Report from Dagstuhl Seminar 12041

Learning in Multiobjective Optimization

Edited by

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Abstract

This report documents the programme and outcomes of the Dagstuhl Seminar 12041 *Learning in Multiobjective Optimization*. The purpose of the seminar was to bring together researchers from the two main communities studying multiobjective optimization, Multiple Criteria Decision Making and Evolutionary Multiobjective Optimization, to take part in a wide-ranging discussion of what constitutes learning in multiobjective optimization, how it can be facilitated, and how it can be measured. The outcome was a deeper, more integrated understanding of the whole problem-solving process in multiobjective optimization from the viewpoint of learning, and several concrete research projects directly addressing different aspects of learning.

Seminar 23.–27. January, 2012 – www.dagstuhl.de/12041
1998 ACM Subject Classification G.1.6 Optimization, H.4.2 Types of Systems, I.2.6 Learning, I.2.8 Problem Solving, Control Methods, and Search, I.5.1 Models
Keywords and phrases multiple criteria decision making, evolutionary multiobjective optimization
Digital Object Identifier 10.4230/DagRep.2.1.50
Edited in cooperation with Richard Allmendinger

1 Executive Summary

Salvatore Greco
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Multiobjective optimization is the study of optimization under competing interests, goals or criteria; it concerns the search for *nondominated* solutions (or Pareto optima) that offer different trade-offs of the competing criteria, as well as methods for choosing among the alternative solutions by the consideration of *preferences*. Multiobjective optimization problems arise naturally in several areas: engineering, economics, operations research/management, and the natural sciences, and today a significant portion of research into optimization is concerned with these problems. The present seminar, the fourth in a series on Multiobjective Optimization (following 04461, 06501 and 09041) dating back to 2004, renewed its ambitions to unite researchers from the two main communities studying multiobjective optimization, MCDM (multiple criteria decision making) and EMO (evolutionary multiobjective optimization) to stimulate new research directions crossing these discipline boundaries.

As with earlier meetings in the series, we chose a strong theme for the seminar, which this time was *Learning*. In multiobjective optimization, learning has a key role to play because, uniquely to the multiobjective case, optimization involves both an exploration of trade-offs and a consideration of user (or decision maker) *preferences*, which are usually implicit in the mind(s) of decision maker(s) at the start of the solution process. Solving a problem therefore involves at least two simultaneous learning processes: the decision maker (DM) learning about the problem, and the optimization process itself learning about the DM's preferences (to achieve a steering of the search toward a preferred solution). Our aim in the seminar was to focus centrally on this learning aspect to give it, for the first time, due attention, as in previous seminars it arose rather peripherally to other themes.

The seminar took place January 22nd–27th 2012. The main goals of the seminar were to explore in depth three different aspects of learning in multiobjective optimization which may be briefly summarized as:

Focus 1: User preferences What should be learnt from user interactions and how should user preferences be captured?

Focus 2: Problem understanding What should be learnt about the problem structure and how can useful information for the DM be extracted?

Focus 3: The problem solving process How do we know if a decision maker has learned? How does a decision maker learn? What factors influence how and what a decision maker learns?

Participants were given some written materials [1, 2] prior to the seminar to orient them to these different aspects and to help them prepare relevant contributions to the seminar programme.

During the seminar, the programme was updated on a daily basis to maintain flexibility and, through this system, we were able to give adequate time both to prepared material and to evolving discussions, mostly taking place in working groups. In particular, breakout working groups were organized initially by lottery (to be purposely disruptive of existing groupings) and then by forming subtopics that individuals could sign up to for the remainder of the week. Six groups emerged in this way. (In the appendix, the complete list of topics suggested can be seen).

The prepared part of the programme included four invited talks of forty-five minutes each and sixteen contributed talks of twenty minutes each. These were spaced to allow time for discussion, and the evenings were kept free to allow further reflection and relaxation. The full programme can be found in Section 5, and the abstracts of all talks are given in the sequel to this summary.

Other notable events during the week included: (i) an interactive demonstration given by Pekka Korhonen on rationality in decision making, which reminded us all of the limits of human (including our own "expert") rationality in the face of complex data; (ii) a presentation session to allow us to share details of upcoming events in our research community; and (iii), rather less formally, a wine and cheese party was offered by Dagstuhl in the name of ESTECO to express appreciation to ESTECO for giving a donation to the Dagstuhl Foundation.

Outcomes

The outcomes of each of the working groups can be seen in the sequel, but a number of key findings are worth brief mention:

DM Sense working group outlined the design for a system that could aid decision-makers rationalize their learning and decisions *in natural language* by pulling together both recent and older research in artificial intelligence and decision making systems.

Pareto Sense working group established a critical agenda of research to undertake in learning and knowledge representation of the combined spaces of Pareto sets and fronts.

Quantifying Learning working group formalized a method for quantifying the learning associated with decision makers steering a search process, and compared this with the algorithmic learning that occurs in some key model-learning MCDM methods.

Navigation working group developed a detailed understanding of search and decision making approaches to identify the most-preferred solution among the Pareto-set (termed "Navigation"), using this to categorize current methods, and identify applications.

Representation working group considered learning in multiobjective optimization from a machine perspective, proposing that learning could be viewed as the process of obtaining parsimonious representations that enable efficient query-answering in support of (particular) search algorithms or decision processes.

Algorithm Design Methods working group considered formally how algorithms for search and decision making should be selected based on information about the decision maker, as well as the problem, and were able to produce first bounds on the number of function evaluations and queries to a decision maker needed to solve a problem.

These findings were reported to the main group during the seminar, and led to lively debate. Further work within the groups (by email correspondence) following the end of the seminar is planned, including several proposals for joint conference and journal papers.

At the wrap-up session of the seminar, we invited written comments from all the participants concerning how the seminar may be improved, what should be maintained, and inviting topics for future seminars. Comments included 'working groups were a great opportunity to discuss [...] common features from different perspectives', 'Not too many talks — very good; staying in focus — very good; atmosphere — very good', 'atmosphere ... is very fruitful, encouraging', and 'maintain: the diversity of the experts / participants; good balance between presentations and group discussions, like this time'.

In summary, the seminar made for a very productive and enjoyable week. It has revealed a number of research problems that need careful consideration and detailed further study. It has allowed us to begin this work in earnest, and make some significant first steps.

Acknowledgments

Many thanks to the Dagstuhl office and its helpful and patient staff; huge thanks to the organizers of the previous seminars in the series for setting us up for success; and thanks to all the participants, who worked hard and were amiable company all week.

In the appendix, we also give special thanks to Kaisa Miettinen and Eckart Zitzler as they step down from the organizer role.

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3 Overview of Talks

3.1 Interactive Multiobjective Optimization From a Learning Perspective

Jürgen Branke (University of Warwick, GB) and Roman Słowiński (Poznan University of Technology, PL)

Joint work of Belton, Valerie; Branke, Jürgen; Eskelinen, Petri; Greco, Salvatore; Molino, Julian; Ruiz, Francisco; Słowiński, Roman
Main reference V. Belton, J. Branke, P. Eskelinen, S. Grecco, J. Molina, F. Ruiz, R. Słowiński, "Interactive Multiobjective Optimization from a Learning Perspective," Chapter 15 in *Branke, Deb, Miettinen, Słowiński*, (Eds.): Multiobjective Optimization: Interactive and Evolutionary Approaches. LNCS 5252, Springer, Berlin, 2008.
URL http://dx.doi.org/10.1007/978-3-540-88908-3

Learning is inherently connected with Interactive Multiobjective Optimization (IMO), therefore, a systematic analysis of IMO from the learning perspective is worthwhile. After an introduction to the nature and the interest of learning within IMO, we consider two complementary aspects of learning: individual learning, i.e., what the decision maker can learn, and model or machine learning, i.e., what the formal model can learn in the course of an IMO procedure. Finally, we discuss how one might investigate learning experimentally, in order to understand how to better support decision makers.

Experiments involving a human decision maker or a virtual decision maker are considered.

3.2 A General Framework for Integrating User Preferences With Evolutionary Multiobjective Optimization: Towards Making the Weighted Hypervolume Approach User-Friendly

Dimo Brockhoff (INRIA Nord Europe – Lille, FR)

Joint work of Auger, Anne; Bader, Johannes; Brockhoff, Dimo; Kaci, Souhila; Hamadi, Youssef; Thiele, Lothar; Zitzler, Eckart

Hypervolume-based selection is nowadays considered a standard technique in multiobjective evolutionary algorithms (MOEAs). In 2007, a generalization of the standard hypervolume indicator to the so-called weighted hypervolume indicator has been proposed and it has been showed how this new indicator can be used in the selection of MOEAs to steer the search towards solutions preferred by the user. In the meantime, several studies both about improving the approach's efficiency for many-objective optimization problems and about understanding its theoretical foundations have been published.

Since its beginnings, the weighted hypervolume indicator approach has been criticized as the definition of the indicator's weight functions might not be intuitive to the user—in particular not if more than two objectives are to be optimized. Two recent studies deal with this criticism and in my talk I presented the main ideas behind both of them. The first study presents a general weight function toolkit with which the user is not only able to define complex weight functions from simple, easy-to-understand and efficient-to-compute basis functions but also to simulate several classical user preference approaches such as weighted Tchebycheff or desirability functions within the same algorithmic framework. The second study aims at interactively changing the weight functions and presents a novel way how a weight function can be extracted from the user's input.

More specifically, in the last study, we allow the user to formalize her preferences by explicit preference statements and corresponding semantics which are then automatically translated into a partial order on the current solutions and further transformed into a weight function for the indicator. As this approach contains the intermediate step of visualizing the user's abstract preference statements and the formal, but difficult to interpret semantics as partial orders in an interactive way, it can help the user to learn how to express intrinsic informal preferences in terms of formal preference statements.

3.3 Innovization: Learning Problem Knowledge Through Multi-Objective Optmization

Kalyanmoy Deb (Indian Inst. of Technology – Kanpur, IN)

In optimization studies, often researchers are interested in finding one or more optimal or near-optimal solutions. In this talk, I describe a systematic optimization-cum-analysis procedure which performs a task beyond simply finding optimal solutions, but first finds a set of near-Pareto-optimal solutions and then analyses them to unveil salient knowledge about properties which make a solution optimal. The proposed 'innovization' task is explained and its working procedure is illustrated on a number of engineering design tasks. The variety of problems chosen and the resulting innovations obtained for each problem amply demonstrate the usefulness of the proposed innovization task. The procedure is a by-product of performing a routine multiobjective optimization for a design task and in our opinion portrays an important process of knowledge discovery which may not be possible to achieve by other means.

3.4 Risk and return in multiobjective optimization

Carlos M. Fonseca (University of Coimbra, PT)

Joint work of Fonseca, Carlos M.; Yevseyeva, Iryna; Emmerich, Michael T. M.

The task of selecting a diverse subset of (non-dominated) solutions from a larger set of candidate solutions according to Decision Maker preference information in evolutionary algorithms is reinterpreted as a (financial) portfolio selection problem. Fitness assignment may then be performed by finding an optimal, risk-adjusted portfolio of candidate solutions, e.g., based on the Sharpe-ratio performance index, which amounts to solving a convex quadratic programming problem in the simplest case.

One particular instance of this general paradigm combines Fonseca and Fleming's preferability relation with the hypervolume indicator in order to arrive at a goal-driven, diversity-promoting, combined fitness-assignment and bounded-archiving procedure for evolutionary multiobjective optimization (EMO) algorithms. Experimental results show that the resulting optimizer is highly competitive with NSGA II and SMS-EMOA on a number of multiobjective knapsack problem instances, and motivate further research on the connection between risk modelling and diversity promotion in EMO.

3.5 Cynefin: Learning, Problem Formulation and MCDA

Simon French (University of Warwick, GB)

Main reference S. French. Cynefin, Statistics and Decision Analysis. Journal of the Operational Research Society, 2012 (In Press).

David Snowden's Cynefin framework, introduced to articulate discussions of sense-making, knowledge management and organisational learning, also has much to offer discussion of problem and issue formulation, value elicitation and learning. In the seminar, I explored its value in helping recognise different problem contexts and which analytic and modelling methodologies are most likely to offer appropriate support. What approaches to optimisation might be relevant? How might this affect our approach to eliciting or capturing decision maker's values?

