SUMMARY OF PROFESSIONAL ACCOMPLISHMENTS

Methodology for computer-aided decision making
based on varied types of indirect preference information
and comprehensive robustness analysis

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I. FIRST AND LAST NAME

Miłosz Kadziński

II. SCIENTIFIC DEGREES

1. **PhD degree in technical sciences** - Poznan University of Technology, Faculty of Computing; discipline - computer science; specialization - computer-aided decision support:
   - awarded on: December 18, 2012;
   - thesis**:** "New Directions in Robustness Analysis and Preference Modeling in Multiple Criteria Decision Aiding";
   - advisor: Professor Roman Słowiński.
2. **Master degree in computer science** - Poznan University of Technology, Faculty of Computing; specialization - intelligent decision support systems:
   - awarded on: September 28, 2008;
   - thesis: "Decision Support System for Multiple Criteria Sorting of Actions Based on Ordinal Regression Principle";
   - advisor: Professor Roman Słowiński.
3. **Bachelor degree in computer science** - Poznan University of Technology, Faculty of Computing and Management:
   - awarded on: February 13, 2007;
   - thesis: "Task Management System for Mobile Devices";
   - advisor: Ewa Łukasik, PhD.

III. EMPLOYMENT IN ACADEMIC INSTITUTIONS

1. **Lecturer**
   - Institute of Computing Science, Faculty of Computing, Poznan University of Technology;
   - period: October 1, 2010 - September 30, 2011.
2. **Research-and-teaching assistant**
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3. **Assistant professor**
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   - period: since March 1, 2013.
4. **Research visits**
   - Cork Constraint Computation Centre, University College Cork, Cork, Ireland; April 2009; participant of the Doctoral School on Decision Theoretic Artificial Intelligence;
   - INESC Coimbra, University of Coimbra, Coimbra, Portugal, April 2010; Short Term Scientific Mission within the scope of COST Action IC0602 (host: Professor Luis Dias);
   - Instituto Superior Tecnico, Technical University of Lisbon, Lisbon, Portugal, April 2010; participant of the Doctoral School on Computational Social Choice;
   - Laboratoire de Génie Industriel, Ecole Centrale Paris, Paris, France; June-July 2010; research visit combined with the participation in the 10th Multiple Criteria Decision Aiding/Making Summer School 2010 (host: Professor Vincent Mousseau);

- Erasmus Research Institute of Management, Erasmus University, Rotterdam, The Netherlands; January 2013; research visit (host: Tommi Tervonen, PhD);
- Dipartimento di Economia e Impresa, University of Catania, Catania, Italy; October 2013; research visit combined with the participation in a scientific conference (host: Professor Salvatore Greco);
- Dipartimento di Scienze Agrarie, University of Perugia, Perugia, Italy; May 2014; lecturer at the 1st Spring School on Multiple Criteria Decision Aiding;
- LUSSI, Telecom Bretagne, Brest, France; October 2014; research visit combined with the participation in a scientific conference (host: Patrick Meyer, PhD);
- Center for Decision Systems and Information Development, Universidade Federal de Pernambuco, Recife, Pernambuco, Brazil; July 2016; lecturer at the 12th Multiple Criteria Decision Aiding/Making Summer School.

IV. SCIENTIFIC ACCOMPLISHMENT

A. TITLE OF THE SCIENTIFIC ACCOMPLISHMENT

Methodology for computer-aided decision making based on varied types of indirect preference information and comprehensive robustness analysis

B. SERIES OF SCIENTIFIC PAPERS

[P1] M. Kadziński, T. Tervonen, Stochastic ordinal regression for multiple criteria sorting problems. *Decision Support Systems*, 55(1):55-66, 2013.

[P2] M. Kadziński, T. Tervonen, Robust multi-criteria ranking with additive value models and holistic pair-wise preference statements. *European Journal of Operational Research*, 228(1):169-180, 2013.

[P3] S. Corrente, S. Greco, M. Kadziński, R. Słowiński. Robust ordinal regression in preference learning and ranking. *Machine Learning*, 93(2-3):381-422, 2013.

[P4] M. Kadziński, S. Greco, R. Słowiński, Robust Ordinal Regression for Dominance-based Rough Set Approach to multiple criteria sorting. *Information Sciences,* 283:211-228, 2014.

[P5] M. Kadziński, S. Corrente, S. Greco, R. Słowiński, Preferential reducts and constructs in robust multiple criteria ranking and sorting. *OR Spectrum*, 36(4):1021-1053, 2014.

[P6] M. Kadziński, K. Ciomek, R. Słowiński, Modeling assignment-based pairwise comparisons within integrated framework for value-driven multiple criteria sorting. *European Journal of Operational Research*, 241(3):830-841, 2015.

[P7] M. Kadziński, R. Słowiński, Parametric evaluation of research units with respect to reference profiles. *Decision Support Systems*, 72:33-43, 2015.

[P8] M. Kadziński, T. Tervonen, J. Figueira, Robust multi-criteria sorting with the outranking preference model and characteristic profiles. *Omega*, 55:126-140, 2015.

[P9] M. Kadziński, R. Słowiński, S. Greco, Multiple Criteria Ranking and Choice with All Compatible Minimal-cover Sets of Decision Rules. *Knowledge-Based Systems*, 89:569-583, 2015.

[P10] M. Kadziński, K. Ciomek, P. Rychły, R. Słowiński, Post factum analysis in robust multiple criteria ranking and sorting. *Journal of Global Optimization*, 65(3):521-562, 2016.

[P11] M. Kadziński, M. Michalski, Scoring procedures for multiple criteria decision aiding with robust and stochastic ordinal regression. *Computers & Operations Research*, 71:54-70, 2016.

[P12] M. Kadziński, K. Ciomek, Integrated framework for preference modeling and robustness analysis for outranking-based multiple criteria sorting with ELECTRE and PROMETHEE. *Information Sciences*, 352:167-187, 2016.

C. Description of the scientific goal of the above mentioned papers, obtained results and prospects of applications

The presented series of papers concerns computer-aided decision making. The essence of this sub-field of computer science consists in developing the tools which support the analysis of complex decision problems involving a set of alternatives evaluated in terms of multiple criteria [Bel02]. The diversity and conflicting character of the pertinent factors that affect a decision imply that usually there is no single objectively best solution. As a result, the role of decision support methods is to deliver a recommendation on how to make a new decision under specific circumstances, while ensuring its consistency with the value system of the stakeholders involved in a decision process.

Multiple criteria decision aiding (MCDA) is one of the most important and fastest developing disciplines within computer science. It is so, because the need for processing data to conclusions that may be useful in decision making is valid in such various domains as economy, education, management, medicine, transport, engineering, or environmental science [Gre06]. Taking into account the way alternatives are perceived during analysis, and the type of expected results, we distinguish three major types of multiple criteria problems [Roy96] (see Figure 1):

- *ranking* the alternatives from the best to the worst; e.g., the well-known international rankings concern world competitiveness, corruption perception, and quality of life;
- *choice* of a subset of the best alternatives; e.g., selecting a new fleet by a company offering passenger tours or granting a scholarship to several distinctive students;
- *sorting* alternatives into pre-defined classes (categories) which are given in a preference order, e.g., countries may be assigned to different classes based on their reliability to repay debts, while patients are often classified with respect to the degree of severity of their illness.

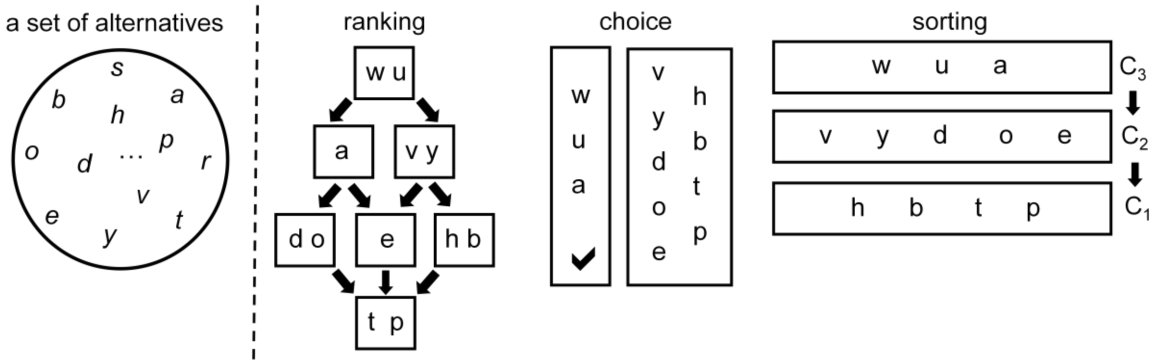

Fig. 1. Major types of multiple criteria problems.

A recommendation that is produced in the course of a decision aiding process derives from some cognitive activities aiming at exploring, interpreting, and debating about a particular ranking, choice, or sorting problem. In general, there are three main components of each decision aiding method. These are responsible for, respectively, querying the decision maker (DM) for suitable inputs, constructing and exploiting a mathematical preference model that is used to represent the DM's preferences and to generate numerical outcomes, and interpreting the results by means of dedicated explanations. All these components decide upon DM's acceptance of both the method and the recommendation arrived with its use. Thus, when designing new decision aiding approaches, one pays great attention to both preference modeling and analysis of robustness of the delivered recommendation.

Preference modeling is about representing subjective statements of the DM in terms of some technical parameters of the assumed preference model. The experience from using decision aiding methods indicates that providing precise values of such parameters or direct specification of the model's form is too demanding in terms of the cognitive effort for most DMs [Gre08]. Thus, more and more focus is being put on incorporating indirect, incomplete and imprecise preference information in decision aiding. In particular, *ordinal regression* (or preference disaggregation) [Jac01] methods are prevailing. These construct preference model instances which are compatible with the DM's preferences in form of some exemplary holistic decisions concerning a small subset of reference *alternatives* or desired requirements that the final results should satisfy. The psychologists confirm that DMs are used to providing preference information in such intuitive forms, which are consistent with their experience and knowledge.

Accounting for preferences affected by such natural imperfections results in the ambiguous definition of a preference model, i.e. existence of multiple model instances compatible with the DM's preferences. The conclusions that can de derived from applying each of these instances on the set of alternatives may differ substantially. As a result, the recommendation strongly depends on which particular instance would be selected for its delivery. This brings about the need for conducting *robustness analysis* [Roy10b], i.e. examination of the ambiguity in representing the DM's preferences on the stability of the recommendation. This approach contrasts with the traditional MCDA methods, which apply some arbitrary rules for selection of a single compatible instance of the preference model, while neglecting all remaining instances compatible with the indirect, incomplete and imprecise preferences.

The series of papers establishes a methodology for computer-aided decision making based on varied types of indirect preference information and comprehensive robustness analysis. The methodology combines in an original way the elements of algorithmic decision theory, artificial intelligence, mathematical modeling, and computer simulations.

The proposed preference elicitation procedures allow to account for different forms of indirect, incomplete and imprecise preference information that have not received due attention in MCDA. The methods for robustness analysis use linear programming (LP) and Monte Carlo simulations to construct necessary, probabilistic, possible, extreme, representative, and univocal results. These represent different levels of certainty with respect to the elements of a recommended decision. Their analysis stimulates the DM to interactively enrich her/his preference information, while the trust in the arrived recommendation is enhanced by the dedicated explanations and investigating consequences of modifying the alternatives' performances. The proposed methods employ various preference models such as an additive value function, an outranking relation, or a set of decision rules. The practical usefulness of the proposed methods has been illustrated with the studies in domains of environmental science, education, economy, and political science.

The main scientific contribution of the presented series of papers will be discussed while grouping the proposed methods and obtained research results into the following nine parts:

- [H1] Robust ordinal regression for multiple criteria sorting based on varied types of indirect preference information and comprehensive robustness analysis with value- and outranking-based preference models [P6, P12].
- [H2] Robust ordinal regression for multiple criteria ranking and choice based on varied types of indirect preference information and comprehensive robustness analysis with a value-based preference model [P3].
- [H3] Stochastic ordinal regression for multiple criteria ranking and sorting with a value-based preference model [P1, P2].
- [H4] Robustness analysis with all minimal-cover sets of rules compatible with the decision maker's holistic preferences for multiple criteria ranking, choice, and sorting [P4, P9].

[H5] Selection of a representative preference model instance emphasizing the outcomes of stochastic robustness analysis [P1, P2, P4, P9].

[H6] Construction of a univocal recommendation by exploiting the outcomes of robustness analysis [P11].

[H7] Robust decision aiding with boundary and characteristic class profiles [P7, P8].

[H8] Explanations of the recommended decision in view of the holistic indirect preference information provided by the decision maker [P5].

[H9] Identifying modifications of the alternative's performances that allow achieving or maintaining some target result [P10].

H1. Robust ordinal regression for multiple criteria sorting based on varied types of indirect preference information and comprehensive robustness analysis with value- and outranking-based preference models

The type of admitted preference information and elements of responses obtained by the DMs have a great impact on the consistency between value system of the stakeholders, the evolution of the decision process and recommendation of a specific decision. Nowadays, the types of admitted preference information, models, procedures, and provided results are more often perceived as a communication and reflection tool. In this spirit, the recent trend in MCDA consists in accounting for types of preference information which have not received due attention in the formal methods, as well as conducting diversified robustness analysis for the delivered results. The previous increases the flexibility of the interactive procedure, which is related to the capacity of incorporating any preference information coming from the DM. The latter aims at increasing the range of tools that can be used for looking more thoroughly into the problem, by exploring, interpreting, or testing scenarios.

In [P6] and [P12], one has established new multiple criteria sorting methods, which construct a set of compatible preference model instances while accounting for the following three types of indirect preference information:

- *possibly imprecise assignment examples* for a subset of reference alternatives (*e.g.,* alternative *a* should be assigned to the *best* class; alternative *b* should not be assigned to the *worst* class);
- *assignment-based pairwise comparisons* for reference alternatives (e.g., alternative *a* should be assigned to a class at least as good as class of alternative *b*; there is a difference of at least two classes between alternatives *c* and *d*; alternative *e* is better than alternative *f* by at most one class; alternatives *g* and *h* represent the same class);
- *imprecise desired class cardinalities* (e.g., we wish to accept at most 10 candidates; we need to reject at least 30 applications).

Although such requirements are often formulated in practical decision situations, the state-of-the-art MCDA methods either had not admitted the above mentioned types of preference information or had not accepted preferences in so varied forms [Gre10, Kok09].

