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Décoration de Bernard Roy par Roman Slowinski

Votre Excellence, Monsieur l'Ambassadeur de la République de Pologne en France, Mesdames Laurence et Isabelle Roy, chers Collègues chercheurs et professeurs français et polonais, notamment, les participants des assises franco-polonaises en chimie!

L'initiative de la décoration de Bernard Roy avec une croix de mérite de la République de Pologne était née pendant la vie du professeur Roy, mais malheureusement le 28 octobre 2017 il nous a quitté soudainement. En tant que collaborateur proche du professeur Roy, je tiens à remercier tout d'abord Monsieur le Président de la République de Pologne, Monsieur Andrzej Duda, d'avoir continué la procédure de décernement de la médaille malgré le décès, ainsi que Monsieur l'Ambassadeur Tomasz Młynarski d'avoir l'amabilité de choisir ce soir pour la cérémonie de la décoration. Le moment est d'autant plus approprié que la réunion de ce soir s'inscrit dans la célébration du centenaire des relations scientifiques franco-polonaises. Bernard Roy était un grand scientifique et humaniste sensible qui avait un impact significatif sur le développement de la recherche en Pologne dans le domaine de l'aide informatique à la décision. Il est né en 1934 à Moulins-sur-Allier. En 1954, il obtient une licence en mécanique théorique de l'Université de Paris et, trois ans plus tard, une maîtrise de l'Institut de statistique de l'Université de Paris (ISUP). A l'issue des études, Bernard Roy épousa Françoise Jolivet, avec qui il eut six enfants, dont Laurence et Isabelle sont ici présentes. Sa thèse de doctorat sur la théorie des graphes et ses applications a été défendue en 1961 à l'Université de Paris et son promoteur était Claude Berge – le fameux expert français de la théorie des graphes. Un an plus tard, Bernard Roy rejoint la direction scientifique d'une société de conseil appelée Société d'Économie et de Mathématiques Appliquées (SEMA), dirigée par Jacques Lesourne (plus tard, rédacteur en chef du journal «Le Monde»). Son objectif était de soutenir les consultants dans l'application de méthodes de recherche opérationnelle. Roy a repris la direction de cette équipe en 1964 et parallèlement, il est devenu le rédacteur en chef du trimestriel METRA-SEMA, qui diffusait des méthodes modernes de gestion et d'aide à la décision. (Entre parenthèses, dans les années 70, en tant qu'étudiant, je suis tombé par hasard sur un des numéros de la revue METRA-SEMA dans un club de la presse EMPIK à Poznań et pour la première fois j'avais vu le nom de Bernard Roy sur un article fascinant présentant sa méthode d'ordonnancement disjonctif – une concurrente de la méthode américaine PERT. Ce sont des méthodes de gestion de projets.) Roy avait exercé ces deux fonctions jusqu'à son passage à l'Université Paris Dauphine en 1974, où il a créé un laboratoire affilié au CNRS, appelé le LAMSADE (Laboratoire d'Analyse et Modélisation des Systèmes pour l'Aide à la Décision). Le LAMSADE est devenu au fil du temps un centre de référence mondial dans le domaine d'aide à la décision. Bernard Roy avait dirigé ce laboratoire jusqu'à son départ à la retraite en 2001. L'aide à la décision est un domaine qui est à la fois d'une grande utilité pratique, et d'un grand intérêt scientifique. Sa méthodologie repose sur la recherche opérationnelle, les mathématiques, l'informatique, la gestion et l'intelligence artificielle. Des liens scientifiques entre Bernard Roy et la Pologne se sont tissés pendant 40 ans. En 1977, quand Bernard Roy, comme Président de l'Association Française pour la Cybernétique, Economique et Technique (AFCET), avait organisé un Congrès de l'AFCET à Versailles, j'avais la chance de participer à ce congrès à mes frais. Au fait, j'avais une chance double, car j'étais écouté par Bernard Roy qui a trouvé que ma présentation valait une discussion à laquelle il m'avait invité par la suite. Trois ans plus tard je me suis trouvé comme chercheur associé au LAMSADE, et en 1981 Bernard Roy est venu en Pologne pour participer au jury de mon habilitation à l'Université de Technologie de Poznań. Dans ce temps fort pour notre pays, Bernard Roy montrait de manière ostentatoire son soutien à la « Solidarność » en portant un badge de solidarité au revers de sa veste. Dans les années suivantes, moi-même et mes multiples doctorants et étudiants polonais ont trouvé un bon accueil scientifique au LAMSADE en renforçant la collaboration dans la recherche et, surtout, en approfondissant la compréhension de l'approche européenne d'aide à la décision dont Bernard Roy était le fondateur et le plus conséquent promoteur. Cet approche mettait en cause certains axiomes de la théorie d'utilité de provenance américaine, et proposait une démarche plus constructive et conviviale au raisonnement humain dans le processus d'aide à la décision. En 1985 Bernard Roy avait publié en français un livre intitulé « Méthodologie Multicritère d'Aide à la Décision », qui résumait cette démarche – j'avais entreprit son traduction en polonais et ans plus tard elle a été publié en 10 milles exemplaires par Wydawnictwo Naukowo-Techniczne à Varsovie. Ce livre avait un impact important sur la recherche en Pologne et sur les collaborations scientifiques franco-polonaises. Il permettait aux étudiants et aux chercheurs polonais de bâtir des nouveaux algorithmes d'aide à la décision fondés sur une autre base axiomatique que celle de la théorie d'utilité. Mes collaborations avec Bernard Roy et les membres du LAMSADE ont abouti aux multiples publications conjointes, notamment avec des doctorants de Bernard : particulièrement avec Daniel Vanderpooten, aujourd'hui professeur à l'Université Paris Dauphine, présent ce soir parmi nous. Mes séjours de travail au LAMSADE ont duré en total 4 ans. En 2001, Paris Dauphine m'avait honoré avec son grade du docteur honoris causa. Plusieurs chercheurs polonais et français ont bénéficié de ces relations, entre autres, dans le cadre du programme d'échange «

