EMO 2025 Program

(Times indicated in AEDT / UTC+11hrs)

Venue: Shine Dome, 15 Gordon St, Acton ACT 2601

- All technical session in Ian Wark Theatre
- All catered events in Jaeger Room

Program outline

Day 1 (04 March, Tuesday)		Day 2 (05 March, Wednesday)		Day 3 (06 March, Thursday)		Day 4 (07 March, Friday)	
9.00-9.10	Brief opening remarks	9.00-9.20	Conference opening	9.00-10.00	Keynote 2 (Kaisa Miettinen)	9.00-10.00	Keynote 3 (Bernhard Sendhoff)
9.10-10.20	Tutorial 1	9:20-10.20	Keynote 1 (Qingfu Zhang)	10.00-10.30	(Mini) Tutorial 6 DESDEO	10.00-10.40	Panel discussion
10.20-10.40	Tea break	10.20-10.40	Tea break	10.30-10.50	Tea break	10.40-11.00	Tea break
10.40-11.50	Tutorial 2	10.40-12.10	Papers x 5 (EMO track)	10.50-12.10	Papers x 4 (MCDM track)	11.00-12.20	Papers x 4 (Industry track)
				12.10-12.20	In-memoriam session		
11.50-13.00	Lunch break	12.10-13.20	Lunch break	12.20-13.20	Lunch break	12.20-13.30	Lunch break
13.00-14.10	Tutorial 3	13.20-15.00	Papers x 5 (EMO track)	13.20-15.00	Papers x 5 (EMO track)	13.30-15.10	Papers x 5 (EMO track)
14.10-15.30	Tutorial 4	15.00-15.20	Tea break	15.00-15.20	Tea break	15.10-15.30	Tea break
15.30-15.50	Tea break	15.20-1700	Papers x 5 (EMO track)	15.20-17.00	Papers x 5 (EMO track)	15.30-16.10	Papers x 2 (EMO track)
15.50-17.00	Tutorial 5					16.10-17.00	Closing
18.30-20.30	Welcome reception			18.30-21.30	Conference dinner		

Day 1 (Tuesday, 04 March 2025)

9.00-9.10	Opening remarks	
9.10-10.20	Tutorial 1	*Evolutionary Multi-Objective Algorithms for Constrained Single-Objective Combinatorial Optimization Problems: Theory and Applications* Dr Aneta Neumann and Prof. Frank Neumann, The University of Adelaide, Australia
10.20-10.40	Tea Break	Catered in Jaeger Room
10.40-11.50	Tutorial 2	*Evolutionary Multi-objective Optimization for Practical Problem Solving* Prof. Kalyanmoy Deb, Michigan State University, USA
11.50-13.00	Lunch	Catered in Jaeger Room
13.00-14.10	Tutorial 3	*Difficulties in Fair Performance Comparison of Evolutionary Multi-objective Optimization Algorithms*, Dr Lie Meng Pang and Prof. Hisao Ishibuchi, Southern University of Science and Technology, China
14.10-15.20	Tutorial 4	*Dynamic Multi-objective Optimization: Introduction, Challenges, Applications and Future Directions*, by Dr Mardé Helbig, Griffith University, Australia
15.20-15.40	Tea Break	Catered in Jaeger Room
15.40-17.00	Tutorial 5	*Multi-objective Algorithm Design using Large Language Models*, Dr Fei Liu, Dr Zhichao Lu, Prof. Qingfu Zhang, City University of Hong Kong, China, and Dr Zhenkun Wang, Southern University of Science and Technology, China
18.30-20.30	Welcome Reception	Catered in Jaeger Room

Day 2 (Wednesday, 05 March 2025)

