize $\{f_1(\vec{x}), f_2(\vec{x}), \dots, f_m(\vec{x})\}$
s. t. $\vec{x} \in S$

Objective vectors $\vec{f}(\vec{x}) = (f_1(\vec{x}), \cdots, f_m(\vec{x}))$ in **objective space $\mathbf{R}^m$**

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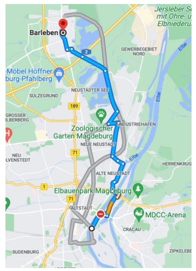
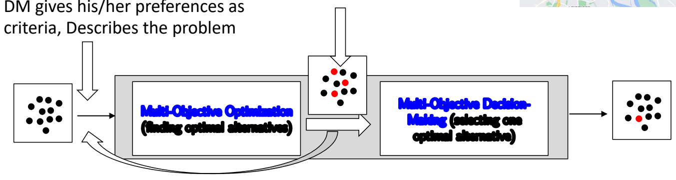
Multi-Objective Pathfinding

- A very old problem, probably as old as humankind
- It has high impact on energy consumption, our time, quality of life, logistics, industry, and our environment
- Role of human Decision Maker(DM): The today's navigation systems consider the human in the loop,
  - Either by asking the preferences, e.g., shortest path, or less CO2 emission, no highway, etc. → Single objective problem
  - Or after the optimization, to select one



Our research:
DM gives his/her preferences as criteria, Describes the problem

Our research:
DM selects one



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Multi-Objective and Many-Objective Pathfinding

Many-Objective Benchmark problem: Scalable in terms of the number of decision variables

Length:

$$f_1(N) = \sum_{i=1}^{K-1} d(n_i, n_{i+1})$$

$$d(u,v) = \|u - v\|_2$$

Elevation (Ascent):

$$f_3(N) = \sum_{i=1}^{K-1} e(n_i, n_{i+1})$$

$$e(m,n) = \begin{cases} h(n) - h(m), & \text{if } h(n) > h(m) \\ 0, & \text{otherwise} \end{cases}$$

Expected Delay:

$$f_2(N) = \sum_{i=1}^{K-1} \operatorname{delay}(n_i, n_{i+1})$$

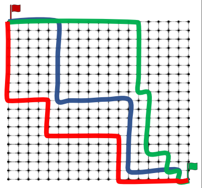
$$\operatorname{delay}(n_i, n_{i+1}) = \begin{cases} 2 & \text{if } v(n) \neq v(n_1) \\ 3 & \text{if } v(n) = \text{ city } \wedge v(n_1) = \text{ city} \\ 1 & \text{if } v(n) = \text{ country } \wedge v(n_1) = \text{ country} \\ \frac{1}{5} & \text{otherwise} \end{cases}$$

Time:

$$f_4(N) = \sum_{i=1}^{K-1} \frac{2d(n_i, n_{i+1})}{v_{\max}(n) + v_{\max}(n_{i+1})}$$

Smoothness:

$$f_5(N) = \sum_{i=2}^{K-1} \arccos\left(\frac{\overrightarrow{n_i n_{i-1}} \cdot \overrightarrow{n_{i+1} n_i}}{|\overrightarrow{n_i n_{i-1}}| \cdot |\overrightarrow{n_{i+1} n_i}|}\right)$$



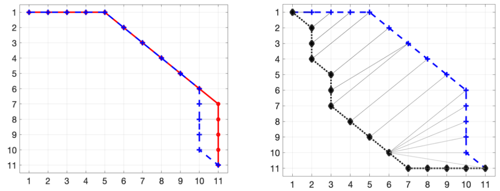
Jens Weise and Sanaz Mostaghim, A Scalable Many-Objective Pathfinding Benchmark Suite, IEEE Transactions on Evolutionary Computation, vol. 26, no. 1, pp. 188-194, Feb. 2022,

5

Multi-Objective and Many-Objective Pathfinding

The main feature in pathfinding is the specific representation of the routes: Variable length individuals and similarity between the individuals

Modified NSGA-II: Usage of Fréchet Density Value (FDV) instead of crowding distance



J. Weise and S. Mostaghim, 'Many-Objective Pathfinding Based on Fréchet Similarity Metric', in 11th International Conference, EMO 2021, Shenzhen, China, March 28-31, 2021, Proceedings, 2021, pp. 375–386.