Polonium ». Depuis 25 ans, l'Université Paris Dauphine et l'Université de Technologie de Poznań collaborent aussi dans le programme d'échange d'étudiants Socrate-Erasme. Plusieurs étudiants ont réalisé leur travaux de maîtrise en cotutelle franco-polonaise. Un grand champ d'activité de Bernard Roy, après le LAMSADE, était le Groupe du Travail Européen sur l'Aide Multicritère à la Décision, qu'il avait initié en 1975 et qui, jusqu'à nos jours s'est réuni 90 fois. Bernard Roy m'a confié la coordination de ce groupe en 2010 et il est devenu président d'honneur. L'ambiance du constructivisme et d'amitié qui catalysait au sein du groupe des collaborations fructueuses était certainement dû à la personnalité de Bernard Roy et, il faut le dire, de son épouse Françoise qui accompagnait souvent Bernard aux réunions. Elle était ces yeux et son parfait compagnon, car Bernard était aveugle une moitié de sa vie. Leur maison à Sèvres rayonnait de chaleur et d'amitié aux invités. Françoise est décédée deux ans avant Bernard. Bernard Roy jouissait toujours d'un grand estime dans le milieu scientifique. Il a été élu président de l'Association Européenne des Sociétés de Recherche Opérationnelle (EURO). Sept universités du monde lui ont conféré le titre du docteur honoris causa (parmi eux, l'Université de Technologie de Poznań). Bernard Roy était aussi lauréat de la médaille d'or d'EURO, de la médaille d'or de la société internationale «Multiple Criteria Decision Making», du prix «Hermès de la recherche» par l'Université Laval, «Distinguished Service Medal Award» par l'EURO, et de la Medaille de L'Académie Polonaise des Sciences «pour des mérites particulièrement liés au rôle social de la science» que nous lui décernions en 2017 dans ce même endroit. Surpris par le décès de Bernard Roy, nous sommes nombreux à exprimer un grand chagrin de sa disparition, mais aussi une grande reconnaissance pour tous ses précieux enseignements. En réponse à l'information sur le décès, un de mes amis m'avait écrit : il est si rare de rencontrer un homme tout aussi brillant qu'affable. Un autre avait écrit : Bernard semblait immortel de par sa vivacité, sa clairvoyance et son enthousiasme dans tous nos travaux. Nous sommes aujourd'hui très heureux par la décision du Président de la République de Pologne qui a élevé à titre posthume le professeur Bernard Roy à la dignité de Chevalier dans l'Ordre de Mérite – il a été un très sincère promoteur de la collaboration scientifique franco-polonaise qui allait bien au-delà de simple échange d'intérêts.
Merci de votre attention.

Roman Słowiński, Paris, le 4 juillet 2019.

Opinion Makers Section

Multi/Many-Objective Optimization in Feature Selection[1]

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Abstract

Feature selection, the removal process of nonessential variables in a dataset, is a crucial step in any machine learning algorithm since not only simplifies the model but also increases the predictor's performance. However, conceding that the removal of unnecessary features does not improve all performance metrics simultaneously, different applications require distinct classifier's performance metrics. Additionally, it might be advantageous to use diverse metrics for the process of finding good feature subsets.
This work's contribution is twofold, both related to binary supervised classification: firstly a set of nine model's performance metrics are studied in terms of redundancy, conjecturing each one's importance in respect to feature selection itself; and then four different sets of metrics are used to evaluate how multi and many-objective algorithms behave in feature selection, testing if the inclusion of more than the traditional 2 objectives is beneficial.
The first analysis shows that, of the nine performance metrics studied, less than four or five, depending on the dataset, are not redundant, i.e., are not simultaneously improved in the feature selection process. Then, using state of the art multi

and manyobjective algorithms, results suggest a better performance, in terms of both convergence and diversity of the solutions offered to the decision maker, of feature selection when using a high number of objectives in binary classification.

Index Terms—Feature Selection, Wrapper Evaluation, Evolutionary Computation, Multi-Objective Optimization, Decision Interface.

I. Introduction

Nowadays data collection and storage are available effortlessly, allowing researchers and scientists to gather and store enormous datasets, frequently prioritizing the storage of all variables, disregarding their importance. There are also applications where variable relevance is unknown *a priori* and all variables end up being collected. Consequently, most datasets became contaminated with redundant, noisy or simply not relevant variables. The data collection and storage evolution was of such magnitude, that only two decades ago a dataset with more than 20 variables was considered largescale, while nowadays that designation is used when dealing with thousands of variables.

Feature selection is the exclusion process of those unnecessary variables. Fewer features results in a simpler, more transparent model, quicker to train and test, and easier to understand. Additionally, removing redundant and noisy variables improves performance by increasing the predictive value of data, avoiding the curse of dimensionality [1].

Feature selection is a complex duty not only considering the enormous search space for medium-sized datasets ($2^N - 1$), which makes feature selection an NP-hard problem, but also due to the intricate interactions between features. These interactions might make features useless by themselves be beneficial when paired with others, and apparently redundant ones can also be advantageous when combined [1].

Any feature selection algorithm is characterized by two main traits: a search procedure which can be exhaustive, based on heuristics or randomized; and an evaluation function, that can be either filter, using no model, wrapper, using a classifier’s performance, embedded, or hybrid. Despite slower and more complex, or perhaps as a consequence of it, combining randomized search procedures, or meta-heuristics, with wrapper evaluation is the most promising approach to feature selection in the current state of technology. Randomized search is undeniably the best approach to successfully explore such an immense search space, for its stochastic nature and ability to avoid local optimums, and is known for its high performance in NP-hard problems. Wrapper approach to feature subset evaluation is the most reliable one, despite the computational costs, being the only approach truly reactive to feature’s interactions.

While most feature selection is handled taking only into account the classifier’s performance, it is obvious that the goal to maximize performance should be accompanied by a drive to reduce the number of features, i.e., when choosing between solutions with the exact same performance the one using fewer features is obviously preferred. Moreover, different classifier’s applications or decision makers might require distinct performance metrics, therefore no single performance metric should be used, but a set of them.

The reasoning behind using several classifier’s performance metrics is, therefore, twofold: firstly, it’s advantageous to present the decision makers with several objectives, allowing them to prioritize and select based on their preferences.

Additionally, using several performance metrics in the search procedure might allow the algorithm to reach better and more diverse solutions.

Including several performance metrics in the optimization process involves, obviously, multi or even many-objective optimization algorithms.

A. Background

Using evolutionary computation in feature selection dates back to the 80’s [2], but only gained popularity in the last decade with the ever-growing size of datasets. The advantages of adding other objectives and using a multi-objective algorithm to tackle feature selection have been a topic for some years, with most research consisting of stating feature selection as a bi-objective problem of the number of features and some performance metric such as accuracy. This is true both for binary classification [3], [4] and for multi-class classification [5]. Advantages of using more performance metrics in binary classification are suggested by [6], that showed an increase in performance when using recall and specificity in comparison to using only accuracy. However, that work as not been pursued and the advantages of using more metrics were not discussed, despite works such as [7] using several metrics.