9.00-9.20	Conference opening	Welcome address by Professor Harvi Sidhu, Deputy Rector of UNSW Canberra, Opening remarks from the EMO 2025 organizing committee
9.20-10.20	Keynote 1	*Modelling and Set Constraints in Multi-objective Evolutionary Computation* Qingfu Zhang, Chair Professor of Computational Intelligence, City University of Hong Kong, China
10.20-10.40	Tea break	Catered in Jaeger Room
10.40-12.10	EMO 1	• *Weights-Guided Random Bit Climber for Binary Many-objective Optimization* (*Tagawa, Aguirre, Tanaka) • *Cumulative Step Size Adaptation for Adaptive SEMO in Integer Space* (Rudolph, *Wagner) • *Encodings for Multi-Objective Free-Form Coverage Path Planning* (*Bostelmann-Arp, Steup, Mostaghim) • *Enhancing NSGA-II with a Knee Point for Constrained Multi-objective Optimization* (*Pang, Ishibuchi, Nan) • *Selective evaluations for expediting multi-objective bilevel optimization* (*Wang, Singh, Ray)
12.10-13.20	Lunch break	Catered in Jaeger Room
13.20-15.00	EMO 2	• *PAES-25: Local Search, Archiving and Multi/Many-objective Pseudo-Boolean Functions* (*Knowles, Liefooghe) • *Adaptive Normal-Boundary Intersection Directions for Evolutionary Manyobjective Optimization with Complex Pareto Fronts* (Elarbi, Bechikh, *Coello Coello) • *Visual Explanations of Some Problematic Search Behaviors of Frequently-Used EMO Algorithms* (*Ishibuchi, Pang) • *On the Approximation of the Entire Pareto Front of a Constrained Multiobjective Optimization Problem* (*Rodriguez-Fernandez, Castellanos, Schuetze) • *Performance Analysis of Constrained Evolutionary Multi-Objective Optimization Algorithms on Artificial and Real-World Problems* (Nan, *Ishibuchi, Pang)
15.00-15.20	Tea break	Catered in Jaeger Room
15.20-17.00	EMO 3	• *Comparative Analysis of Indicators for Multi-objective Diversity Optimization* (Pereverdieva, Deutz, Ezendam, *Baeck, Hofmeyer, Emmerich) • *When Is Non-deteriorating Population Update in MOEAs Beneficial?* (*Zhang, Li, Tang, Yao) • *Small Population Size is Enough in Many Cases with External Archives* (Nan, *Ishibuchi, Pang) • *Analysis of Merge Non-dominated Sorting Algorithm* (*Mishra, Prakash, Coello Coello) [Online] • *Multi-Objective Multi-Agent Reinforcement Learning for Autonomous Driving in Mixed-Traffic Environments* (*Herm, Mazumdar, Chugh) [Online]

Day 3 (Thursday, 06 March 2025)

