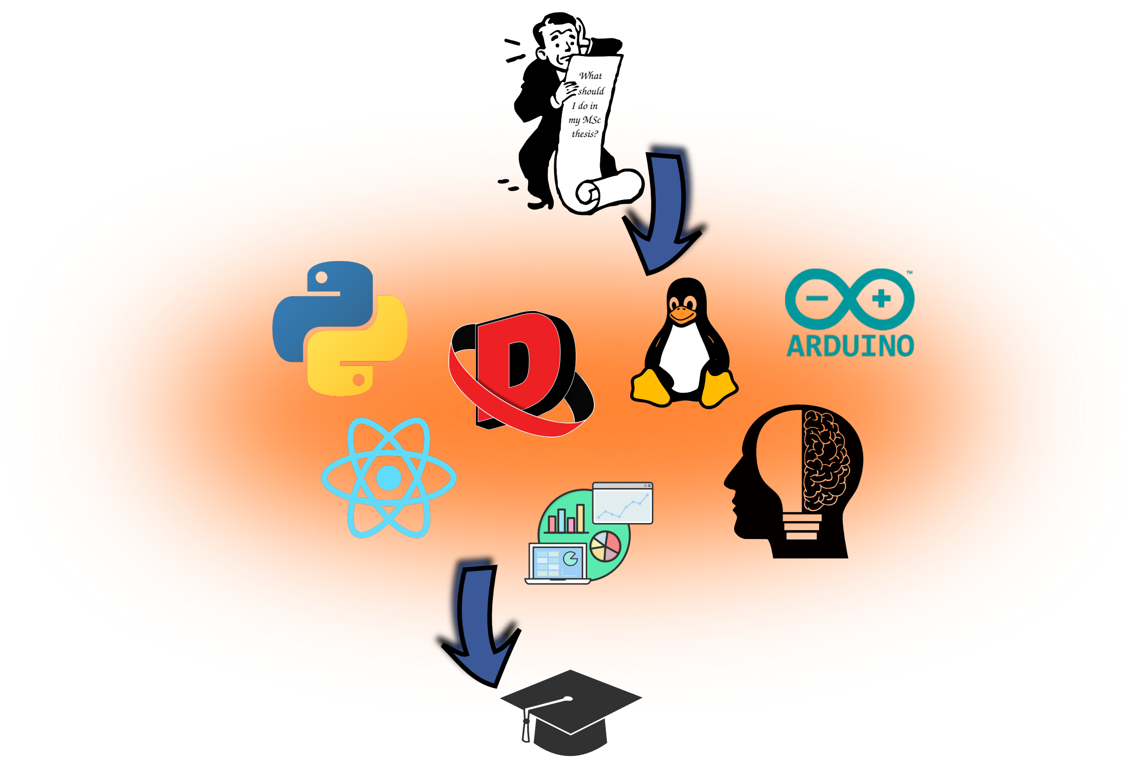
DEMO MSc topics

The DEMO profiling area (`jyu.fi/demo`)

Last updated: October 26, 2021



Contents

1 Contact information

Many decision-making problems arising from real-world applications can be expressed as multiobjecive optimization problems, where several, typically conflicting, perspectives need to be considered simultaneously. All these MSc thesis topics are related to supporting decision making with multiobjective optimization. Decision supporting skills are needed in practically all fields of life and, thus, preparing a MSc thesis of any of these topic increases your employability.

If you find any of the topics listed in this document interesting or want to know more, please contact one of the supervisors listed at the beginning of each topic. The emails of these members of the Multiobjective Optimization Group are in Table 1. Note that many of the topics have a lot of possibilities to tailor the topic, this list just gives ideas.

Name	Email
Atanu Mazumdar	`atanu.a.mazumdar at student.jyu.fi`
Babooshka Shavazipour	`babooshka.b.shavazipour at jyu.fi`
Bhupinder Singh Saini	`bhupinder.s.saini at jyu.fi`
Bekir Afsar	`bekir.b.afsar at jyu.fi`
Giovanni Misitano	`giovanni.a.misitano at jyu.fi`
Johanna Silvennoinen	`johanna.silvennoinen at jyu.fi`
Kaisa Miettinen	`kaisa.miettinen at jyu.fi`
Pouya Aghaei pour	`poaghaei at jyu.fi`

Table 1: Contact information of the supervisors.

2 Adaptive parameter control in computationally expensive multiobjective optimization evolutionary algorithms

Supervisors: Kaisa Miettinen and Pouya Aghaei Pour.