B. Contents

Firstly, the datasets and classifier used throughout this work are presented in section II. In section III, several traditional classifier’s performance metrics are tested to check redundancy, i.e., to verify if all are improved simultaneously by feature selection, and promising sets of metrics are chosen. Having several metrics, the area of multi and manyobjective optimization is introduced in section IV, where high-performing evolutionary algorithms are selected to tackle feature selection, and specifics about each one are discussed. The advantages of using several metrics in the feature selection process by the wrapper evaluation method are presented in section V, as well as the best-performing algorithm of the five presented for feature selection.

II. Subset Evaluation

Traditionally, in the field of feature selection, the classifiers used include decision trees, support vector machines, and k-nearest neighbours [1], [8]. These classifiers do not have inherent tacit feature selection techniques such as neural networks. Decision trees were chosen in this work for exhibiting a great accuracy/computational time trade-off [9]. Nevertheless, a classifier in feature selection needs not have exceptional prediction abilities, but merely to be reactive to CART decision tree implementation in MatLab was used.

Different benchmark datasets were used for binary classification Table I. All were selected from UCI repository, except for AldoA, which is a confidential dataset from medical applications. These have a wide range of features, instances, types of data and not all are balanced.

Table I: Datasets for binary classification.

Name	Features	Instances	% Positives
AldoA	74	1434	89.1
Mushroom	112	8124	48.2
Musk	166	476	43.5
Phishing	68	11055	55.7
Sonar	60	208	46.6
Spectf	44	267	79.4

Pre-processing of these datasets included normalizing features, eliminating instances with missing values, expanding categorical variables into several binary ones, and dividing the data into training and testing sets. This data division was chosen in detriment of cross-validation, for example, for its simplicity, an important issue considering the number of subset evaluations to be performed during a randomized algorithm. The ratio used was 75% and 25% for training and testing, respectively, keeping the training set balanced, i.e., having an equal number of instances corresponding to each label.

III. Metrics in Wrapper Feature Selection

As mentioned in the introductory section, it’s advantageous to present several classifier’s performance metrics to the decision makers so they are able to prioritize *a posteriori* the ones they prefer.

Nine traditional metrics were selected to study binary classification: accuracy, precision, recall, specificity, F1-score, Cohen’s kappa, non predictive value, Matthews coefficient and markedness.

Intuition suggests that removing unwanted features from a dataset improves a classifier and therefore all its performance metrics. Figure 1 is a binary map for Spectf and Vehicle datasets, where each column represents a feature and a line a solution. Blue squares indicate selected features. The solutions presented are the ones that maximize the metrics mentioned above, of a universe of 30000 randomly generated solutions, after eliminating duplicate solutions.

Fig. 1: Best solutions’ subsets for Spectf dataset.

The great amount of unused features justifies the process of feature selection. Moreover, it’s evident in Figure 1 that different metrics prefer totally distinct feature subsets, justifying the need to present several wrapper’s performance metrics to the decision maker. Therefore, these results encourage the application of multi/many-objective optimization in feature selection, since the idea of overall unwanted features disappears, and a feature’s importance becomes relative to the performance metric. Nevertheless, 4 different solutions are present in the Spectf, with similar results for the remaining datasets, suggesting some redundancy between the nine metrics.

There’s a need to study the relationship between metrics, not only for presentation purposes but also taking into account that multi-objective optimization algorithms might have their performance decreased when dealing with redundant objectives [10]. The relationships between objectives are pairwise, and can be of three types: independent, if objectives are autonomous in their optimization, i.e., optimizing one does not affect the other; harmonious if objectives are improved or deteriorated simultaneously; and conflictual if enhancing one objective imperatively damages the other as a sideeffect. Independent objectives can be optimized separately and harmonious objectives are redundant and therefore only one of them should be optimized. Only conflictual objectives truly justify the use of multi/many-objective algorithms, since they result in a trade-off.

To identify these relationships, a quantitative analysis using parallel coordinates plot was used. The reasoning is that conflictual objectives have plenty of crossings in a parallel coordinate plot, while independent or harmonious have very few. In Figure 2 four different solutions are displayed in a parallel coordinate plot. While objectives 2 and 3 have exactly the same solution ordering and therefore are harmonious and one should be dismissed, objectives 1 and 5 only discrepancy is the ordering of the blue and grey solutions. These should also be, to a certain degree, considered harmonious.

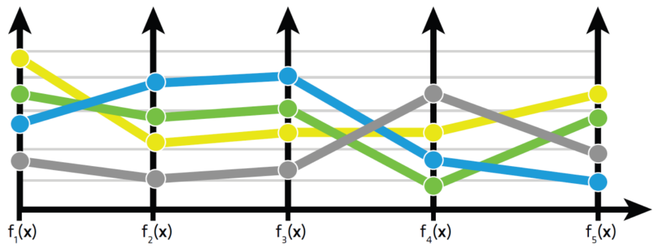


Fig. 2: Parallel coordinates plot.

For the end of quantifying the degree of conflict based on the ordering of solutions, Kendall’s correlation was used. Benchmark problems such as DTLZ were tested to get a threshold value above which two objectives are considered harmonious. The attained value is roughly $K_c = 0.3$. Thirty thousand randomly generated solutions for each dataset were used, which in most of them represents a very small part of the search space. The pairwise Kendall’s correlation was calculated and while the results are not constant over the datasets, the averaged results for all binary datasets using the metrics mentioned above are still interesting and therefore are presented in Figure 3.

Foremost, the first conclusion is that the most conflictual objectives are recall and specificity, with an average −81% of Kendall’s correlation. Further analysis can be made not by finding the most conflictual but the most redundant and then eliminate it. For example, markedness and Matthews coefficient are made redundant by most other metrics. F1-score is highly correlated to accuracy, and therefore is eliminated, precision is also made redundant by specificity. NPV is not eliminated, despite its high correlation value, because it is conflictual in some datasets. Table II summarizes the combi- nations of metrics chosen for binary classification to analyse in multi-objective optimization.

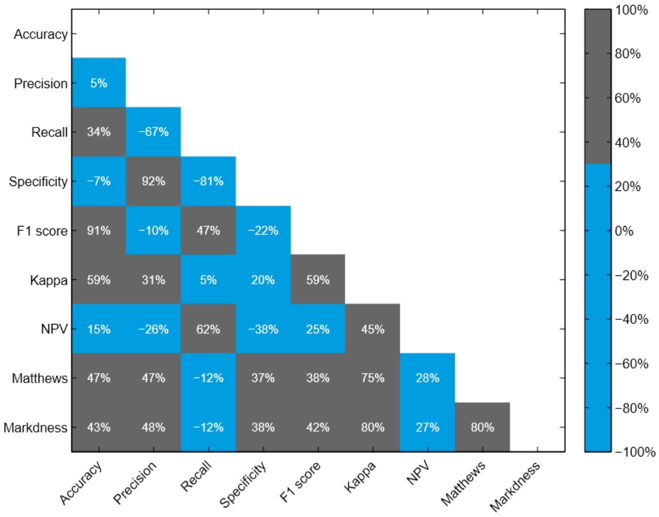


Fig. 3: Kendall correlation averaged.