3.6 A Comparison of Hypervolume- and Approximation-Guided MOEAs

Tobias Friedrich (MPI für Informatik – Saarbrücken, DE)

Joint work of Bringmann, Karl; Friedrich, Tobias; Neumann, Frank; Wagner, Markus
Main reference K. Bringmann, T. Friedrich, F. Neumann, M. Wagner, "Approximation-Guided Evolutionary Multi-Objective Optimization," in Proc. of the 22nd Int'l Joint Conf. on Artificial Intelligence (IJCAI 2011), pp. 1198–1203, 2011.
URL http://www.mpi-inf.mpg.de/~tfried/paper/2011IJCAI_AGE.pdf

We propose to measure the quality of a set of solutions of a multi-objective problem by its approximation factor. The theoretical analysis of the approximation factor of single-objective problems is well established and extends nicely to many objectives problems. In the first part of the talk we use this concept to analyze the quality achieved by sets maximizing the hypervolume indicator [1, 2, 3]. In the second part of the talk we present a new MOEA which is directly guided by the approximation factor and has a runtime which scales linearly in the dimension [4].

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3.7 Adapting MOEAs to solve practical complex engineering problems

Antonio Gaspar-Cunha (University of Minho – Guimarães, PT)

Joint work of Gaspar-Cunha, Antonio; Ferreira, Jose; Fonseca, Carlos; Covas, Jose
Main reference A. Gaspar-Cunha, J.A. Covas, Eds., "Optimization in Polymer Processing," 1st ed., Nova Science Publishers, 2011.
URL https://www.novapublishers.com/catalog/product_info.php?products_id=20015

In general, real engineering design problems are complex and multidisciplinary and thus difficult to solve adequately within reasonable timings. The scientific and technological advances in some fields (e.g., computational fluid dynamics, heat transfer, structural mechanics), together with the availability of highly performing computing techniques (e.g., parallel and/or grid computing) and facilities, provide the possibility of considering more problem aspects, thus generating improved solutions. However, since significant computational resources must be available, their efficient use must be guaranteed.

Multidisciplinary Design Optimization (MDO) can be defined as a methodology to design complex integrated engineering structures, which combines different disciplines and takes into account in a synergistic manner the interaction between the various subsystems. Examples of its practical application include aircrafts, cars, building structures and manufacturing systems.

A practical way to deal with engineering problems consists of using Multi- Objective Evolutionary Algorithms (MOEA), since at a certain point of the design process it will be necessary to provide information regarding the relative importance of every problem objective, i.e., the preferences of a Decision Maker (DM) must be considered. Furthermore, the solutions must also be robust, i.e., the performance of the prospective optimal solution(s) should be only slightly affected by perturbations of the design variables, or of environmental parameters. Two additional issues concerning the application of MOEAs to complex engineering problems are: i) the large number of objective functions evaluations that are necessary to attain an acceptable solution and ii) the high number of objectives to be taken in simultaneously. The former can be dealt with through the hybridization of MOEAs with local search procedures, while the latter involves the application of techniques to reduce the number of objectives.

The aim of this work is to present and discuss approaches to solve complex problems by employing tools that are able to simultaneously deal with multiple objectives, decision making and robustness of the solutions, among others, with a view to demonstrating that multi-objective engineering problems can be solved efficiently through the combination of optimization methodologies with engineering and design tools.

Two examples, from the fields of polymer engineering and aesthetic design, will be used to illustrate the methodologies proposed above.

3.8 Optimization in Logistics from a Learning Perspective: The Case of the Multi-Objective Vehicle Routing Problem

Martin Josef Geiger (Helmut-Schmidt-Universität – Hamburg, DE)

Joint work of Geiger, Martin Josef; Wenger, Wolf
Main reference W. Wenger, M.J. Geiger, "Hybrid Interactive Planning Under Many Objectives: An Application to the Vehicle Routing Problem," in Proc. of the 8th Int'l. Conf. on Hybrid Intelligent Systems (HIS'08), Sept. 10–12, 2008, Barcelona, Spain, pp. 302-307, ISBN 978-0-7695-3326-1.
URL http://dx.doi.org/10.1109/HIS.2008.91

Many logistical problems are characterized by numerous, often conflicting objectives. In combination with the underlying, often NP-hard optimization problems, this leads to a combination of search (for efficient outcomes) and decision making, i.e. choice of a most-preferred alternative.

Interactive systems supporting such a process should possess at least two characteristics. On the one hand, an adaptivity must be present, so that the presented results change w. r. t. evolving preference statements. On the other hand, the results should be of high quality, i.e. Pareto-optimal (or close to the efficient outcomes) [1].

In the talk, we consider the case of the multi-objective vehicle routing problem, for which an interactive optimization and decision making system has been developed [2, 3]. On the basis of benchmark data taken from the literature, the adaptivity of the system is investigated for different types of decision makers, i.e. decision makers with different preferences for the considered objectives.

In the interactive, alternating process of optimization and choice of a most-preferred solution, learning takes place both from the point of view of the optimization system (algorithm) and the decision maker. For the algorithm, 'learning' is a simple, adaptive process, improving the current solution in a direction given by the decision maker. For the decision maker, the 'learning' has two components.

First, preferred characteristics of the most-preferred solution have to be detected. Second, disadvantageous properties should be learned, that have to be avoided in the final solution. Both together describe a process of preference building, in which the expert is presented a series of alternatives. A convergence can be detected once the decision maker does not alter his/her preference statements any more, and thus does not seek for alternatives in another direction of the outcome space.

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3.9 Learning-Oriented Method Pareto Navigator for Interactive Nonlinear Multiobjective Optimization

Jussi Hakanen (University of Jyväskylä, FI)

Joint work of Eskelinen, Petri; Miettinen, Kaisa; Klamroth, Kathrin; Hakanen, Jussi
Main reference P. Eskelinen, K. Miettinen, K. Klamroth, J. Hakanen, "Pareto Navigator for Interactive Nonlinear Multiobjective Optimization," OR Spectrum, pp. 211–227, 32, 2010.
URL http://dx.doi.org/10.1007/s00291-008-0151-6

We describe a new interactive learning-oriented method called Pareto navigator for convex multiobjective optimization. In the method, first a polyhedral approximation of the Pareto optimal set is formed in the objective function space using a relatively small set of Pareto optimal solutions representing the Pareto optimal set. Then the decision maker can navigate around the polyhedral approximation and direct the search for promising regions where the most preferred solution could be located. In this way, the decision maker can learn about the interdependencies between the conflicting objectives and possibly adjust one's preferences. Once an interesting region has been identified, the polyhedral approximation can be made more accurate in that region or the decision maker can ask for the closest counterpart in the actual Pareto optimal set. If desired, (s)he can continue with another interactive method from the solution obtained. Pareto navigator can be seen as a nonlinear extension of the linear Pareto race method. After the representative set of Pareto optimal solutions has been generated, Pareto navigator is computationally efficient because the computations are performed in the polyhedral approximation and for that reason function evaluations of the actual objective functions are not needed. Thus, the method is well suited especially for problems with computationally costly functions. Furthermore, thanks to the visualization technique used, the method is applicable also for problems with three or more objective functions, and in fact it is best suited for such problems. After introducing the method, we demonstrate how it works with an implementation which has been created as a part of the IND-NIMBUS multiobjective optimization framework.

3.10 Extreme ranking analysis and rank related requirements in multiple objective optimization

Milosz Kadzinski (Poznan University of Technology, PL)

We present a new interactive procedure for multiple objective optimization. The procedure is composed of two alternating stages. In the first stage, a representative sample of solutions from the Pareto optimal set is generated. In the second stage, the Decision Maker (DM) is asked to provide preference information concerning some solutions from the generated sample. In particular, (s)he may refer to the holistic judgments concerning these solutions such as, e.g., pairwise comparisons or desired ranks. As far as the latter option is concerned, real-life experience indicates that people willingly refer to the range of allowed ranks that a particular solution should attain (e.g., a should take place on the podium, b should be ranked in the upper/lower half, c should be among the 10% of best/worst solutions). Referring to the rank- related requirements, the DM rates a given solution individually, at the same time collating it with all the remaining solutions jointly. This preference information is used to build a preference model composed of all general additive value functions compatible with the obtained information. The set of compatible value functions is then applied on the whole Pareto optimal set. The recommendation which can be obtained for any compatible value function can vary substantially. An interesting way to examine this diversity is to determine the best and the worst rank that each solution can attain. In this way, we are able to assess its performance relative to all the solutions considered simultaneously, and not only in terms of pairwise comparisons, as it is the case in the original multiple objective optimization methods based on the principle of robust ordinal regression, such as GRIP. These extreme results are used to select a new sample of solutions, which is presented to the DM, and the procedure cycles until a satisfactory solution is selected from the sample or the DM comes to conclusion that there is no satisfactory solution for the current problem setting.

3.11 Can a Linear Value Function Explain Choices? An Experimental Study

Pekka Korhonen (Aalto University, FI)

We investigate in a simple bi-criteria experimental study, whether subjects are consistent with a linear value function while making binary choices.

Many inconsistencies appeared in our experiment. However, the impact of inconsistencies on the linearity vs. non-linearity of the value function was minor. Moreover, a linear value function seems to predict choices for bi- criteria problems quite well. This ability to predict is independent of whether the value function is diagnosed linear or not. Inconsistencies in responses did not necessarily change the original diagnosis of the form of the value function. Our findings have implications for the design and development of decision support tools for Multiple Criteria Decision Making problems.

3.12 Offline Automatic Configuration in Multi-Objective Optimization

Manuel Lopez-Ibanez (Université Libre de Bruxelles, BE)

Joint work of López-Ibánez, Manuel; Stutzle, Thomas

Most of the current literature on machine learning in multi-objective optimization concerns the problem of learning while solving a particular problem instance, that is, *online learning* for the purposes of learning the decision maker's preferences [1], adapting the parameters of an algorithm [2] or approximating the landscape for expensive multi-objective optimization problems [3]. Few works in multi-objective optimization deal with *offline learning*, that is, learning during a training phase and repeatedly using what has been learned in a secondary production (or testing) phase.

One of the most prominent applications of offline learning in single-objective optimization is offline tuning [4], and more generally, automatic configuration [5] and programming by optimization [6]. The key idea behind automatic configuration is to automatically learn from examples the best design choices to build a fully-specified optimization algorithm tailored for a particular user context. An example could be to tune the parameters of a general-purpose solver, such as an evolutionary algorithm, to solve instances of a particular family of optimization problems, such as the traveling salesman problem. In single-objective optimization, this approach has led to notable successes. One notable example is the application of an automatic configuration tool to a framework of SAT solvers that won several prizes in the International SAT competition [7].

Existing automatic configuration tools may be used for multi-objective optimization algorithms by means of unary quality measures, such as the hypervolume [8]. Using this approach, Wessing et al. [9] have presented results for configuring the variation operator of a multi-objective evolutionary algorithm to a continuous function, and López-Ibáñez & Stützle [10, 11] automatically configured a flexible multi-objective ant colony optimization framework for tackling the bi-objective traveling salesman problem.

Despite these initial successes, it is currently an open research question how to effectively carry out offline automatic configuration in a multi-objective context without relying on unary quality measures. In order to achieve this goal, several challenging issues must be tackled, which are closely related to the question of how to design meaningful experiments in order to investigate learning [12].

The first challenge is how to assess the relative performance of multi-objective optimizers in an automatic fashion, not on an individual application, but over a series of training instances/examples. This is straightforward if the preference information available is enough to reduce the multi-objective problem to a single utility value, since then classical techniques from experimental design and statistical inference are applicable [13]. However, such preference information may not be always available, and although there are some initial results on extending statistical inference methodologies to the multi-objective context [14], there are no methods equivalent to those used in automatic configuration tools.

The various preference models pose an additional challenge. If preferences are defined a priori, and are common to all training examples, then it becomes possible to tune the optimization method for that particular preference model. However, one can easily imagine that each training example may have its own preference model, or even that the goal may be to choose the preference model itself, e.g., each training instance involving a different, possibly virtual, decision maker (DM). The challenge here is how to evaluate and compare different preference models.

Lastly, how to include the role of the DM in an offline learning procedure is far from clear. Perhaps the most straightforward strategy is to reuse the knowledge available about interactive approaches, making the offline configuration process a semi-automatic approach where a DM is asked about her preferences w.r.t. the quality of alternative algorithmic configurations. The automatic configuration tool may implicitly build a model of the DM preferences and use it to guide the automatic configuration process. However, the preference elicitation process will likely be more complex than in classical interactive approaches, since the DM will be asked to decide over a number of training examples. Moreover, there is the issue of how to define training examples of decision-making that correlate to the expected behavior of the, possibly multiple, DMs that will use the final system in the production phase.