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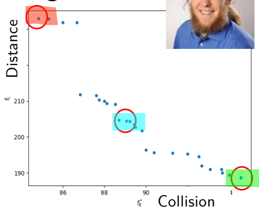
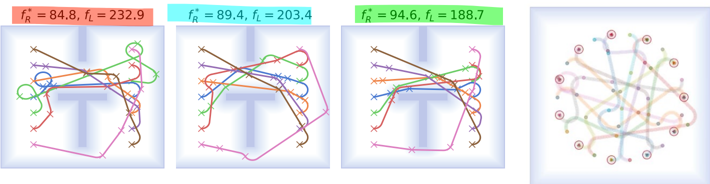
Multi-Objective Multi-Agent Pathfinding

Several robots navigating to several POIs and minimize:

f_R: Collision (max distance to others and obstacles)
f_L: Distance to the goal (shortest path)
Considering a vehicle model:
(incl. sensor failures and movement constraints)





Sebastian Mai, Tobias Benecke and Sanaz Mostaghim, MACO: The Multi-Agent Coordination Problem, Evolutionary Multi-Criterion Optimization. EMO 2023.
Sebastian Mai and Sanaz Mostaghim, Collective Decision-making for Conflict Resolution in Multi-Agent Pathfinding, ANTS 2022
Sebastian Mai and Sanaz Mostaghim, Modeling Pathfinding for Swarm Robotics. ANTS 2020
Jens Weise, Sebastian Mai, Heiner Zille and Sanaz Mostaghim, On the Scalable Multi-Objective Multi-Agent Pathfinding Problem, IEEE Congress on Evolutionary Computation, 2020

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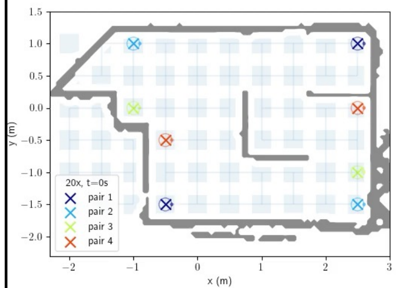

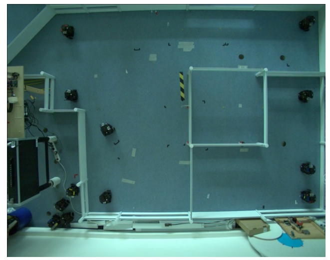

Sebastian Mai and Sanaz Mostaghim, Decentralized Collective Conflict Resolution for Cooperative Multi-Robot Navigation, Submitted to ICRA 2024
Sebastian Mai, Nele Traichel and Sanaz Mostaghim, Driving Swarm: A Swarm Robotics Framework for Intelligent Navigation in a Self-organised World, In the proceedings of International Conference on Robotics and Automation (ICRA), 2022

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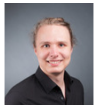
MACO Benchmark: Multi-Agent Coordination Problem

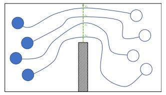
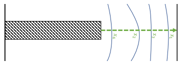



A new problem about a real-world problem: to coordinate multiple agents to move in an environment without any collisions.

The goal is to simplify the problem to a single, critical time step:

Fast to compute, Pareto front and Pareto sets are known, Real world challenges for algorithms remains

Highly multi-modal problem

Two objective functions:

1) Objective 1: Minimize the driving time and the energy cost. The average distance to the obstacle should be as small as possible
2) Objective 2: Maximize safety. The smallest distance between two agents should be as large as possible

Related works: High computational cost and optimal solutions not known in the continuous version

Sebastian Mai, Tobias Benecke and Sanaz Mostaghim, MACO: The Multi-Agent Coordination Problem, Evolutionary Multi-Criterion Optimization. EMO 2023.