9.00-10.00	Keynote 2	*Interactive Multiobjective Optimization from MCDM and EMO Perspectives* Kaisa Miettinen, Vice-rector and Professor of Industrial Optimization at the University of Jyväskylä, Finland
10.00-10.30	(Mini) Tutorial 6	*Interactive Evolutionary Multiobjective Optimization using DESDEO* by Bhupinder Saini and Giomara Lárraga, University of Jyväskylä, Finland
10.30-10.50	Tea break	Catered in Jaeger Room
10.50-12.10	MCDM 1	• *Reliability-based MCDM Using Objective Preferences Under Variable Un-Certainty* (Yadav, Ramu, *Deb) • *Preference Learning for Multi-objective Reinforcement Learning by Means of Supervised Learning* (*Fernández Noguez, Castellanos, Pineda) • *Bayesian preference elicitation for decision support in multi-objective optimization* (Huber, *Rojas-Gonzalez, Astudillo) • *An Efficient Iterative Approach for Uniformly Representing Pareto Fronts* (*Saini, Singh, Shavazipour, Miettinen)
12.10-12.20	In-memoriam	Remembering Jeffery Horn, Pekka Korhonen, Theodor Stewart
12.10-13.20	Lunch break	Catered in Jaeger Room
13.20-15.00	EMO 4	• *An MaOEA/Local Search Hybrid Based on a Fast, Stochastic BFGS Using Achievement Scalarizing Search Directions* (Sousa, Vargas, Wanner, *Knowles) • *Towards an Efficient Innovation Path Seeking Algorithm Using Directed Domination* (*Khan, Deb) • *MOAISDX: A New Multi-objective Artificial Immune System based on De-Composition* (Arroyo, *Coello Coello) • *VBEA: Voting-Based Evolutionary Algorithm for Multi-Objective Planning* (*Merino, Korpan) • *Bilevel Optimization-based Decomposition for Solving Single and Multiobjective Optimization Problems* (*Sinha*, Pujara, Singh) [Online]
15.00-15.20	Tea break	Catered in Jaeger Room
15.20-17.00	EMO 5	• *Single and Multi-Objective Optimization Benchmark Problems Focusing on Human-Powered Aircraft Design* (*Namura) • *An Extension of the Welded Beam Problem that Includes Multiple Interacting Design Concepts* (*Kenny, Ray, Singh) • *Extended Results on Analytical Hypervolume Indicator Calculation of Linear and Quadratic Pareto Fronts* (*Singh) • *MO-IOHinspector: Anytime Benchmarking of Multi-Objective Algorithms using IOHprofiler* (*Vermetten, Rook, Preuß, de Nobel, Doerr, López-Ibáñez, Trautmann, Baeck) • *A Study on Optimistic & Pessimistic Pareto-fronts in Multiobjective Bilevel Optimization via δ-Perturbation* (*Antoniou, Sinha, Papa) [Online]
18.30-21.30	Conference dinner	Catered in Jaeger Room

Day 4 (Friday, 07 March 2025)

9.00-10.00	Keynote 3	*Multi-X and Panta Rhei: Challenges and Opportunities in Optimization for Complex Applications* Bernhard Sendhoff, CEO, Global Network Honda Research Institutes, Germany
10.00-10.40	Panel discussion	EMO/MCDM in Industry Moderator: Frank Neumann Panellists: Bernhard Sendhoff, Kaisa Miettinen, Joshua Knowles
10.40-11.00	Tea break	Catered in Jaeger Room
11.00-12.20	Industry / Applications	• *Interactive evolutionary reoptimization for groundfish survey planning* (*Runarsson) • *Impact of Environmental Changes on Optimized Robotics Collective Motion for Multi-Objective Coverage Tasks* (*Ghanem, Ali, Kasmarik, Garratt) • *Multi-Objective Sequential Decision Making for Holistic Supply Chain Optimization* (*Rachman, Tingey, Allmendinger, Shukla, Pan) [Online] • *A Multi-Objective Competitive Co-Evolutionary Framework with Progressive Shrinking for Wargame Scenarios* (*Guha, McKendrick, Feest, Deb) [Online]
12.20-13.30	Lunch break	Catered in Jaeger Room
13.30-15.10	EMO 6	• *Knowledge Gradient for Multi-Objective Bayesian Optimization with Decoupled Evaluations* (Buckingham, Branke, *Rojas-Gonzalez) • *Surrogate Strategies for Scalarisation-based Multi-objective Bayesian Optimizers* (Mo, *Duro, Purshouse) • *Large Language Model for Multiobjective Evolutionary Optimization* (*Liu, Lin, Yao, Wang, Tong, Yuan, Zhang) • *Efficient and Accurate Surrogate-Assisted Approach to Multi-Objective Optimization Using Deep Neural Networks* (*Yang, Sato) • *A Mixed-Fidelity Evaluation Algorithm for Efficient Constrained Multi- and Many-Objective Optimization: First Results* (*Santoshkumar, Deb) [Online]
15.10-15.30	Tea break	Catered in Jaeger Room
15.30-16.10	EMO 7	• *Parallel TD3 for Policy Gradient-based Multi-Condition Multi-Objective Optimisation* (*Balasooriya, Blai, Wilks, Wheeler, Jauhar, Chalup) • *Numerical Analysis of Pareto Set Modeling* (Shu, *Ishibuchi, Nan,Pang)
16.10-17.00	Closing	