2.1 Introduction

The use of evolutionary algorithms to solve real-world optimization problems has been getting increasing attention. These problems are typically characterized by the following characteristics:

1. Several conflicting objectives have to be optimized simultaneously.
2. Function evaluations are computationally expensive, i.e., for each input we have to wait a considerable time to get the output.
3. Functions to be optimized are bound by some constraints.

To develop evolutionary algorithms for these problems, we need to use many different components. For example, using different machine learning predictive algorithms to reduce the computation time, algorithms for handling the constraints, algorithms to find the best balance between the conflicting objectives, and so on.

Each of these algorithms have several parameters that needs to be set priori to solving any problem. Setting these parameters based on each individual problem can be a very difficult task. Besides, sometimes we may not have enough information about the domains of the problem and we have to guess these parameters which may lead to unoptimal solutions.

In this thesis, you will learn about the existing algorithms and the effect of their parameters on their performance, and develop a way to adjust these parameters during the optimization process. For example, you can focus on developing an artificial intelligence unit that monitors the performance of the method and tunes the parameters accordingly. Obviously, in case the results are promising, there is an option to write a scientific paper and publish it. Also, you will have the option to be part of our software development team and implement your method in the DESDEO framework (desdeo.it.jyu.fi).

2.2 Required skills

Expertise in Python, basics of multiobjective optimization or willingness to learn, algorithmic thinking and familiarity with basic concepts of machine learning.

2.3 Learning outcomes

You will get first-person experience working in or with a research group. Your knowledge in artificial intelligence and algorithm development will increase significantly. You may also expect your master's thesis to be eligible to be extended into a conference or journal article.

3 Applying agents in the DESDEO framework: modeling decision maker's preferences with belief-desire-intention frameworks

Supervisors: Bekir Afsar and Giovanni Misitano

3.1 Introduction

Problems considered in multiobjective optimization consist of multiple conflicting objectives to be optimized simultaneously. Identifying a best solution to these kinds of problems mathematically is an ill-defined problem. Instead of mathematically finding the best solution, the expertise of a domain expert, known as a decision maker (DM), is employed. The DM can express one's preferences, which are then used to find the solution to the multiobjective optimization problem that best matches the preferences. A special class in multiobjective optimization methods is so-called interactive methods. These methods involve the DM in the optimization process, during which the preferences expressed by the DM are used to guide the optimization process in an iterative fashion to find the best compromise among the conflicting objectives.

Eliciting and modeling the preferences of a DM is a challenging task. Many methods exist to accomplish this. However, they often leave much to be desired. One interesting approach is to look at agents able to support the DM to express and model their preferences. Agents adhering to a belief-desire-intention architecture - a software model that can accommodate for qualitative knowledge - are a promising kind of agent that can address this issue.

The agents should be able to model a DM's preferences in such a way that they could be used to find solutions that satisfy the DM. The implemented agents will be made part of the DESDEO framework - the modular and open source Python framework for interactive multiobjective optimization (https://desdeo.it.jyu.fi). The agents can be implemented as standalone entities or be made part of some existing interactive methods by enhancing them.

This topic has a lot of potential for novel contributions in the multiobjective optimization field of research. This topic is ideal for someone who is interested in pursuing doctoral studies after graduating or is simply interested in a challenging MSc thesis topic.

3.2 Required skills

Prior experience in multiobjective optimization is desired. You should also be proficient in Python and Linux environments. Prior experience in agent systems is also beneficial, but not required.

3.3 Learning outcomes

You will get first-person experience working in a research group. Your knowledge in interactive multiobjective optimization will increase significantly, and you will have made significant contributions to open source software. This is a good opportunity to boost your GitHub profile, if desired. Moreover, you will be ready to pursue doctoral studies after your thesis. You may also expect your master's thesis to be eligible to be extended into a conference or journal article.

4 Cognitive biases in interactive multiobjective optimization

Supervisors: Johanna Silvennoinen and Giovanni Misitano

4.1 Introduction

Decision making with multiple conflicting objectives is a complex cognitive-affective process. Interactive multiobjective optimization methods are in a central role in aiding decision makers to solve complex problems. Research is required to understand what kind of cognitive biases occur and affect decision making processes and how interactive multiobjective optimization methods could be designed to inform decision makers of cognitive biases enabling making better decisions.

Overall, cognitive and affective processes in decision making with interactive methods in multiobjective optimization is a vast research area with many research topics. This includes, for example, examinations of what cognitive and affective biases are central within this decision making context and how to implement information of these in a manner that aids the decision makers. Multiobjective optimization with interactive methods is a unique research context for human-computer interaction, therefore other biases besides the most frequently mentioned in the judgment and decision making literature (e.g., anchoring and availability), can have an important role. Thus, research is required to understand context-specific biases for enabling better decisions.