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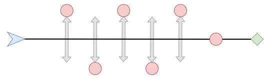
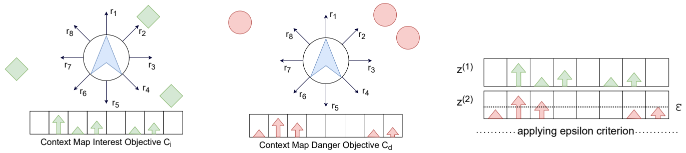
Multi-Objective Context Steering

Multi-Objective Navigation Problem:

- Minimize the distance to point of interest (■)
- Minimize damage caused by obstacle (●)

$$\min \vec{f}(t) = (D_{POI}(t), f_{damage}(t))$$

Alexander Dockhorn, Sanaz Mostaghim, Martin Kirst and Martin Zettwitz, Multi-Objective Optimization and Decision-Making in Context Steering, In the Proceedings of the IEEE Conference on Games, 2021, doi: 10.1109/CoG52621.2021.9619155

Alexander Dockhorn, Martin Kirst, Sanaz Mostaghim, Martin Wieczorek, Heiner Zille, Evolutionary Algorithm for Parameter Optimization of Context-Steering Agents, in IEEE Transactions on Games, vol. 15, no. 1, pp. 26-35, March 2023, doi: 10.1109/TG.2022.3157247

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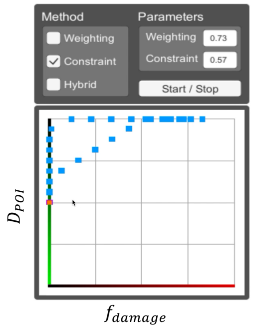

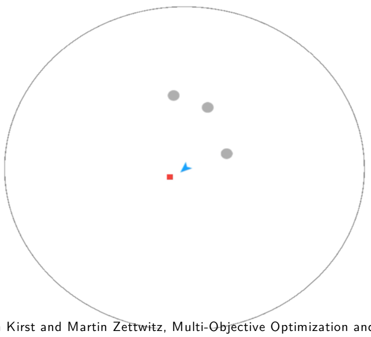

Alexander Dockhorn, Sanaz Mostaghim, Martin Kirst and Martin Zettwitz, Multi-Objective Optimization and Decision-Making in Context Steering, Proceedings of IEEE Conference on Games, 2021, doi: 10.1109/CoG52621.2021.9619155

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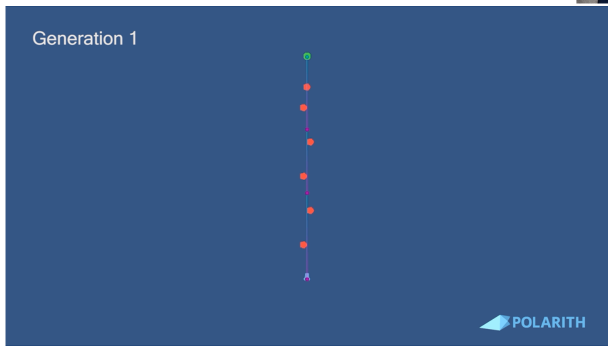
Multi-Objective Context Steering

Learning the parameters using evolutionary algorithms



Alexander Dockhorn, Martin Kirst, Sanaz Mostaghim, Martin Wieczorek, Heiner Zille, Evolutionary Algorithm for Parameter Optimization of Context-Steering Agents, in IEEE Transactions on Games, vol. 15, no. 1, pp. 26-35, March 2023, doi: 10.1109/TG.2022.3157247

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Many- and Multi-Objective Path-Paving Problem

A new problem about a real-world problem:

In this problem the agent can move obstacles

→ It changes the environment

→ It requires energy to move obstacles, depending on the weight of obstacles

Objectives:

The same objectives as for many-objective pathfinding

Additional new objective: Cost (Energy)

Julia Heise, Jens Weise and Sanaz Mostaghim, Towards Benchmarking of Pathfinding Algorithms in Path-Influenced Environments, In Proceedings of the Companion Conference on Genetic and Evolutionary Computation (GECCO '23 Companion). 2023, https://doi.org/10.1145/3583133.3596434

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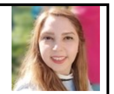
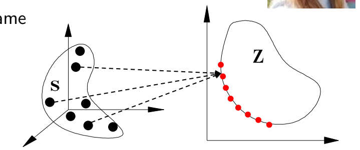
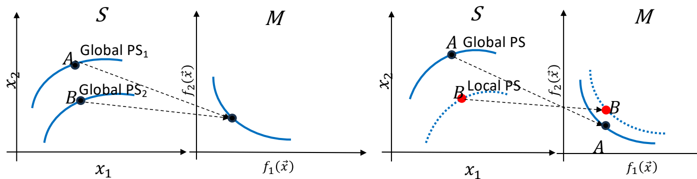
Multi-Objective Multi-Modal Optimization Problems