On one hand, in [P6] one has employed the sorting procedures which incorporate a preference model in form of an additive value function [Kee76, Zop02]. These additionally account for other types of preference information concerning, e.g., the shape of the marginal value functions (e.g., concavity or convexity) and newly introduced desired comprehensive values of alternatives assigned to a given class or class range (e.g., alternatives assigned to class at most *medium* should have value not greater than 0.4 or the difference of values between alternatives assigned to class *good* and *bad* should be at least 0.7). On the other hand, in [P12] one has focused on multiple criteria sorting with outranking-based preference model [Bra86, Roy90], admitting some imprecise constraints on criteria weight or a majority threshold. Accounting for all these preference statements, one provides the most flexible sorting methods that incorporate a wide spectrum of indirect, incomplete and imprecise preference information coming from the DM.

Obviously, the ultimate goal of using such preference information consists in applying the inferred compatible preference model on the whole set of alternatives. In this perspective, one has proposed a framework for deriving a variety of results with Mixed-Integer Linear Programming (MILP). The introduced mathematical models account for the specificity of:

- sorting procedures with class boundaries defined either by the thresholds on the scale of a comprehensive value [Zop02] or explicitly by the assignment examples [Gre10];
- preference models typical for the families of Utadis [Zop02], Electre [Gov16], and Promethee [Beh10] methods.

Additionally, in [P12] one has proposed a more general procedure which can be used with all models and methods that provide precise assignments for the alternatives.

Taking into account indirect preference information results in the ambiguous definition of a model, i.e., existence of its multiple instances compatible with the DM's preferences. To exploit a set of all compatible preference model instances, one has proposed mathematical programming models which derive the following robust outcomes [P6, P12]:

- *necessary and possible assignments* which need to be confirmed by, respectively, all or at least one compatible preference model instance (e.g., alternative *a* is always (necessarily) assigned to class *good*; the possible evaluation of alternative *b* as *bad* or *medium* depends on the selected model instance);
- *necessary and possible assignment-based preference relations* which indicate for all pairs of alternatives if one of them is assigned to a class at least as good as the other for all or at least one compatible model instance, respectively (e.g., alternative *c* is always assigned to a class at least as good as alternative *d*; alternative *e* is assigned to a class better than alternative *f* for at least one compatible model instance);
- *extreme class cardinalities*, i.e., the maximal and minimal numbers of alternatives which are simultaneously assigned to a given class for some compatible model instance (e.g., at least 5 and at most 10 alternatives are assigned to class *medium*).

These outputs offer three different perspectives on the robustness of the arrived recommendation concerning individual alternatives, pairs of alternatives and decision classes. Additionally, they contribute to the input-output correspondence with respect to these perspectives, which is important for at least two reasons.

Firstly, the preference information of each type is reproduced in the respective outcome. In this way, the DM may observe the impact of her/his preferences on the sorting recommendation concerning the whole set of alternatives (in case of assignments), all pairs of alternatives (in case of assignment-based preference relations), and all classes (in case of extreme class cardinalities). For example, if (s)he required that between 3 and 5 alternatives should be assigned to the *best* class, then the observed extreme class cardinalities would confirm that indeed there are at least 3 and at most 5 alternatives simultaneously placed in this class. Further, the assignment of some reference alternative to a class at least *medium* would be respected by the computed possible assignment, i.e., its range would certainly not be wider.

Secondly, by exhibiting three types of results the DM can be encouraged to add some exemplary decisions or requirements that lead to a final recommendation. For example, having analyzed the possible assignments, (s)he may judge that some of them are too wide and supply less ambiguous assignment examples in the next iteration. Having analyzed the necessary assignment-based preference relation, the DM may supply preference information that is missing in it, that is analyze pairs of alternatives for which the order of classes depends on the compatible model instance and make them more comparable. Finally, (s)he may view the extreme class cardinalities and wish to make the desired cardinalities more precise. By exhibiting such different sorting results, one forces the DM to confront her/his value system with the results of applying the inferred model. This leads her/him to gaining insights about her/his preferences, providing reactions in the subsequent iteration, as well as to better understanding of the employed approach.

From the practical point of view, the interactive enrichment of preference information contributes to the contraction of the space of all compatible preference model instances, which, in turn, increases the robustness of the suggested recommendation. In [P6], one has formulated a theorem which summarizes the evolution of the robust results with the growth of preference information. In particular, the ranges of possible assignments and class cardinalities can become narrower, whereas the necessary and possible assignment-based preference relations are, respectively, enriched or impoverished. The main steps of the proposed multiple criteria sorting methods are provided in Figure 2.

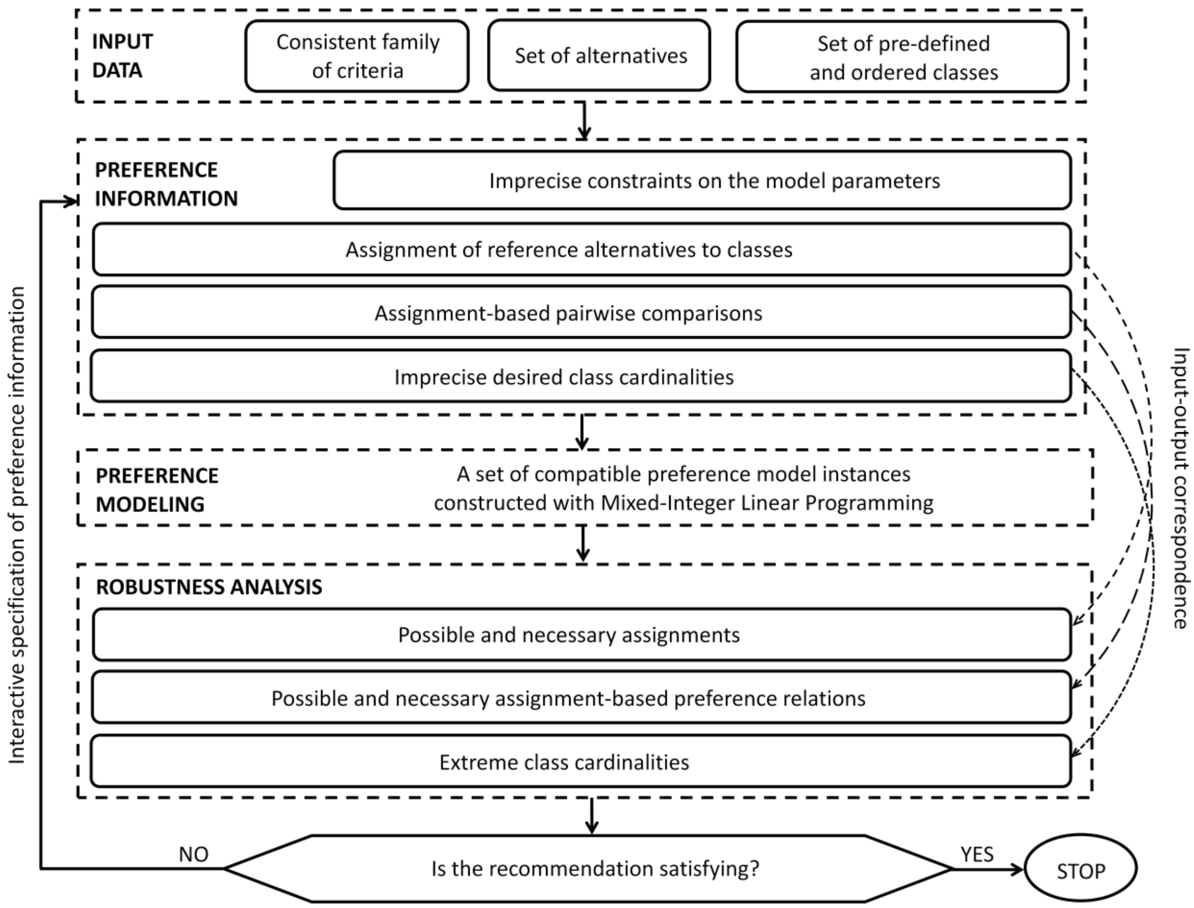

Fig. 2. Decision aiding process with the proposed robust ordinal regression methods for multiple criteria sorting.

The practical usefulness of the proposed methods has been illustrated by applying them to the problems of evaluating either cities in terms of liveability [P6] or research units with respect to the acquired effects and activities undertook in the evaluation period [P12].

H2. Robust ordinal regression for multiple criteria ranking and choice based on varied types of indirect preference information and comprehensive robustness analysis with a value-based preference model

The aim of ordinal regression methods is to learn (i.e., to faithfully reconstruct) the DM's preferences by the preference model. The results of an application of such model on the set of alternatives can be also used by the DM to learn about her/his preferences (i.e., to assess and understand preferences on the considered set of alternatives) [Roy10a]. Such *mutual learning of the model and the DM* is peculiar to the methods proposed in the presented series of papers. Its nature is iterative, i.e., the learning should be continued until the DM judges the suggested recommendation as convincing and decisive enough, and (s)he is satisfied with the correspondence between the output of the preference model and the preferences that (s)he has at the moment.

Such constructive approach to decision aiding has been discussed in detail in [P3] with the proposed robust ordinal regression method for multiple criteria ranking and choice. It incorporates a preference model in form of an additive value function. This approach accepts varied forms of indirect preference information and offers a wide spectrum of robust results. The construction of a set of compatible value functions is based on the following four types of indirect, incomplete and imprecise preference information:

- *pairwise comparisons* for a subset of reference alternatives (e.g., alternative *a* is preferred to alternative *b*; alternatives *c* and *d* are indifferent);
- *comparison of intensities of preference* for different pairs of reference alternatives (e.g., the intensity of preference of alternative *e* over alternative *f* is greater than for the comparison of alternatives *g* and *h*);
- *imprecise rank-related requirements* (e.g., alternative *i* should be ranked in the *top 5*; alternative *j* should be placed in the *lower half of the ranking*);
- *constraints on the comprehensive values* attained by the reference alternatives (e.g., comprehensive value of alternative *k* should be greater than 0.7).

Accepting such exemplary decisions and requirements on the desired results allows to avoid direct specification of the parameters related to the value function such as criteria weights or the range of variation of piecewise linear marginal value functions. It is so, because in the proposed method a set of compatible value functions is constructed in an indirect way.

A comprehensive analysis in view of robustness of the recommendation that can be arrived with all inferred functions leads to the following four outcomes:

- *necessary and possible preference relations* and *intensities of preference* for, respectively, pairs and quadruples of alternatives (e.g., alternative *a* is preferred to alternative *b* for at least one compatible value function; alternative *c* is preferred to alternative *d* at least as much as *e* to *f* for all compatible value functions);
- *extreme ranks* and *extreme comprehensive values* attained by each alternative in the set of compatible value functions (e.g., alternative *g* is ranked third and sixth in the most and the least advantageous cases, respectively; the comprehensive values observed for alternative *h* in the set of all compatible functions are within the range [0.4, 0.7]).

In the proposed method, the DM's preferences and derived results may be holistic, i.e., referring to all relevant points of view jointly, or limited to a subset of criteria in their hierarchical structure. Note that the analysis of such comprehensive results enables the DM to establish the preferences that previously had not pre-existed in her/his mind, to accept the recommendation, and to appropriately use it.

In [P3], one has proposed the mathematical programming models which allow to jointly represent all above mentioned types of preference information as well as to conduct multidimensional robustness analysis. Both preference modeling and computation of the outcomes concerning pairwise preference relations, intensities of preference and alternatives' comprehensive values are based on *linear programming*. In case of rank-related preferences and results, one needs to additionally incorporate *binary variables* into the models

When introducing the method presented in [P3], special attention has been paid to formalizing the relations between the preferences provided by the DM and the outcomes of robustness analysis as well as to the presentation of the evolution of results with incremental specification of preference information. These issues are essential in the context of a postulated paradigm of mutual learning of the model and the DM. The main steps of the proposed robust ordinal regression for multiple criteria ranking are presented in Figure 3. Its practical usefulness has been illustrated with the study concerning evaluation of innovation in European countries.

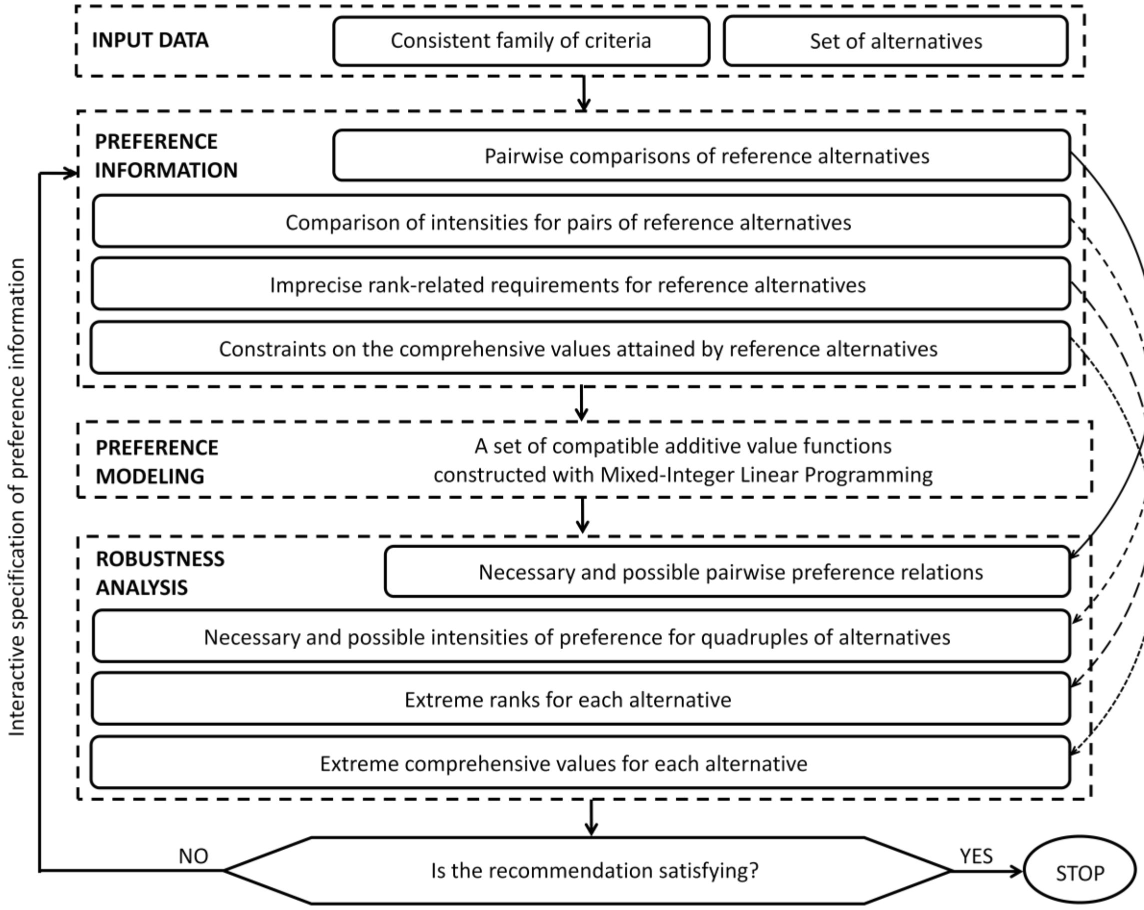

Fig. 3. Decision aiding process with the proposed robust ordinal regression method for multiple criteria ranking.