In addition, efficient cognitive and affective de-biasing methods are important to be studied. These can include approaches, such as the role of metacognitive processes and possibilities of group decision making procedures towards debiased decision making, to name a few. Also, expert thinking in decision making as its own sub-discipline is essential to be examined within this interaction-context. All of the issues raised above can also be examined from expert thinking perspective.

All the research topics introduced above have a lot of potential for novel contributions in the multiobjective optimization field and within decision making research. These research topics are ideal for someone who is interested in pursuing doctoral studies after graduating but can also be conducted within a master's thesis (with a more narrowly scoped research topic).

4.2 Required skills

Prior knowledge of multiobjective optimization and cognitive science, especially regarding decision making is desired, but not mandatory for master's thesis. For doctoral studies, a master's degree from applicable research areas is required.

4.3 Learning outcomes

You will get experience in working in an interdisciplinary research group, combining multiobjective optimization and cognitive science. This kind of knowledge and expertise is essential for current and future human-centered technology development. If the master's thesis is completed within one of these research topics, this gives you excellent capabilities of pursuing doctoral studies. There is also a possibility to extend your master's thesis into a conference or journal article with moderately little effort, if you prosper in your thesis.

5 Data-driven multiobjective optimization in personalized medicine

Supervisors: Bekir Afsar and Babooshka Shavazipour.

5.1 Introduction

When a clinician selects an exercise therapy for a patient, (s)he must simultaneously consider several perspectives like reducing pain, improving physical function, reducing the number of supervised sessions, increasing adherence, keeping the cost reasonable, etc. Some of them are conflicting since improving physical function may need extra supervised sessions and increase cost, and the task is to find the best balance, i.e., the best compromise. However, there are no explicit guidelines or tools available to support clinicians. Therefore, decision support tools are needed to compare several compromises with different trade-offs and confidently choose the best-fitted exercise therapy considering the characteristics of individual patients.

Recently, in the Multiobjective Optimization Group, we have started developing data-driven interactive multiobjective optimization methodology, which is different from the conventional meta-analyses carried out in the clinical field of research, to find a straightforward way to choose a personalized best-fitted exercise therapy for each patient based on the available research data.

As a part of it, we need prediction models for our data-driven consideration to estimate the efficiency measurements of the selected trials based on several identified objectives. Unfortunately, most of the available trials include only a few tens of participants/samples, while state-of-the-art predictors (e.g., (deep) neural network and Gaussian regression) often need several hundred/thousand samples to provide predictions with reasonable accuracy. So, they cannot be simply applied in exercise therapy studies.

In this thesis, you will explore the existing literature on handling small datasets (with machine learning/statistical methods or both) and identify potential ways/methods to be used as prediction models in dealing with small datasets. Your thesis can also consist of testing various prediction models in a real case study to compare their performances. In this case, you may contribute to the literature that can lead to a scientific publication. This topic can also be extended to a Ph.D. thesis if you wish.

5.2 Required skills

Prior knowledge of artificial intelligence, statistics, and multiobjective optimization is desired. You should also be proficient in programming with Python/R or both.

5.3 Learning outcomes

You will get first-person experience working in or with a research group. Your knowledge in decision support in general and in data-driven interactive multiobjective optimization and sport-based applications will increase significantly. Moreover, you will be ready to pursue doctoral studies after your thesis if you like.

6 Design of a dynamic layout for an interface for some interactive method (in DESDEO)

Supervisors: Johanna Silvennoinen, Giovanni Misitano and Bhupinder Singh Saini.

6.1 Introduction

Multiobjective optimization considers problems with multiple conflicting objectives. Finding a best solution to these problems needs the involvement of a domain expert, known as a decision maker (DM), whose knowledge and preferences can be used to find preferred solution(s). An optimization process in multiobjective optimization typically consists of exploring a particular set of (compromise) solutions known as Pareto optimal solutions.

Based on how preferences are incorporated in the solution process, multiobjective optimization methods can be divided into three distinct categories: a priori, a posteriori, and interactive methods. As the name suggests, preferences are incorporated in the solution process before and after an optimization process has taken place in the first two kind of methods, respectively. But in interactive methods preferences, and correspondingly the DM, are incorporated during the optimization process. This has many advantages. For instance, interactive methods can focus on a particular subset of the Pareto optimal solutions that is interesting to the DM based on their preferences. This can not only save computational costs, but it also allows the DM to focus on solutions that best meet their current preferences.

Designing interfaces for interactive multiobjective optimization methods is a challenge. The data being visualized is often multidimensional (more than three dimensions) and the interface must support the DM in expressing their preferences in different ways. Moreover, different DMs may prefer the same data to be visualized in different ways, or they may prefer to express their preferences in varying ways as well. These needs make the design and implementation of interfaces for interactive methods challenging.