Table II: Metrics' combinations used in binary classification.

Nr. of Metrics	Perfomance Metrics
2	Accuracy
3	Recall, Specificity
6	Accuracy , Recall, Specificity, Kappa, NPV
10	All

IV. Search Procedure

Multi-objective optimization is mathematically similar to single-objective, but the global optimal concept is traditionally replaced by Pareto optimality. In a bi-objective problem with two solutions, if a solution is better in one objective but worse in the other one, no solution is globally worse nor better. Instead, these solutions are non-dominated and together form a trade-off which can only be solved by the decision maker. Formally, a solution A strictly dominates solution B, when there's at least one objective in which A is better while being no worse in all others [11]. This is defined as weak Pareto dominance ($A \preceq B$), while strong Pareto dominance ($A \prec B$) requires all objectives to be better. The Pareto front is defined as the ideal trade-off curve.

Using several objectives in an optimization procedure is a relatively established field. There are three main types of algorithms: *a priori*, interactive and *a posteriori*. The latter is usually preferred for not requiring knowledge that the decision maker might not have, and for not limiting the search space [11].

A posteriori randomized methods are heavily based on single-objective optimization ones, differing in the selection mechanism, which can be either based on Pareto dominance, decomposition or indicator. Of the three, Pareto dominance based are undoubtedly the most well-known and used. However, these are notorious for their scalability issues: when the number of objectives increases so does the percentage of nondominated solutions in the population, weakening the selection pressure to the Pareto front [12]. A quick fix to this problem is to increase the population's size, which naturally becomes infeasible.

This phenomenon results in denominating problems with more than 4/5 objectives many-objective problems [12], which can be, as discussed previously, important to the problem being handled. Considering the previous analysis of wrapper performance metrics relationships, the combinations considered promising range from 2 objectives up to 10, and therefore both multi and many-objective problems are being considered. Keeping this in mind and considering the most recent surveys in this field [12], [13], five different methods were chosen.

1) NSGA-II
2) NSGA-III
3) MOEA/D
4) HypE
5) PICEA-g

NSGA-II is the most well-known algorithm for multi-objective optimization, for its simplicity and for lacking extra parameters. It's a Pareto based method and therefore suffers from the scalability issues mentioned above. As a response to those scalability issues, the same authors created NSGA-III, a decomposition based algorithm which has shown great results for many-objective problems. However, not always does the NSGA-III perform better than its ancestor, particularly in the many-objective knapsack problem [14], which is discrete and binary-coded, and therefore somewhat similar to feature selection. MOEA/D, another decomposition based algorithm that creates several sub-problems, has also become a benchmark problem for multi-objective optimization, with [15] showing it frequently outperforms NSGA-II. Additionally, the work in [16] compared several algorithms (NSGA-III was still unborn) and found that PICEA-g and HypE had better performance, the first being also decomposition based, in which there's simultaneous evolution of a solutions and a goals population, and the second is indicator based.

All these algorithms involve a population and therefore a single run is capable of providing a non-dominated front to the decision maker. PlatEmo [17] was used for the algorithm's implementation in MatLab environment.

A. Algorithms Performance Indexes

A multi-objective optimization algorithm should be evaluated according not only to convergence, but also on its ability to provide diverse solutions. Consider solutions A and B for the bi-objective problem illustrated in Figure 4. Solution B is well converged but its solutions are poorly spread. For that reason three different indexes were used: set coverage, hypervolume and spacing.

Set Coverage: Set coverage is a pairwise comparison between populations convergence. *C*(*A*,*B*), as defined in Equation 1, computes the ratio of population in B dominated by any solution in A. This index is not symmetrical, therefore both *C*(*A*,*B*) and *C*(*B*,*A*) should be calculated.

$$C(A,B) = \frac{|\{b \in B; \exists a \in A : a \succeq b\}|}{|B|} \tag{1}$$

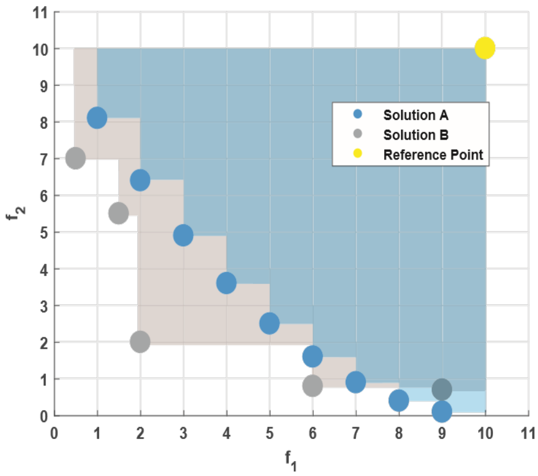


Fig. 4: Two example solutions for a bi-objective problem.

Spacing: Spacing, S, is a measure of standard deviation between solution’s distance, as described in Equation 2, where $d_i(A) = min_{k\in A\wedge k\neq i} \sum_{m=1}^{M} \left|f_m^i - f_m^k\right|$ and $\overline{d(A)} = \sum_{i=1}^{|A|} \frac{d_i}{|A|}$. When the solutions are uniformly spaced, this metric is small, since the distance vectors are similar. Therefore, unlike set coverage, the intention is to minimize it.

$$S(A) = \sqrt{\frac{1}{|A|} \sum_{i=1}^{|A|} \left(d_i - \overline{d}\right)^2} \tag{2}$$

Hypervolume: Finally, the well known hypervolume metric can measure both convergence and diversity. It calculates the area/volume created by the non dominated front in the objective space, given an reference point. High value of hypervolume is synonym of a well-spread and/or converged solution. Hypervolume computation is simple in a bi-objective problem, but with increasing number of objectives become highly demanding. Table III presents the three metrics values of solutions A and B of Figure 4.

Table III: Indices results to the solutions presented in Figure 4, with best results highlighted.