While taking the specific interpretation of the concept of *preference learning* as a starting point, [P3] offers also a comprehensive comparison between the disciplines of MCDA and Machine Learning [Fur10]. This comparison concerns a few dozens of issues such as a structure of the considered problems, a role of the DM or user, types of admitted preference information, a character of the employed preference models, procedures for its construction, techniques to arrive at a final recommendation, interpretation of the concept of robustness, tolerating inconsistencies and risk of erroneous decisions, and ways of comparing different methods.

H3. Stochastic ordinal regression for multiple criteria ranking and sorting with a value-based preference model

Robust ordinal regression contrasts with the traditional MCDA methods which arbitrarily select a single preference model instance compatible with the DM's preference information [Jac01]. Exploiting a set of all such instances, it delivers the results deemed as necessary (i.e., confirmed by all compatible instances), possible (i.e., confirmed by at least one compatible instance), or extreme (i.e., the most and the least advantageous for each alternative or class). These outcomes are constructed by solving some dedicated mathematical programming problems. However, in practice, when the set of all compatible preference model instances is large, the robustness of the delivered results can be low. In this case, the necessary relation leaves many pairs of alternatives incomparable, the possible class assignments are imprecise, while the difference between extreme ranks is great.

Thus, robust ordinal regression is useful to provide information on which particular outcomes occur with all, some, or no compatible preference model instances. However, it is not appropriate for estimating the probability of the results which are possible though not necessary. To allow this, in the presented series of papers one has proposed *stochastic original regression* methods for multiple criteria ranking [P2] and sorting [P1]. These methods vastly extend the well-known Stochastic Multi-criteria Acceptability Analysis [Lah01]. Although the introduced approaches have been originally designed for dealing with the basic forms of incomplete preference information (i.e., pairwise comparisons [P2] or assignment examples [P1]) and a preference model in form of an additive value function, they can be easily adapted to other types of preferences and models.

The essence of stochastic ordinal regression consists in using Monte Carlo simulations for estimating the probability of different outcomes based on the sufficiently numerous sample of all compatible preference model instances. In [P1] and [P2], one has provided algorithms for rejection-sampling a set of value functions.

The outcomes of stochastic ordinal regression for multiple criteria ranking are materialized with the acceptability indices for each alternative either attaining a particular rank or being weakly preferred to another alternative. These are called, respectively, rank and pairwise outranking acceptability indices. Instead, for multiple criteria sorting one computes the acceptability indices either for the class assignments or for one alternative being assigned to a class at least as good as other alternative. Formally, the value of each acceptability index indicates the share of all compatible preference model instances that confirm a particular result. Thus, such stochastic results allow to answer how probable it is for an alternative to be preferred over another, what are the most likely ranks an alternative can attain, or what is the probability that an alternative is assigned to its best or worst possible class. Such conclusions support the indication of the parts of recommendation which are more robust and these being sensitive for small changes in DM's preferences

Although the acceptability indices can be estimated to within acceptable error bounds [Ter07], they are not accurate. Therefore, estimated indices of 0% or 100% cannot be regarded with certainty, because they, respectively, do not exclude the possibility and do not confirm the necessity of some result. Thus, in the presented series of papers one recommends to analyze the estimations of these stochastic indices in the context of necessary, possible, and extreme results.

In [P1] and [P2], one has clearly defined all interrelations between the outcomes of robust and stochastic ordinal regression, emphasizing their complementarity (for its intuitive illustration in terms of the results typical for ranking problems, see Figure 4). One has also discussed the impact of the holistic preference statements on the robust outcomes arrived with both linear programming and Monte Carlo simulations. An additional contribution of [P2] is a proof of theorem on no jumps in the range of possible ranks attained by each alternative in the set of additive value functions compatible with the DM's pairwise comparisons. It is based on the observation that such set of functions is convex. The practical usefulness of stochastic ordinal regression has been illustrated with the studies concerning ranking European countries based on the quality of their universities [P2] and assigning Asian countries to different types of democracy regimes [P1].

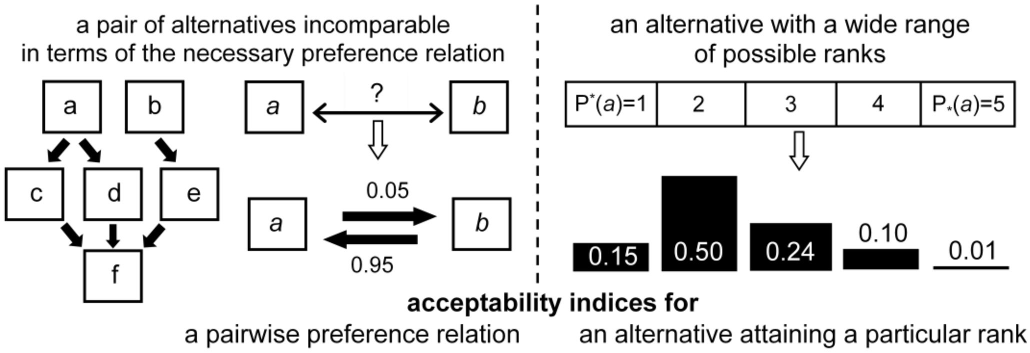

Fig. 4. An example of the complementarity of the results
derived from robust and stochastic ordinal regression for multiple criteria ranking.

H4. Robustness analysis with all minimal-cover sets of rules compatible with the decision maker's holistic preferences for multiple criteria ranking, choice, and sorting

Robustness analysis is one of the most prevailing trends in MCDA. It is so, because it allows to establish the level of certainty of the arrived recommendation, which is essential for its acceptance and implementation. Such concerns have been first raised in view of the functional [Gre08] and relational [Gre11] preference models. When it comes to the use of decision rules, the recommendation has been usually derived from a single minimal set of rules representing the exemplary holistic judgments in the most concise way (i.e., without any redundant statements) or a limited subset of these sets to be integrated within an ensemble [Bla10, Bla11, Ste01]. Obviously, such a choice is either arbitrary or requires involvement of the DM, which is not easy for most of them. This is particularly true if DM's expectations need to be specified prior to the rule induction.

To address these problems, in the presented series of papers one has proposed *robust ordinal regression using decision rules*. The method has been adapted to deal with multiple criteria ranking and choice [P9], or sorting [P4]. It takes into account all minimal-cover sets of minimal decision rules compatible with the DM's preferences and verifies the consequences of their use on the set of alternatives. In particular, one employs preference information in form of holistic exemplary decisions, i.e., possibly imprecise class assignments for sorting problems or pairwise comparisons related to the truth of outranking or non-outranking relation in view of ranking and choice.

When using a preference model in form of an additive value function or an outranking relation, all compatible model instances are defined with a set of linear constraints. To derive the necessary, possible, and extreme results, this set is exploited by solving dedicated mathematical programming problems. The peculiarity of decision rules implies that all minimal-cover sets of rules need to be discovered explicitly.

The algorithms for inducing all these sets that have been discussed in [P4] and [P9] are composed of four main steps. These are presented in Figure 5. At different stages they incorporate suitably adapted or extended: Dominance-based Rough Set Approach [Slo12], an algorithm for inducing an exhaustive set of minimal rules for some lower or upper approximation of a given class union or preference relation, and an algorithm for constructing all minimal-cover sets of rules for some union or relation which is based on an analogy to solving the minimal-cover set problem [Vaz01].

Each compatible set of rules is individually applied to derive a recommendation, and the role of robustness analysis is just to aggregate the results obtained with all such sets of rules. When dealing with ranking problems, the robust results are materialized with the necessary and possible outranking relations, extreme ranks, and respective acceptability indices [P9]. One has also proposed the procedures for exploitation of the preference structure imposed by the necessary or stochastic relations. These order the alternatives from the best to the worst based on their net flow scores. At this stage, one has accounted for either a two valued logic with outranking and non-outranking relation or a four valued logic with true, false, unknown, and contradictory outranking.

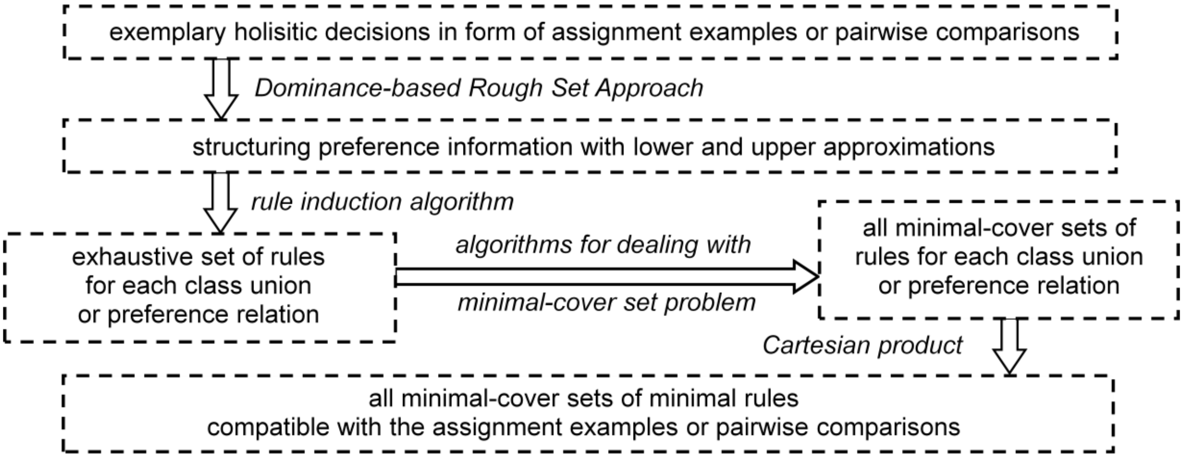

Fig. 5. Algorithm for generating all minimal-cover sets of minimal rules.

As far as sorting problems are concerned, the necessary, possible and extreme results as well as acceptability indices concern class assignments [P4], but they can be also considered in the context of assignment-based preference relation and class cardinalities. Some further added value of the papers derives from:

- definition of the concept of decisive rule which contributes to the recommendation delivered for a given alternative for the greatest share of compatible sets of rules [P4];
- illustration of the practical usefulness of the proposed methods with studies concerning risk assessment of zoning the watershed in Low Normandy [P4] and ranking Polish cities according to their innovativeness [P9].

H5. Selection of a representative preference model instance emphasizing the outcomes of stochastic robustness analysis

The majority of MCDA methods implementing the paradigm of preference disaggregation select a single compatible instance of the preference model. Its role is to approximate the "true" parameter vector of the DM [Beu01, Jac01]. Such representative instance is usually selected with some mathematical programming techniques that find the instance deemed as "central", "mean", or "the most discriminant" [Bou01]. On the contrary, robust and stochastic ordinal regression take into account all compatible preference model instances to examine how different can be recommendation for all of them. Such robust results are by definition more reliable than the outcomes following the use of a single model instance. Nevertheless, in many decision situations it is desirable to assign precise values to the parameters of the preference model. It is so, because for the majority of users the analysis of a single model instance and the respective results is less abstract than consideration of a complete set of such instances.

In the presented series of papers, one has proposed a set of procedures for selection of *a representative preference model instance* that emphasize the outcomes of robustness analysis. These approaches aim at indicating the instance that represents all remaining compatible instances, which, in turn, contribute to its definition. In this regard, one has proposed two different ways of proceeding. The first one is oriented towards selection of a representative instance that would highlight the consequences of applying all compatible instances [P1, P2]. The other aims at identifying an instance which suggests the elements of recommendation that are confirmed by the greatest share of all compatible instances [P4, P9].

In [P1] and [P2], one has formulated the procedures for *selection of a representative value function for multiple criteria ranking and sorting* that emphasize the outcomes of stochastic ordinal regression. They exploit the outcomes of robustness analysis to determine a desired difference between comprehensive values for all pairs of alternatives. In general, they assume that the greater the share of compatible value functions confirming the advantage of one alternative over the other, the greater should be the difference between their representative comprehensive values. In this spirit, the procedures emphasize an evident advantage of some alternatives over the others, which can be observed for all compatible preference model instances, and highlight the ambiguity in the comparison of other pairs of alternatives. Thus, by exploiting the stochastic acceptability indices they do not lose the advantage of knowing all compatible value functions, and by concisely representing the robust results they contribute to the comprehension of the outcomes of stochastic ordinal regression.

While selection of a representative value function is performed by solving dedicated linear programming models, *selection of a representative set of rules* requires an analysis of the properties of all explicitly constructed compatible minimal-cover sets of rules. In [P4] and [P9], one has proposed such procedures for multiple criteria sorting and ranking, respectively. The representative set of rules is expected to produce a robust recommendation with respect to the non-univocal preference model stemming from the input preference information. Thus, the proposed procedures aim at selecting the set of rules whose recommendation is confirmed by as many other sets of rules as possible. Obviously, this general idea may be implemented in several ways which are discussed in the papers. In particular, one may select the set of rules for which the minimal acceptability index for a class assigned to each alternative or a relation imposed for each pair of alternatives is maximal in view of the results provided by all compatible sets of rules.

H6. Construction of a univocal recommendation by exploiting the outcomes of robustness analysis

In the context of preference disaggregation, three major approaches have been proposed in the literature to deal with the indetermination of the DM's preference model. These are represented by robust and stochastic ordinal regression, and procedures for selection of a representative preference model instance based on the analysis of robsut outcomes. In the presented series of papers, one has also initiated a new stream of research which aims at constructing *a recommendation by directly exploiting the outcomes of robustness analysis* though without singling out a specific preference model instance (see Figure 6).