The field of multi-objective optimization has advanced to the point that there are many high-quality approaches to solve problems. The choice of the most appropriate approach depends greatly on the user's context. However, users do not have the knowledge and expertise to make informed choices in order to choose and adapt existing approaches to solve their own problem. What they often have is examples of the kind of problems they want to solve. The ideal automatic configuration method for multi-objective optimization problem will not only be able to automatically design an algorithm given the user context, but also to choose the most appropriate preference model.

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3.13 User preferences in EMO: What can be learned from preference elicitation?

Vincent Mousseau (Ecole Centrale – Paris, FR)

An important perspective in EMO concerns the optimization process that interacts with the user and tries to infer formal information to guide the search and adapt the model. The key questions here are "What can and should be learnt from user interactions? how can user preferences be inferred? how can such user preference model guide the search?" The field of multiple criteria preference elicitation has developped a variety of concepts and procedures to capture DMs preferences from hollistic preferences. The proposed elicitation techniques propose interaction protocols and algorithms to infer a formal preference model from assertions made by DMs.

In this presentation, we will show on two examples, how preference elicitation ideas can be integrated into evolutionary multiobjective optimization algorithms so as to focus the computation of solutions judged as good by the DM. The first example involves a utility based preference model while the second represents preferences using a binary (outranking) relation.

3.14 Simulation-Based Innovization using Data Mining and Visual Analytics for Production Systems Analysis

Amos H. C. Ng (University of Skövde, SE)

Joint work of Ng, Amos H. C.; Dudas, Catarina; Deb, Kalyanmoy
Main reference A.H.C. Ng, C. Dudas, K. Deb, "Simulation-Based Innovization using Data Mining for Production Systems Analysis," in *L. Wang, A. Ng, K. Deb*, (eds.): Evolutionary Multi-objective Optimization in Product Design and Manufacturing, Springer, pp. 401–430, 2011.
URL http://dx.doi.org/10.1007/978-0-85729-652-8_15

The aim of this talk is to introduce a novel methodology for the optimization, analysis and decision support in production systems development. The methodology is based on the innovization procedure, originally introduced for unveiling new and innovative design principles in engineering design problems. Although the innovization method is based on multi-objective optimization and post-optimality analyses of optimized solutions, it stretches the scope beyond an optimization task and attempts to discover new design/operational rules/principles relating to decision variables and objectives, so that a deeper understanding of the design problem can be obtained (i.e. problem understanding). By integrating the concept of innovization with discrete-event simulation and data mining techniques, a new set of powerful tools can be developed for general systems analysis, particularly suitable for production systems development. The uniqueness of the integrated approach introduced in this talk lies on applying data mining and visual analytics to the data sets generated from simulation-based multi-objective optimization, in order to automatically or semi-automatically discover and interpret the hidden relationships and patterns for optimal production systems design/reconfiguration and then present to the decision maker in an interactive manner. After describing such a simulation-based innovization (SBI) using data mining procedure and its difference from conventional simulation analysis methods, results from several industrial-based case studies for production systems design and/or improvement will be presented. As illustrated with the experience learnt from the decision making process in these industrial case studies, the talk will convince that SBI not only helping production managers/engineers to explore optimal design and decision variable settings, but also gaining better knowledge and insight about production systems development in general.

3.15 Problem Understanding with Data Mining of Pareto-Optimal Designs in Space Engineering

Akira Oyama (JAXA – Sagamihara, JP)

Multiobjective design exploration (MODE) is a framework that can obtain useful knowledge for design optimization problems. MODE finds Pareto-optimal solutions with a multiobjective design optimization method and then extracts useful knowledge to understand the problem from the solution database with data mining approachs. In this presentation, how MODE are used to understand real-world design problems that Japan Aerospace Exploration Agency actually have is presented.

3.16 Problem solving process in engineering applications: multiobjective optimization and user preferences

Silvia Poles (EnginSoft S.p.A. – Padova, IT)

Designing real products is an enormous task that requires a multiobjective and multidisciplinary perspective involving many decision makers and departments.

At later stages of the design phase, engineers are force to respect predefined characteristics. Conversely, it is exactly in the early phase that designers can look for product innovation making decisions that can have a great influence in the final design.

What is necessary during the entire phase is a common framework in which decision makers can interact, run multiobjective optimizations, construct models, extract values and plot meaningful charts for exploring the cross influences of the design, discovering pattern and similarities between different configurations.

The most important part is the feedback/learning phase in which engineers can gain knowledge of the problem at hand. By clicking on charts it is possible to filter solutions or to run the optimizer to explore more deeply a specific area of the Pareto front. In this way, engineers are not just waiting for optimization solutions, they are part of the optimization process, they are learning on the job.

3.17 Modelling bipolar interactions in robust ordinal regression: the UTAGSS method

Johannes Siebert (Universität Bayreuth, DE)

We present in analogy to Figueira et al. [1] an interactive method for multiobjective optimization, which is based on the use of a set of value functions as a preference model built by an ordinal regression method. Initially we generate a sample of solutions from the Pareto optimal set (or from its approximation). Subsequently the DM has to provide additional preference information in terms of holistic pairwise comparisons of some solutions from the generated sample. Based on this information we build a preference model composed of all general additive value functions compatible with the obtained information under consideration of bipolar interactions between criteria. The set of compatible value functions is then applied on the whole Pareto optimal set, which results in possible and necessary rankings of Pareto optimal solutions.

Using these rankings a new sample of solutions has to be pairwise evaluated by the DM. This interactive cycle stops when the DM comes to conclusion that there is no satisfactory solution for the current problem setting. The set of compatible value functions is constructed using ordinal regression methods called UTAGSS, the most general approach in the UTAGMS/GSS familiy. This method generalizes UTA-like methods and is competitive to AHP and MACBETH methods.

The problem of representing interactions has been dealt with different methodologies, such as polynomial conjoint measurement, multilinear value functions, and nonadditive integrals, like Choquet integral and Sugeno integral.

Recently Greco, Mousseau and Słowiński [2] presented a decision model able to represent interaction by adding to the classical additive utility function some additional terms expressing a bonus or a penalty related to evaluations of pairs, triples and, in general, n-tuples of criteria. [2] presents a method called UTAGMS-INT in which the decision model is assessed using robust ordinal regression. This means that starting from some preference information given by the Decision Maker (DM), the set of compatible value functions is defined such that alternative a is necessarily weakly preferred to alternative b if a is at least as good as b for all compatible value functions, while a is possibly weakly preferred to b if a is at least as good as b for at least one compatible value function. The interactions modelled in [2] are synergy and redundancy, which yield a bonus or a penalty, respectively, when values of the considered n-tuple of criteria improve together.

UTAGSS, that extends the UTAGMS-INT method by considering criteria values under consideration of the idea of bipolarity [4]. In this case, synergy and redundancy (i.e. bonus and penalty) depend on the relative position of values of the considered n-tuple of criteria with respect to a neutral level. To gain the highest degrees of freedom we use the idea of bipolarity to distinguish between different areas of interaction effects. This allows considering different neutral levels for each pair of interacting criteria. Considering so called bipolar interactions we are able to get a representation of DM's preferences, which is more faithful with respect to the information supplied by the DM. If the DM has no idea about the interactions, then we use a mixed integer linear program to determine sets of pairs of interacting criteria. In UTAGSS it is possible but not necessary to consider bipolar scales for all criteria. UTAGSS is a generalization of UTAGMS-INT, because it produces in the special case, all neutral levels regarding interactions between two criteria are located at the worst performance of the criteria, the same results as UTAGMS-INT. UTAGSS is the most flexible method able to represent the most complex interactions. We introduce an example of a bipolar interaction which takes effect like a two-dimensional knock-out criterion, a straightforward extension of vetos and pushers based on one criterion [3]. This phenomenon can only be modelled with UTAGSS and not with UTAGMS-INT.

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3.18 Learning from Pareto-Front Approximations of Real-World Optimization Problems – A Clustering Approach

Tamara Ulrich (ETH Zürich, CH)

Multiobjective problems usually contain conflicting objectives. Therefore, there is no single best solution, but a set of solutions that represent different tradeoffs between these objectives. For real-world problems, an interpretation of the front is usually not straightforward.

We have proposed a method to help the decision maker by clustering a given set of tradeoff solutions. We do so by extending the standard approach of clustering the solutions in objective space, such that it finds clusters which are compact and well separated both in decision and in objective space. It is not the goal of the method to provide the decision maker with a single preferred solution.

Instead, it helps the decision maker by eliciting information from the front about what design types lead to what regions in objective space. The novelty of the presented approach over existing work is its general nature, as it does not require the identification of distinct design variables. Instead, our method only requires that a distance measure between a given pair of solutions can be calculated both in decision and in objective space. This makes it applicable to any real-world problem.

3.19 Hybrid Evolutionary Multi-Objective Optimization: Different Interaction Styles and an Approach

Jyrki Wallenius (Aalto University, FI)

We describe different man-computer interaction styles, which are commonly embedded within existing Multiple Criteria Decision Making techniques to elicit the Decision-Maker's preferences in problems involving more than two objective functions. The elicitation process reflects Decision- Maker's learning of his/her preferences, based on realizing what is possible and feasible to achieve regarding objective function values. A case in point is pairwise comparisons, which have been found easy to elicit. Two example methods, which are representatives of hybrid Evolutionary Multiobjective Optimization methods, are explained in some detail. We also discuss computational results. The talk concludes with a discussion of future research questions. The talk highlights the importance of the role of a human decision-maker, and more broadly understanding the behavioural foundations of decision making, in Evolutionary Multiobjective Optimization.

3.20 Learning Tradeoffs in Multiobjective Optimization: A Cone-based Approach

Margaret M. Wiecek (Clemson University, USA)

Optimality in multiobjective optimization problems (MOPs) is governed by a partial order in the objective space and produces a set of solutions to the optimization problem rather than a unique optimal solution. The partial order implied by the binary relation of the componentwise comparison of two vectors has traditionally been used and is known as the Pareto optimality. In the process of multicriteria decision making (MCDM), the decision maker faces the challenge of choosing a preferred solution from the set of Pareto solutions. While Pareto solutions are equivalent in the mathematical sense, they are not equivalent for the decision maker (DM) because they are not equally preferred with respect to preferences that the DM may have or be developing in the course of decision making. The DM's preferences may be changing due to a learning process he or she is engaged in while searching through the Pareto solutions.

In the MCDM literature there is a great variety of models of DM's preferences on the Pareto set and there are numerous procedures making use of those models. In this talk we are interested in models developed with convex cones since we believe that the concept of cone is inherent to multiobjective optimization. After Yu [1] developed grounds for relating cones to the Pareto optimality, cones turned out to be an effective concept for modeling DM's preferences from the perspective of tradeoffs associated with the Pareto solutions in the objective space.

We will review the state of the art in cone-based modeling of preferences. Berman and Naumov [2] are perhaps the first to use interval tradeoffs and construct a matrix of a cone to represent DM's preferences. Noghin [3] uses weights as the coefficients of relative importance between criteria, constructs a direction in the objective space, and models DM's preferences by the convex hull of the Pareto cone and this direction. The ideas of Noghin [3] are extended in [4] and [5] to construct an estimate of the Pareto set, and in [6] to derive conditions for consistency of relative importance information. Hunt and Wiecek [7] and Hunt et al. [8] build on Noghin's approach and allow more directions to be appended to the Pareto cone to construct a new preference cone. DMs preferences are quantified by the so called allowable tradeoffs between objectives, or the maximum amount the DM is willing to allow one objective to decay to obtain one unit of improvement in one other objective. Using these values, convex polyhedral cones are constructed and their complete algebraic descriptions are derived.

In the second part of the talk we will discuss the use of cone-based models in decision making [9]. They reduce the Pareto set to a subset of decisions that are representative for the DM's preferences and satisfy certain bounds on tradeoffs. In this way the models offer a tool being a compromise between the models relying on scalarizing approaches and set-oriented methods. The former reduce the Pareto set to a singleton, which may be rather limiting for the DM, while the latter (e.g., evolutionary methods) yield a representation of the Pareto set in the form of many points, which can be overwhelming and difficult to use.