Solution	Hypervolume	Spacing	Set Coverage
A	350.50	0.51	1/5=0.20
B	362.15	0.61	7/9≈0.78

B. Benchmark Comparison

To validate the algorithms’ implementation, DTLZ test suit was used [18] in addition to the multi-objective knapsack problem (MOKP) for its similarity to feature selection, being both discrete and binary-coded. For each benchmark problem $M \in \{2,4,10\}$ were used. The results in DTLZ were as expected, with NSGA-II having decreased performance when increasing the number of objectives and NSGA-III having the exact opposed behaviour. Moreover, HypE showed high performance across all objectives, similarly to PICEA-g.
The results in MOKP are not in the same direction as the DTLZ problems. The algorithms are stochastic and therefore a variance analysis is done using box plots. For smaller objectives Figure 5 shows the hypervolume performance, after performing a min-max normalization, in relation to each objective.
It’s visible that for $M = 2$, MOEA/D performs very well, closely followed by NSGA-II and HypE. Increasing the number of objectives, HypE becomes the top-performer. NSGA-III is inferior across all range of objectives, likely explained by its decomposition mechanism based on normalisation not being suited for discrete problems.

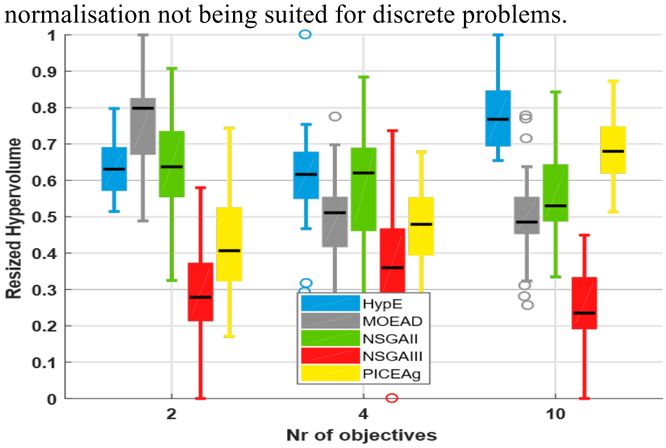


Fig. 5: Hypervolume comparison for MOKP

Spacing analysis, in Figure 6, shows that MOEA/D performs the best in terms of solution’s uniformity, except when $M = 10$, where HypE outperforms it. Nevertheless, the results are very similar for all algorithms, except NSGA-II which has very poor uniformity in the highest dimensional example.
The results of set coverage, being pairwise, are of harder visualization. Keeping in mind that each bar represents the domination of that bar’s respective algorithm, it’s visible that the results are similar to the hypervolume’s. for $M \in [2,4]$ MOEA/D is the top-performer.

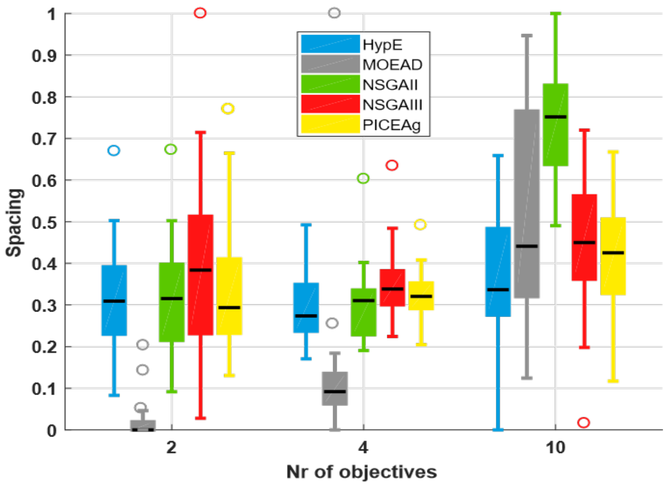


Fig. 6: Spacing comparison for MOKP.

However, when M = 10, HypE performs slightly better. This coincides with the results in [19].

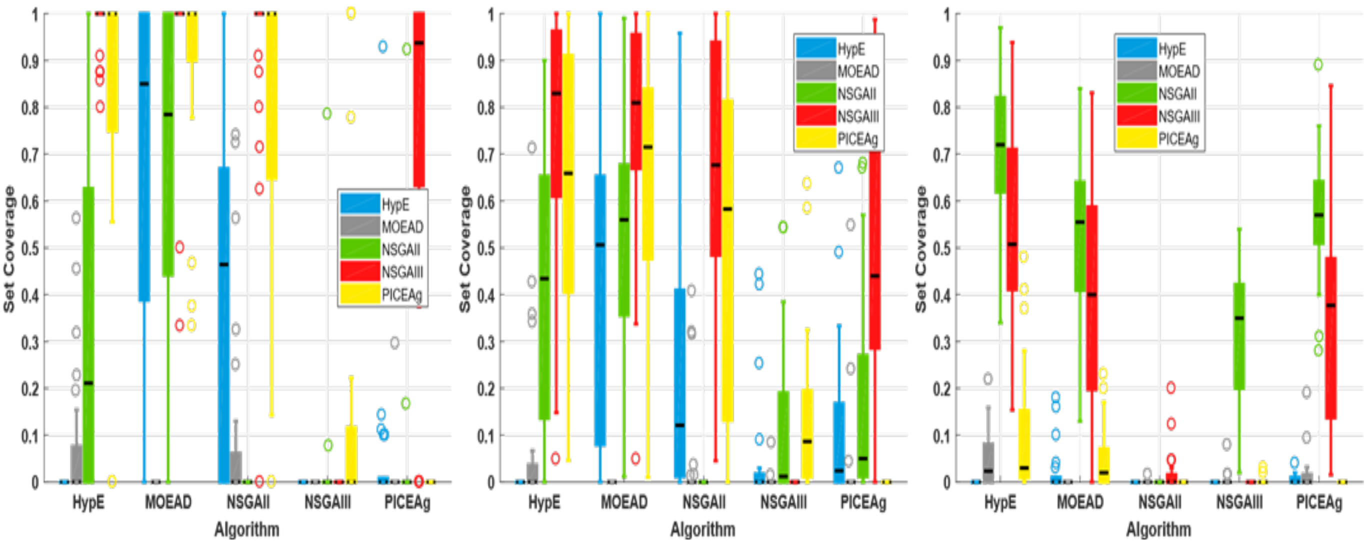
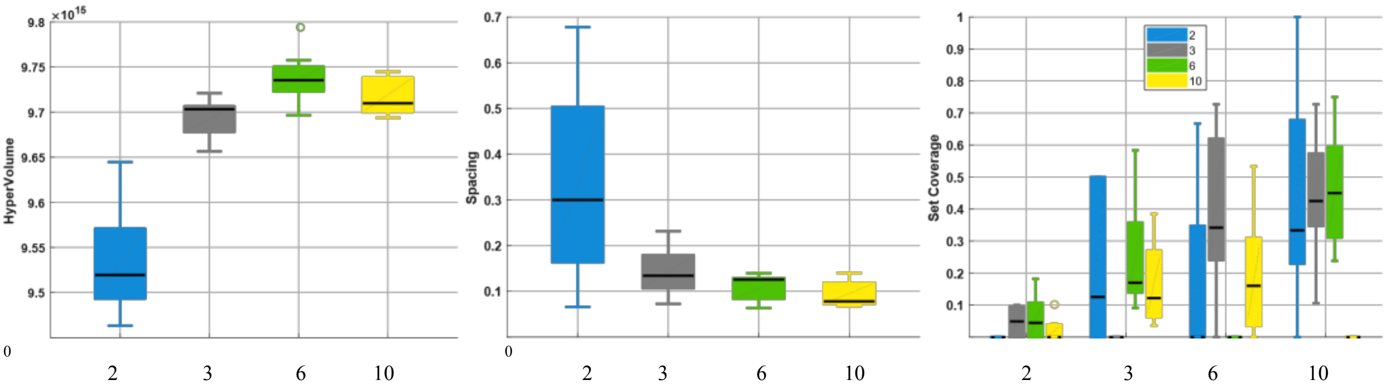