In this thesis, you will be working with the various components found in the DESDEO framework. DESDEO is an open source Python framework for interactive multiobjective optimization. Your focus will be in extending the existing web-based interface with a dynamic layout for some existing interactive method. You will be doing full-stack web development with a particular focus on the front-end.

6.2 Required skills

Prior experience in multiobjective optimization is useful, but not required. You should be proficient in Python, TypeScript and Linux environments. Particularly, you should have at least some prior experience in developing React apps. Knowledge of D3.js is also an advantage. The focus in this thesis is on the practical side.

6.3 Learning outcomes

You will get first-person experience working in a research group. Your knowledge in interactive multiobjective optimization will increase significantly. You will be making contributions to open source software, which can boost your GitHub profile to the next level. You will also gain considerable experience in web development.

7 Development of physical interfaces for interactive multiobjective optimization

Supervisors: Atanu Mazumdar, Johanna Silvennoinen, Bhupinder Singh Saini and Giovanni Misitano.

7.1 Introduction

Multiobjective optimization problems are problems with multiple conflicting objectives. Such problems have multiple Pareto optimal solutions that represent the different trade-offs among the various objectives. Hence, solving such problems also involves a decision-making component, where a domain expert, known as a decision maker (DM) chooses the necessary trade-offs to solve the problem. Interactive multiobjective optimization algorithms solve problems while actively involving the DM during the solution process, letting the DM guide the direction of search for better solutions. Consequently, user interface design can have a significant impact on the effectiveness of such algorithms.

In this thesis, you will work on the development of fully modular physical user interfaces for interactive multiobjective optimization algorithms. This work will be done as an extension to the DESDEO framework (desdeo.it.jyu.fi), which implements interactive algorithms and supports the use of physical interfaces (such as buttons and sliders) built using microcontrollers such as Arduinos. Additionally, you can integrate haptic feedback and braille script modules. Your work will include creating new ways of physically interfacing with interactive algorithms, creating custom hardware to try out and test these new interfaces, and implementing software connect the hardware to the algorithms. This is a novel field where you are expected to mix engineering and design mindsets. This can also include examinations of how humans represent tactual information and how this kind of knowledge can be incorporated into tactual design of components within physical user interfaces. Further investigation can be conducted with brain interface devices to understand the effect of using physical interfaces. You will be able to write a publication based on your work, if you wish.

7.2 Required skills

Knowledge of multiobjective optimization is useful but not required. You should be comfortable with Python and JavaScript/TypeScript programming (for working with the DESDEO framework). Experience in working with Arduinos (ATmega series, STM32, ESP32 etc.) and other electronic components, and hence C/C++ programming is also required. Prototyping circuits on breadboards, basic soldering skills and PCB designing will be helpful.

7.3 Learning outcomes

You will get experience in working with a research group on an open-source project under active development. You will learn about the current state-of-the-art in interactive multiobjective optimization. You will gain experience in creating custom hardware using microelectronics and learn about how to create good user interface designs.

8 Explainable artificial intelligence/machine learning in modeling data-driven multiobjective optimization problems

Supervisors: Bekir Afsar, Pouya Aghaei pour and Giovanni Misitano

8.1 Introduction

Multiobjective optimization considers problems with multiple conflicting objectives. To find a best solution to these problems, it is necessary to involve a domain expert, known as a decision maker (DM), whose knowledge and preferences can be used to find preferred solution(s). An optimization process in multiobjective optimization typically consists of exploring a particular set of compromise solutions known as Pareto optimal solutions.

In data-driven multiobjective optimization the problems considered are often based on some real-world data. Before any optimization process, the multiobjective optimization problem must be modeled. In other words, the objectives, constraints, and decision variables must be defined. Domain knowledge of the problem is therefore necessary, which is why the presence of the DM or some other domain expert is crucial during the modeling process.

Machine learning is often used in modeling the multiobjective optimization process due to the complexity of the data. Typically, the machine learning models used are black-box in nature, i.e., it is not clear to an outside observer how the model makes predictions. This can be a problem for example in the case objectives in a multiobjective optimization problem are modeled with black-boxes in a high-stakes domain, such as healtcare. The predictions made by the machine learning model must be justifiable and explainable, for example, to a patient.

Explainable artificial intelligence (XAI) is a research field that studies the prospect of explaining the predictions made by black-box machine learning models among other things. While machine learning has been utilized in multiobjective optimization before, the inclusion of XAI is still a novel concept. XAI could help make the predictions in data-driven multiobjective optimization less oblique, justifiable, and explainable.