In [P11], one has presented a few dozens of scoring procedures for transforming the results of robustness analysis to a univocal recommendation when using an additive value function as a preference model. These select the best alternative or construct a complete ranking by exploiting four types of outcomes: necessary preference relation, pairwise outranking indices, extreme ranks, and rank acceptability indices. The proposed methods are distinguished by an aggregation operator (e.g., maximum, minimum, or sum) that is used to compute the net flow scores, and by incorporating single- or multi-stage ranking methods [Bou92, Sze14]. The former assign a score to each alternative in a single stage, whereas the latter iteratively (downward) apply a particular scoring function on the set of alternatives. The exemplary three procedures introduced in the paper order the alternatives by considering their best ranks, or the number of objects over which they are necessarily preferred, or the least advantageous pairwise preference index derived from the comparison with some other alternative. In each case, a choice or ranking recommendation is obtained without singling out a specific value function.

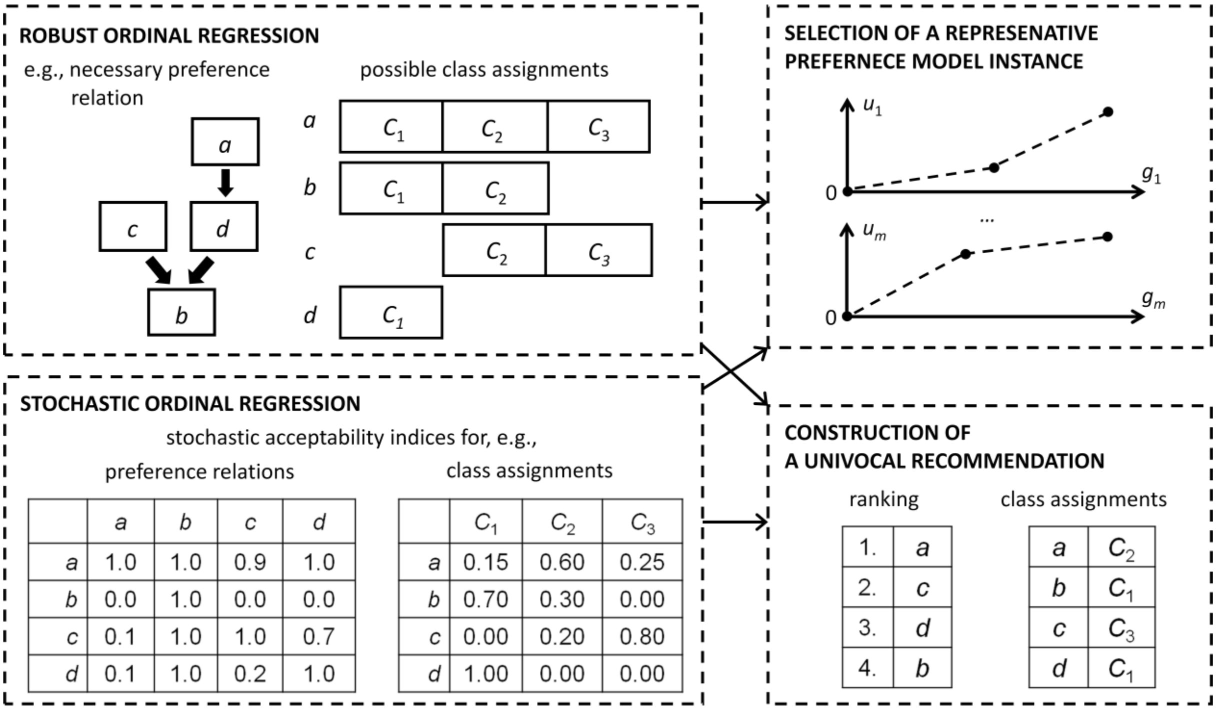

Fig. 6. Four different streams of research represented in preference disaggregation methods.

The proposed scoring procedures have been thoroughly tested in an extensive computational experiment [P11]. The experiment aimed at investigating the ability of the procedures to suggest the same recommendation as the one obtained with the assumed DM's "true" value function, which was represented in the method by a limited number of pairwise comparisons. The comparison involved five measures (including three newly proposed ones) for quantifying such agreement in view of the recommendation delivered for the choice and ranking problems. The best performing methods turned out to be problem specific. In choice problems, it is most beneficial to account for the acceptability indices for the top rank or the least advantageous pairwise comparisons against some other alternative. In ranking problems, in turn, it is useful to analyze a comprehensive performance in view of all pairwise preference relations or all attained ranks. Precisely, to reproduce the "true" ranking one should refer to the balance between how much each alternative outranks and is outranked by all other alternatives or to the expected ranks that alternatives attain.

H7. Robust decision aiding with boundary and characteristic class profiles

One of the most important characteristics of the MCDA methods derives from the interpretability of the procedures they use for arriving at a recommendation. In this regard, when dealing with multiple criteria sorting, more and more attention is paid to the methods which derive the class assignments from the comparison of alternatives with some reference profiles. Such profiles represent the requirements or norms on the particular criteria that should be attained by the alternatives aiming at the assignment to a given class. In the presented series of papers, one has proposed a pair of new outranking-based MCDA methods whose assignment rules incorporate the reference profiles.

The development of a method presented in [P7] has been motivated by the parametric evaluation of research units in Poland which is conducted by the Ministry of Science and Higher Education. This evaluation, called categorization, consists in assigning each unit to one of a few classes corresponding to different qualities of acquired effects and activities undertook in the evaluation period. The assignment is derived from scoring the units based on their comparison with all remaining units in the so called group of joint evaluation.

The paper is focused on the presentation of mathematical modes for construction of some reference profiles (artificial reference research units) separating the classes. This allows to enhance the interpretability of the results and to transform the ranking to class assignments based on the attained scores. Precisely, each class accumulates the units with a score not worse than the corresponding lower profile and worse than the respective upper profile. Moreover, the profiles are constructed so that to be considered jointly with the existing research units and to respect desired class cardinalities, i.e., shares of units that can be judged as, e.g., leading, average, or weak (see Figure 8).

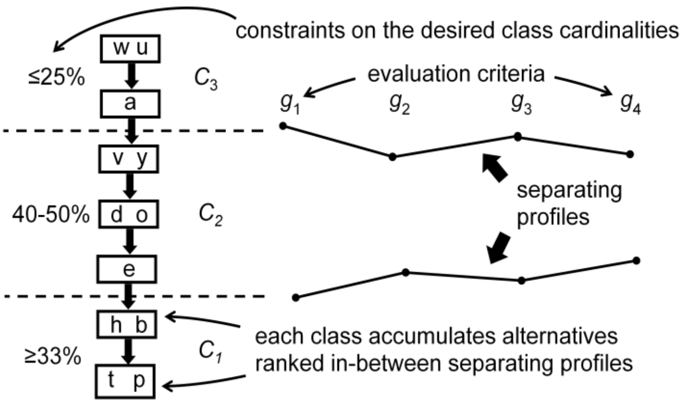

Fig. 8. Exemplary requirements concerning construction of the separating reference profiles for the problem of parametric evaluation of research units.

The uniqueness of the proposed approach derives from the fact that it considers multiple criteria sorting and ranking jointly. It is so, because the units assigned to the same class are not considered indifferent, instead being ordered from the best to the worst according to their comprehensive scores. This allows to differentiate over- and under-performing units within each class, and to provide all of them with a feedback on their effectiveness against all other units.

The paper exhibits the mathematical models that incorporate MILP to allow:

- performing non-compensatory pairwise comparisons in the spirit of Promethee [Beh10] while taking into account indifference and preference thresholds;
- accounting for different scoring procedures that grant either a fuzzy or a binary score to an alternative designated better in each comparison;
- analysis of robustness of the suggested recommendation with the possible assignments and extreme ranks in view of the potential existence of multiple sets of reference profiles consistent with the preference information of the DM.

The other method in this group is a new multiple criteria sorting approach that uses characteristic profiles for defining the classes and outranking relation [Gov16] as the preference model. Unlike boundary (separating) profiles, the characteristic profiles are formed from the representative attribute values for each class (see Figure 8). The main motivation underlying the methodological developments presented in [P8] came from the analysis of properties of the Electre TRI-C method [Alm10]. It employs two rules, called ascending and descending, to delimit a possibly imprecise interval of classes for the assignment of each alternative. However, Electre TRI-C requires the DM to directly specify precise values for the outranking model parameters, which is very demanding. Moreover, as far as the interpretability of the method is concerned, it is rather problematic that depending on the results of a comparison of an alternative with the characteristic profiles, the order of classes indicated by the descending and ascending assignment rules may vary. In view of the above drawbacks, the contribution of [P8] was to make outranking-based sorting with characteristic profiles more usable and transparent by introducing the following four developments.

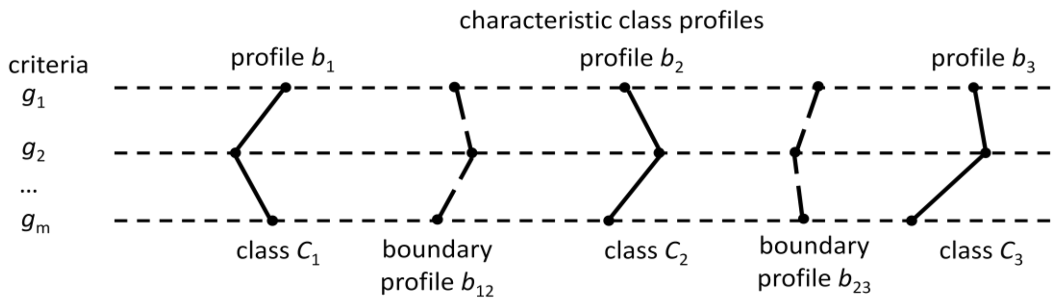

Fig. 8. Exemplary characteristic and boundary profiles for defining the classes in multiple criteria sorting.

Firstly, one has analyzed in detail the assignments provided by the ascending and descending rules of Electre TRI-C and the conditions under which the ascending rule indicates an assignment to a better class than the descending rule, or vice versa. This led to the reformulation of these rules so that they indicate the lower and upper classes unambiguously while respecting the assumptions and providing the same results as Electre TRI-C.

Secondly, one has formulated the mathematical programming models for disaggregating the preferences in the context of Electre TRI-C. The proposed disaggregation procedure has been the first outranking-based approach in the literature that admits specification of imprecise assignment examples. This increases flexibility of the preference elicitation process by allowing preference statements reflecting hesitation with respect to the desired assignment (e.g., alternative *a* should be assigned to class *medium* or *good*) as well as these concerning classes excluded from the set of desired assignments (e.g., alternative *b* should not be assigned to class *bad*). The introduced procedures infer a set of inter-criteria parameters related to the formulation of an outranking model (such as criteria weights, the majority or veto thresholds), which are hard to elicit in a direct way.

Thirdly, to avoid an arbitrary definition on selection of a single model instance for the final classification, one has adapted robust ordinal regression to Electre TRI-C. The proposed MILP models exploit the whole set of outranking-based model instances compatible with the DM's assignment examples to derive the possible and necessary assignments for each alternative.

Fourthly, one has introduced revised, simpler version of the Electre TRI-C assignment procedures, thus giving a birth to a new Electre TRI-rC method. The results obtained with the revised procedures differ from those of Electre TRI-C only in very specific problem instances. However, the new procedures have significant implications for the interpretability of the provided results and the respective disaggregation approach. On one hand, the translation of the revised assignment rules to the explanations formulated in the natural language is straightforward. For example, if C_h is indicated as the worst class for alternative *a*, it can be justified with *a* being preferred to the characteristic profiles of all classes worse than C_h and there existing sufficiently strong arguments in support of alternative *a* being at least as good as the characteristic profile of C_h. On the other hand, the space of Electre TRI-rC model instances compatible with the assignment examples is now convex. Consequently, one has proved a no class jumps property for the possible assignments computed with the revised procedures, leading to easier interpretation of the results.

H8. Explanations of the recommended decision in view of the holistic indirect preference information provided by the decision maker

Each MCDA method should guarantee that the DM not only learns about the problem, but also that (s)he is convinced about the psychological convergence of the process and relative advantage of the indicated solution. The latter requires some dedicated explanations that should justify that the recommendation is logical, valid, and correct. Although such explanations prove to be useful in making explicit the experts logic and assumptions, the explanation module is often neglected in the decision support systems. To fill this gap in the context of robust ordinal regression, in [P5] one has proposed a method for generating the explanations that show the direct impact of pieces of DM's preference information on the observed outcomes. In this regard, one has focused on using preference information in form of pairwise comparisons or assignment examples and a preference model in form of an additive value function. The main contribution of the paper consists in defining three types of explanations and formulating the algorithms for their generation.

In particular, a *preferential reduct* is the minimal set of preference information pieces which justifies some result observable for the whole set of compatible preference model instances. For example, a preferential reduct for a pair of alternatives related by the necessary preference is a minimal set of pairwise comparisons provided by the DM inducing the truth of this relation. Analyzing such a reduct, the DM could observe that, e.g., alternative *a* is necessarily preferred to alternative *b* just because (s)he preferred *c* over *d* and *e* over *f*, while all remaining pairwise comparisons (s)he provided have no impact on this particular result.

Thus, a preferential reduct is minimal in a sense that any of its proper subsets does not imply the truth of the considered part of recommendation. In [P5], one has provided two alternative algorithms for identification of the preferential reduct: an additive method and a deletion filer. These are based on drawing an analogy to isolating an *irreducible infeasible system* [Chi08], i.e., a subset of constraints in the mathematical programming model that defines the overall initial set of constraints that itself is infeasible, but for which any proper subset is feasible.

The motivation underlying the second type of explanation derives from the potential existence of multiple preferential reducts for the same part of recommendation. The intersection of all such reducts is called a *preferential core*. From the practical point of view, the core contains preference information pieces which are most crucial for implying the truth of some currently observable result. In [P5], one has formulated an additive method for generating the preferential core.

Finally, the third type of explanation refers to the maximal set of preference information pieces, called a *preferential construct*, revealing the conditions under which some result currently non-observable for the whole set of compatible preference model instances would be possible. For example, a preferential construct for an alternative that cannot be possibly assigned to a given class is a maximal set of assignment examples provided by the DM that would admit such an assignment. Analyzing such a construct, the DM could realize that, e.g., alternative *a* would be possibly judged as *good* if (s)he removed evaluation of alternative *b* as *medium*, while leaving all remaining assignment examples.

In [P5], one has formulated a MILP model for identification of a preferential construct. It is based on an analogy to computation of the *maximum feasibility subset* [Chi08], i.e., a subset of constraints defining an overall initial set of constraints that itself is feasible, but for which any proper superset is infeasible. Thus, a preferential construct is maximal in a sense that it is composed of all preference information pieces that do not contradict each other, admitting in this way the truth of some currently non-observable result.

The algorithms for generating all above explanations have been formulated for the context of different results typical for both multiple criteria ranking and sorting. One has also discussed their extensions that account for either credibility of preference information or some background knowledge indicated by the DM that should be included in the generated explanations.