Fig. 7: Set coverage behaviour of the algorithms for MOKP.



Nr of objectives (a) Hypervolume | Nr of objectives (b) Spacing | Nr. of Objectives (c) Set Coverage

Fig. 8: HypE performance in Spectf dataset.

C. Encoding for Feature Selection Initial Population, Size and Stopping Criteria

In order to motivate genetic operators to reach solutions with a low number of features in the first generations, the method used consisted, for each individual, in generating a uniformly random number K =∈ [1;Nfeat] and then randomly choosing K features to be selected.

Population size was set to 100, allowing both diverse populations and also keep the final population and computational time manageable. The number of generations was set as the stopping criteria.

Genetic Operators

All chosen algorithms are genetic based, meaning they use the typical selection, crossover and mutation operators. Only NSGA-II and HypE use non-random selection to choose the parents, and both use binary tournament. The first with rank level and crowding distance as second criteria, and HypE with hypervolume-based fitness value of each solution. So they have no extra parameters.

For the remaining genetic operators, two-point crossover was used and bitwise mutation, with a mutation probability of p_m=1/L , was selected, where L is the size of the genome, i.e., the number of features.

Algorithms Parameters

Only NSGA-II and NSGA-III are parameter-free, except for the usual genetic operators. MOEA/D, HypE and PICEA-g all samples used to estimate the hypervolume metric, and PICEAg uses the goal’s population size. All these were tested using time, hypervolume and spacing analysis, for the MOKP, due to its similarity to feature selection. The best parameters are shown in Table IV.

Table IV: Parameters values

Algorithm	Parameter Name	Value
HypE	Nr. of Samples	1000
MOEA/D	Nr. of Neighbours	10
NSGA II	-	-
NSGA III	-	-
PICEA-g	Nr. of Goals	5000

V. Results

Considering that HypE performed consistently very well in the multi-objective knapsack problem over all objectives, it was chosen to test if it’s beneficial to use several wrapper’s performance metrics in feature selection, i.e., if the algorithm using more metrics is able to find better solutions both in terms of convergence and diversity.

The four sets of wrapper performance metrics listed in Table II were tested in all datasets using 100 generations composed of 100 individuals, repeated 20 times. When using less than 10 objectives, the final population was then reevaluated in order to obtain those 10 performance metrics so that it’s possible to fairly compare the results. The results are similar in all datasets, and Figure 8 illustrates Spectf dataset’s performance in terms of hypervolume, spacing and set coverage. It’s visible that using only accuracy yields poor performance in all metrics. Moreover, despite $M = 6$ presenting slightly better hypervolume, both spacing and set coverage analysis suggests that the population resulting from using HypE with $M = 10$ is more uniformly spread and has overall better solutions than $M = 6$.

To easily visualize these results, the populations resulting from using mRMR, a well-known feature selection method, $M = 2$ and $M = 10$ are compared in Figure 9, with evidently improved performance for $M = 10$, reaching “peak solutions“, i.e., solutions that have very high performance in one objective while being average or poor in others.

Further, study showed that of the five algorithms presented in section IV, NSGA-II performs the best in binary classification feature selection using $M = 10$, closely followed by HypE. These results are represented by set coverage in Figure 10. NSGA-II’s performance might be explained by the high level of redundancy between objectives, as shown in Figure 3, which lowers the value of true conflicting objectives.

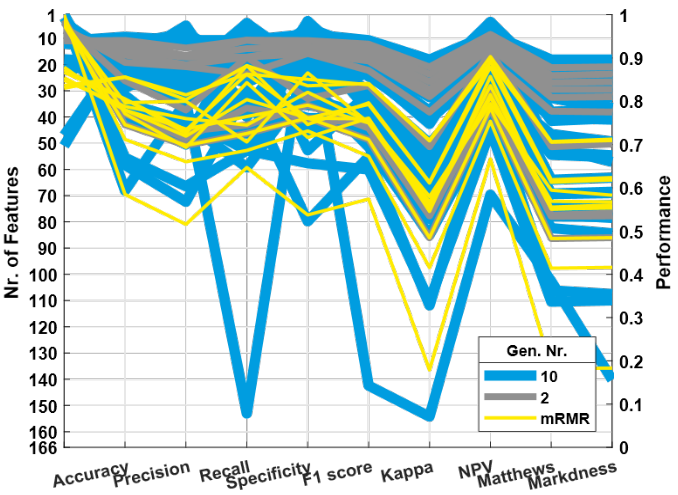


Fig. 9: Three different approaches for feature selection in Musk dataset.

Despite the advantages of using several objectives to guide the feature selection search procedure into better solutions, this produces a high number of different non-dominated solutions, making the selection process similar to “finding a needle in a haystack“.

For that reason, and entering the multi-criteria decision making field, a decision interface was created in MatLab, which allows the user to set minimum values for each objective, observe both the search space and the design space simultaneously, and aids in the selection by allowing the decision maker to assign weights to each metric and finding the best solution.