- Several decision variables map to the same or similar objective values



- A fundamental problem in almost all decision-making problems!!
- Due to lack of knowledge in problem formulation, sometime a slightly deteriorate solution might be of interest as well!
- There are two types of MMOPs



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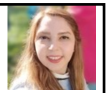
Multi-Objective Multi-Modal Optimization Problems



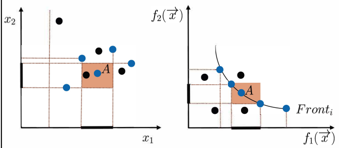
Our research:

- Enhanced tournament selection, mutation, and environmental strategies to not only find but also retain the best solutions in the search space

  E.g., weighted crowding distance (CD) $WSCD_{S_i} = W_1 \cdot CD_{S_i}(obj) + W_2 \cdot CD_{S_i}(dec)$
- A new way to classify selection methods, distinguishing between inter-front and intra-front selections.

Intra-Front Selection Operation

- CD within the same front



Inter-Front Selection Operation

- Consider solutions within the same front (*Front$_i$*) and
- Also neighboring solutions on previous fronts (*Front$_1$ to Front$_{i-1}$*)

Benefits of Inter-Front Selection

- Improves environmental selection
- Enhances diversity within the population
- More accurate calculation of CD

Javadi, M. and Mostaghim, S.. Using neighborhood-based density measures for multimodal multi-objective optimization.In Evolutionary Multi-Criterion Optimization: 11th International Conference, EMO 2021

Javadi, M. and Mostaghim, S.. Analysis of inter and intra-front operations in multi-modal multi-objective optimization problems. Natural Computing, 22(2), 2023

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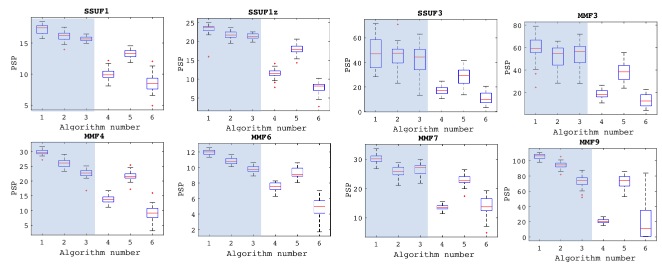
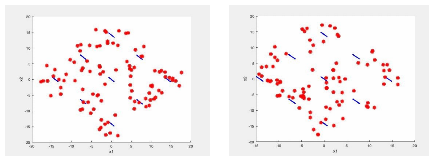
Some results

1=NxEMMO 2=NSGA-II-GrCDdec 3=NSGA-II-WSCD 4=MOEADM 5=Mo-Ring-PSO-SCD 6=NSGA-II



$$\mathrm{PSP}(P^*, R) = \frac{CR(P^*, R)}{\mathrm{IGDX}(P^*, R)}$$



NxEMMO

NSGA-II

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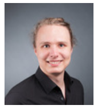
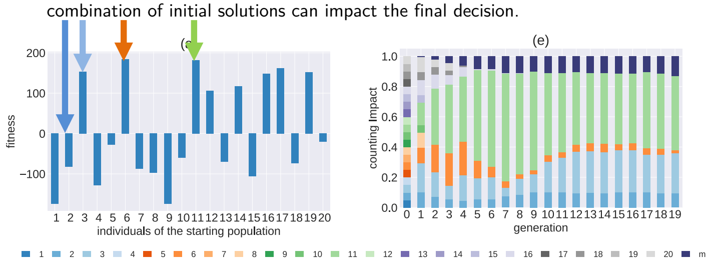
Understanding Decision-Making



- Traceable EA (T-EA): Study the impact of initial solutions on the final decision.
- Observation: only some of the initial solutions in the decision space have an impact on the entire learning process → The idea is to understand which combination of initial solutions can impact the final decision.