In this thesis, you will explore the novel prospect of utilising XAI methods in data-driven multiobjective optimization. For example, your thesis could consist of a real-life case study where a data-driven multiobjective optimization problem is modeled using XAI. Being novel, this topic can lead to a scientific publication.

8.2 Required skills

Prior experience in multiobjective optimization is desired. You should also be proficient in Python and Linux environments. Prior experience in agent systems is also beneficial, but not required.

8.3 Learning outcomes

You will get first-person experience working in a research group. Your knowledge in multiobjective optimization will increase significantly. Moreover, you will be ready to pursue doctoral studies after this thesis. Lastly, you may also expect your master's thesis to be eligible to be extended into a conference or journal article, if you like.

9 Implementing utilities to support subject studies in the DESDEO interface

Supervisors: Johanna Silvennoinen, Giovanni Misitano, Bekir Afsar and Babooshka Shavazipour.

9.1 Introduction

Multiobjective optimization considers problems with multiple conflicting objectives. Finding a best solution to these problems needs the involvement of a domain expert, known as a decision maker (DM), whose knowledge and preferences can be used to find preferred solution(s) for multiobjective optimization problems. An optimization process in multiobjective optimization typically consists of exploring a particular set of compromise solutions known as Pareto optimal solutions.

Based on how preferences are incorporated in the solution process, multiobjective optimization methods can be divided into three distinct categories: a priori, a posteriori, and interactive methods. As the name suggests, preferences are incorporated in the solution process before and after an optimization process has taken place in the first two kinds of methods, respectively. But in interactive methods preferences, and correspondingly the DM, are incorporated during the optimization process. This has many advantages. For instance, interactive methods can focus on a particular subset of the Pareto optimal solutions that is interesting to the DM based on their preferences. This can not only save computational costs, but it also allows the DM to focus on solutions that best meet their current preferences.

A particular challenge is validating interactive methods. Since the usefulness of the method is highly dependent on the support it can offer the DM, validation must consider the subjective experiences of the DM. For example, user satisfaction, cognitive load, and biases are all concerns in these subjective experiences. Research is needed to develop validated measurements for these because existing validated measurements, for example of cognitive load are not applicable in measuring how cognitive load occurs in DMs utilizing interactive multiobjective methods in complex decision making processes. So far, the best way to collect such data has been utilizing varying questionnaires, but these have not been validated to ensure that these measure exactly the phenomenon under investigation. Recently, these questionnaires advanced with gamification can make the experience more attractive and enhance the motivation of the participants.

In this thesis, you will be expanding the DESDEO interface with practical utilities that support conducting subject studies to validate and evaluate interactive multiobjective optimization methods (DESDEO, desdeo.it.jyu.fi, is an open source Python framework for multiobjective optimization). Among implementing support to collect data via questionnaires, you will also have the opportunity to work on the automation of some aspects of the subject studies, such as the randomization of stimuli and design topic-relevant games for preference elicitations.

9.2 Required skills

Prior experience in multiobjective optimization is useful, but not required. Experience of method development in human sciences is needed. You should be proficient in Python, TypeScript, and Linux environments. Particularly, you should have at least some prior experience in developing React apps and Flask-based backends. The focus in this thesis is on the practical side.

9.3 Learning outcomes

You will get first-person experience working in a research group. Your knowledge in interactive multiobjective optimization will increase significantly. You will be making contributions to open source software, which can boost your GitHub profile to the next level. You will also gain considerable experience in web development. Lastly, you will gain experience in how subject studies are conducted, and how questionnaires are made. This can be a very relevant skill in HR and PR positions in the industry.

10 Implementation of interactive visualizations for decision support in scenario-based multiobjective optimization problems

Supervisor: Babooshka Shavazipour.

10.1 Introduction

Simultaneous optimization of multiple (conflicting) objectives is known as multiobjective optimization. Multiobjective optimization problems often have several Pareto optimal solutions with different trade-offs, instead of a single optimal solution. In these kinds of problems, the goal is to support decision-makers (DM) to compare the trade-offs between objectives and identify the most preferred solution. Besides multiple conflicting objectives, real-life problems are characterized by uncertainty. It is desirable to make robust decisions that are not too sensitive to the consequences of uncertainty, i.e., they perform well in a wide range of future states or events (scenarios).

In scenario-based multiobjective optimization problems, the performance of a decision should be evaluated regarding each objective in different scenarios, bringing an additional dimension to the performance evaluation and complicating the DM's task. Visualization supports are needed to help the DM understand and compare trade-offs between different objective functions and evaluate and analyze trade-offs between the performances of a solution in various scenarios (called trade-offs between scenarios). Recently, two visualization methods: a novel extension of empirical attainment functions for scenarios and an adapted version of heatmaps, have been proposed[1] to help a DM gain insight into realizations of trade-offs and comparisons between objective functions in different scenarios.