The models can be incorporated into the MCDM process either a priori, a posteriori, or interactively because they can work in concert with any MCDM method. The advantage of the a priori approach is that Pareto solutions that do not satisfy the DM's preferences are never considered. If DMs are unfamiliar with the problem and/or unsure of their preferences, they have the freedom to interactively explore the set of feasible solutions by adjusting the models. This exploration allows them to familiarize themselves with the problem and learn about which solutions are the least sensitive to small changes in preferences. The models extract the solutions from the Pareto producing a short list of "strong" or "privileged" solutions with preferred tradeoffs. The short list may be long or even include one solution. In any case, DMs retain the right to choose and exercise their right within a small subset of candidate solutions.

We will also report on the applications of Hunt et al. [10, 11] and [12] models in engineering design and present the accompanying learning process an automotive designer is engaged in. We will conclude the talk with future research directions on the development of cone-based models of preferences for MCDM.

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3.21 Multiobjective optimization in self-optimizing systems and applications

Katrin Witting (Universität Paderborn, DE)

Joint work of Witting, Katrin; Dellnitz, Michael; Trächtler, Ansgar; Geisler, Jens; Böcker, Joachim; Schulz, Bernd; Fröhleke, Norbert
Main reference J. Geisler, A. Trächtler, K. Witting, M. Dellnitz, "Multiobjective optimization of control trajectories for the guidance of a rail-bound vehicle," 17th IFAC World Congress, Seoul, Korea, 2008.
URL http://dx.doi.org/10.3182/20080706-5-KR-1001.00738

In the Collaborative Research Center "Self-optimizing concepts and structures in mechanical engineering" (SFB614) at the University of Paderborn, Germany, methods for the design of tomorrow's mechanical engineering products are developed. The concept of self-optimization developed within this research project goes beyond the classical adaptation techniques for mechatronical systems. It includes three steps that are repeated during operation time: (i) Analysis of the current situation, (ii) Determination of the system's objectives, (iii) Adaptation of the system behaviour.

For model-based self-optimization of mechatronical systems, multiobjective optimization is an important approach. Having formulated suitable objectives the determination of the system's objectives in step (ii) of the self-optimization process can be seen as decision making on the Pareto set. Depending on the current situation, adequate Pareto points have to be chosen. For several technical applications like for example the operating point assignment of a linear drive [1] and the guidance of a rail-bound vehicle [2] we have constructed special heuristics that allow to choose Pareto points fitting to the current situation during operation time. These heuristics have been developed in close cooperation with the engineers who developed the technical systems. In case of the driving module the Pareto optimal solution is adapted during operation time making use of numerical path following methods.

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4 Working Groups

4.1 Drafting a Manifesto for DM-DSS Interaction (Working Group "DM Sense")

Salvatore Corrente, Simon French, Salvatore Greco, Milosz Kadzinski, Joshua Knowles, Vincent Mousseau, Johannes Siebert, Roman Słowiński

4.1.1 Introduction

The DM Sense group, as it was called, met several times during the Dagstuhl Seminar to discuss intelligent user interactions in decision support with an emphasis on the need to create dialogues between decision makers and their decision support tools which explained the process and the underlying reasoning so bringing understanding and insight to the decision makers. The challenge was to develop dialogues that facilitated the user's thinking. In a way the challenge paralleled that of Turing's test: could a machine interact with a decision maker in a way that was indistinguishable from how a decision analyst might interact?

Naturally the task we set ourselves in the opening discussion was somewhat simpler. We decided that our aims could be summarised as:

Aims and Objectives

Construct a system able to generate contextual explanations in natural language in support of the decision.

- Generate sentences which materialise the explanations and support further interactions with the Decision Maker.
- Keep trace of arguments that led to the decision in order to present them to other stakeholders.
- Expressing preference information should not require great cognitive effort from the Decision Maker.
- The explanations should be accessible to inexperienced and unsophisticated users.

By the end of our discussions we felt that there was need for much more work on this topic that recognised its importance if multi-objective decision support systems were truly to support the growth in decision makers' understanding and their confidence in the final decision. We needed to prepare a *Manifesto for Interactions between Decision Makers and Decision Support Systems.*

The following are our notes as they were generated during the several sessions of the Dagstuhl Seminar and reported back to the plenary session on the final day.

4.1.2 Assumptions

During our discussions we made a number of assumptions. Some we explored in detail, others we left for further discussion after Dagstuhl (see Section 4.1.7 below)

- Decision making is a stepwise learning process.
- At each step the Decision Maker interacts with the system:
  - providing specific preference information,
  - getting explanations in terms of consequences of this information on a preference structure in a sample of solutions,
  - being informed by the system of inconsistencies of preference statements with respect to the model,
  - being able to revise previous preference statements.
- The generation of the explanations relies on a preference model.
- Expressed preference information is either solution-based (indirect) or model-based (direct).
- The set of solutions is fixed or is progressively discovered along the iterative process.

One assumption that we did not make explicit in our discussions but was implicit throughout is that we assumed that all interactions should be in natural language supported by tables and charts, exactly as they would be if a human decision analyst led them. We also recognised that the process of interaction needs to be driven by both sides. The System needs to elicit judgements and explore issues, moving the decision maker through a series of stages defined by a multi-objective decision analytic methodology. But equally the Decision Maker needs to be able to interrupt the flow and ask for explanation of a particular point in the reasoning or perhaps volunteer information that he or she believes is relevant. There also needs to be the possibility for the Decision Maker to reject the preference model being used — or, equivalently, its assumptions — and similarly for the System to recognise that a different model may be needed and adjust the interaction strategy accordingly.

4.1.3 Previous work

The group were aware of several pieces of earlier work in this area including [1, 2, 3, 4, 5, 6, 7, 8, 9, 10].

4.1.4 Questions that might arise during interactions

We were concerned to think about the types of question that might be asked during the interaction. Some might be posed by the analyst with the aim of eliciting judgements or stimulating reflection on the part of the decision maker; others might be asked by the decision maker to seek an explanation for part of the developing reasoning or step in the process.

The following lists are not intended to be exhaustive.

Questions that might be asked by the decision maker

- Why should I consider a instead of b? Give me an explanation that involves this kind of preference information? Why is the model not able to compare a and b?
- Why should I consider a as the best solution?
- Is the best solution unique?
- Why do I have to work with that set of solutions?
- If I could change constraints on the decision space, what is the best I could do?
- How much of the work have I already done? If I stop now, what can you tell me?
- What will happen if I change some preference information?
- What should be changed now that b is equal to a?
- Questions regarding inconsistencies:
  - Why did you tell me I am inconsistent?

- Why I am not acting rationally?
- When have I provided inconsistent preference information? Which alternatives have I already seen?
- When did I tell you this?

Questions that might be asked by the System

- What is the argument to eliminate these solutions? (e.g. from the search)
- Please confirm you earlier choice because it is particular influential on the solution.
- You are departing from linearity... are you really like this?
- Do you agree that there could be interactions?
- Could it be possible to have a pair to explain the reason for non-independence of criteria?
- How important this particular criteria was in the selection (at the end)?
- "Do you really think safety is unimportant?"

4.1.5 Two examples

To give some substance to our discussions we divided into two subgroups and developed two examples of interactions between a Decision Maker and the System.

Even Swap

The first is based on Keeney, Hammond and Raiffa's Even-Swap approach [11, 12]. The example below suggests how a System might use this approach in supporting a Decision Maker in choosing the location of an office. Remember that it is simplified: real problems and real interactions would need be more complex.

	b	b'	c	c'	c''	d	d'
Commute	25	25	20	25	25	25	25
Clients	80	80	70	78	78	85	85
Services	B	B	C	C	B	A	B
Size	700	950	500	500	500	950	950
Cost	1700	1950	1500	1500	1750	1900	1800

DM: which is the best alternative among b, c, d ?

	b	b'	c	c'	c''	d	d'
Commute	25	25	**20**	**25**	25	25	25
Clients	80	80	**70**	**78**	78	85	85
Services	B	B	C	C	B	A	B
Size	700	950	500	500	500	950	950
Cost	1700	1950	1500	1500	1750	1900	1800

System: Your earlier answers suggest that c and c' are worth the same to you because increasing the commute time from 20 to 25 is balanced by increasing the clients from 70 to 78.

Is that right ?

[If no, it would be a more complex interaction]

	b	b'	c	c'	c''	d	d'
Commute	25	25	20	25	25	25	25
Clients	80	80	70	78	78	85	85
Services	B	B	C	C	B	A	B
Size	700	950	500	500	500	950	950
Cost	1700	1950	1500	1500	1750	1900	1800

System: Hence we can compare c' to b and d instead of comparing c.

System: Notice that Commute is now 25 for all three options.

	b	b'	c	c'	c''	d	d'
Commute	25	25	20	25	25	25	25
Clients	80	80	70	78	78	85	85
Services	B	B	C	**C**	**B**	A	B
Size	700	950	500	500	500	950	950
Cost	1700	1950	1500	**1500**	**1750**	1900	1800

System: Your earlier answers suggest that c' and c'' are worth the same to you because improving the service from C to B is balanced by an increase in cost from 1500 to 1750.

Is that right ?

[If no, it would be a more complex interaction]

	b	b'	c	c'	c''	d	d'
Commute	25	25	20	25	25	25	25
Clients	80	80	70	78	78	85	85
Services	B	B	C	C	B	A	B
Size	700	950	500	500	500	950	950
Cost	1700	1950	1500	1500	1750	1900	1800

System: Hence we can compare c'' to b and d instead of comparing c'.

	b	b'	c	c'	c''	d	d'
Commute	25	25	20	25	25	25	25
Clients	80	80	70	78	78	85	85
Services	B	B	C	C	B	A	B
Size	700	950	500	500	500	950	950
Cost	1700	1950	1500	1500	1750	1900	1800

System: Now compare b and c''. Notice that b is as good as or better than c'' on all criteria. So, b dominates c'', and c'' can be eliminated.

	b	b'	c	c'	c''	d	d'
Commute	25	25	20	25	25	25	25
Clients	80	80	70	78	78	85	85
Services	B	B	C	C	B	A	B
Size	700	950	500	500	500	950	950
Cost	1700	1950	1500	1500	1750	1900	1800

System: So c'' can be eliminated (hence c' and c)

	b	b'	c	c'	c''	d	d'
Commute	25	25	20	25	25	25	25
Clients	80	80	70	78	78	85	85
Services	B	B	C	C	B	**A**	**B**
Size	700	950	500	500	500	950	950
Cost	1700	1950	1500	1500	1750	**1900**	**1800**

System: Your earlier answers suggest that d and d' are worth the same to you because reducing service level from A to B is balanced by an decrease in cost from 1900 to 1800.

Is that right ?

[If no, it would be a more complex interaction]

	b	b'	c	c'	c''	d	d'
Commute	25	25	20	25	25	25	25
Clients	80	80	70	78	78	85	85
Services	B	B	C	C	B	A	B
Size	700	950	500	500	500	950	950
Cost	1700	1950	1500	1500	1750	1900	1800

System: Hence we must compare b to d' instead of comparing b to d.

	b	b'	c	c'	c''	d	d'
Commute	25	25	20	25	25	25	25
Clients	80	80	70	78	78	85	85
Services	B	B	C	C	B	A	B
Size	**700**	**950**	500	500	500	950	950
Cost	**1700**	**1950**	1500	1500	1750	1900	1800

System: Your earlier answers suggest that b and b' are worth the same to you because an increase in size from 700 to 950 is balanced by an increase in cost from 1700 to 1950.

Is that right ?

[If no, it would be a more complex interaction]

	b	b'	c	c'	c''	d	d'
Commute	25	25	20	25	25	25	25
Clients	80	80	70	78	78	85	85
Services	B	B	C	C	B	A	B
Size	700	950	500	500	500	950	950
Cost	1700	1950	1500	1500	1750	1900	1800

System: Hence we must compare b' to d' instead of comparing b to d'.

	b	b'	c	c'	c''	d	d'
Commute	25	25	20	25	25	25	25
Clients	80	80	70	78	78	85	85
Services	B	B	C	C	B	A	B
Size	700	950	500	500	500	950	950
Cost	1700	1950	1500	1500	1750	1900	1800

System: Now compare b' and d'. Notice that b' is as good as or better than d' on all criteria. So, b' dominates d', and d' can be eliminated.

System: So b is the best solution among b, c, and d.