Tobias Benecke and Sanaz Mostaghim, Effects of Optimal Genetic Material in the Initial Population of Evolutionary Algorithms Accepted at IEEE SSCI 2023, Symposium on Foundations of CI (FOCI), Mexico, December 2023
T. Benecke and S. Mostaghim, Estimating the Quality of Initial Populations in Multi-Objective Evolutionary Algorithms, GECCO '22: Proceedings of the Genetic and Evolutionary Computation Conference Companion, July 2022
T. Benecke and S. Mostaghim, "Tracking the Heritage of Genes in Evolutionary Algorithms," 2021 IEEE Congress on Evolutionary Computation (CEC), 2021, pp. 1800-1807, doi: 10.1109/CEC45853.2021.9504916
C. Ramirez-Atencia, T. Benecke and S. Mostaghim, "T-EA: A Traceable Evolutionary Algorithm," 2020 IEEE Congress on Evolutionary Computation (CEC), 2020, pp. 1-8, doi: 10.1109/CEC48606.2020.9185615.

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Real-World Applications of EMO

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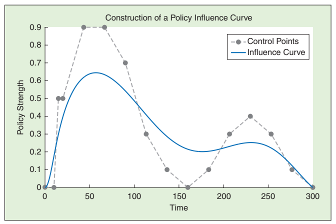
Exploring Dynamic Pandemic Containment Strategies

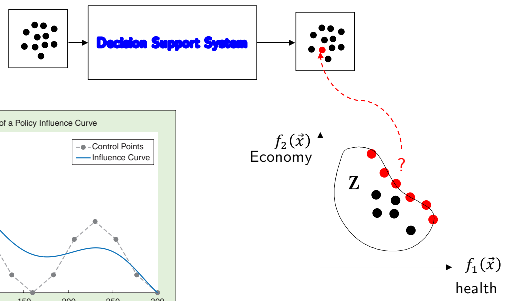
The health economy dilemma (HED) problem:

The goal is to find strategies which are optimal regarding concurrent infections, economic growth, and required intensity of employed interventions.

Each point is one strategy, Lockdown, Quarantine, etc.

13 degree of freedom, start, duration, intensity, ….





Dominik Fischer, Sanaz Mostaghim and Thomas Seidelmann, Exploring Dynamic Pandemic Containment Strategies Using Multi-Objective Optimization, IEEE Computational Intelligence Magazine, Volume 17, Number 3, Pages 54 - 66, August 2022

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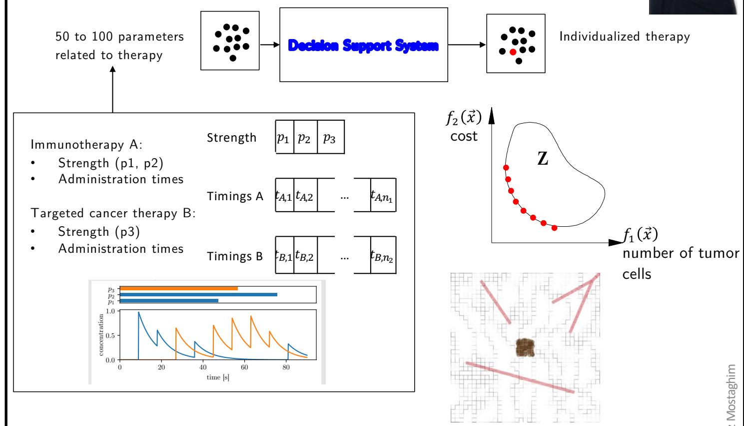
Decision-Making in Skin Cancer Therapy



Lukas Bostelmann-Arp, Sanaz Mostaghim, Andreas Braun, Thomas Tüting, Multi-Objective Evolutionary Game Theory: A case study in cancer therapy, In the Proceedings of the ALIFE 2022

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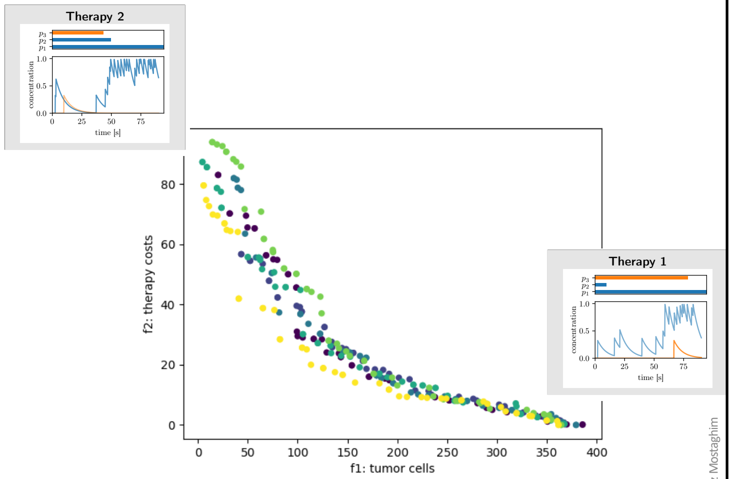