Overall, the preferential reducts, cores, and constructs can be interpreted as transparent and easily understandable arguments that can be used to justify and explain the decision. This is particularly important in fields where difficult and risky decisions need to be made, e.g., in medical diagnosis.

H9. Identifying modifications of the alternative's performances that allow achieving or maintaining some target result

The analysis of recommendation suggested by a particular MCDA method often stimulates the DM to ask the following questions: "what would happen if...?". Usually, these questions concern the alternatives or criteria that are of particular interest to the DM. To find a satisfying answer, one needs to perform a *sensitivity analysis* that verifies the impact of varying values of the parameters related to the formulation of the problem on the delivered recommendation. In this regard, the majority of sensitivity analysis approaches assess the influence of uncertainty in the preference model parameters (e.g., criteria weights). Only few existing approaches investigate the impact of variability in the performance values on the attained results [Bey08]. Nevertheless, the performance values which are assigned to the alternatives are usually obtained from models, derived from the available data, or defined by expert judgment. Since each of these sources of information is uncertain, it is desirable to account also for the performances in the sensitivity analysis.

In [P10], one has proposed a framework of *post factum analysis*, which is designed for answering questions regarding the stability of results. Indeed, knowledge about the necessary, possible, and extreme consequences of the provided preference information may stimulate the DM to wonder how the improvement or deterioration of some performances influences the sort of an alternative in the obtained recommendation. The exemplary useful questions that can be answered with the proposed framework have the following form: "what improvement on all or some performances of a given alternative should be made, so that it achieves a better result in the recommendation obtained with a set of compatible preference model instances?" or "what is the margin of safety in some or all performances of a given alternative, within which it can maintain some rank or class assignment as in the obtained robust recommendation?". Answering this type of questions is very useful for the DM who wants to assess the opportunities and threats for particular alternatives. Such a preoccupation is typical for environmental management, engineering design, business consult, marketing, and public sector institutions. This contrasts with more passive traditional sensitivity analysis [Roy10b], which just verifies how the recommendation would change for input parameters different than the currently assumed ones.

The paper considers a wide spectrum of decision targets within the proposed framework of post factum analysis. On one hand, in case of falsity of some result concerning a given alternative, the DM may wish to know the minimal improvement that would warrant feasibility of the investigated part of the recommendation. On the other hand, if some result is already attained by an alternative, the DM may be interested in the maximal deterioration for which this outcome still holds. Taking into account the setting of multiple criteria ranking and sorting, such questions may concern pairwise preference relations, attaining a particular rank or assignment. Considering the plurality of compatible preference model instances, reaching or preserving the target may be investigated for all or at least one compatible model instance. Further, the required improvement or allowed deterioration may be quantified in terms of changing performances either on all criteria or only some selected subsets of criteria. Finally, one can consider different ways of modifying the performances. Although the paper is focused on the relative changes, i.e., multiplying the performance values by a common factor, one may also derive the absolute modifications. In this way, post factum analysis offers a rich framework addressing multivariate robustness and sensitivity concerns.

For each of the above scenarios, one has formulated the optimization problems for determining the improvement that an alternative needs to make to achieve some target result, or deterioration that it can afford in order to maintain it. One has also defined some concepts to name the solutions of such problems. For example, a *comprehensive necessary improvement* in view of acquiring some target is the minimal improvement of the alternative's performances on all criteria by which the target is achieved for all compatible preference model instances. Further, a *partial possible deterioration* in view of maintaining some target is the maximal deterioration of the alternative's performances on a subset of criteria by which the target is still achieved for at least one compatible preference model instance. Although the formulated optimization problems are non-linear, they can be easily solved using some simple heuristic approaches such as the binary search method (in case of relative performance changes) or the genetic algorithms (in case of absolute modifications).

The paper exhibits also a set of propositions concerning the comparison of outcomes of post factum analysis for different scenarios. For example, the more demanding the target (e.g., attaining the first vs. the third rank, or assignment to the best class in the necessary or the possible sense), the greater improvement is required to attain it. Analogous properties have been formulated for the comparison of the required changes on different subsets of criteria. The practical usefulness of the post factum analysis has been illustrated with a problem of assessing environmental impact of European cities.

In general, the discovered modifications may be useful in formulating the guidelines, design, and planning. This kind of analysis is also important for robustness concern because it finds which parts of the computed necessary, possible, and extreme results are indeed robust. With small required improvement or allowed deterioration the recommended decision can be regarded as sensitive, whereas in case the modification of performance values is large the DM can be more confident of the validity of result. From another perspective, the discovered modifications can be used to define a proximity recommendation that may potentially differ from the original recommendation. This can be achieved, e.g., by studying which alternatives are close to being ranked first or assigned to the best classes. Finally, post factum analysis may be used to indicate how critical different performance values are in the ranking or assignment of the alternatives. This can provide direction to the DM for further analysis or stimulate re-evaluation of the most critical values more accurately.

Software

The introduced methods for multiple criteria decision analysis have been implemented in R, Python or Java. The majority of these approaches have been made available on *diviz* [Mey12]. *Diviz* is a software platform gathering modular components which may be complete MCDA methods, elements common to a large range of decision making procedures, or graphical tools. It is a joint initiative of several leading researchers in algorithmic decision theory who are contributing to the *Decision Deck* project.

The presented methods for preference modeling, robustness analysis and processing multidimensional data are available on *diviz* in form of some programming components. These can be combined into so called *algorithmic flows* (see Figure 9). This allows a decision analyst to adjust the method to her/his needs and even to construct new approaches without any programming or mathematical skills. From the technical point of view, these components are *web-services* which read inputs and write outputs in the dedicated XML-based format, called XMCDA. Addressing the needs of practitioners, scientists, and teachers, the source code of most developed methods is available on-line. This allows wider dissemination of the methods which should result in both their in-depth testing by other users as well as the increase of real-world applications

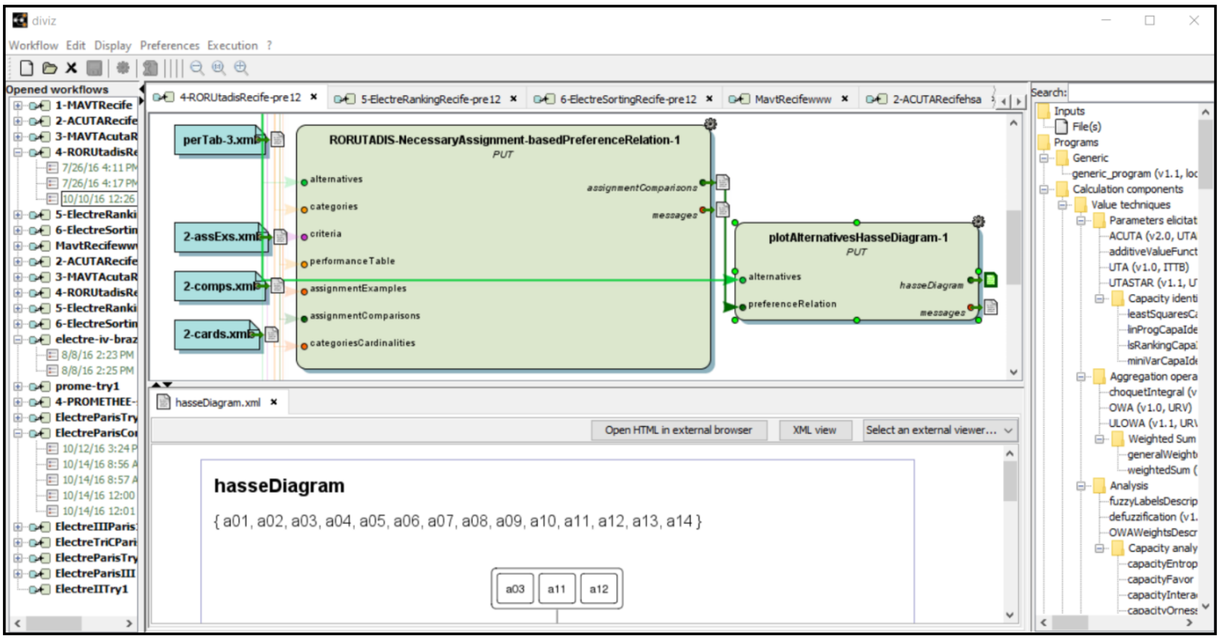

Fig. 9. Graphical user interface of *diviz* (an exemplary algorithmic workflow is presented in the central part).

Summary

The research results presented in the series of papers vastly contribute to the development of the discipline of computer-aided multiple criteria decision making. The main goals of the introduced methods and algorithms consisted in accounting for the preferences affected by some natural imperfections, verification of the robustness of the suggested recommendation, and presentation of the results of such analysis in a transparent and interpretable way. This has been achieved by combining the elements of algorithmic decision theory, artificial intelligence, mathematical modeling, and computer simulations. The more detailed contribution of the 12 papers contained in the presented series is the following:

- establishment of the methodology for an exact comprehensive robustness analysis for multiple criteria sorting [P4, P6, P7, P8, P12], ranking and choice [P3, P7, P9];
- formulation of the linear programming models that allow to infer compatible preference model instances from varied types of indirect, incomplete and imprecise preference information (including these which had not received due attention in MCDA) [P3, P6, P7, P8, P9, P12];
- presentation of the algorithms for generation of all minimal-cover sets of minimal rules consistent with the DM's indirect preference information [P4, P9];
- proposing the methods for computing the necessary, possible, and extreme consequences of using all compatible instances of a preference model in form of an additive value function [P3, P6], an outranking relation [P7, P8, P12], and a set of decision rules [P4, P9];
- establishment of the methodology of stochastic multiple criteria acceptability analysis for ordinal regression in the context of sorting [P1] and ranking [P2] problems;
- presentation of the computer simulation algorithms for estimating the value of stochastic acceptability indices when using a preference model in form of all compatible value functions [P1, P2] and sets of decision rules [P4, P9];
- formulation of the theorems and propositions concerning the impact of preference information on the results of robust [P3, P4, P6, P8, P9] and stochastic [P1, P2] ordinal regression, evolution of these results with an incremental specification of preferences [P1, P2, P3, P6, P8], the interdependencies between acceptability indices and the necessary, possible, and

extreme results [P1, P2, P4, P9], and continuity (no jumps) in the ranges of possible ranks [P1] or classes [P8];

- proposing the methods for selection of a representative preference model instance [P1, P2, P4, P9] and construction of a univocal recommendation [P11] by exploitation of the outcomes of robust and stochastic ordinal regression;
- experimental evaluation investigating the ability of procedures for construction of a univocal ranking to suggest the same recommendation as the one obtained with the assumed DM's true value function [P11];
- establishment of the methods aiming at increasing interpretability of the results derived from multiple criteria analysis by means of using reference profiles [P7, P8], providing explanations of the suggested recommendation [P5], or simulating scenarios with the modified performances of alternatives [P10];
- defining the concepts of preferential reduct, core, and construct in view of multiple criteria ranking and sorting, and specification of the exact algorithms for their generation [P5];
- defining the concepts of necessary and possible, comprehensive or partial modifications of the alternative's performances that allow it to attain or maintain some target result, and specification of the heuristic algorithms for estimating their values [P10];
- illustration of the practical usefulness of the proposed methods with studies in the domains of environmental management [P4, P8, P10], education [P2, P7, P12], economy [P3, P6, P9], and political science [P1, P5].

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V. SUMMARY OF RESEARCH ACCOMPLISHMENTS

My research results have been published in the journal papers whose comprehensive list is provided below. List A includes papers published in the international journals covered by the Journal Citation Reports (JCR). For each work, we report the respective Impact Factor (IF), 5-year Impact Factor (5-y IF), and the number of points granted by the Polish Ministry of Science and Higher Eduction. List B is composed of the conference papers, book chapters and works published in the journals which are not covered by JCR. Both lists are divided into papers published before and after being awarded PhD.

A. Papers published in journals covered by the Journal Citation Reports

[D1] S. Greco, M. Kadziński, V. Mousseau, R. Słowiński. ELECTRE^{GKMS}: Robust ordinal regression for outranking methods. *European Journal of Operational Research*, 214(1):118-135, 2011.

- Publisher: Elsevier; Impact Factor (IF): 2.679; 5-year IF (5-y IF): 3.109; points granted by the Polish Ministry of Science and Higher Education (PM): 40;
- Citations: Web of Science - 34, Scopus - 41, Google Scholar - 62.

[D2] S. Greco, M. Kadziński, R. Słowiński. Selection of a representative value function in multiple criteria sorting. *Computers & Operations Research*, 38(11):1620-1637, 2011.

- Publisher: Elsevier; IF: 1.988; 5-y IF: 2.382; PM: 35;
- Citations: Web of Science - 35, Scopus - 42, Google Scholar - 57.

[D3] M. Kadziński, S. Greco, R. Słowiński. Extreme ranking analysis in robust ordinal regression. *Omega*, 40(4):488-501, 2012.

- Publisher: Elsevier; IF: 3.962; 5-y IF: 4.289; PM: 45;
- Citations: Web of Science - 32, Scopus - 38, Google Scholar - 58.

[D4] S. Greco, M. Kadziński, V. Mousseau, R. Słowiński. Robust ordinal regression for multiple criteria group decision problems: UTA^{GMS}-GROUP and UTADIS^{GMS}-GROUP. *Decision Support Systems*, 52(3):549-561, 2012.

- Publisher: Elsevier; IF: 2.604; 5-y IF: 3.271; PM: 40;
- Citations: Web of Science - 32, Scopus - 33, Google Scholar - 46.

[D5] M. Kadziński, S. Greco, R. Słowiński. Selection of a representative set of parameters for robust ordinal regression outranking methods. *Computers & Operations Research*, 39(11):2500-2519, 2012.

- Publisher: Elsevier; IF: 1.988; 5-y IF: 2.382; PM: 35;
- Citations: Web of Science - 9, Scopus - 9, Google Scholar - 14.

[D6] M. Kadziński, R. Słowiński. Interactive robust cone contraction method for multiple objective optimization problems. *International Journal of Information Technology & Decision Making*, 11(2):327-357, 2012.

- Publisher: World Scientific; IF: 1.183; 5-y IF: 1.502; PM: 30;
- Citations: Web of Science - 5, Scopus - 5, Google Scholar - 11.

[D7] M. Kadziński, S. Greco, R. Słowiński. Selection of a representative value function in robust multiple criteria ranking and choice. *European Journal of Operational Research*, 217(3):541-553, 2012.
- Publisher: Elsevier; IF: 2.679; 5-y IF: 3.109; PM: 40;
- Citations: Web of Science - 25, Scopus - 33, Google Scholar - 50.

