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

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Decision Science

Why is decision-making so hard?

Several conflicting objectives

By selecting one alternative, we lose others

It requires time

Having several alternatives is good → it gives a sort of confidence to the decision-maker

Decision Science

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

Minimize \( f(x) \) \( \text{s.t. } x \in S \)

Objective vectors \( f(x) = (f_1(x), \ldots, f_m(x)) \) in objective space \( \mathbb{R}^m \)

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
Multi-Objective and Many-Objective Pathfinding

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

| Length: $f_1(N) = \sum_{i=1}^{K-1} d(n_i, n_{i+1}) - d(n_0, n_1)$ |
| Elevation (Ascent): $f_{d}(N) = \sum_{i=1}^{K-1} c(n_i, n_{i+1})$ |
| Expected Delay: $f_{d}(N) = \sum_{i=1}^{K-1} \text{delay}(n_i, n_{i+1})$ |
| Smoothness: $f_{s}(N) = \sum_{i=1}^{K-1} \text{smooth}(n_i, n_{i+1}) + \text{smooth}(n_{K-1}, n_0)$ |


Multi-Objective Multi-Agent Pathfinding

Several robots navigating to several POIs and minimize:

- $f_c$: Collision (max distance to others and obstacles)
- $f_d$: Distance to the goal (shortest path)

Considering a vehicle model: (incl. sensor failures and movement constraints)


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 remain.

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.

Multi-Objective Context Steering

Multi-Objective Navigation Problem:
- Minimize the distance to point of interest ( □ )
- Minimize damage caused by obstacle ( ● )

\[
\min f(t) = (D_{pos}(t), f_{damage}(t))
\]

Learning the parameters using evolutionary algorithms

Generation 1

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/CoG.2021.9619553
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

Intra-Front Selection Operation
- CD within the same front

Inter-Front Selection Operation
- Consider solutions within the same front (Front) and
- Also neighboring solutions on previous fronts (Front, to Front)

Benefits of Inter-Front Selection
- Improves environmental selection
- Enhances diversity within the population
- More accurate calculation of CD
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.

Real-World Applications of EMO

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, ...

Decision-Making in Skin Cancer Therapy

Immunotherapy A:
- Strength (p1, p2)
- Administration time

Targeted cancer therapy B:
- Strength (p3)
- Administration time

Timings A

Timings B

Individualized therapy: $f_c(x)$ cost

Number of tumor cells

Lukas Bostelmann-Arg, Sanaz Mostaghim, Andreas Braun, Thomas Tüting, Multi-Objective Evolutionary Game Theory. A case study in cancer therapy. In the Proceedings of the ALIFE 2020
amounts of materials to be sourced. Both challenges make it di-
sourced at the supplier. Furthermore, each material
and can be sold for
The CSC problem models a factory that produces products
Purchase Quantities
introduce the circular supply chain problem as a benchmark for MOEAs, modeling the challenges of optimizing both the production plan and material sourcing
which marks recycled or virgin materials.

Factory

✓

Each product
funded by the Ministry for Science, Energy, Climate Protection and the Environment of the State of Saxony-Anhalt.

Raw materials

Products

Sells (sp,m)

Sustainability

Coevolution/bi-objective optimization to decompose the problem into ma-

Explore more material sources

What is next?

E MO for Circular Economy: Profit vs.
Sustainability

EMO for Circular Economy: Profit vs. Sustainability

2-objective maximization problem:

\[ f_1 = \sum_{i=1}^{n} C_i x_i - \sum_{j=1}^{m} P_j y_j - \sum_{j=1}^{m} y_j M_j \]

\[ f_2 = \sum_{j=1}^{m} P_j y_j - \sum_{j=1}^{m} y_j M_j \]

subject to

\[ x_i \leq C_i x_i, y_j \in M_j \]

\[ y_j \leq P_j y_j, y_j \in M_j \]

\[ y_j \in \{0,1\}, y_j \in M_j \]

\[ y_j \in M_j \]

\[ y_j \in P \]

Tobias Biehnen, 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 Companion), 2022
Tobias Biehnen, Sanaz Mostaghim, Oliver Antons and Julia Arlinghaus, A Convoluated approach for the Multi-objective Circular Supply

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
Multi-Objective Task Allocation Problem

In the context of IOTs:

\[ G_{\text{net}} = (N(t), E_{\text{node}}(t)) \]

\[ G_{\text{task}} = (T(t), E_{\text{comm}}(t)) \]

**Network Graph (Node Attributes):**
- Battery \( E(t) \)
- Position \( x(t) \)
- Hardware capabilities

**Edge Attributes:**
- Transmission cost \( E_{ij} \)
- Latency \( L(t) \)
- Reliability
- Security

**Task Graph (Node Attributes):**
- Processing cost \( p \)
- Spatial constraints \( S \)
- Hardware requirements

**Edge Attributes:**
- Communication cost \( c_{ij} \)
- Security constraints
- Reliability constraints

3 Objectives:
- **Network Lifeline:** \( N_q(t) = \max(\{\zeta|\xi(t)\}) \)
  - Critical nodes assigned less load
  - More usage of redundant nodes
  - Minimal communication links
  - Heavy load on critical nodes
- **Latency:** \( L_a(t) = \max(\{\zeta_i|\xi(t)\}) \)
  - Improved Latency
  - Better load balance
  - Critical nodes less taxed

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

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**Decision-Making for Critical Infrastructures**

Fast Decision-Making during the flight using EMO

**Characteristics:**
- Wind speed
- Wind direction
- Runway
- Weather
- Altitude

**Options:**
- Airport 1
- Airport 2
- Airport 3

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**EMO in Reinforcement Learning**

Multi-Objective Monte Carlo Tree Search

\[ s^* = \arg \max \left( \frac{H(V)}{|V|} + \sqrt{\frac{2 \ln(N)}{|V|^2}} \right) \]

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**Multi-Objective Data Analysis**

Parkinson’s disease is one of the most important challenges of our society → 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:
Front Clustering

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

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

Interfront Hypervolume (HV): The space between two fronts

$\text{InterHV}(r - 1, r) = \frac{HV_{r-1} - HV_r}{\prod_{i=1}^{n-1} \max_{x \in \mathcal{X}} (f_i(x)) - \min_{x \in \mathcal{X}} (f_i(x))}$

Intrafront Spread: It measures the spread of a given front

$\text{Spread}(x) = \frac{\prod_{i=1}^{n-1} \max_{x \in \mathcal{X}} (f_i(x)) - \min_{x \in \mathcal{X}} (f_i(x))}{\prod_{i=1}^{n-1} \max_{x \in \mathcal{X}} (f_i(x)) - \min_{x \in \mathcal{X}} (f_i(x))}$

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).