This even-swap approach could be programmed up into a decision support system with some effort, but without significant conceptual difficulty. There are even-swap codes already developed but these run through the analysis without 'explaining' the logic fully. Nonetheless adding such explanation would be achievable task with today's language processing methods. Generally, however, we were thinking of a much less structured process which worked through the entire decision analysis process: identifying the issues and choice, structuring them into a decision model, identifying appropriate constraints on preference models to 'fit' the decision maker's preferences subject to some rationality requirements, eliciting judgements, and identifying the optimal choice or choices, all the time explaining what the system was doing. The second group discussed this more sophisticated approach.

4.1.6 User-System interaction: possible scope and example

We distinguish five different types of information which has to be communicated between system and user:

- Information regarding concepts and methods and procedures.
- Problem related information (data).
- User related information.
- Preference information.
- Self-evident output and detailed explanations derived from prior articulated preference information.

Table **??** illustrates based on a possible interaction five different types of information which has to be communicated between system and user.

In the following paragraphs, the numbering (n) refers to the interaction identifier in Table **??**.

The first type is the *information regarding concepts, methods and procedures.* For a user friendly navigation through the decision process, the system should upon request explain

Table 1 Table illustrates based on a possible interaction five different types of information which has to be communicated between system and user.

'Speaker'	Interaction	Interaction Identifier.
System:	Hello user. How can I help you?	1
User:	I want to buy a car. But I do not know which one is the best for me.	2
System:	Are you experienced in exercising this kind of a decision?	3
User:	Yes, I am.	4
System:	Could you describe the decision problem?	5
User:	Yes.[user describes the problem].	6
User:	I would like to identify the best five alternatives. Six criteria are relevant.	7
System:	Are you interested in a rough approximation which could realized with not much effort or are you interested in an optimized solution which would cost you time and much cognitive effort?	8
User:	I do not have that much time. I am interested in a rough approximation.	9
System:	Are you familiar with holistic pairwise comparisons?	10
User:	No.	11
System:	In a holistic pairwise comparison you have to compare two alternatives. For example you could prefer a to b, you are indifferent or you are not able to do the comparison.	12
User:	Why you are asking me about pairwise comparisons?	13
System:	Psychologists confirm that DMs are more confident exercising their decisions than explaining them. The most natural is a holistic pairwise comparison of some alternatives relatively well known to the DM. You told me earlier that you do not have much time. The use of pairwise comparisons in preference elicitation could achieve this best.	14
System:	Please compare this six pairs [system provides six pairs].	15
User:	[Does five pairwise comparisons].	16
User:	I am not able to execute the sixth pairwise comparison. Please provide me another one.	17
User:	Which alternatives are the best?	18
System:	There are 10 alternatives which could be possibly the best.	19
User:	I do not understand this. Could you explain it?	20
System:	Based on the information you gave me these ten alternatives are not dominated by other ones. They all could possibly be the best alternative.	21
System:	Would you like me to suggest further pairs for comparison?	22
User:	Yes.	23
System:	Please compare this four pairs.	24
User:	Why these particular four pairs?	25
System:	They will cut the number of alternatives that could be considered best.	26
User:	[Does comparisons].	27
System:	Please consider these five alternatives which could be the best.	28
User:	Why these five alternatives are the best?	29
System:	Gives explanation by values. Alternatives X, Y, Z have at least value 80 on criterion speed.	30
User:	Could you explain this in terms of preference information that I have provided?	31
System:	Gives a chain for each. The screen fills with 15 chains]. D > Q because you said that R > T.	32
User:	I would like to include alternative Q which is not in the five best you proposed. Is this possible?	33
System:	Yes, you need to revise R better T. Do you agree?	34
User:	Yes, I agree.	35
System:	Now these seven alternatives are the best ones. Would you provide preferences for these three pairs?	36
User:	How many more would I have to do until I am finished?	37
System:	Probably overall six to eight additional pairs.	38
User:	Please show the result if I would stop now.	39
System:	The result is the following...	40
User:	I like the results.	41
User:	Please print a report.	42

which options the user has (8) and which input will be required if she chooses this optional procedure (22, 37). All user questions and commands are part of this task. If the user is not familiar with a method or concept she should be able to ask the system (13) and get an answer of the system (12). It is important that the user decides on the progress through the procedure and that she never faces a situation in which the system does not offer help or alternatives. For instance, if the user is not able to make a suggested pairwise comparison, the system has to suggest another pairwise comparison (18). Also, if she does not want to provide additional preference information the system must offer the option of asking for the preliminary results based on already given preference information (39) and allow ending the procedure (42) if the user is satisfied with these results. The information that the system provides the user already exists or should relatively easily be created. There are different accepted and proven forms for the system to transmit the relevant information to the user. The flow of information in the other direction, from user to system, is more difficult because the system has to understand what the user wants. The challenge for this type of information lies in the individual tailoring.

The second type is *problem related information (data).* For example the description of the decision problem and constraints which do not depend on the preferences of the user (2, 6). The challenge is to provide an interface which is able to deal with and interpret whatever kind of information. The more structured and based on numbers this information are, the easier is the further processing for the system.

The third type is *user related information* for example whether the user is experienced in exercising decisions (3) or whether she knows special concepts or methods (11). This information is necessary for individual tailored explanations and an efficient as well as effective procedure. An expert for decisions is able to understand more complicated argumentations in comparison to a layman. This requests that the code adopts itself to different types and differently experienced users require the use of different approaches, i.e. either selecting different approaches or limiting the validity of the results. The difficulty here consists of the elicitation of the relevant information and the integration in the decision process.

The fourth type is *preference information.* The user can articulate her goals (9) and carry out some given pair wise comparisons (16, 27). Thereupon the user should have the opportunity to articulate her preferences proactively, for example, if she does not agree on preliminary results based on her earlier articulated preferences (33) or if she confirms preference information (35). The structured questions of the system can relatively easily been modeled since they can be derived from the used models. The challenge lies in the proactively provided information by the user. The system has to be able to deal with any kind of preference information articulated by the user.

The fifth type of information contains *self-evident output and detailed explanations derived from prior articulated preference information.* If a system should be accepted by the user it "must give plausible and credible recommendations and provide convincing justification for those recommendations using terminology and logic understood and trusted by the users" [4].

Greer et al. [4] summarize the following by Kass [5, 6] raised issues regarding explanations:

1. "A good explanation is relevant, convincing, and understandable to the user.
2. A relevant explanation answers the immediate question and addresses the user's higher goals.
3. An explanation must convince the user that the recommendation is correct.
4. An explanation can be readily understood if:
   - it is appropriate to the user's knowledge of the domain
   - it is economical and concise

- it is organized
- it is expressed in terms of familiar concepts, and
- it requires little cognitive processing or indirect inference by the user."

Most simple is the communication of (intermediate) results (19, 40). The system can justify which method it suggests based on the information the user has earlier provided. For example that pairwise comparisons should be used for the elicitation of the preferences because they could lead fast to a rough approximation as requested by the user (14) or the system can provide the user a pairwise comparison which the user should confirm if she is consistent in her preferences (34). Thereupon the system can explain results (21). Such an explanation can be more complicated and based on information the user has not directly articulated (30). The system can also explain how long the whole process will take based on the already elicited preference information (38).

4.1.7 Future work

The group agreed to continue work after the Seminar and develop these ideas into a *Manifesto for Interactions between Decision Makers and Decision Support Systems.* The intention is to prepare such a paper and submit it to a mainstream journal with a view to stimulating further work.

Since the Workshop two papers have been drafted:
1. Salvatore Corrente, Salvatore Greco and Roman Slovinski (2012) "Rough set and rule-based explanatory decision support".
2. Milosz Kadzinski (2012) "Review of some explanatory decision support systems and underlying methods".

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4.2 What and how can we learn from Pareto fronts and sets? (Working Group "Pareto Sense")

Susanne Bürklen, Kalyanmoy Deb, Michael Emmerich,Karlheinz Kuefer, Boris Naujoks, Amos H. C. Ng, Akira Oyama, Silvia Poles, Tamara Ulrich, Katrin Witting

Our working group was concerned with the question what and how a decision maker can learn from the Pareto set, Pareto front and the mapping between these sets. We discussed several topics:

1. What and how can we learn from Pareto fronts?
2. What and how can we learn from Pareto sets in decision space and from the mapping into objective space?
3. How do constraints influence the solution sets?

The discussions resulted in a broad collection of properties of Pareto fronts and how these can be interpreted in a decision context. Moreover a range of methods, in particular visualization methods, for measuring properties and analysing Pareto optimization results were brought together put into a structured view. Interesting question for future research were identified and ideas for an extended report (white paper) with a collection of properties and analysis methods with examples for the interpretation and explanation of the observed properties.

Already when looking at only the Pareto front many structural properties can be observed that have an interpretation for decision making. Among others these are special points and regions (knees, bents, gaps, elbows, cusp points, etc.), correlation between objectives, convex and concave shapes of the Pareto front or projections of it. Well-balanced compromise solutions are often located at knees. Gaps and cusp points often indicate structural transitions (e.g. discrete choices, hysteresis, bifurcations, etc.).

To gain a better understanding of these can reveal interesting insights into the structure of the optimization problems or help the decision maker in navigation across the Pareto front. In the engineering context design principles could be derived from this. Additional analysis focusing on critical regions can be used to identify parameters that are responsible for their occurence and this can reveal interesting design principles for instance in the context of innovization.

There are various tools for visualizing Pareto fronts. 2-D and 3-D scatter plots and surface plots are very common. In particular in 3-D, plotting also the attainment surface can help to visually locate the position of points in a 3-D plot. In 4-D and higher dimensions we may use shapes, colors, size of points and even blinking patterns to indicate additional objective function values in 3-D projections (as for instance done in the LIONSolver). For dense approximation sets it can occur that the points that are overshadowed are not visible. Slicing can be used in this case, or even movies that remove layers of non-dominated solutions in the 3-D projection. In N-dimensions, techniques from multidimensional data visualization can be used and a variety of methods is available, such as Parallel coordinates diagrams, heatmaps, interactive decision diagrams, clustering-based approaches. Besides, textual and rule based descriptions of the Pareto front might reveal its structure and interesting patterns.

In order to learn from Pareto optimization, decision space information should be combined with information from the objective space. In particular, the preimage of the Pareto front is of interest. In parametric spaces (e.g. decision space is real valued) it is possible to combine decision variables and objective function variables in diagrams, for instance in the Parallel coordinates diagram. A challenging question is how to gain intuition about the mapping and decision space in case of non-parametric decision spaces or structures, such as molecules, bridge constructions or airfoil shapes. For this case it was rendered to be a good approach to show animations along the Pareto front (2-D case), across the Pareto front (higher dimensional Pareto fronts). Moreover, viewing animations moving from non-optimal subspaces towards the Pareto front can teach intuition of what makes solutions Pareto optimal.

An important information is, whether Pareto optimal solutions occur at the boundary of constraints, and if so, which constraints are active. It is important to know this, because it might be possible to relax constraint boundaries, for instance if a constraint occurs at the preferred solution and relaxing the constraint can further improve it. There are even techniques that relax the constraints until an ideal solution can be found, but it is questionable whether these techniques have a wide scope. In addition, solutions at the constraint boundary are often not robust solutions, and a decision maker might prefer a solution, if less constraints are active.

Therefore, constraints data is important for decision making.

4.3 Evaluating, Measuring, Quantifying Learning (Working Group "Quantifying Learning")

Jürgen Branke, Jussi Hakanen, Markus E. Hartikainen, Hisao Ishibuchi, Enrico Rigoni, Karthik Sindhya, Theodor J. Stewart, Margaret M. Wiecek

4.3.1 First Phase of Discussions

It was agreed to focus, initially at least, on learning experienced by the decision maker in using the methods, in contrast to learning by the algorithm (but see the final section). The purpose of measuring learning is perhaps primarily to assess and to compare methods, but it was recognized that inevitably there would also be an evaluation of decision makers.

Within this context, three issues were discussed, namely: What can be learnt? What information is potentially available to provide measures of learning? How can such information be exploited to provide an operational measure of learning?

What can be learnt?

The following items were identified:

1. Whether a solution is Pareto-optimal
2. Whether a target is achievable

3. Range of each objective
4. Shape of frontier/Identification of knees
5. Own preferences, relative importance of objectives
6. Criteria that may be missing
7. Constraints that may be missing
8. The absence of a satisfying solution, and the need to increase the search space
9. Causes for trade-offs and the mapping between decision and objective spaces (to give insight into problem and to support "innovization")
10. Mapping between preference and objective spaces (to identify what preferences lead to what areas in the objective space and ultimately the corresponding decision space).