In this thesis, you will implement an interactive version of these visualizations in the DESDEO-components library and connect them to the DESDEO user interface (DESDEO, desdeo.it.jyu.fi, is an open-source Python framework for multiobjective optimization). Note that the static version of the codes is available in the R programming language. Your thesis can also consist of designing an experimental study (e.g., with some students) to test the utility of these visualizations compared to some others. In this case, you may contribute to the literature that can lead to a scientific publication.

10.2 Required skills

Prior knowledge of multiobjective optimization is desired. You should also be proficient in Python. Prior background in mathematics is also beneficial.

10.3 Learning outcomes

You will get first-person experience working in or with a research group. Your knowledge in decision support in general and in scenario-based multiobjective optimization will increase significantly, and you can make significant contributions to open source software development.

11 Investigating switching: how to support the decision maker in switching between interactive multiobjective optimization methods?

Supervisors: Kaisa Miettinen, Bekir Afsar, Johanna Silvennoinen, Pouya Aghaei pour and Bhupinder Singh Saini.

11.1 Introduction

Many decision-making problems arising from real-world applications can be expressed as multiobjecive optimization problems, where several, typically conflicting, perspectives need to be considered simultaneously. These problems have several so-called Pareto optimal solutions (or compromises) with different trade-offs and additional preference information from a decision maker (DM) is needed to find the best balance among the conflicting objectives. Multiobjective optimization methods differ from each other based on when preference information is incorporated in the solution process. In interactive methods, the DM provides preference information iteratively and directs the solution process to find the most preferred solution. Interactive methods allow the DM to learn about the

[1] Shavazipour B, López-Ibáñez M, Miettinen K. Visualizations for decision support in scenario-based multiobjective optimization. Information Sciences 578:1–21, 2021. Available at https://doi.org/10.1016/j.ins.2021.07.025

trade-offs between the conflicting objectives and the feasibility of the preference information. Interactive methods differ based on the types of preference information, ways of exchanging information between the method and the DM, solving mechanisms, and stopping conditions of the solution process.

We can divide the solution process into two phases: learning and decision phases. During the learning phase, the DM explores different solutions to identify a region of interest. In the decision phase, the DM finds the most preferred solution by fine-tuning the search in the region of interest. Some interactive methods support the DM better during the learning phase, whereas others are better at exploiting the region of interest.

Typically, only one interactive method is selected and applied in the solution process, and the type of preference information is specific to the method used. However, switching the method during the solution process can offer benefits. In this thesis, you will investigate approaches for switching interactive methods based on the DM's needs and preferred preference styles in different phases. In other words, you find ways to enable the DM to switch the method (and the type of preference information) during the solution process. You will implement the mechanism you proposed as a part of the DESDEO framework (desdeo.it.jyu.fi). The DESDEO framework is an open source Python framework for interactive multiobjective optimization developed in the Multiobjective Optimization research group.

11.2 Required skills

Prior experience in multiobjective optimization is desired. You should also be proficient in Python and Linux environments.

11.3 Learning outcomes

You will get first-person experience working in or with a research group. Your knowledge in decision support and interactive multiobjective optimization will increase significantly. You may also refine your findings as a conference or journal paper, if you like.

12 Navigation methods for multiobjective optimization: making a synthesis and implementing contents to DESDEO

Supervisors: Kaisa Miettinen and Giovanni Misitano.

12.1 Introduction

When making decisions, the decision maker must typically balance among multiple conflicting perspectives. Simultaneous optimization of multiple conflicting objectives is known as multiobjective optimization. These problems have so-called Pareto optimal solutions (or compromises) representing different trade-offs and to find the best solution, it is necessary to involve a domain expert, known as a decision maker (DM), whose knowledge and preferences can be used to find preferred solution(s).

Based on how preferences are incorporated in the solution process, multiobjective optimization methods can be divided into different categories. In interactive methods, the DM takes actively part in the solution process and preferences are incorporated during the optimization process. This has many advantages. For instance, interactive methods can focus on a particular subset of the Pareto optimal solutions that is interesting to the DM. This does not only save in computation costs, but also allows the DM to focus on solutions that best meet their current preferences.

A particular class of interactive multiobjective optimization methods is navigation methods. In these methods, the DM can see in real-time how preferences affect the solution process, what kind of solutions are available, and what kind of solutions could become available with different preferences. An example of a navigation method is NAUTILUS Navigator, which is show-cased in the following video: https://www.youtube.com/watch?v=gjvIG8PiPBo.