[D8] M. Kadziński, S. Greco, R. Słowiński. RUTA: a framework for assessing and selecting additive value functions on the basis of rank related requirements. *Omega*, 41(4):735-751, 2013.
- Publisher: Elsevier; IF: 3.962; 5-y IF: 4.289; PM: 45;
- Citations: Web of Science - 18, Scopus - 18, Google Scholar - 26.

[D9] M. Kadziński, S. Greco, R. Słowiński. Selection of a representative value function for robust ordinal regression in group decision making. *Group Decision and Negotiation*, 22(3):429-462, 2013.
- Publisher: Springer; IF: 1.112; 5-y IF: 1.394; PM: 30;
- Citations: Web of Science - 18, Scopus - 20, Google Scholar - 33.

[D10] M. Kadziński, R. Słowiński. DIS-CARD: a new method of multiple criteria sorting to classes with desired cardinality. *Journal of Global Optimization*, 56(3):1143-1166, 2013.
- Publisher: Springer; IF: 1.219; 5-y IF: 1.293; PM: 30;
- Citations: Web of Science - 10, Scopus - 9, Google Scholar - 18.

before being awarded PhD ↑

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after being awarded PhD ↓

Papers contained in the scientific accomplishment

[P1] M. Kadziński, T. Tervonen, Stochastic ordinal regression for multiple criteria sorting problems. *Decision Support Systems*, 55(1):55-66, 2013.
- Publisher: Elsevier; IF: 2.604; 5-y IF: 3.271; PM: 40;
- Citations: Web of Science - 23, Scopus - 26, Google Scholar - 38.

[P2] M. Kadziński, T. Tervonen, Robust multi-criteria ranking with additive value models and holistic pair-wise preference statements. *European Journal of Operational Research*, 228(1):169-180, 2013.
- Publisher: Elsevier; IF: 2.679; 5-y IF: 3.109; PM: 40;
- Citations: Web of Science - 16, Scopus - 19, Google Scholar - 32.

[P3] S. Corrente, S. Greco, M. Kadziński, R. Słowiński. Robust ordinal regression in preference learning and ranking. *Machine Learning*, 93(2-3):381-422, 2013.
- Publisher: Springer; IF: 1.719; 5-y IF: 2.454; PM: 35;
- Citations: Web of Science - 25, Scopus - 25, Google Scholar - 43.

[P4] M. Kadziński, S. Greco, R. Słowiński, Robust Ordinal Regression for Dominance-based Rough Set Approach to multiple criteria sorting. *Information Sciences*, 283:211-228, 2014.
- Publisher: Elsevier; IF: 3.364; 5-y IF: 3.683; PM: 45;
- Citations: Web of Science - 13, Scopus - 14, Google Scholar - 17.

[P5] M. Kadziński, S. Corrente, S. Greco, R. Słowiński, Preferential reducts and constructs in robust multiple criteria ranking and sorting. *OR Spectrum*, 36(4):1021-1053, 2014.
- Publisher: Springer; IF: 1.395; 5-y IF: 2.191; PM: 30;
- Citations: Web of Science - 5, Scopus - 5, Google Scholar - 8.

[P6] M. Kadziński, K. Ciomek, R. Słowiński, Modeling assignment-based pairwise comparisons within integrated framework for value-driven multiple criteria sorting. *European Journal of Operational Research*, 241(3):830-841, 2015.
- Publisher: Elsevier; IF: 2.679; 5-y IF: 3.109; PM: 40;
- Citations: Web of Science - 8, Scopus - 8, Google Scholar - 13.

[P7] M. Kadziński, R. Słowiński, Parametric evaluation of research units with respect to reference profiles. *Decision Support Systems*, 72:33-43, 2015.
- Publisher: Elsevier; IF: 2.604; 5-y IF: 3.271; PM: 40;
- Citations: Web of Science - 4, Scopus - 3, Google Scholar - 6.

[P8] M. Kadziński, T. Tervonen, J. Figueira, Robust multi-criteria sorting with the outranking preference model and characteristic profiles. *Omega*, 55:126-140, 2015.
- Publisher: Elsevier; IF: 3.962; 5-y IF: 4.289; PM: 45;
- Citations: Web of Science - 5, Scopus - 6, Google Scholar - 13.

[P9] M. Kadziński, R. Słowiński, S. Greco, Multiple Criteria Ranking and Choice with All Compatible Minimal-cover Sets of Decision Rules. *Knowledge-Based Systems*, 89:569-583, 2015.
- Publisher: Elsevier; IF: 3.325; 5-y IF: 3.433; PM: 35;
- Citations: Web of Science - 4, Scopus - 4, Google Scholar - 9.

[P10] M. Kadziński, K. Ciomek, P. Rychły, R. Słowiński, Post factum analysis in robust multiple criteria ranking and sorting. *Journal of Global Optimization*, 65(3):521-562, 2016.
- Publisher: Elsevier; IF: 1.219; 5-y IF: 1.293; PM: 30;
- Citations: Google Scholar - 1.

[P11] M. Kadziński, M. Michalski, Scoring procedures for multiple criteria decision aiding with robust and stochastic ordinal regression. *Computers & Operations Research*, 71:54-70, 2016.
- Publisher: Elsevier; IF: 1.988; 5-y IF: 2.382; PM: 35;
- Citations: Google Scholar - 2.

[P12] M. Kadziński, K. Ciomek, Integrated framework for preference modeling and robustness analysis for outranking-based multiple criteria sorting with ELECTRE and PROMETHEE. *Information Sciences*, 352:167-187, 2016.
- Publisher: Elsevier; IF: 3.364; 5-y IF: 3.683; PM: 45.

Papers not contained in the scientific accomplishment

[F1] D. O'Sullivan, Sz. Wilk, W. Michalowski, R. Słowiński, R. Thomas, M. Kadziński, K. Farion, Learning the preferences of physicians for the organization of result lists of medical evidence articles. *Methods of Information in Medicine*, 53(5):344-56, 2014.
- Publisher: Schattauer; IF: 2.248; 5-y IF: 1.744; PM: 25;
- Citations: Web of Science - 3, Scopus - 3, Google Scholar - 3.

[F2] T. Tervonen, A. Sepehr, M. Kadziński, A multi-criteria inference approach for anti-desertification management. *Journal of Environmental Management*, 162:9-19, 2015.
- Publisher: Elsevier; IF: 3.131; 5-y IF: 4.049; PM: 35;
- Citations: Web of Science - 1, Scopus - 2, Google Scholar - 3.

[F3] M. Kadziński, R. Słowiński, S. Greco, Robustness Analysis for Decision Under Uncertainty with Rule-based Preference Model. *Information Sciences*, 328:321-339, 2016.
- Publisher: Elsevier; IF: 3.364; 5-y IF: 3.683; PM: 45;
- Citations: Web of Science - 1, Scopus - 1, Google Scholar - 1.

[F4] S. Corrente, S. Greco, M. Kadziński, R. Słowiński. Inducing probability distribution on the set of value functions by Subjective Stochastic Ordinal Regression. *Knowledge-Based Systems*, 112:26-36, 2016.
- Publisher: Elsevier; IF: 3.325; 5-y IF: 3.433; PM: 35.

[F5] M. Kadziński, A. Labijak, M. Napieraj, Integrated framework for robustness analysis using ratio-based efficiency model with application to evaluation of Polish airports. *Omega*, doi:10.1016/ j.omega.2016.03.003, 2016.
- Publisher: Elsevier; IF: 3.962; 5-y IF: 4.289; PM: 45.

B. Other peer reviewed monographs, papers and chapters

[B1] S. Greco, M. Kadziński, R. Słowiński, The most representative value function for robust ordinal regression in group decision problems. Proceeding of 25th Mini-Euro Conference "Uncertainty and Robustness in Planning and Decision Making" (*URPDM 2010*), Coimbra, ISBN 978-989-95055-3-7, 2010.

[B2] M. Kadziński, New Directions in Robustness Analysis and Preference Modeling in Multiple Criteria Decision Aiding, *Poznan Monographs in Computing and Its Applications*, NAKOM, Poznań, ISBN 978-83-89529-94-7 (Edition 1, Volume 7), 2012.

before being awarded PhD ↑

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after being awarded PhD ↓

[B3] M. Kadziński, R. Słowiński, Preference-Driven Multiobjective Optimization Using Robust Ordinal Regression for Cone Contraction, *Multiple Criteria Decision Making*, University of Economics in Katowice, 8:67-83, 2013.

[B4] S. Corrente, S. Greco, M. Kadziński, R. Słowiński, Robust Ordinal Regression, *Wiley Encyclopedia of Operations Research and Management Science*, 1-10, doi:10.1002/9780470400531.eorms1090.

[B5] R. Słowiński, M. Kadziński, S. Greco, Robust Ordinal Regression for Dominance-Based Rough Set Approach under Uncertainty, *Rough Sets and Intelligent Systems Paradigms*, Volume 8537 of the series Lecture Notes in Computer Science, 77-87, 2014.

[B6] M. Kadziński, M. Tomczyk, Using ordinal regression for interactive evolutionary multiple objective optimization with multiple decision makers, *Outlooks and Insights on Group Decision and Negotiation*, Volume 218 of the series Lecture Notes in Business Information Processing, 185-198, 2015.

[B7] M. Kadziński, R. Słowiński, M.Szeląg, Dominance-based rough set approach to multiple criteria ranking with sorting-specific preference information, *Studies in Computational Intelligence* 605, 155-171, 2016.

VI. Bibliometric data

A. Papers published in the JCR Journals

- Number of papers published in the JCR journals: **27** (including 17 after being awarded PhD);
- Number of papers published per JCR journal: European Journal of Operational Research - 4, Omega - 4, Information Sciences - 3, Computers & Operations Research - 3, Decision Support Systems - 3, Knowledge-Based Systems - 2, Journal of Global Optimization - 2, International Journal of Information Technology & Decision Making - 1, Group Decision and Negotiation - 1, Journal of Environmental Management - 1, OR Spectrum - 1, Methods of Information in Medicine - 1, Machine Learning - 1.

B. Total Impact Factor

- Total Impact Factor:
  according to the report published in 2016 - **70.31** (including 46.93 after being awarded PhD);
  according to the reports in the respective years of publications - **66.16** (including 45.76 after being awarded PhD);
- Total 5-year Impact Factor:
  according to the report published in 2016 - **80.39** (including 53.37 after being awarded PhD);
  according to the reports in the respective years of publications - **76.22** (including 52.27 after being awarded PhD).

C. Points awarded by the Polish Ministry of Science and Higher Education (PMSHE)

- Total number of points granted by PMSHE for papers published in the JCR journals: according to the list published in 2015 - **1015** (including 645 after being awarded PhD); according to the lists in the respective years of publications - **1000** (including 640 after being awarded PhD).
- Average number of points granted by PMSHE for papers published in the JCR journals: **37.59** (37.94 after being awarded PhD);
- Number of papers published grouped by the number of PMSHE points: 45p. - 7 papers, 40p. - 7 papers, 35p. - 7 papers, 30p. - 5 papers, 25p. - 1 paper.

D. Citations

- Web of Science: **322** (176 without self-citations);
  citations of individual papers: 34, 34, 32, 31, 25, 24, 23, 18, 17, 15, 12, 10, 8, 8, 5, 5, 5, 4, ...
  citing articles: 126 (101 without self-citations);
- Scopus: **367**;
  citations of individual papers: 42, 41, 38, 34, 33, 26, 25, 20, 19, 18, 14, 9, 9, 8, 6, 5, 5, 4, ...
  citing articles: 150;
- Google Scholar: **584**;
  citations of individual papers: 62, 58, 57, 50, 46, 43, 38, 33, 32, 26, 18, 17, 14, 14, 13, 11, ...

E. Hirsch index

- Web of Science - **11**, Scopus - **11**, Google Scholar - **14**.

VII. Description of the main contribution of the papers not included in the scientific accomplishment

The papers which have not been included in the series considered as the scientific accomplishment raise the methodological and practical issues related to preference modeling and robustness analysis. Although these are are often close to the ones presented in [P1]-[P12], many of them concern other disciplines than MCDA. Nevertheless, these disciplines are also focused on the analysis of objects or actions described in terms of multiple dimensions. The main scientific contribution of the papers not included in the scientific accomplishment will be discussed while grouping the proposed methods and obtained research results into the following six parts:

[C1] Comprehensive robustness analysis for data envelopment analysis using a ratio-based efficiency model [F5].
[C2] Evolutionary multiple objective optimization guided by incremental specification of holistic decision examples [B6].
[C3] Supporting decision under uncertainty [F3, F4].
[C4] Group decision aiding [F1, F3, B6].
[C5] Merging ideas specific to different types of decision problems [B7].
[C6] Analysis of real-world decision problems [F1, F2, F5].

Note that when referring to the papers, we use the notation that has been introduced in Section V.

C1. Comprehensive robustness analysis for data envelopment analysis using a ratio-based efficiency model

The framework of Data Envelopment Analysis (DEA) offers a variety of methods for evaluating the relative efficiency of Decision Making Units (DMUs) which consume multiple inputs and produce multiple outputs [Cha78]. Typically, DEA methods have been used to classify the DMUs into efficient and inefficient ones. By definition, the former ones have an efficiency score equal to one, whereas for the latter ones this measure is less than one. For the inefficient DMUs, such scores convey information on how close to being efficient they are.

Although DEA has proven its usefulness when applied to a variety of real-world problems [Coo10], some criticism has been leveled against its discriminative power and the way the efficiency scores are computed. This criticism concerns, e.g., accounting for an extremely small share of feasible weights in the analysis, the need of formulating some arbitrary assumptions about possible returns to scale, high sensitivity of the results to the inclusion or removal of a single DMU, and the lack of discrimination among the DMUs deemed as efficient.

In [F5], one has proposed *an integrated framework for efficiency analysis* which comprehensively addresses all above mentioned concerns. One has assumed the use of a ratio-based efficiency model, which defines efficiency as the ratio between virtual output and virtual input, i.e., respectively, elementary outputs or inputs aggregated using some weights assigned to these factors [Cha78, Sal11]. Thus, robustness analysis concerns here the whole set of weights that are compatible with the preference information concerning input/output variables. In this regard, one has taken advantage of some clear relations between DEA and MCDA [Ste96].