What information is potentially available to provide measures of learning?

A wealth of information is potentially available to assess learning, varying from quantitative performance measures of the algorithmic implementation to subjective assessments of the extent of learning experienced. Types of information available in principle includes:

1. The process, or sequence of interactions followed, e.g.:
   - Number of solutions (Pareto or non-Pareto optimal) visited
   - Inconsistency of responses
   - Backtracking
2. Number of relationships identified/explored (if available in method)
3. Rate of change in response times
4. Does the DM prefer the solution found to all in a sample of Pareto optimal solutions?
5. Subjective evaluation of learning demonstrated, as assessed by the analyst or an external observer
6. Can the DM explain the rationale behind the choice (judged by analysts or external observer)
7. Direct questions posed to the DM before and/or after process, e.g.:
   - Expressed preferences before and after process
   - Compare final solution with prior assessments of attainable outcomes
   - Sketches of perceptions of 2-dim slices through the Pareto frontier
   - Statements of importance of objectives (before and after process)
   - Confidence and satisfaction in solution found
   - Is the DM still happy with answer two weeks later?
   - Other questions in a structured questionnaire
8. Changes in process or result with repeated analysis using the same or a different method

How can such information be exploited to provide an operational measure of learning?

This is the primary challenge to future research. Some of the issues identified are the following:

1. How should we set up hypothetical (simple but realistic) test problems, on which experiences with different methods on sets of "decision makers" (e.g. students) can be evaluated.
2. We should develop a variety of test cases for different contexts (e.g. business, engineering, environment)
3. The operational feasibility of the potential measures needs to be investigated, for example:

- How do we seek the right balance between "objective" and "subjective" measures?
- How should we interpret even objective measures, e.g. whether visiting a larger number of solutions is an indicator of poor or rich learning.
- The design of an effective questionnaire?

The group split into two sub-groups on the last day, in order to probe some of the above issues further. The results of these discussions are summarized in the next sections.

4.3.2 Second Phase of Discussions

Sub-group 1: Evaluating/measuring DM's learning by monitoring him/her

This sub-group looked into evaluating and/or measuring DM's learning by monitoring him/her while he/she is using an interactive method to solve the multiobjective optimization problem. The idea was that if the analyst had kinds of rules, the analyst could further develop methods to support learning, to determine whether the DM has learned (without asking him/her), to help the DM learn by guiding him/her and even to suggest a change of method if the analyst can determine that the DM is not learning.

First, the sub-group made different hypotheses on what the behavior of the DM could look like when he/she learns and what distinguishes it from one that is not learning. However, this turned out rather difficult and it was concluded by the sub-group that it seems to be hard to distinguish between DM's learning and his/her growing confusion – both of these may lead to changes in the DM's behavior. Thus, the sub-group decided to pursue an alternative direction of thought.

It was concluded that one should set up an experiment for determining the rules for whether whether the DM is learning. In the experiment, all the interaction between the DM and the interactive method should be recorded and whether the DM has learned or not should be determined through a questionnaire. With a sample that is large enough, data mining techniques can be used to derive rules that distinguish the ones that have not learned from the ones that have. Particular attention must naturally be payed to designing the questionnaire and to designing the monitoring tools and there are also other issues to resolve before doing the experiment. However, the benefits of the rules that could be the result of this experiment would be great, as explained also previously. An outline of the designed experiment is shown in Figure 1.

Even though the sub-group decided that they could not come up with the rules without an experiment, they were able to give some hypotheses on what distinguishes the behavior of a learning DM from a one that is not learning. The sub-group agreed on the following rules for a learning DM:

1. There is change in search direction and consistency after that.
2. Step size of the interactive method decreases when the area of preferred solution has been found.
3. On the later stages of using the method, there is an almost monotonic convergence to the final solution.
4. Response time of the DM decreases in the end.

On the other hand, it was agreed that learning may not happen, when the following rules apply:

1. The DM stays in a small area for the whole time that he/she is using the method.
2. There are continuous (almost random) changes in the search direction

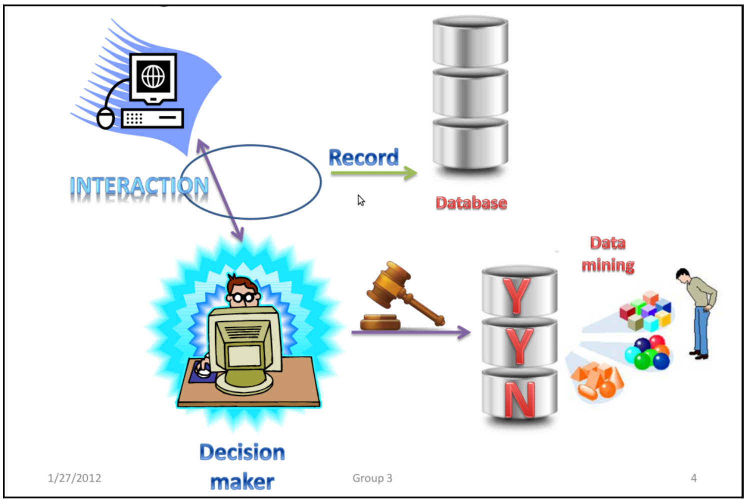

Figure 1 A graphical illustration of the experiment to derive rules that determine whether the DM has learned

The rules for a learning DM imply a change in the DM's thinking that then stays consistent after the change and the rules for a non-learning DM imply either a continuous changes or unwillingness to try anything new. However, as stated earlier the validity of these hypothesis must be evaluated through the experiment shown in Figure 1.

Sub-group 2: Quantifying algorithmic learning

Our first observation when considering the learning of algorithms was that only some approaches learn explicitly a model of the user preferences.

Examples include

- The Zionts/Wallenius method
- MACBETH
- UTA/GRIP/ ...
- AHP in the absolute measurement mode.

Other approaches don't learn explicitly, but rely more on the user to learn from the interaction in order to guide the search. Examples include

- Reference point methods
- ELECTRE
- Geoffrion/Dyer/Feinberg.

Because the concept of algorithmic learning makes more sense in the first, explicit model learning group of algorithms, we decided to focus on these.

We concluded that the learned model is only really useful if it can generalize to previously unseen alternatives.

So we assume that a method is "trained" (used) on a particular training set (e.g., a given set of preference relations) or interactively with a particular DM.

It is then validated on an additional set of solutions, preferably a representative sample of Pareto optimal solutions with known total preference information.

Then, the following things could be measured:

- How many preference relations can be decided?

- How many of those are decided correctly?
- If they are incorrect, by how much? Note that it may be interesting here to look at the DM's opinion as well as the difference in estimated value.
- Even if the preference relation is determined correctly, does the magnitude of value difference match the DM's?

With all these measures, some relationships may be considered more important than others. For example, a correct ranking of the best solutions may be more important than a correct ranking of the worst solutions.

These concepts open the way to empirical (experimental) research in which the approaches can be evaluated (within student groups for example) on the basis of the above measures.

4.4 Navigation in Multi Objective Optimization Methods (Working Group "Navigation")

Richard Allmendinger, Heinrich Braun, Matthias Ehrgott, Xavier Gandibleux, Martin J. Geiger, Kathrin Klamroth, Pekka Korhonen, Mariano Luque, Eckart Zitzler

4.4.1 Introduction

Many practical problems can best be described involving several criteria. In the case of optimization problems, this leads to the loss of the formal, but straight-forward definition of optimality. Contrary to the existence of a single optimal solution, an entire set of Pareto-efficient outcomes might exist that 'optimizes' the considered criteria. Besides the complexity of such problems, this raises the problem of making a selection of a, from a decision makers point of view, most-preferred solution.

Numerous different preference elicitation methods are available to facilitate the process of constructing representations of the decision makers' preferences. Besides, other techniques exists that allow an interactive search for a most-preferred solution, without necessarily relying on the construction of an explicit notion of the actual preferences. With the rise of human-machine-interfaces, and the availability of powerful computer hardware, we believe such techniques to play in increasingly important role in the future. Consequently, some formal considerations of this field of research are needed, which ultimately should lead to a structuring of existing approaches, and a stipulation of future research.

One way of approaching the above sketched topic can be found in the introduction of the concept of *navigation*, which we define in the following.

▶ **Definition 1** (Navigation). *Navigation* is the interactive procedure of traversing through a set of points in objective space guided by a decision maker (DM). The ultimate goal of this procedure is to identify the most-preferred Pareto-optimal solution.

The following Figure 2 depicts the concept of *navigation*, its' integration in an IT-landscape, and its' relation to reasoning/preference learning.

4.4.2 Key Aspects of Navigation

Following the rather general definition above, some more precise elaborations are needed in order to fully understand the concept of *navigation*. We believe the following integral aspects

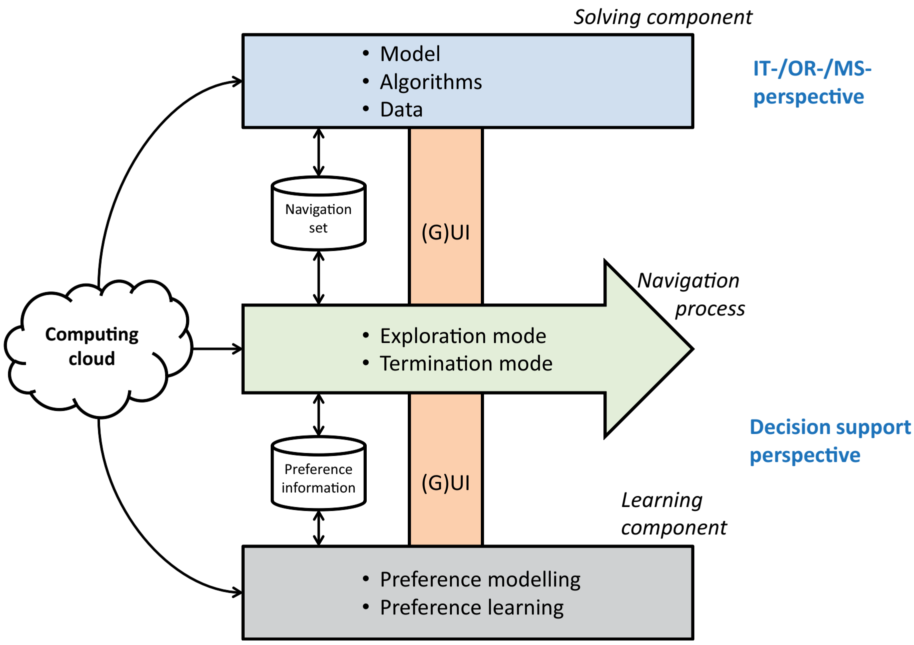

Figure 2 A framework of navigation.

to be of relevance:

1. *What is the set to be navigated?*
   The set could be: The entire Pareto-front, a true subset of the Pareto- front, or any other set of points. Consequently, this includes *a posteriori* approaches in which the Pareto-front is identified/approximated before the navigation phase. A further special case is found in most classical *interactive approaches*, which consider a single outcome and progress from there.
2. *How to navigate?*
   In general, the iterations of the *navigation procedure* are triggered by actions of the decision maker. Once such statements become apparent, the system reacts such that new points are computed in real time/selected and presented to the decision maker. Potentially, this action modifies the navigation set.
   Consequently, any navigation procedure therefore describes an alternation of *move*- and *dialog*- phases.
   Optionally, the DM also takes into consideration the information from the decision space. Prominent examples are found in engineering design applications, vehicle routing, and other complex decision problems.
3. *Guidance provided by the navigation*
   Exploration mode: During the exploration process, the control is fully in the hand of the decision maker. In this mode, the decision maker learns about the problem. Guidance/support provided by the method can facilitate this process. Relevant examples of such guidance include (i) cycle detection, (ii) information about the possible alternatives, (iii) direction derived from the navigation history, (iv) statistics of the navigation history, (v) intensification/diversification characteristics of navigation steps.