In this thesis, you will explore the existing literature in multiobjective optimization for navigation-based methods. Particularly, you will be making a synthesis of these methods. This sort of synthesis, if done well, can be readily made into an article leading to a scientific publication. You will also have the option to implement navigation-based method in the DESDEO framework (desdeo.it.jyu.fi). The DESDEO framework in an open source Python framework for interactive multiobjective optimization developed in the Multiobjective Optimization research group. Thus, you can have a more methodological or implementational focus.

12.2 Required skills

Prior experience in multiobjective optimization is desired. You should also be proficient in Python and Linux environments if you choose to also implement a navigation-based method in DESDEO.

12.3 Learning outcomes

You will get first-person experience working in or with a research group. Your knowledge in decision support and interactive multiobjective optimization will increase significantly. You may also expect your master's thesis to be eligible to be extended into a conference or journal article.

13 Quality indicators for interactive multiobjective optimization methods

Supervisors: Kaisa Miettinen, Bekir Afsar, Giovanni Misitano and Pouya Aghaei pour.

13.1 Introduction

When making decisions, the decision maker must typically consider several conflicting perspectives simultaneously and usually needs support. Such methods are called multiobjective optimization methods. They help the decision maker in finding the most preferred one among so-called Pareto optimal solutions (or compromises) representing different trade-offs. The decision maker can direct the solution process towards solutions reflecting one's needs with preference information. In so-called interactive methods, the DM is involved in the optimization process iteratively, gains insight into the phenomena in question and learns about the feasibility of one's preference and can adjust them.

Currently there are very few ways of comparing the performance of interactive methods. There are several research questions in this field that can be explored:

1. What are the important criteria for judging the performance of a method?
2. How to indicate if solutions are following the DM's preferences?
3. Different DMs may have different expertise and the type of preferences they provide may be different. How to use these different types of information to evaluate the performance of a method?

These research questions are very fundamentals and there is a lot of room to grow in this direction. In this thesis, you will learn about the existing interactive methods and different type of preferences. You will have the chance to develop approaches (e.g. an artificial decision maker) to compete different interactive methods to decide which one is better. Also, you will have the option to be part of our software development team and implement your ideas in the DESDEO framework (desdeo.it.jyu.fi). DESDEO is an open source Python framework for interactive multiobjective optimization developed in the Multiobjective Optimization research group.

13.2 Required skills

Expertise in Python, familiarity with multiobjective optimization or willingness to learn and algorithmic thinking.

13.3 Learning outcomes

You will get first-person experience working in or with a research group. Your knowledge in decision support and algorithm development will increase significantly. If you succeed in developing good indicators, you may also expect your master's thesis to be eligible to be extended into a conference or journal article.

14 Showcasing the modularity of DESDEO

Supervisors: Kaisa Miettinen and Giovanni Misitano.

14.1 Introduction

DESDEO is an open-source Python based software framework for developing and experimenting with interactive multiobjective optimization methods. One of DESDEO's strengths lies in its modularity. We claim that one can choose and match pieces from different interactive multiobjective optimization methods to combine them into a new method in DESDEO. However, a practical demonstration of this modularity is still absent.

By choosing this topic, you will be embarking on a journey during which you will learn about different interactive multiobjective optimization methods. You will delve into the practicalities of each method and will get a hands-on experience on solving multiobjective optimization problems based on real-life cases. You will also experience collaboration on an open-source project, which is a seldom taught but ever needed skill; both in industry and in the academic world.

In this thesis, we expect that you will combine pieces of existing multiobjective optimization methods creating new composite methods using DESDEO. These new methods should be tested on real-life problems and mutually compared. We expect a sound scientific analysis in the comparison of the methods. We also expect you to contribute to the DESDEO framework during your thesis work. These contributions should be related to combining existing methods, for example, contributions easing the combination process are more than welcome.

To our knowledge, this kind of "mix and matching" of interactive multiobjective optimization methods has not been studied much in the current literature. Therefore, you can also expect to be able to write a publication based on your master's thesis.

14.2 Required skills

Prior experience in multiobjective optimization is desired. You should also be proficient in Python and Linux environments.

14.3 Learning outcomes

You will get first-person experience working in or with a research group. Your knowledge in decision support and interactive multiobjective optimization will increase significantly. You may also expect your master's thesis to be eligible to be extended into a conference or journal article.

15 Supporting decision making with visualizations

Supervisors: Kaisa Miettinen, Johanna Silvennoinen, Giovanni Misitano and Bhupinder Singh Saini.