Keynotes

Keynote 1: Modelling and Set Constraints in Multi-objective Evolutionary Computation

Speaker: Prof. Qingfu Zhang, City University of Hong Kong, China**. Time:** 5 March 2025, 9.20-10.20am

Abstract: It is well-known that the Pareto set of a continuous multi-objective optimization problem is piecewise continuous under mild conditions. However, most current multiobjective evolutionary algorithms can only generate a finite number of optimal solutions. In this talk, I will first introduce our recently developed Pareto Set Learning algorithm. It treats the task of find the Pareto set as a function approximation problem and uses neural network learning methods to produce a math model for approximating the Pareto set. I will introduce the basic idea and techniques behind PSL. The other topic in my talk is on structure constraints on the optimal solution set. Where modular or personalized designs are required, a decision maker needs to consider such constraints. These constraints can be used for supporting so-called "innovization". I will explain how trade off Pareto optimality with set constraints in Pareto set learning.

Qingfu Zhang received the BSc degree in mathematics from Shanxi University, China in 1984, the MSc degree in applied mathematics and the PhD degree in information engineering from Xidian University, China, in 1991 and 1994, respectively. He is a Fellow of IEEE and Chair Professor of Computational Intelligence at the Department of Computer Science, City University of Hong Kong. He heads a research group of more than 30 members with a focus on metaheuristics and artificial intelligence. His MOEA/D algorithms have been widely studied and used in many application fields. He is a Web of Science highly cited researcher in Computer Science for eight times since 2016. Web: https://www.cs.cityu.edu.hk/~qzhan7/index.html

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Keynote 2: Interactive Multiobjective Optimization from MCDM and EMO Perspectives

Speaker: Prof. Kaisa Miettinen, University of Jyväskylä, Finland. **Time:** 6 March 2025, 9.00-10.00am

Abstract: In various domains, when we must make a decision by considering several conflicting objective functions simultaneously, we need multiobjective optimization methods. Pareto optimal solutions represent different trade-offs, and we need some additional information to order them. If we can get preference information from a decision maker, a domain expert, we can integrate this information in the solution process and support the decision maker in finding the best balance among the trade-offs, that is, the most preferred solution.

In interactive methods, a decision maker augments the problem formulation with domain expertise and directs an iterative solution process with preferences. In an iterative fashion, the decision maker provides preferences and obtains solutions reflecting them. In this way, the decision maker gains insight into the interdependencies and trade-offs among the conflicting objective functions and learns about the feasibility of the preferences. Based on the learning, the decision maker can update the preferences and eventually get convinced of the quality of the most preferred solution. By generating only solutions that are of interest to the decision maker, we can save in computation cost, and also decrease cognitive cost when only a limited number of solutions is to be considered at a time.

I discuss the similarities and differences of some interactive methods representing multiple criteria decision making (MCDM) and evolutionary multiobjective optimization (EMO) perspectives. I pay attention to expectations related to method development when a human being is involved. I also demonstrate the advantages of some interactive methods with real examples and introduce the modular, open-source software framework DESDEO that hosts different interactive methods. The implementation of interactive methods involves many requirements. We must also pay attention to the user experience of the decision maker in graphical user interfaces. As an example of visualizations developed to support the decision maker, I show SCORE bands. All this aims at supporting a decision maker in making better decisions.