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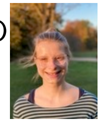
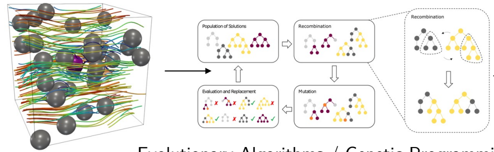
Learning complex symbolic regressions with EMO



- Aim for a human-readable/interpretable model: to allow for the iterative introduction of expert knowledge
- Using simulation data: learn models for a fluid dynamic problem



$$u_r = u_\infty \cos(\theta)\left(1 + \frac{a^3}{2r^3} - \frac{3a}{2r}\right)$$

$$u_\theta = -u_\infty \sin(\theta)\left(1 - \frac{a^3}{4r^3} - \frac{3a}{4r}\right)$$

Evolutionary Algorithms / Genetic Programming + Graph Networks

Julia Reuter, Pravin Pandey and Sanaz Mostaghim, Multi-Objective Island Model Genetic Programming for Predicting the Stokes Flow Around a Sphere, Accepted at IEEE SSCI 2023, Symposium on Multicriteria Decision-Making (MCDM), Mexico, December 2023

Julia Reuter, Sanaz Mostaghim, Hani Elmestikawy, Fabien Evrard, and Berend van Wachem, Graph Networks as Inductive Bias for Genetic Programming: Symbolic Models for Particle-Laden Flows, Accepted at EuroGP 2023

Julia Reuter, Fabien Evrard, Sanaz Mostaghim and Berend van Wachem, Towards Improving Simulations of Flows around Spherical Particles Using Genetic Programming, 2022 IEEE Congress on Evolutionary Computation

Julia Reuter, Christoph Steup and Sanaz Mostaghim, Genetic Programming-Based Inverse Kinematics for Robotic Manipulators, In: Medvet, E., Pappa, G., Xue, B. (eds) Genetic Programming. EuroGP 2022

Heiner Zille, Fabien Evrard, Julia Reuter, Sanaz Mostaghim and Berend van Wachem, Assessment of Multi-objective and Coevolutionary Genetic Programming for predicting the Stokes Flow around a Sphere, In the Proceedings of the 14th International Conference on Evolutionary and Deterministic Methods for Design, Optimization and Control (EUROGEN 2021), ECCOMAS, Athens, Greece, June 2021

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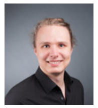
EMO for Circular Economy: Profit vs. Sustainability

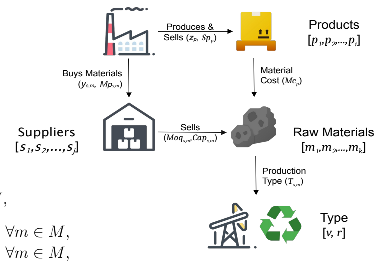


2-objective maximization problem:

$$f_1 := \underbrace{\sum_{p\in P} z_p Sp_p}_{\text{Revenue}} - \underbrace{\sum_{m\in M}\sum_{s\in S} y_{s,m} Mp_{s,m}}_{\text{Material Costs}} - \underbrace{Fc}_{\text{Fixed Costs}}$$

$$f_2 := \frac{\overbrace{\sum_{s\in S}\sum_{m\in M} T_{s,m}\cdot y_{s,m}}^{\text{Sustainable Resources}}}{\sum_{s\in S}\sum_{m\in M} y_{s,m}}$$

$$\begin{aligned}
\text{subject to}\quad \sum_{s\in\mathbb{S}} y_{s,m} &\geq \sum_{p\in P} z_p MC_{p,m}, \forall m \in M,\\
y_{s,m} &\leq Cap_{s,m}, && \forall s\in S \quad \forall m \in M,\\
y_{s,m} &\geq x_{s,m} Moq_{s,m}, && \forall s\in S \quad \forall m \in M,\\
x_{s,m} &\in \{0,1\}, && \forall s\in S \quad \forall m \in \mathbb{M},\\
y_{s,m} &\in \mathbb{Z}, && \forall s\in S \quad \forall m \in \mathbb{M},\\
z_p &\in \mathbb{Z}, && \forall p \in P
\end{aligned}$$