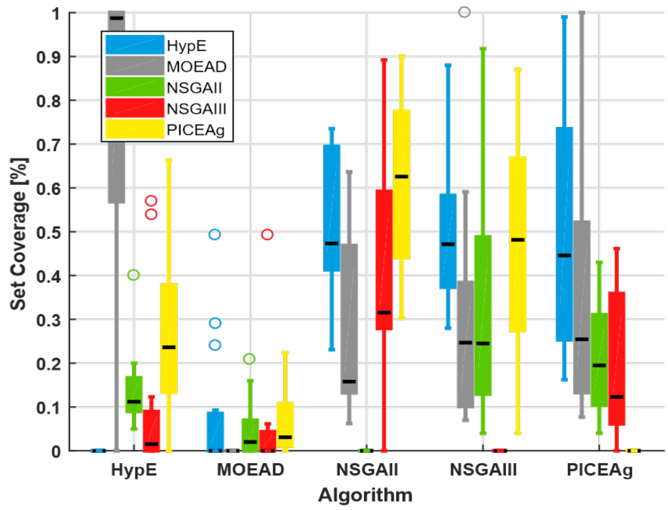


Fig. 10: Set coverage comparison in Musk dataset.

VI. Conclusion

This work’s investigation is a contribution to the necessarily growing field of feature selection, in an age where data acquisition and storage is done effortlessly.In addition to a study of the relationships between wrapper’s performance metrics, where conflictual sets of metrics were selected using a method based on Kendall’s correlation, this study has shown great advantages to the arduous feature selection task when using many objectives, not only reaching better solutions, i.e., well-converged, but also yielding a wider set of solutions, capable of describing all search space and providing many different solutions to the decision maker.

The result of that process is a big number of trade-off solutions for the decision makers to select. To help in this process, a decision interface was created to support the decision makers find the solutions that are most suited to their needs/priorities.

With this work, research is surely motivated. Not only could these results be tested and verified using other classifiers such as k-NN or SVM, but also using different datasets. Additionally, various other multi-objective algorithms can be tested, seeking the most suitable for the feature selection problem.

Finally, adding flexibility to the decision interface, such as fuzzy decision making, could make it an indispensable tool for any feature selection process.

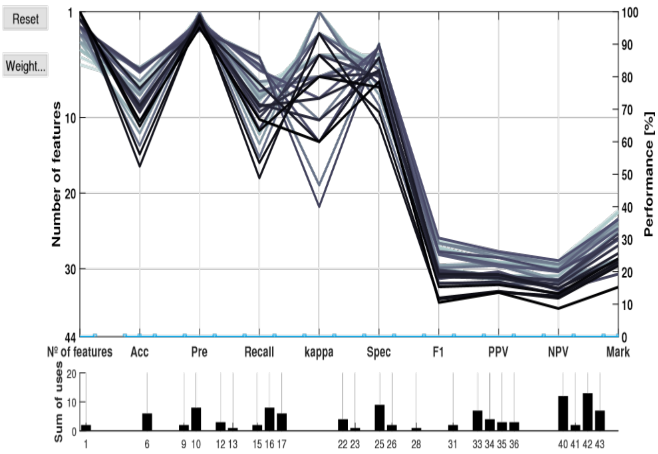


Fig. 11: Decision interface created.

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Perspectives on Multi-Criteria Decision Analysis and Life-Cycle Assessment

Luis C. Dias, Fausto Freire and **Jutta Geldermann**

1. Introduction

Environmental Life Cycle Assessment (LCA) and "life cycle thinking" are enjoying increasing international recognition in the scientific community, in industry, and in environmental policy. LCA is a well-known methodology that aims at quantifying the environmental impacts of a product or service in a holistic and integrated manner, over its life cycle, on different dimensions called impact categories, e.g., depletion of resources, impacts of emissions on the environment and on human health, all expressed in different units of measurement.

Many authors have proposed joining LCA and Multi criteria decision analysis (MCDA) for a combined assessment. In our book chapter "Perspectives on Multi-criteria Decision Analysis and Life-Cycle Assessment", in: M. Doumpos, J.R. Figueira, S. Greco and C. Zopounidis: New Perspectives in Multiple Criteria Decision Making. Springer International Publishing, pp. 315–329 (2019), we discuss how LCA can be useful for MCDA practitioner and vice versa how MCDA can complement LCA. In this newsletter contribution, we waive the references in favour of brevity. Instead, we focus on main challenges and perspectives in application of LCA and MCDA.

2. Life cycle assessment (LCA)

The first studies addressing product life cycles are from the late 1960s. At that time, the focus was on energy and raw materials. Since the 1990s, the International Organization for Standardization (ISO) published the first LCA standards, the ISO 14000 series, comprising four phases.

The goal and scope definition as the first phase includes the system boundaries, functional unit, and level of detail, which depends on the intended use of the study. The functional unit provides a reference for the subsequent calculations and ensures the comparability of LCA results, which is particularly critical when different systems are being compared.

Next, the life cycle inventory analysis (LCI) involves the compilation and quantification of the input/output data of the product system. The third phase is the life cycle impact assessment (LCIA) which associates LCI data with specific environmental impact categories and category indicators. It uses factors calculated by impact assessment models based on impact pathways, generally considering three areas of protection: human health, natural environment, and, natural resource use.

LCIA has mandatory elements, such as selection, classification and characterization, which lead to the calculation of category indicator results, as well as optional elements, such as normalization, grouping, and weighting. Normalization — the calculation of the magnitude of the category indicator results relative to some reference information — serves to highlight the relative magnitude of each indicator. It can use external references (e.g., the total impacts for a given area: global, regional, or national) or internal references (e.g., a baseline scenario, such as a given alternative product system). Grouping is the assignment of impact categories to one or more sets. Weighting aggregates different impact category results into a single score based on weights allocated to each impact category. These optional steps may be very subjective — and hence, controversial — as they imply value judgements, which may influence the results and conclusions of an LCA.

The final phase of the LCA is interpretation, in which results are summarized and discussed as a basis for conclusions, recommendations, and decision making. LCA is iterative and as data are collected or LCIA is performed, various aspects may require modification, including the goal and scope definition.

3. Challenges and perspectives for aggregation of LCA results from an MCDA viewpoint

Choosing between environmental profiles involves balancing different types of environmental impacts and is typical of multi-criteria decision problems, in which explicit or implicit trade-offs are considered to construct an overall judgment. Generally, MCDA methods are applied to provide decision support to one or more Decision Makers (DMs) in choosing an alternative based on multiple criteria. As well known to the readers of this newsletter, several aggregation methods are available to formally evaluate a discrete set of options. Depending on the underlying decision context, some methods are more suitable than others. Naturally, different decision methods may generate different results from the same data. Therefore, the choice of a particular method or combination of methods should be matched to the application. In the following, we comment on several issues that confront LCA experts and MCDA analysts in LCA-MCDA applications.