Kaisa Miettinen is Vice-rector and Professor of Industrial Optimization at the University of Jyväskylä. Her research interests include theory, methods, applications and software of nonlinear multiobjective optimization, in particular, interactive approaches. She heads the Research Group on Multiobjective Optimization and leads the thematic research area Decision Analytics utilizing Causal Models and Multiobjective Optimization (www.jyu.fi/demo). She has authored over 230 refereed journal, proceedings and collection papers, edited 20 proceedings, collections and special issues and written a monograph Nonlinear Multiobjective Optimization. She is a member of the Finnish Academy of Science and Letters and has been the President of the International Society on Multiple Criteria Decision Making (MCDM) and Finnish Operations Research Society. She has served in the editorial boards of ten international journals and belongs to the Steering Committee of Evolutionary Multiobjective Optimization. She has worked at IIASA, International Institute for Applied Systems Analysis in Austria, KTH Royal Institute of Technology in Stockholm, Sweden and Helsinki School of Economics, Finland. She has received the Georg Cantor Award of the International Society on MCDM for developing innovative ideas in the theory and methodology and was appointed as the OR Person of the year in 2023 by the Finnish Operations Research Society. Web: http://users.jyu.fi/~miettine/engl.html

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Keynote 3: Multi-X and Panta Rhei - Challenges and Opportunities in Optimization of Complex Applications

Speaker: Prof. Bernhard Sendhoff, Honda Research Institute, Germany**. Time:** 7 March 2025, 9.00-10.00am

Using the two examples of engineering design optimization and system optimization, challenges of complex applications will be discussed and the role of the quality model, the many different "X" in multi-X and the challenges of the continuous change of many conditions of optimization of complex applications will be outlined. A scaled energy approach to topology optimization as an example of managing multi-disciplinary targets will be presented as well as the reference vector guided EAs as an example for handling many objectives including their application to the energy management domain. Multi-task optimization for design optimization and the research direction of robust and dynamic optimization in the context of multiple criteria will be discussed. Finally, the opportunity that the recent developments in AI research have created for rethinking the role of tools in the development process of complex applications will be highlighted together with the need to strengthen and apply research into hybrid team management for the future of optimization of complex applications.

Bernhard Sendhoff is currently Operating Officer at Honda R&D Co., Ltd., Chief Executive Officer of the Global Network Honda Research Institutes and Managing Director of the Honda Research Institute Europe GmbH. He is Honorary Professor at the Technical University of Darmstadt, Germany. Bernhard Sendhoff is a Fellow of the IEEE, a Senior Member of the ACM, and a Member of the SAE. He has authored or co-authored more than 200 peer reviewed journal and conference papers and over 40 patents and has a Google Scholar h-index of 52. Bernhard Sendhoff's research interests include several topics in the domains of intelligent systems, computational and artificial intelligence and industrial engineering optimization and design. Website: https://www.honda-ri.de/people/ LinkedIn: https://de.linkedin.com/in/bernhard-sendhoff-90304656

Tutorials

Tutorial 1: Evolutionary Multi-Objective Algorithms for Constrained Single-Objective Combinatorial Optimization Problems: Theory and Applications

Speakers: Dr Aneta Neumann and Prof. Frank Neumann, University of Adelaide, Australia
Time: 4 March 2025, 9.10-10.20am

Evolutionary multi-objective algorithms have been widely applied to problems with conflicting objectives. In addition to this classical multi-objective setting, multi-objective formulations of constrained single objective optimization problems have been used to more efficiently solve such problems than by classical single-objective formulations. This tutorial will cover multi-objective formulations and approaches for constrained single-objective combinatorial optimization problems both from a theoretical and practical perspective. Thereby, we will cover a wide range of results and approaches that have been obtained over the last 20 years. We will start with formulations involving static constraints and show that taking the constraint as an additional objective provably leads to a different way of solving constrained single-objective problems. This often results to better performance guarantees of evolutionary algorithms. We will provide such insights for important problems from the literature such as minimum spanning trees, covering, and the optimization of monotone submodular functions. Problems where constraints are dynamically changing often occur in real-world settings where resources might be added or lost over time. We will investigate evolutionary multi-objective algorithms for problems with dynamically changing constraints and examine the case where the bound of a given constraint is dynamically changing. We will discuss theoretical and empirical results that show that multi-objective formulations are well suited for dealing with such situations and exemplify this by considering the classical knapsack problem and monotone submodular problems with dynamically changing constraints. In the last part of this tutorial, we turn to stochastic constraints and show that problems with these constraints can often be solved more efficiently by formulating the stochastic constraint by one or two additional objectives. We focus on single-objective combinatorial optimization problems with chance constraints and show that formulating the expected cost and variance of the stochastic components as additional objectives allows to solve such problems often more effectively than through classical single-objective formulations. Furthermore, we discuss the ability of evolutionary multi-objective problems to provide solutions for stochastic problems matching a wide range of confidence levels instead of just a single one usually targeted through single-objective formulations.