Tobias Benecke, Sanaz Mostaghim, Oliver Antons and Julia Arlinghaus, A Generalized Circular Supply Chain Problem for Multi-objective Evolutionary Algorithms, In Proceedings of the Companion Conference on Genetic and Evolutionary Computation (GECCO '23 Companion). 2023

Tobias Benecke, Sanaz Mostaghim, Oliver Antons and Julia Arlinghaus, A Coevolution approach for the Multi-objective Circular Supply Chain Problem, 2023 IEEE Conference on Artificial Intelligence (CAI), pp. 222-223, doi: 10.1109/CAI54212.2023.00103, 2023

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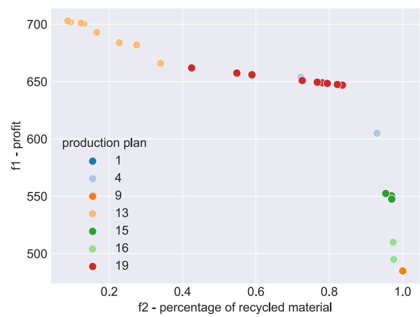

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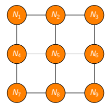
Multi-Objective Task Allocation Problem

In the context of IOTs:

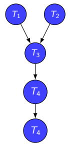
Network Graph $G_{Net} = (\mathcal{N}(t), E_{Com}(t))$



Node Attributes:
- Battery $E_i(t)$
- Position $x_i(t)$
- Hardware capabilities

Edge Attributes:
- Transmission cost $E_{ij}(t)$
- Latency $l_{ij}(t)$
- Reliability
- Security

Task Graph $G_{Task} = (\mathcal{T}(t), E_{Task}(t))$



Node Attributes:
- Processing cost p_i
- Spatial constraint S_i
- Hardware requirements

Edge Attributes:
- Communication cost c_{ij}
- Security constraints
- Reliability constraints

3 Objectives:

Network Lifetime:
$NL(a_i) = -max(t_i)$ where a_i is valid
- Critical nodes assigned less load
- More usage of redundant nodes

Latency:
$L(a_t) = \max_{T_k, T_l \in V_{Tasks}} \left(\sum_{e_{ij} \in P_{kl}(a_t)} l_{ij} + l_i(q_k) \right)$
- Minimal communication links
- Heavy load on critical nodes

Balanced:
- Improved Latency
- Better load balance
- Critical nodes less taxed

D. Weikert, C. Steup, and S. Mostaghim, "Availability-Aware Multi-Objective Task Allocation for Wireless Sensor Networks", IEEE Internet of Things Journal, 2023
D. Weikert, C. Steup, and S. Mostaghim, "Multi-Objective Task Allocation for Wireless Sensor Networks", IEEE SSCI 2021

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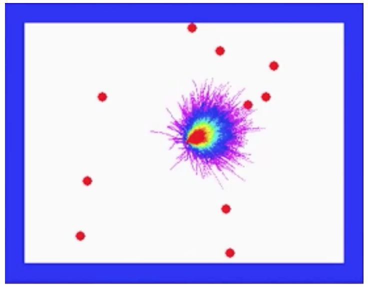
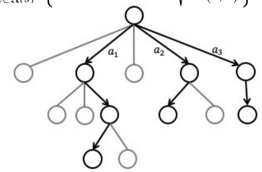
EMO in Reinforcement Learning

Multi-Objective Monte Carlo Tree Search



$$a^* = \operatorname*{argmax}_{a \in A(s)} \left\{ HV(P)/N(s) + C\sqrt{\frac{\ln N(s)}{N(s,a)}} \right\}$$