The contribution of [F5] should be perceived in terms of the original algorithms for the exploitation of the whole set of feasible weights. In the proposed framework, robustness concerns three points of view: efficiency scores, pairwise efficiency preference relations, and efficiency ranks. On one hand, one has proposed linear programming models to derive extreme efficiency measures and extreme ranks as well as to verify the truth of the necessary and possible efficiency preference relations. On the other hand, the stochastic indices are computed with the suitably adapted Hit-And-Run algorithm [Ter13]. Overall, the delivered results exhibit different levels of certainty with respect to the suggested evaluation. The formulated propositions confirm that the proposed way of data processing in DEA allows to comprehensively describe the efficiency of DMUs, while requiring less arbitrary assumptions, being less sensitive to a set of considered units, and offering greater discriminative power.

C2. Evolutionary multiple objective optimization guided by incremental specification of holistic decision examples

Multiple objective optimization (MOO) aims at identifying solutions which are acceptable or satisfactory for the DMs on each considered objective. For decades, in MOO one has observed the development of two separate methodological streams: interactive and evolutionary ones [Bra08]. On one hand, interactive multiple objective optimization deals with identification of the most preferred solution by means of questioning the DMs. On the other hand, the evolutionary multiple objective optimization algorithms aim at discovering the best possible approximation of the entire Pareto front (a set of all non-dominated solutions).

In [B6], one has presented a hybrid method which combines NSGA-II [Deb02], a well-known evolutionary algorithm, with some interactive value-based approaches based on the principle of ordinal regression. Precisely, NSGA-II has been adapted so that to bias the search on the DMs' pairwise comparisons and their representative value functions. In this regard, one has proposed different variants of the method. In particular, the population of solutions can be evolved separately for each DM or in common for the entire group. Further, a representative function can be derived individually for each DM or constructed for all group members considered jointly.

The experimental results confirmed that all proposed approaches were able to focus the search on the group-preferred solutions. However, different variants of the method - being distinguished by how they integrate preferences provided by various DMs - differ with respect to both part of the Pareto front to which they converge as well as the convergence speed measured in terms of a quality of the returned solutions.

C3. Supporting decision under uncertainty

Decision under uncertainty is a classical topic of decision [Fis88]. In this case, the DM considers a set of acts whose consequences are uncertain. There are many possible states of the world with given probabilities. Depending on the actual state, an act can yield a corresponding outcome with a given probability. In [F3], one has presented a method for supporting decision problems under uncertainty formulated in terms of a multi-attribute classification. One has referred to both additive and non-additive probability distributions over the states of the world.

In the proposed approach, the DM provides desired classification for a small subset of reference acts. Such preference information is structured using Dominance-based Rough Set Approach, and the non-ambiguous assignment examples are represented with all compatible minimal-cover sets of minimal rules. The condition parts of these rules are suitably adapted to the specific context of decision under uncertainty. The work exhibits also some algorithms for constructing all satisfactory sets of decision rules which are consistent with user's requirements concerning, e.g., the minimal support of rules, non-redundant covering of a set of reference examples, or the maximal number of criteria to be used in the set of rules.

The use of all minimal-cover or all satisfactory sets of rules on a set of all acts allows to draw conclusions about the certainty of arrived recommendation. In particular, we analyze the diversity of class assignments, assignment-based preference relations, and class cardinalities. Then, we solve an optimization problem to get a univocal (precise) classification for all acts, taking into account the robustness concern. The procedure is built on the assumption that for each act an assignment to a class with the highest acceptability can be considered as the most robust with respect to the indirect preference information provided by the DM. This basic idea has been extended to respect additional indirect and imprecise preferences in form of desired class cardinalities and assignment-based pairwise comparisons.

Questions related to uncertainty modeling have been also raised in the context of MCDA. The traditional decision aiding methods accept solely certain preference information. In [F4], one has presented a new ordinal regression method for multiple criteria ranking that admits also *uncertain preference information*. For example, when comparing a pair of alternatives *a* and *b*, the DM may admit that *a* could be preferred to *b*, and *b* could be preferred to *a*, but the preference of *a over b* is more credible than preference of *b* over *a*. To handle such information, one has proposed a new approach that builds a probability distribution over the space of all value functions compatible with the DM's certain holistic judgments. When referring to the above example, the inferred distribution needs to ensure that a sum of probabilities associated with functions for which alternative *a* is preferred to *b* is greater than a sum of probabilities related to functions for which this preference is inverse.

C4. Group decision aiding

The vast majority of MCDA methods have been originally designed to deal with the preferences of a single DM. However, it is group decision making that is among the most important and frequently encountered processes within companies and organizations [Mat01]. On one hand, group decision making may benefit from a diversity of knowledge, information and experience of the DMs. On the other hand, the preferences of the DMs are often conflicting and different parties need to reach a consensus to arrive at a joint decision. In [F1], [F3] and [B6], one has proposed different algorithms for dealing with such inconsistency in a group decision setting.

The procedures presented in [F1] and [F3] construct a group compromise preference model (in particular, an additive value function) that would represent the preferences of all DMs. In [F1], one has considered a problem where different DMs compared the same pairs of alternatives. In this case, a compromise model aimed at respecting the comparisons given by the greatest number of DMs. On the contrary, the procedure introduced in [F3] maximizes the minimal number of pairwise comparisons of any DM which are representable by a single additive value function. In this way, it aimed at balancing the viewpoints of different DMs in the final model.

Further, an approach presented in [F3] searches for the spaces of consensus and disagreement between DMs only at the stage of analyzing robustness of the recommendation arrived individually by each DM. The basic idea concerns reasoning in terms of the necessary and the possible not only on the ground of relations or assignments, but also with respect to the agreement reached by a set of DMs. One has also defined some group acceptability indices which reflect either the proportion of DMs that accept some part of the recommendation or an average of individual acceptabilities for a given outcome.

C5. Merging ideas specific to different types of decision problems

The traditional MCDA methods incorporate preference information and results whose form is fully consistent with the type of a considered decision problem. For example, in case of ranking problems, the methods may accept pairwise comparisons at the input and impose a complete or partial order on the set of alternatives. However, more and more often the boundaries between different types of problems become blurred, and some components of the MCDA methods which are applicable when dealing with one problem type, prove to be useful when approaching problems of another type.

In this regard, in [B7] one has introduced a method which delivers a recommendation characteristic for ranking problems but employs preference information typical for sorting problems. Precisely, the sorting examples are used to build a rule preference model which is applied on a considered set of alternatives, yielding a recommendation in terms of weak order of these alternatives. Although such preference information is purely ordinal, the number of quality classes separating two assigned alternatives is meaningful for an intensity of preference. To represent preference information in such form one has extended the Dominance-based Rough Set Approach [Gre02] so that it effectively deals with pairs of class unions (e.g., pair (class at least *good*, class at most *medium*)). Moreover, one has suitably extended the form of decision rules as well as the algorithms for their induction to the specific context of the considered problem. Finally, one has also presented the procedures for exploitation of the derived preference graph whch allow to compute for each alternative its comprehensive quality score.

C6. Analysis of real-world decision problems

Many methods introduced in the presented series of papers have been already used to analyze some real-world problems. In what follows, we mention three exemplary applications dealing with multiple criteria sorting [F2] and ranking [F1], or efficiency analysis [F5].

In [F2], one has presented a procedure for *selection of a representative value function for multiple criteria sorting*. It exploits the outcomes of robust ordinal regression to determine a desired difference between comprehensive values for all pairs of alternatives. The procedure has been used within a real-world case study in the domain of anti-desertification management [F2]. Precisely, it has been employed to classify 28 administrative regions of the Khorosan Razavi province in Iran into three equilibrium classes: collapsed, transition, and sustainable zone. The model has been parameterized with enhanced vegetation index and other natural or anthropogenic indicators for the status of each region. The representative model instance suggests that grazing density and land use change are the main factors affecting desertification in the region, while additionally indicating scale ranges where high value gains can be achieved with moderate measurement improvements.

Further, a group decision aiding method introduced in [F1] has been used for capturing physician preferences for lists of medical articles in order to learn how to organize medical knowledge for decision making. The preferences on an article's relevance for a query and its position on a list have been expressed by pairwise comparisons representing different combinations of element lists. The derived compromise value function confirmed the importance of placing the most relevant article at the very top. It also revealed that the importance paid to a position on a list significantly diminishes after the second position. The arrived results may be used by developers of clinical decision support applications.

Finally, the benefits of the methodology introduced in [F5] have been illustrated on the problem of assessing efficiency of Polish airports based on real-world data. The analysis involved four inputs (i.e., capacities of a terminal, runways, and an apron, and a catchment area) and two outputs (i.e., passenger traffic and number of aircraft movements) related to the terminal services and movement model. The formulated conclusions indicate the airports which are efficient or inefficient, but also characterize their comprehensive performance in view of all feasible input/output weights.

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[Cha78] Charnes, A., Cooper, W., Rhodes, E., Measuring the efficiency of decision making units. *European Journal of Operational Research* 2(6):429-444, 1978.

[Coo10] Cooper, W., Seiford, L., Zhu, J., Handbook on Data Envelopment Analysis. *International Series in Operations Research & Management Science*. Springer, New York, 2011.

[Deb02] Deb K., Agrawal S., Pratap A., Meyarivan T., A fast and elitist multi-objective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2):182-197, 2002.

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[Gre02] Greco S., Matarazzo B., Słowiński R., Rough sets methodology for sorting problems in presence of multiple attributes and criteria. *European Journal of Operational Research*, 138:247–259, 2002.

[Mat01] Matsatsinis, N.F. , Samaras, A.P. , MCDA and preference disaggregation in group decision support. *European Journal of Operational Research,* 130(2):414–429, 2001.

[Sal11] Salo, A., Punkka, A., Ranking intervals and dominance relations for ratio-based efficiency analysis. *Management Science,* 57, 200-214, 2011.

[Ste96] Stewart, T., Relationships between Data Envelopment Analysis and Multicriteria Decision Analysis. *The Journal of the Operational Research Society*, 47(5):654-665, 1996.

[Ter13] Tervonen, T., van Valkenhoef, G., Basturk, N., Postmus, D., Hit-And-Run enables efficient weight generation for simulation-based multiple criteria decision analysis. *European Journal of Operational Research*, 224(3):552-559, 2013.

VIII. ACHIEVEMENTS IN TEACHING

Since 2008, I have been leading the following courses for computer science students at both bachelor and master levels (Faculty of Computing, Poznan University of Technology):

- decision support (DS; since 2008; full-time and part-time bachelor studies; number of students per year: 75; number of course hours: 30; since 2015 also classes in English for students participating in the Erasmus program);
- web mining (WM; since 2009; full-time and part-time master studies; specialties: Intelligent Decision Support Systems, Software Development Process, Data Processing Technologies; number of students per year: 60; number of course hours: 30);
- multiple criteria decision aiding (MCDA; since 2010; full-time Master studies; specialty: Intelligent Decision Support Systems; number of students per year: 30; number of course hours: 30);
- statistics and data analysis (SDA; between 2010 and 2011; part-time bachelor studies; number of students per year: 60; number of course hours: 15).

For each of the above mentioned courses I have prepared the original materials and exercises. My classes have been evaluated by the students as extremely valuable and interactive, and my teaching style as clear and helpful. Over the years, I have attained the highest notes among all lecturers at the Faculty of Computing according to the questionnaires filled by the students for each of the following three courses: DS, WM, and MCDA.

I have deepened my teaching experience as a lecturer at the international doctoral schools on multiple criteria decision aiding:

- 1st Spring School on Multiple Criteria Decision Aiding (May 26-31, 2014; Perugia, Italy; number of participants: 60);
- 12th Multiple Criteria Decision Aiding/Making Summer School (July 18-29, 2016; Recife, Brazil; number of participants: 50).

My lectures concerned the value- and outranking-based methods as well as their practical use with decision support systems that had been developed within the Decision Deck project.

Starting from 2013, I have been supervising doctoral, master and bachelor students at the Faculty of Computing. At present, I supervise 3 doctoral students (Krzysztof Ciomek (since 2014), Michał Tomczyk (2015) and Anna Labijak (2016)) conducting their research in algorithmic decision theory. For the last 3 years, I have been a supervisor of 12 master students and 4 groups of bachelor students as well as a subsidiary supervisor of 2 other master students. The vast majority of the thesis realized under my supervision have been written in English. Two of my master students have been appointed as the most distinguishing graduates by the Rector of Poznan University of Technology. Another 5 thesis are currently being conducted and they are expected to be defended in 2017. The complete lists of the master and bachelor thesis conducted under my supervision are provided below.

For many students I have served as a tutor within their individual programs of studies. Moreover, I have been actively involving the most talented students into the scientific research. Six of them have already co-authored at least one paper published in the JCR journal, while four students have participated, under my direction, in the scientific projects supported by the Polish National Science Center or Polish Ministry of Science and Higher Education.

A. SUPERVISED MASTER'S THESIS

1. M. Napieraj, Integrated framework for robustness analysis using data envelopment model, 2014.
2. K. Lewandowski, Interactive evolutionary cone contraction method for multiple objective optimization problems, 2014.
3. M. Michalski, Preference learning methods based on robust and stochastic ordinal regression, 2014.
4. K. Ciomek, Modular decision support system for multiple criteria sorting with preference model in form of an additive value function, *subsidiary supervisor*, 2014.
5. P. Rychły, Modular decision support system for multiple criteria ranking with preference model in form of an additive value function, *subsidiary supervisor*, 2014.
6. M. Tomczyk, Application of selected multi-objective optimization methods to green supply chain design problem, *distinguished by the Rector of Poznan University of Technology,* 2015.
7. J. Wąsikowski, On non-monotonicity, expressiveness and robustness of additive value function in multiple criteria decision aiding, 2015.
8. R. Gołębiewski, Interactive methods based on stochastic ordinal regression for evolutionary multiple objective optimization problems, 2015.
9. Labijak, Robustness analysis with data envelopment models incorporating hierarchical input-output structure and imprecise data, *distinguished by the Rector of Poznan University of Technology,* 2016.
10. Szczepański, Learning the parameters of an outranking-based preference model with characteristic class profiles from large sets of assignment examples, 2016.
11. P. Jankowska, Experimental comparison of the procedures for selection of a representative value function in multiple criteria ranking and sorting problems, 2016.
12. H. Kuczka, Constructing univocal recommendation for multiple criteria ranking based on the outcomes of robustness analysis, 2016.
13. Ł. Antczak, Dominance-based Rough Set Approach to Multiple Criteria Ranking with Sorting-Specific Preference Information, 2016.
14. P. Ptaszyński, Robust election rules for computational social choice theory, 2016.
15. M. Biernacki, Learning the parameters of an additive value model from large sets of pair-wise comparisons, expected defense in 2017.
16. Laskowski, Methods for multiple criteria ranking and choice based on sport tournament systems, expected defence in 2017.
17. J. Toczek, Algorithms for construction of a group compromise ranking in multiple criteria problems, expected defense in 2017.
18. M. Kuźma, Learning the parameters of a value-driven threshold-based sorting procedure from large sets of assignment examples, expected defense in 2017.