15.1 Introduction

Interactive multiobjective optimization methods are in a central role in aiding decision makers to solve complex problems. These methods are based on interactive visualizations as the concrete contact points between the decision support system and the human decision maker. Thus, in the core of this research area are interactive information visualizations. Visual information can be presented in numerous different ways. In-depth knowledge can be obtained in studying different visual elements of visualizations and the ways these are understood and how these can be designed in a way that supports decision makers. For example, knowledge of human visual information processing can be implemented as design solutions giving more predictability to the way decision makers cognise visualizations. For interactive visualizations to aid decision makers, it is highly important to examine how information is needed to be presented. This topic includes, at least, the following research topics: reviewing possible visualizations to be implemented, examinations of how different visualizations affect decision making processes and solutions, experiments on how different visualizations are cognised with different interactive multiobjective methods, how to enhance interactivity of visualizations and, how to incorporate decision maker's cognitive styles with different visualizations. Research is required to understand what kind of visualizations are efficient in this human-computer interaction context from varying perspectives.

In addition to the topics introduced above, much research is needed in developing research methods on how to study decision maker's understandings and experiences of utilizing interactive multiobjective optimization methods. These includes, for example, developing validated measurements within this research contexts for cognitive load, usability, understandability of visualizations, and for example, user satisfaction. These research topics have a lot of potential for novel contributions in the multiobjective optimization and information visualization fields. The presented research topics are ideal for someone who is interested in pursuing doctoral studies after graduating but can also be conducted within a master's thesis (with a more narrowly scoped topic). These topics can also be conducted as pair-wise master's theses, combining expertise from students of cognitive science and mathematical information technology.

15.2 Required skills

Prior knowledge of multiobjective optimization and cognitive science, especially regarding decision making, information visualization, and method development in human sciences are desired, but not mandatory for a master's thesis. For doctoral studies, a master's degree from applicable research areas is required.

15.3 Learning outcomes

You will get first-person experience working in or with an interdiscplinary research group combining multiobjective optimization and information visualization design from the perspective of cognitive science. This kind of knowledge and expertise is essential for current and future human-centered technology development. If a master's thesis is completed within one of these research topics, this gives excellent capabilities for pursuing doctoral studies. There is also a possibility to extend the master's thesis into a conference or journal article with moderately little effort, if you prosper in your thesis.

16 Ways to utilize PAINT (PAreto front INTerpolation): dealing with computationally expensive problems

Supervisors: Kaisa Miettinen, Babooshka Shavazipour and Giovanni Misitano.

16.1 Introduction

In many decision-making problems, the decision maker must find the best balance among multiple conflicting perspectives. Simultaneous optimization of multiple conflicting objectives is known as multiobjective optimization. Typically, multiobjective optimization problems have several Pareto optimal solutions with different trade-offs. In so-called interactive methods, the DM guides the solution process with one's preference information. The ultimate goal is to support a decision-maker (DM) in comparing the trade-offs among the objectives and identify the most preferred solution.

The PAINT (PAreto front INTerpolation) method[2] is aimed at solving computationally expensive multiobjective optimization problems, where function evaluations are time-consuming (e.g. based on simulations). PAINT formulates a computationally inexpensive surrogate problem to replace the original one so that the Pareto optimal solutions of the surrogate problem approximate those of the original one. In practice, the method interpolates between a given set of Pareto optimal solutions to derive a mixed integer linear surrogate problem which can be solved with any interactive method to yield a preferred solution for the original problem in a faster way.

[2]Hartikainen M, Miettinen K, Wiecek MM. PAINT: Pareto front interpolation for nonlinear multiobjective optimization. Comput Optim Appl. 2012;52:845–67.

In this thesis, you will explore the existing literature on approximation methods and the implementation of the PAINT method in the DESDEO framework (desdeo.it.jyu.fi) to connect PAINT to the functionalities of DESDEO. DESDEO is an open source Python framework for interactive multiobjective optimization developed in the Multiobjective Optimization research group. Your thesis can also consist of a real-life case study using PAINT to approximate the Pareto optimal solutions and solve the problem with an interactive method. In this case, you may contribute to the literature that can lead to a scientific publication.

Moreover, here is room for further extensions of PAINT or integration with other methods. This topic has potential to be extended as a PhD thesis.

16.2 Required skills

Prior knowledge of multiobjective optimization is desired. You should also be proficient in Python. Prior background in mathematics is also beneficial.

16.3 Learning outcomes

You will get first-person experience working in or with a research group. Your knowledge in decision support in general and in interactive multiobjective optimization and approximation methods for handling computationally expensive problems will increase significantly, and you can make significant contributions to open source software development.