   Termination mode: At the moment of termination, the decision maker might ask for strong support in order to be convinced that he/she has found the most-preferred

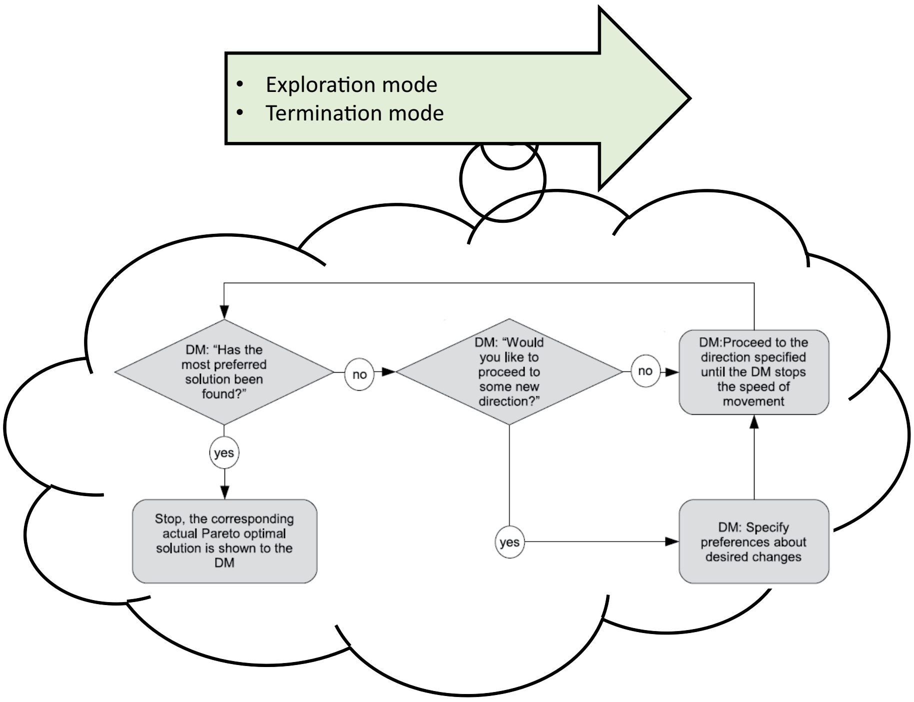

Figure 3 Navigation including *move*- and *dialog*- phases.

solution. This information could be provided by the use of value functions which are e. g. extracted from the statements made by the decision maker. In this mode, the system learns from the DM.

4.4.3 Features of Navigation

Out of the integral properties of *navigation*, several features arise.

- Pareto vs. non-Pareto search?
  On the one hand, when navigating in the Pareto set only, any navigation direction implies the worsening of at least a single objective. On the other hand, navigation between feasible (non Pareto-optimal) points may allow for a simultaneous improvement without 'sacrificing' the current values.
  This has some implications for possible navigation directions of the actions given by the DM. In any case, and ultimately, the final outcome of navigation should be a point of the current navigation set for which there is no other point known dominating it.
- Different starting points
  A key question is whether the same ultimate point is reached when starting from different points. We believe this to be the case if certain assumptions are made with respect to the value function of the DM and the consistency of the navigation and the preference/direction statements.
- Behavioral aspects (e. g. inconsistent behavior)
  Especially in the exploration phase, a certain amount of 'inconsistent' behavior is to be expected. This stems from the fact that the DM explores the navigation set in order to learn about the problem. As a consequence, any method implementing *navigation* should account for this issue.

Following the implications from prospect theory, decision makers may not judge symmetrically with respect to gains and losses of previously obtained outcomes. Navigation methods can take this into account by selecting a dominated starting point.

- Discrete vs. continuous, linear vs. nonlinear, convex vs. non- convex
  The precise properties of the problem are important. Whether the considered problem is discrete or continuous influences the type of navigation which can be used. In both cases, discrete representations satisfying different aspects (hypervolume, uniformity, coverage, approximation error, ...) can be used as the basis for navigation.

4.4.4 Previous Research Related to Navigation

Methods

- Pareto navigator
  Pareto Navigator [1] extends the ideas of Pareto Race [2] to nonlinear convex and mildly nonconvex problems with multiple objectives. 1. In a preprocessing (*initialization phase*), a convex polyhedral approximation of the nondominated set is computed using an appropriate approximation method. In this way, the Pareto Race concept can be transferred to nonlinear problems, and expensive objective function evaluations can be avoided during the interactive navigation phase. 2. After specifying an initial solution (e.g., from the previously computed approximation), the decision maker can explore the nondominated set and collect trade-off information by navigating in the polyhedral approximation.
  In each iteration of this *navigation phase*, the decision maker specifies a search direction, for example, by a classification approach or by directly specifying a reference point. The movement towards this direction is realized using parametric linear programming on the polyhedral approximation, and is visualized using, for example, value paths with appropriate steplengths. 3. At any time during the navigation, the decision maker can change the speed of the movement, the direction, or request the computation of the closest nondominated point, i.e., the projection of the current solution to the actual Pareto optimal set. This point can then be included in the approximation and the search can be continued, or the decision maker may choose to terminate the search at this point.
  When the decision maker has completed the learning phase with the Pareto Navigator, he or she may wish to continue with some other interactive method to complete the decision phase, or simply stop with the final solution found.
- Nautilus
  NAUTILUS [3] is an interactive method based on an unusual set of navigation: through a set of points that can be feasible or unfeasible and where all points are dominated by at least one non-dominated objective vector except the last solution. This last solution will be an efficient solution and should result the most preferred solution.
  Plenty of the interactive methods for multiobjective optimization are based on the sequential determination of non-dominated objective vectors, by introducing new preferential information at each iteration. This means that the decision maker must always allow the impairment of at least one objective function to produce the next iteration.
  The main purpose of this method is to eliminate 'the sacrifice' of at least one objective function at each iteration, due to the the psychological assumption that people do not react symmetrically to gains and losses.

Other important purpose is to avoid the anchoring effect mainly due to the starting point.
In this method, each solution dominates the previous one, whereupon the navigation is always carried out improving all objective functions in a given direction. This direction is obtained through the consideration of preferential weights that reflect the DM's preferences and where, by minimizing an achievement scalarizing function, the search is oriented towards the part of the Pareto front that the DM prefers. In this navigation process, useful information for the DM is the range of the attainable values for each objective function at each iteration (upper and lower bounds). These ranges are contracted at each iteration, allowing guide the search toward the desired part of the Pareto front.

Applications

- Closed-loop optimization scenarios
  Closed-loop optimization scenarios are characterized by the feature that the evaluation of candidate solutions involves to conduct real experiments, e.g. physical or biochemical experiments, and/or to run expensive computer simulations [4, 5, 6, 7, 8]. Examples of such applications include many scientific and technological problems including in areas like drug discovery and manufacturing [9, 10], analytical biochemistry [11], experimental quantum control [12], robotics [13], electronics design [14], food science [15]. In addition to expensive evaluations, closed-loop problems are often subject to multiple objectives, limited resources, and user preferences may be available too (further challenges include noisy fitness values, uncertainty, and constraints). A common situation in closed-loop optimization is that the Pareto-front of a problem needs to be approximated within a relatively small number of evaluations (due to limited resources). Subsequently, navigation can be employed (offline) to explore the front (e.g. correlations between objective values and/or decision variables) and to account for user preferences in an interactive manner. Ultimately, navigation supports an experimentalist in the (i) process of selecting the most-preferred solution in the Pareto-front, which is then realized in real-world, and in (ii) understanding the importance of specific control variables and certain (manufacturing) processes.
- Multi-objective vehicle routing
  Applications of the *vehicle routing problem* (VRP) are typically found in the physical distribution of goods. Customers are visited by vehicles which ship/collect certain goods from/to one or several depots. Obviously, cost criteria are important, with the minimization of the traveled distances as a prominent example of an objective function. Besides, the service provided by the logistical companies comes into play, often being expressed as the agreement of service with promised delivery dates or time windows.
  Consequently, vehicle routing presents itself as a multi-objective problem, in which the balancing of the considered objectives is of importance [16].
  Interactive approaches involving concepts of navigation have recently been adopted to the application domain of the multi-objective VRP. In the work of [17, 18], the decision maker is given the opportunity to state his/her preferences by means of an overall utility function, combining different objectives into an overall evaluation. The system then computes an alternative maximizing the currently stated utility function, and reports it back to the DM. In a subsequent *navigation phase*, changes to the utility function are permitted, and an adaptation of the presented solution to the altered utility function definition is tried by the optimization approach. In this spirit, the search for

alternatives follows the directions given by the DM. The traveled navigation set depends on the properties of the global utility function. In case of a function employing a convex combination of criteria, the search navigates towards solutions lying on the convex hull of the Pareto front. However, and this is due to the heuristic nature of the implemented optimization approach which relies on local search, sub-optimal alternatives might be reported back also.

Interactive search finally terminates when the DM chooses so. In a practical application, this is the case when the DM has visited enough alternatives to build his/her preferences, thus converging towards a most-preferred solution.

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4.5 Representations (Working Group "Representation")

Carlos A. Coello Coello, José Rui Figueira, Carlos M. Fonseca, António Gaspar-Cunha, Kaisa Miettinen, Sanaz Mostaghim, Dmitry Podkopaev, Pradyumn Kumar Shukla, El-ghazali Talbi, Margaret M. Wiecek

This working group focused on the issue of learning about the Pareto-optimal set in both decision and objective space from a machine perspective. In this context, learning was understood as the process of obtaining a parsimonious representation of the Pareto-optimal set and/or front, either explicitly by storing points or implicitly by building a model, so as to allow relevant information to be produced in response to Decision Maker queries. A taxonomy of representations was outlined, raising awareness of the distinct requirements of approximate optimization methods, such as evolutionary multiobjective optimizers, and exact optimization methods.

4.6 Which questions should be asked to find the most appropriate method for decision making and problem solving? (Working Group "Algorithm Design Methods")

Anne Auger, Dimo Brockhoff, Manuel López-Ibáñez, Kaisa Miettinen, Boris Naujoks, Günter Rudolph

The group started with a general discussion about two different perspectives when designing methods for decision making and problem solving. One perspective is to define clearly delimited goals, benchmarks and/or evaluation criteria, and analyze existing methods according to these criteria, acknowledging their characteristics as a simplification of the real-world. This is the approach typically followed in single-objective optimization, where the selection of an optimization method can be even done automatically in some cases. In multi-objective optimization, such selection would require not only information about the optimization problem, but also about the decision maker (DM).

A different perspective is to address the more challenging issues in real-world applications. For example, objectives may be unknown a priori, there is no well-defined utility function, there may exist noise or inconsistencies in the objective functions or the behavior of the DM.

Another challenging issue is how to help the DM to learn, but this was a topic covered by a different working group.

The consensus reached was that the selection among existing method, or the design of new methods, should be guided by:

- The goals of the DM. For example, (i) explore trade-offs, (ii) identify the most preferred solution, or (iii) maximize the confidence in the preferred solution. We can only compare different methods as long as they have the same goals.
- The constraints of the problem. There may be a budget for the algorithm (time per iteration) and a different budget for the DM (in terms of number of queries to the DM).
- Assumptions about the DM behavior. For example, we can probably assume rationality and the existence of domain knowledge, but not consistency. Moreover, any practical model of learning must assume that human learning can be (theoretically) modeled by a *learning algorithm*.
- The semantics of the DM's answers, that is, DM's preferences are *"values with semantic"*.

The outcome of the above consensus was a general model of the interaction of the DM and an optimization algorithm. This model assumes that the DM has an internal (but unknown) utility function. This internal utility function is not necessarily static, but it can evolve according to the set of visited solutions. A preference model is how the DM communicates her internal utility function to the algorithm, which may be a ranking of solutions, a search direction, aspiration levels, an explicit model, etc. The algorithm (implicitly or explicitly) tries to build a model of the DM's utility function. The ideal algorithm would be an oracle that gives always the same answer as the DM, that is, an algorithm that is able to predict the answer of the DM, taking into account the set of visited solutions, and the previous interactions with the DM.

With respect to this model, it would be very useful to have simulated/virtual DMs that may be used to define different benchmark scenarios for interactive algorithms, such as, (i) goal-driven, (ii) exploring trade-offs, (iii) find knee-points, (iv) find infeasible regions, etc.

The final goal would be to have open source benchmarks for interactive algorithms, such that different algorithms may compete using different virtual DMs on a particular benchmark scenario. The final conclusion on this topic was that the first step should be a survey of the literature about DM models, including the literature of multi-criteria decision-making, machine learning and artificial intelligence.

The second part of the discussion focused on what can be said starting from the most simplified version of the above model. Possible questions are: *"How fast can an algorithm identify the most preferred solution?"* and *"How many times the algorithm has to ask the DM to identify it?"*. In this manner, we defined a very simple DM and a (1+1) interactive EA (iEA) applied to a simple binary problem (Leading-Ones-Trailing-Zeroes). The conclusion is that one can compute an expected number of function evaluations to identify the most preferred solution, and the expected number of queries to the DM. Further work should focus on extending these initial results to more complex DM models, algorithms and problems.