Tutorial 2: Evolutionary Multi-objective Optimization for Practical Problem Solving

Speaker: Prof. Kalyanmoy Deb, Michigan State University, USA.
Time: 4 March 2025, 10.40-11.50am

Started in early nineties, evolutionary multi-objective optimization (EMO) field has undergone a phenomenal progress. New and efficient algorithms and easy-to-difficult test problem suites were proposed to construct well-tested methods. Performance metrics to evaluate sets of optimal solutions helped compare different algorithms. EMO algorithms were applied to solve critical applications demonstrating the advantages of using the EMO solution principle. EMO algorithms have been extended to solve many-objective optimization problems involving four or more objectives. EMO algorithms were applied to find a single optimal solution for difficult single-objective problems in more efficient ways than they were traditionally solved. Efforts have also been made to address multi-objective optimization and multi-criterion decision-making tasks together and in interactive manner.

However, a considerable and esoteric effort has been put to extend EMO algorithms for handling different practicalities often faced in real-world problems. Note that this tutorial is not a collection of practical applications to standard EMO algorithms, rather it will demonstrate how a number of practical aspects can be addressed by foundational modifications to standard EMO algorithms. In this tutorial, we present some the key efforts in specifically address the following practical problem solving tasks:

1. Extracting common knowledge in terms of variable relationships that arguably a part or the entire Pareto-optimal set possesses. Such nuggets of knowledge are valuable to users, as, in addition to a set of Pareto-

optimal solutions. They bring out key properties which make a solution Pareto-optimal. Different machine learning based methods for knowledge extraction from Pareto-optimal set will be presented.

2. The knowledge common to Pareto-optimal solutions need not always be interpretable or easy to comprehend in certain problems. If not interpretable, the extracted knowledge discussed in item 1, need not be useful to users. In this part of tutorial, we shall describe a recently proposed regularized EMO (RegEMO) procedure which finds a set of non-dominated solutions possessing user-specified bounded interpretable complexity close to the original Pareto-optimal set. The minimal sacrifice of Pareto-optimality for being boundedly interpretable makes the task worth in practical problem-solving tasks. A recently proposed bi-level EMO algorithm to find a "regularized front", rather than a Pareto set, will be presented with examples.
3. Most EMO and EMaO studies focus on finding a Pareto-optimal solution set which is well-distributed on the objective space. Clearly, the obtained set provides a good representation of the Pareto front, but for a decision-making point of view, decision-makers may be interested in visualizing the PO solutions on a different space, other than the objective space. In this part of the tutorial, we present six different identifier spaces for possible decision-making tasks and present three different types of EMO/EMaO algorithms for finding a well-distributed set of PO solutions directly on a suitable identifier space of interest to DMs, making the EMO task practical for decision-makers.
4. EMO or EMaO algorithms are stochastic. Hence, the obtained solutions are also likely to be imperfect with gaps and noise. Next, we shall discuss machine learning based Pareto learning methods to fill new PO solutions in gaps on EMO-obtained fronts, or check extremes for any new solutions which were missed in the EMO/EMaO run, or reduce noise in Pareto set computation. This will be followed with presentation of a recently proposed three-stage reliable EMaO algorithm which finds an exact and desired number of well-distributed Pareto solutions reliably.
5. Finally, a computationally efficient surrogate-assisted EMaO algorithm which uses a mixed-fidelity evaluated population of solutions for solving problems with heterogenous evaluation times of objectives and constraints will be presented. The determination of high-fidelity evaluations of a solution is achieved based on its time of objective and constraint evaluations, potential of staying non-dominated in the population, closeness to constraint boundaries, and its surrogate error. The ability to apply such efficient methods in blocked evaluation of objectives and constraints make the whole approach practically sound and useful.