Perez, Mostaghim, Samothrakis and Lucas, Multi-objective Monte Carlo Tree Search for Real-Time Games in *IEEE Transactions on Computational Intelligence and AI in Games*, vol. 7, no. 4, pp. 347-360, Dec. 2015

Neufeld, Brand and Mostaghim, A Hybrid Approach to Planning and Execution in Dynamic Environments Through Hierarchical Task Networks and Behavior Trees, AAAI 2019
Neufeld, Mostaghim, Sancho-Pradel and Brand, Building a Planner, IEEE Transactions on Games, 2018
Perez, Mostaghim and Lucas, Multi-Objective Tree Search Approaches for General Video Game Playing, IEEE Congress on Evolutionary Computation, 2016

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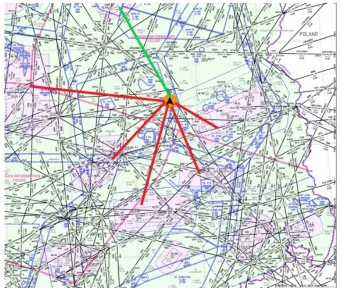
Decision-Making for Critical Infrastructures

Fast Decision-Making during the flight using EMO



Choose 1 option from a possible set of alternatives, characterized by multiple attributes

m

Option	Wind speed	Wind direction	Runway length	Runway status	Weather pehnomena	...
Airport 1						
Airport 2						
Airport 3						
...						

Characteristic

n

Boris Djartov and Sanaz Mostaghim, Multi-objective Multiplexer Decision Making Benchmark Problem, MCDC Workshop, In Proceedings of the Companion Conference on Genetic and Evolutionary Computation (GECCO '23 Companion). 2023, https://doi.org/10.1145/3583133.3596360

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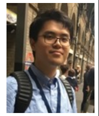
Multi-Objective Data Analysis

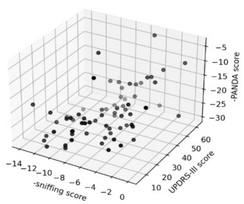


Parkinson's disease is one of the most important challenges of our society → **is called silent pandemic.**

Most of the cases are different in many ways. There is no generic profile!

The goal of this work is to unfold the variability behind the data and understand the underlying common features for various groups of patients.

We have 3 conflicting Objectives:



Data → Pre-Process →

Multi-Objective Analysis
- Defining Objectives
- Non-dominated Sorting
- Interfront & Intrafront Clustering
- Feature Extraction for each cluster

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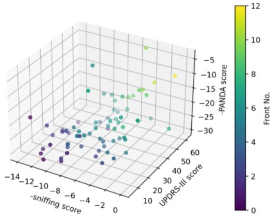
Front Clustering

Front clustering is proposed to cluster the data according to the objectives.



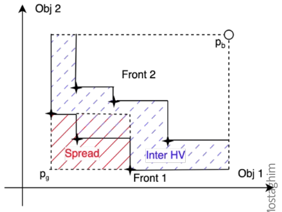
To differentiate between the cluster of fronts, w proposed the following:

Interfront Hypervolume (HV): The space between two fronts

$$InterHV(r-1,r) = \frac{HV_{r-1} - HV_r}{\Pi_{i=1..M}[\max_{a \in A}(f_i(a)) - \min_{a \in A}(f_i(a))]}$$

Intrafront Spread: It measures the spread of a given front

$$Spread(r) = \frac{\Pi_{i=1..M}[\max_{a \in A_r}(f_i(a)) - \min_{a \in A_r}(f_i(a))]}{\Pi_{i=1..M}[\max_{a \in A}(f_i(a)) - \min_{a \in A}(f_i(a))]}$$



S. Mostaghim et al., "Medical and Behavioral Knowledge Discovery using Multi-Objective Analysis," 2023 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB), Eindhoven, Netherlands, 2023, pp. 1-8, doi: 10.1109/CIBCB56990.2023.10264881.

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Summary

- Due to better computing power and the fact that we have more data, computational intelligence methodologies can be used on a vast variety of problems.
- Multi-objective optimization can be used to simultaneously find several alternatives for a decision problem.
- Having several (optimal) alternatives for decision-making, gives more confidence to the decision-maker.
- Team and collective decision-making is easier when having several alternatives.
- Ethical implications of decision-making for autonomous systems is an important aspect (collaboration with TU Braunschweig).

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