B. SUPERVISED BACHELOR'S THESIS

1. N. Adamkiewicz, J. Galewska, M. Jaśkiewicz, M. Tomczyk, A system for the analysis of electrocardiographic and graphomotor signals (in Polish), 2014.
2. P. Białecki, M. Czarnecki, M. Jankowski, P. Olejniczak, A system for the execution and analysis of Trail Making Tests System on tablet (in Polish), 2014.
3. T. Mieszkowski. Modular decision support system for the ELECTRE methods, 2014.
4. Ł. Antczak, P. Jankowska, H. Nowak, A system for execution and analysis of selected memory procedural tests, 2015.
5. M. Dzięcielska, S. Nowak, M. Sarbinowicz, M. Uniejewski, Construct your own PROMETHEE method, expected defense in 2017.

IX. ACHIEVEMENTS IN POPULARIZING SCIENCE

My research results have been presented at the international conferences, seminars, and doctoral schools. The specification of such presentations and talks is provided below.

1. **Invited talks (6) at the international conferences and seminars** (Complex System Modeling 2009, Dagstuhl Seminar 12041 - Learning in Multiobjective Optimization, 22nd International Conference on Multiple Criteria Decision Making (MCDM Doctoral Dissertation Award 2013 session), 26th EURO-INFORMS Conference (EURO Doctoral Dissertation Award 2013 session), Dagstuhl Seminar 15031 - Understanding Complexity in Multiobjective Optimization, 12th Decision Deck Workshop);
2. **Presentations (43) during international scientific conferences** (including 31 talks as a presenter; i.a., European Conference on Operational Research (EURO 2009, 2013, 2015, 2016), Conference of the International Federation of Operational Research Societies (IFORS 2014), International Conference on Multiple Criteria Decision Making (MCDM 2011, 2013, 2015), INFORMS Annual Meeting (INFORMS 2014, 2015), Decision Deck (D2) Workshop (2009, 2010, 2014, 2016), Meeting of the EURO Working Group on Multiple Criteria Decision Aiding (MCDA 2009-2016), Uncertainty and Robustness in Planning and Decision Making (URPDM 2010), Joint Rough Set Symposium (JRS 2014), Group Decision and Negotiation (GDN 2015));
3. **Invited talks (4) at seminars** at European universities and research units.
4. Lecturer at **2 international doctoral schools** on Multiple Criteria Decision Aiding (1st Spring School on Multiple Criteria Decision Aiding and 12th Multiple Criteria Decision Aiding/Making Summer School).

Moreover, I have been a member of the editorial team of a bulletin of the EURO Working Group on Multiple Criteria Decision Aiding (2 issues per year) which is distributed to over 400 members of the group.

X. PARTICIPATION IN RESEARCH PROJECTS, SCIENTIFIC COLLABORATIONS, ORGANIZATIONAL ACTIVITIES

Much of my research has been conducted within the projects supported by the Polish National Science Center and Polish Ministry of Science and Higher Education. In particular, I have been directing projects realized within the Sonata, Młoda Kadra and Iuventus Plus programs. Over the years, I have been actively cooperating with researchers based at several foreign universities and research units. This cooperation has resulted in the joint papers, common projects, participation in the international conferences and scientific committees as well as reviewing manuscripts for the major journals. A brief summary of these aspects of my research is provided below.

A. RESEARCH PROJECTS

1. **Participant** in a research project: Decision support methods based on knowledge models induced from alphanumeric and text data:
   - supported by the Polish National Science Center, N N519 314435;
   - period: **2009-11**.
2. **Participant** in a research project: Techniques of modeling, optimization and simulation of complex adaptive systems:
   - supported by the Polish National Science Center, N N519 441939;
   - period: 2010-13.

3. **Participant** in a research project: Application of methods for multiple criteria decision support and machine learning to real-world decision problems:
   - supported by the Polish Ministry of Science and Higher Education, N 91-516 (under Młoda Kadra program);
   - period: 2012-2013.
4. **Principal investigator** of a research grant: New directions in multiple criteria decision aiding based on holistic preference information:
   - supported by the Polish National Science Center, UMO-2013/11/D/ST6/03056 (under SONATA program);
   - period: 2014-17.
5. **Principal investigator** of a research grant: Interactive algorithms for evolutionary multiple objective optimization: group decision perspective and organization of interaction with the decision maker:
   - supported by the Polish Ministry of Science and Higher Education, 09/91/DSMK/0582 (under Młoda Kadra program);
   - period: 2015.
6. **Principal investigator** of a research grant: New methods and applications of robustness and sensitivity analysis in decision theory:
   - supported by the Polish Ministry of Science and Higher Education, IP2015 029674 (under Iuventus Plus program);
   - period: 2016-19.

B. INTERNATIONAL SCIENTIFIC COLLABORATION

1. **Decision Deck project**
   - aim: collaborative development of *open source* software tools to support Multiple Criteria Decision Aiding process (*diviz*, Decision Desktop, XMCDA web-services);
   - Decision Deck Consortium, which steers and manages the project, involves researchers from the leading European universities conducting research in MCDA, such as CentraleSupelec, Universite Paris-Dauphine, Telecom Bretagne, Univerity of Coimbra, Technical University of Lisbon, Universite Libre de Bruxelles, University of Mons, University of Luxembourg, Tarragona University, and Poznan University of Technology; currently, I am a vice president of the consortium.
2. Participant of the **Cost Action IC0602 Algorithmic Decision Theory**.
3. Professor Salvatore Greco and Salvatore Corrente, PhD (**University of Catania**, Italy): preference modeling and robustness analysis in multiple criteria decision aiding methods.
4. Tommi Tervonen, PhD (**Erasmus University Rotterdam**, The Netherlands; Evidera Ltd., London, United Kingdom): stochastic ordinal regression and algorithms for sampling the space of preference model instances compatible with the decision maker's preferences.
5. Professor Vincent Mousseau (**Ecole Centrale Paris**, CentraleSupelec, France): robustness analysis in outranking-based and group decision making methods.
6. Professor Jose Rui Figueira (**Technical University of Lisbon**, Portugal): multiple criteria decision analysis with outranking-based preference model.
7. Professor Kannan Govindan (**University of Southern Denmark**, Odense, Denmark): decision aiding methods for problems of supplier selection and supply chain evaluation.

8. Patrick Meyer, PhD and Sebastien Bigaret (**Telecom Bretagne**, Brest, France): development of decision support systems and construction of new decision aiding methods from the elementary algorithmic components.
9. Professor Luis Dias (**University of Coimbra**, Portugal): efficiency analysis methods with an additive value model.
10. Professor Nuria Agell and Mohammad Ghaderi, PhD (**ESADE Business School**, Barcelona, Spain): ordinal regression methods; robustness and expressiveness of preference models.
11. Valentina Ferretti, PhD (**London School of Economics**, London, United Kingdom): decision aiding methods for applications in environmental management.
12. Marco Cinelli, PhD (**University of Warwick**, United Kingdom): multiple criteria decision aiding applications in nanotechnology.
13. Jafar Rezaei, PhD (**TU Delft**, The Netherlands): multiple criteria sorting methods for supplier evaluation.
14. Professor Rudolf Vetschera (**University of Vienna**, Austria): algorithms for construction of a univocal recommendation based on the results of robustness analysis.

C. MEMBERSHIP OF THE ORGANIZING AND PROGRAM COMMITTEES, ORGANIZATION OF CONFERENCE SESSIONS

1. Member of the Organizing Committee for the 28th European Conference on Operational Research (EURO 2016):
   - Poznan University of Technology, Poznań, July 3-6, 2016;
   - number of participant: 1900 (from over 70 countries); the greatest conference on operational research in Europe;
   - major duties: editing the conference handbook, managing the conference web-site and mobile application; contacts with the sponsors, and cooperation with the program committee.
2. Member of the Organizing Committee for the Meetings of the EURO Working Group on Multiple Criteria Decision Aiding (MCDA) as a secretary of the group between 2011 and 2016:
   - conferences in Corte (MCDA 73), Yverdon (MCDA 74), Tarragona (MCDA 75), Portsmouth (MCDA 76), Rouen (MCDA 76), Catania (MCDA 78), Athens (MCDA 79), Quebec (MCDA 80), Annecy (MCDA 81), Odense (MCDA 82), Barcelona (MCDA 83), and Vienna (MCDA 84).
3. Member of the Program Committee for 4 international conferences (12th and 13th Decision Deck Workshop, International Joint Conference on Rough Sets 2017, Evolutionary Multi-Criterion Optimization 2017).
4. Stream and session organizer at 4 international conferences (EURO 2015 and 2016; International Conference on Multiple Criteria Decision Making (MCDM) 2013 and 2015).
5. Session chair at 12 international conferences (MCDA 75, 78, 80, 81, 82, 83 and 84, MCDM 2013 and 2015, IFORS 2014, EURO 2015 and 2016).

D. EDITORIAL BOARD MEMBERSHIP

Guest editor of three special issues in the JCR journals:

1. **European Journal of Operational Research**: "Learning perspectives in Multiple Criteria Decision Analysis" (publisher: Elsevier; co-editor: Professor Salvatore Greco);
2. **Annals of Operations Research**: "Multi-Criteria Decision Making for Sustainable Development" (publisher: Springer; co-editor: Professor Kannan Govindan);

3. **Journal of Air Transport Management**: "Multiple Criteria Decision Making in Air Transport Management" (publisher: Springer; co-editor: Jafar Rezaei, PhD).

Since 2017 member of the editorial board of the EURO Journal on Decision Processes (invitation of editor-in-chief Professor Vincent Mousseau).

E. REVIEWING

1. **Reviewer for 13 international JCR journals** (93 reviews): European Journal of Operational Research (60 reviews), Omega (8), Knowledge-Based Systems (6), Computers & Operations Research (3), Decision Sciences (3), 4OR (3), Group Decision and Negotiation (3), OR Spectrum (2), Decision Support Systems (1), Expert Systems with Applications (1), Asia-Pacific Journal of Operational Research (1), International Journal of General Systems (1), Annals of Operations Research (1).
2. **Reviewer for 3 international journals which are not covered by JCR** (12 reviews): Journal of Multicriteria Decision Analysis (7 reviews), International Journal of Multiple Criteria Decision Making (4), EURO Journal on Decision Processes (1).
3. **Reviewer for 2 national journals** (5 reviews): Foundations of Computing and Decision Sciences (4 reviews), Operation Research and Decision (1).
4. **Reviewer for the international conferences** such as International Conference on Modeling Decision for Artificial Intelligence, International Conference on Multiple Criteria Decision Making, International Joint Conference on Rough Sets, International Conference on Evolutionary Multi-Criterion Optimization, and Uncertainty and Robustness in Planning and Decision Making.

F. MEMBERSHIP OF THE INTERNATIONAL SCIENTIFIC ORGANIZATIONS AND SOCIETIES

1. **EURO Working Group on Multiple Criteria Decision Aiding**: member since 2009 and **secretary since 2010** (responsible for the coordination of group meetings, financial administration, and web-mastering).
2. **International Society on Multiple Criteria Decision Making**: member since 2010.
3. **Decision Deck Consortium**: member since 2009 and **vice president since 2016**.

XI. AWARDS AND DISTINCTIONS

My research outcomes have been appreciated with the prizes granted by the international societies, journals and conferences as well as with the major scientific awards for young researchers in Poland. A comprehensive list of these distinctions is provided below.

1. **MCDM Doctoral Dissertation Award 2013:**
   - awarded by the International Multiple Criteria Decision Making Society;
   - participants in the competition: a few tens of researchers (from five continents) who defended their PhD thesis on multiple criteria decision making between 2009 and 2013;
   - the final of the competition was held during *22nd International Conference on Multiple Criteria Decision Making* (Malaga, Spain, June 2013).
2. **EURO Doctoral Dissertation Award (EDDA) 2013 (top 3):**
   - awarded by EURO – The Association of European Operational Research Societies;
   - participants in the competition: a few tens of researchers who defended their PhD thesis on operational research between 2011 and 2013;

- the final of the competition was held during 26th European Conference on Operational Research (Rome, Italy, July 2013).

3. **START Scholarship (Foundation for Polish Sciences) - twice in 2013 and 2014:**
   - each year the START Scholarship is awarded to about 120 researchers from over 1200 candidates, no older than 30, at the outset of their career, who have already achieved some success in their field.
4. **Award of the Polish Ministry of Science and Higher Education for the scientific achievements:**
   - one of the only three awards of this type granted in Poland in 2013 to scientists with PhD degree.
5. **Scholarship of the Polish Ministry of Science and Higher Education for outstanding young scientists between 2013 and 2016.**
6. **Scientific Award of the Department of Technical Sciences of the Polish Academy of Sciences in 2016:**
   - awarded for the series of papers presenting the original methodology for computer-aided decision making based on varied types of indirect preference information and comprehensive robustness analysis.
7. **Best Paper Award in Technical Sciences for young researchers in 2013:**
   - awarded by the Polish Academy of Sciences (Poznań Branch) for the paper entitled "Extreme ranking analysis in robust ordinal regression" published in Omega - International Journal of Management Science.
8. **Best Paper Award JRS 2014:**
   - awarded during the Joint Rough Set Symposium 2014 held in Madrid and Granada in 2014 for the paper entitled "Robust Ordinal Regression for Dominance-Based Rough Set Approach under Uncertainty".
9. **EJOR Best Reviewer Award - 5 times in 2012, 2013, 2014, 2015 and 2016:**
   - awarded by Elsevier as a recognition of the efforts, dedication and professionalism in conducting the reviews for European Journal of Operational Research (one of the greatest and most prestigious JCR journals in the category of operational research);
   - each year this award is given to about 20 reviewers from over 6000 researchers who are conducting reviews for EJOR; I have been honored with this award as the youngest researcher ever and as the only one in 5 consecutive years.
10. **Scientific Awards from the City of Poznan**:
    - Award of the City of Poznan for the doctoral dissertation in 2014;
    - Award of the Poznan City Council for Young Researchers in 2012.
11. **Awards of the Rector of Poznan University of Technology:**
    - Special team award for the scientific achievements in 2014;
    - Individual awards for the scientific achievements between 2012 and 2016;
    - Individual awards for the achievements in teaching in 2012 and 2013;
    - Individual award for the effective collaboration with the most talented students in 2016.

Miłosz Kadziński

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