Each of these practically useful extensions of the EMO and EMaO algorithms should provide EMO-2025 participants with directions and new ideas for further research and application and will definitely paint a picture of ways to broaden the scope of the EMO act for practical applications. The computational models developed for each of the above tasks will be demonstrated with results on test and practical problems.

Tutorial 3: Difficulties in Fair Performance Comparison of Evolutionary Multi-objective Optimization Algorithms

Speakers: Dr Lie Meng Pang and Prof. Hisao Ishibuchi, Southern University of Science and Technology, China.
Time: 4 March 2025, 13.00-14.10pm

Evolutionary multi-objective optimization (EMO) has been a very active research area in recent years. Almost every year, new EMO algorithms are proposed. When a new EMO algorithm is proposed, computational experiments are usually conducted in order to compare its performance with existing algorithms. Then, experimental results are summarized and reported as a number of tables together with statistical significance test results. Those results usually show higher performance of the new algorithm than existing algorithms. However, fair comparison of different EMO algorithms is not easy since the evaluated performance of each algorithm usually depends on experimental settings. This is also because solution sets instead of solutions are evaluated.

In this tutorial, we will explain and discuss various difficulties in fair performance comparison of EMO algorithms related to the following four issues: (i) the termination condition of each algorithm, (ii) the population size of each algorithm, (iii) performance indicators, (iv) test problems. For each issue, its strong effects on comparison results are clearly demonstrated. Our discussions on those difficulties are to encourage the future development of the EMO research field without excessively focusing on the proposal of overly-specialized new algorithms in a specific setting. This is because those algorithms are not likely to work well on various real-world tasks. Then, we will discuss the handling of each issue for fair comparison. We will also suggest some promising future research topics related to each issue.

Tutorial 4: Dynamic Multi-objective Optimization: Introduction, Challenges, Applications and Future Directions

Speaker: Dr Mardé Helbig, Griffith University, Australia.
Time: 4 March 2025, 14.10-15.20pm

Most optimization problems in real-life have more than one objective, with at least two objectives in conflict with one another and at least one objective/constraint that changes over time. These kinds of optimization problems are referred to as dynamic multi-objective optimization (DMOO) problems (DMOPs). Instead of re-starting the optimization process after a change in the environment has occurred, previous knowledge is used and if the changes are small enough, this may lead to new solutions being found much quicker.

Most research in multi-objective optimization has been conducted on static problems and most research on dynamic problems has been conducted on single-objective optimization. The goal of a single-objective dynamic optimization algorithm is to find the most optimal solution where only one optimal solution exists. However, due to the conflicting objectives of a DMOP, a single optimal solution does not exist. Therefore, the goal of a DMOO algorithm (DMOA) is to find a set of trade-off solutions that is as close as possible to the true set of optimal solutions and that contains a diverse set of solutions (similar to algorithms solving static MOO). However, in addition to these goals a DMOA must track the changing set of optimal solutions over time. Therefore, the DMOA also has to deal with the problems of a lack of diversity and outdated memory (similar to algorithms solving dynamic single-objective optimization).

This tutorial will introduce the participants to the field of DMOO by discussing:

- Differences between solving dynamic single-objective optimization problems, static multi-object optimization problems and dynamic multi-objective optimization problems, as well as the impact of these differences on the design of algorithms for these types of problems
- Main types of algorithms (both evolutionary and swarm intelligence) that have been proposed to solve DMOO, highlighting the difference between prediction-based and non-prediction-based algorithms
- Issues when comparing DMOAs' performance, ensuring a fair comparison and highlighting why traditional approaches used for static MOO are not necessarily adequate for DMOO
- Approaches to solve problems containing constraints (both static and dynamic) when the objectives are dynamic
- Incorporating a decision maker's preference in DMOAs and important aspects to consider when applying these algorithms to real-world problems
- Emerging research fields (such as many-objective optimization, bi-level optimization, and fitness landscape analysis) that provide interesting research opportunities in the field of DMOO