5 Seminar schedule

Monday 23rd January (Theme: Learning and Interaction)	
7.30-8.45	Breakfast
8.45-9.15	Opening welcome and introduction (Joshua Knowles)
9.15-9.45	Round of personal introductions (all participants)
9.45-10.30	Opening Invited Talk – **Interactive Multiobjective Optimization from a Learning Perspective** (Jürgen Branke, Julian Molina, Roman Słowiński)
10.30-10.45	Questions and discussion
10.45-11.00	Coffee break
11.00-11.45	*Keynote Talk* – **User preferences in EMO: what can be learned from preference elicitation?** (Vincent Mousseau)
11.45-12.00	Questions and discussion
12.15-13.15	Lunch
13.15-13.45	Contributed Talk – **Modelling bipolar interactions in robust ordinal regression: the UTA GSS method** (Salvatore Greco, Johannes Siebert, Roman Słowiński) (20min talk + 10 min questions and discussion)
13.45-14.15	Contributed Talk – **Pareto Navigator: Learning-Oriented Method for Interactive Multiobjective Optimization** (Jussi Hakanen, Kathrin Klamroth, Kaisa Miettinen, Vesa Ojalehto) (20 + 10min)
14.15-15.30	Participants to suggest questions as topics for working groups
15.30-16.00	Coffee break
16.00-17.00	Discussion of proposed questions and arrangement of participants into working groups
17.00-18.00	First meeting of discussion/working groups.
18.00-19.00	Dinner

Tuesday 24th January (Theme: User Preferences)	
7.30-8.45	Breakfast
8.45-9.15	Contributed Talk – **Can a Linear Value Function Explain Choices? An Experimental Study** (Pekka Korhonen, Kari Silvennoinen, Jyrki Wallenius and Anssi Öörni) (20 + 10min)
09.15-10.00	*Keynote Talk* – **Cynefin: Problem Formulation and Uncertainty** (Simon French)
10.00-10.15	Questions and discussion
10.15-10.45	Coffee break
10.45-11.15	Contributed Talk – **A General Framework for Integrating User Preferences With Evolutionary Multiobjective Optimization – Towards Making the Weighted Hypervolume Approach User-Friendly** (Dimo Brockhoff) (20 + 10min)
11.15-11.45	Contributed Talk – **Optimization in Logistics from a Learning Perspective: The Case of the Multi-Objective Vehicle Routing Problem** (Martin J Geiger) (20 + 10min)
11.45-12.15	Contributed Talk – **Extreme ranking analysis and rank related requirements in multiple objective optimization** (Milosz Kadzinski, Salvatore Greco and Roman Słowiński) (20 + 10min)
12.15-13.45	Lunch
13.45-14.15	Contributed Talk – **Risk and Return in Multiobjective Optimization** (Carlos Fonseca, Iryna Yevseyeva and Michael Emmerich) (20 + 10min)
14.15-14.45	Contributed Talk – **Approximation Factor as the Aim of Multiobjective Optimization and the Hypervolume Indicator** (Tobias Friedrich) (20 + 10min)
14.45-18.00	Second meeting of working groups (includes coffee break)
18.00-19.00	Dinner

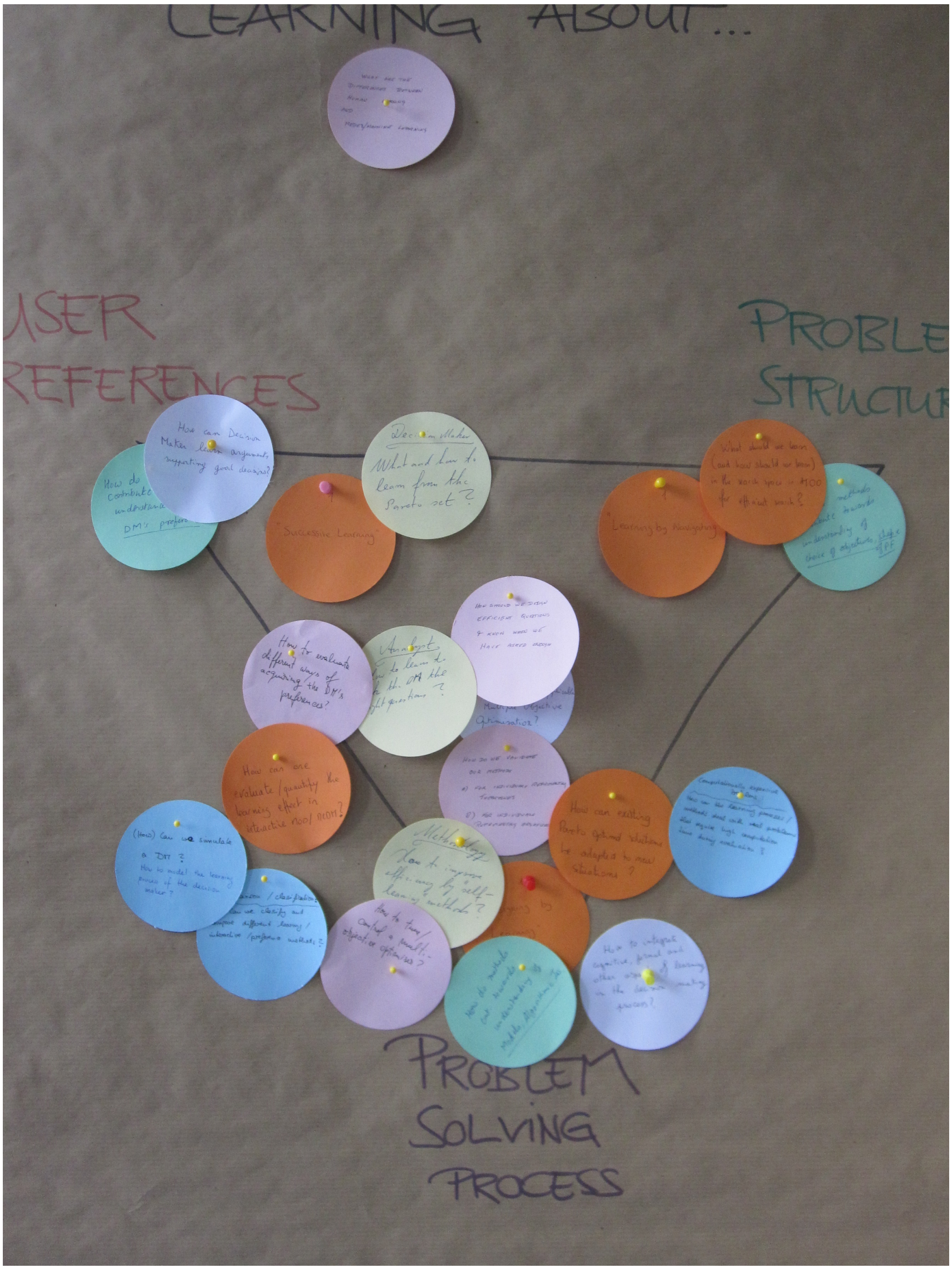
Wednesday 25th January (Theme: Problem Understanding)	
7.30-8.45	Breakfast
8.45-9.15	Contributed Talk – **Learning from Pareto-Front Approximations of Real-World Optimization Problems — A Clustering Approach** (Tamara Ulrich) (20+10min)
09.15-10.00	*Keynote Talk* – **Innovization: Learning Problem Knowledge Through MultiObjective Optmization** (Kalyanmoy Deb)
10.00-10.15	Questions and discussion
10.15-10.45	Contributed Talk – **Adapting MOEAs to solve practical complex engineering problems** (António Gaspar-Cunha, José Carlos Ferreira, Carlos M. Fonseca, José A. Covas) (20min talk + 10 min questions and discussion)
10.45-11.00	Coffee break
11.00-11.30	Contributed Talk – **Simulation-Based Innovization using Data Mining and Visual Analytics for Production Systems Analysis** (Amos HC Ng) (20 + 10min)
11.30-12.00	Contributed Talk – **Problem Understanding with Data Mining of Pareto-Optimal Designs in Space Engineering** (Akira Oyama) (20 + 10min)
12.15-13.15	Lunch
13.30	Group photo outdoors
	Excursion (Hike)
18.00-19.00	Dinner
19.30-20.30	Summaries of Working Group Discussions and Next Steps

Thursday 26th January (Theme: The Problem Solving Process)	
7.30-8.45	Breakfast
8.45-9.15	Contributed Talk – **Learning Tradeoffs in Multiobjective Optimization: A Cone-based Approach** (Margaret M Wiecek) (20 + 10min)
09.15-10.00	*Keynote Talk* – **Hybrid Evolutionary Multi-Objective Optimization: Different Interaction Styles and an Approach** (Jyrki Wallenius)
10.00-10.15	Questions and discussion
10.15-10.45	Contributed Talk – **Offline Automatic Configuration in Multi-Objective Optimization** (Manuel López-Ibánez and Thomas Stützle) (20 + 10 min)
10.45-11.00	Coffee break
11.00-11.30	Contributed Talk – **Problem solving process in engineering applications: multiobjective optimization and user preferences** (Silvia Poles) (20 + 10min)
11.30-12.00	Contributed Talk – **Multiobjective optimization in self-optimizing systems and applications** (Katrin Witting) (20+10min)
12.15-13.15	Lunch
13.30-18.00	Working groups (includes coffee break)
18.00-19.00	Dinner
20.00	Wine and Cheese Event (Music Room)

Friday 27th January (Wrap-Up))	
7.30-8.45	Breakfast
8.45-10.15	Working Group Presentations
10.15-10.30	Coffee
10.30-12.00	Whole Group Discussion and Wrap-Up
12.15-13.15	Lunch and goodbye

6 Topics emerging from discussions in working groups on Day One

Photograph of the topics returned from the randomized groups.



7 Changes in the seminar organization body

7.1 Kaisa Miettinen steps down as co-organizer

On behalf of all the participants of the seminar, SG, JK and EZ would like to extend our warm thanks to Kaisa Miettinen for her contributions to this Dagstuhl seminar series on Multiobjective Optimization as she steps down from the role of co-organizer, which she has held since the first seminar in this series in 2004.

Kaisa has been a keystone of the Series and we will all miss her being on the team. She has worked tirelessly to make the Seminars work on an organizational level, and has always engaged actively in pursuit of high scientific goals. She has also reflected wonderfully the mood and thoughts of the participants in many group discussions (often with an observation or word that has united us in laughter too).

7.2 Eckart Zitzler leaves us for pastures new – Pedagogy in Bern

On behalf of all the participants of the seminar, SG, JK and KM would like to extend our warm thanks to Eckart Zitzler for his contributions to this Dagstuhl seminar series on Multiobjective Optimization as he steps down from the role of co-organizer, which he has held for two terms of office.

Eckart has used all his considerable knowledge and skills to ensure the Seminars are scientifically strong and very well-organized. During Seminar weeks he has played a very central role both in leading and facilitating discussions, always with enviable ease and good humour.

Eckart will leave us in a more fundamental way too, as he explained to the floor during the Seminar. He is now working in a new academic role and direction in his career as a Professor of Pedagogy at PHBern — University of Teacher Education, and has now ceased activities in optimization research. We all wish him the best in this new venture and thank him for his great contributions to our field of study. It is no exaggeration to state that Eckart's research — and that of his collaborators — has shaped much of the landscape in evolutionary multiobjective optimization over the last dozen or more years. He has made very significant contributions to both theory and practice, which we're sure will prove of enduring worth, he has built bridges between communities, and he has nurtured a very large number of young researchers to success.

Ecki, we all wish you well in your new work and position, and hope that you will find the time to join us again at Dagstuhl in the future.

7.3 Welcome to Kathrin Klamroth and Günter Rudolph

Finally, joining the organizing team for next time, the current organizers wish to welcome our esteemed colleagues, Kathrin Klamroth and Günter Rudolph.

Participants

- Richard Allmendinger
University College London, GB
- Anne Auger
INRIA Saclay – Orsay, FR
- Jürgen Branke
University of Warwick, GB
- Heinrich Braun
DHBW – Karlsruhe, DE
- Dimo Brockhoff
INRIA Nord Europe – Lille, FR
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- Matthias Ehrgott
University of Auckland, NZ
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- Kaisa Miettinen
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