This tutorial aims to:

- Introduce participants to the field of DMOO
- Create an understanding of the challenges and opportunities in the field
- Entice both researchers and practitioners to contribute to the field

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Tutorial 5: Multi-objective Algorithm Design using Large Language Models

Speakers: Dr Fei Liu, Dr Zhichao Lu, Prof. Qingfu Zhang, City University of Hong Kong, China, and Dr Zhenkun Wang, Southern University of Science and Technology, China.
Time: 4 March 2025, 15.40-17.00pm

Algorithm design plays a pivotal role in computational optimization and decision-making. Traditionally, this process has been characterized by intensive trial-and-error methodologies, heavily reliant on deep domain expertise. The emergence and rapid advancement of Large Language Models (LLMs) over the past three years have revolutionized numerous fields, including algorithm design. The integration of LLMs into the algorithm design process, referred to as LLM for Algorithm Design (LLM4AD), has shown promising results in enhancing and automating complex algorithm design tasks.

Among existing LLM4AD works, Evolutionary Multi-objective Optimization (EMO) has gained much attention. This exploration has been carried out on two sides: 1) the use of LLMs to design EMO algorithms and 2) the application of LLMs within an EMO framework to develop algorithms that optimize multiple performance criteria.

This tutorial is designed to offer an introduction to the fundamentals, developments, and practical applications of LLM4AD, with a specific focus on multi-objective optimization. Attendees will gain insights into how LLMs can be leveraged to streamline and enhance the algorithm design process across various domains. The tutorial will be structured into three main sections, each designed to build upon the previous, ensuring a cohesive learning experience:

- **Introduction to LLM-based Algorithm Design**
  - Introduction to the capabilities and functionalities of LLMs in algorithm design.
  - Single-objective evolutionary optimization with LLMs for algorithm design.
  - Multi-objective evolutionary optimization with LLMs for algorithm design.
- **Applications and Case Studies**
  - Design of single- and multi-objective continuous optimization algorithms using LLMs.
  - Design of combinatorial optimization algorithms using LLMs, focusing on real-world applications such as routing and scheduling.
  - Design of reinforcement learning agents via LLMs, demonstrating adaptive strategies in dynamic environments.
- **Code Demonstrations and Hands-on Sessions**
  - An introduction to LLM4AD, a Python-based platform.
  - Code demonstrations hosted on Google Colab, providing participants with practical experience in implementing LLM4AD solutions.
  - Step-by-step guidance on applying LLM4AD to the discussed application cases, enabling attendees to explore the potential of LLMs in real time.

Tutorial 6: Interactive Multiobjective Optimization using DESDEO

Speakers: Dr Bhupinder Saini and Dr Giomara Larraga, University of Jyväskylä, Finland.
Time: 6 March 2025, 10.00-10.30am

Multi-objective optimization aims to identify the best trade-offs among conflicting objectives, resulting in a set of solutions known as the Pareto optimal set. However, simply finding this set may not be enough to solve a real-world problem. A decision-maker (DM), the problem owner who is an expert in the problem domain, is typically interested in finding their most preferred solution from this set based on their preferences. One way to find such solutions is through the use of so-called interactive methods which help the DM understand and solve the problem iteratively.

DESDEO is an open-source framework which provides implementations of many interactive methods from the EMO and MCDM domains. This tutorial will be divided into three parts. First, we will briefly introduce DESDEO and talk about its features and latest developments. Then, we will showcase the EMO side of DESDEO by solving a real-world data-driven multiobjective optimization problem. Through this, we will show how to use DESDEO programatically. Finally, we will showcase the MCDM side of DESDEO by taking the results from the previous step to solve the same problem interactively through a graphical user interface.