3.1 Criteria selection

The standardized LCA methodology addresses only environmental aspects, usually giving rise to multiple impact indicators (e.g., depletion of resources, impacts of emissions on the environment and on human health). Over time, however, LCA-based approaches are expanding in three dimensions: i) broadening impacts by including social and economic indicators, ii) broadening level of analysis from predominantly product-related questions to sector-wide and economy-wide questions and analyses, and iii) deepening analysis to add physical, economic, and behavioral relations to the existing technological relations, and to include more mechanisms to account for interrelations among the system elements, uncertainty analysis, and stakeholder involvement. Here, the application of MCDA can be very helpful, as it provides established approaches for problem structuring as well as evaluation and aggregation of indicator results.

Special care should be taken when weighting the plethora of criteria. Redundancies (double-counting) might arise if LCIA indicators from different methods are used. Moreover, some impacts are included as a single indicator in some LCIA methods (e.g., eutrophication), but as multiple indicators in other methods (e.g., maritime eutrophication and freshwater

eutrophication). This affects results when the analysis considers all criteria on an equal basis rather than eliciting weights. Even if weights are elicited, however, the splitting bias might cause the total weight to increase when an indicator is decomposed.
To address these issues, MCDA has a rich literature on problem structuring that can be useful in guiding criteria selection and on weighting biases that might derive from these choices. Adequate communication between analysts and DMs is essential to ensure that the meaning of the indicators is well understood in weight elicitation processes.

3.2 Actors to be involved

The majority of environmental decision problems involve uncertainty and risk. By their very nature, the estimates and long-term forecasts required in LCA are uncertain. The scale of the impacts and when they are incurred is also an important differentiator. In particular, there is little agreement on how to evaluate options with very long term impacts.
There are many parties to such decisions. DMs are responsible for making the decision; they ‘own the problem’. They are accountable to some, but not necessarily to all the stakeholders in the problem. Stakeholders share, or perceive that they share, the impacts arising from a decision, and request that their perceptions and values should be considered. Experts provide economic, engineering, scientific, environmental, and other professional advice used to model and assess the likelihood of the impacts. Whereas experts support decision making by providing information on the content of the decision, analysts provide process skills, thus helping to structure the analysis and interpret the conclusions. This separation of roles is much idealized; some of those involved may take on several roles.

3.3 Criteria weighting

MCDA typically elicits preferences from a DM or a group of DMs, acknowledging the legitimacy of considering their subjective preferences. In LCA, however, there is often no DM involved in the analysis, and the implicit perspective is that the alternatives are being objectively evaluated according to the best scientific state of the art. This is probably why the LCA standard ISO 14044:2006 states that weighting LCIA indicators is an optional step in the methodology and should not be used for comparative assertions intended to be disclosed to the public.
Given the concern about the subjectivity of weighting, many LCA studies simply assume all indicators have the same weight, sometimes considering other “scenarios” (i.e., weight vectors) that place more weight in different groups of criteria. From an MCDA perspective, however, the concept of equal weights is meaningless in some methods (e.g., when a normalization or a value function is used) and setting all weights to the same value is still a subjective choice. Ultimately, one might simply accept that obtaining a purely objective result is an impossible goal, since there is subjectivity in the choice of alternatives that are evaluated, the choice of what criteria are considered, and even the choice of an MCDA method. One might even argue that LCA itself already brings subjective choices when defining system boundaries, allocation methods, etc.

3.4. Relative vs. absolute evaluation

MCDA usually compares several alternatives, which is not the case in many LCA studies. Indeed, some LCAs are devoted to assessing the impacts of a single product or service, for instance, with the aim of learning which stages of the life cycle have the greatest impacts. Often an LCA study is performed to compare a new or modified product with an existing one. Clearly, MCDA methods that base their recommendations on a competition among alternatives, assessing how each one compares to each other one (e.g., AHP, PROMETHEE and most ELECTRE methods), cannot be used if there is a single alternative to be evaluated.

4. Conclusions

LCA is already multi-criteria by its very nature. The impact categories are assessed separately in incommensurable units of measurement and are usually in conflict with each other. Therefore, LCA and MCDA share the perspective that the consideration of multiple criteria is in general the most adequate way of supporting decision making. Each field offers something to complement the other. LCA can be helpful for the MCDA practitioner, since it aids in defining the set of criteria and how performance on these criteria can be measured. Conversely, MCDA can be useful for the LCA practitioner, since it assists DMs in making sense of the results without inadvertently biasing them.
Increasingly, DMs in engineering and business settings are required to select the “most sustainable” alternative, or to at least consider environmental and social responsibility concerns. MCDA practitioners involved in such decision problems might easily forget important issues. In such settings, using the LCA framework can contribute to a more comprehensive evaluation and can ensure that all the concerns of DMs and stakeholders are included in the analyses.
Conversely, MCDA theory and methods are needed to make adequate use of LCA results for decision aiding purposes. This applies not only to the aggregation of impact categories from LCA, but also when additional criteria not encompassed by LCA are important (e.g., reliability, ease of use and maintenance, throughput time, comfort, etc.). MCDA is a field of knowledge that offers methods to define and structure a set of evaluation criteria, to guide the dialogue between analysts and DMs, to set parameters that reflect preferences (namely criteria weights), and to aggregate all the information in a logical manner. Moreover, MCDA makes decisions transparent and auditable, which is especially important if there is no absolute truth.
Therefore, we expect that the already large number of MCDA-LCA/LCSA applications will continue to grow, and that LCA practitioners will become increasingly knowledgeable about MCDA methods, and vice versa. LCA practitioners will tend to use a reduced number of MCDA approaches that will become increasingly popular in this area. We thus expect that proper application of LCA and MCDA will become state of the art both in science and in practice. Yet, many more studies are needed regarding the acceptability of different approaches and their adequacy to inform decision making in real-world situations.

Sat4jMOCO: Minimal Correction Subsets for Multi-Objective Combinatorial Optimization

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Abstract

During the first decade of the century, advances in Propositional Satisfiability (SAT) algorithms resulted in a new generation of optimization algorithms for Maximum Satisfiability (MaxSAT) and Pseudo-Boolean Optimization (PBO). These new algorithms are based on iterative calls to a SAT solver and are several orders of magnitude faster than previous ones, in particular when the solution space is not large. Despite the success of using highly effective constraint solving algorithms in single-objective optimization problems, the usage of constraint solving for Multi-Objective Combinatorial Optimization (MOCO) is still in its infancy.

In this paper, we describe a novel approach for MOCO based on Minimal Correction Subset (MCS) enumeration. Experimental results on instances of the Virtual Machine Consolidation (VMC) problem show that for several classes of instances, enumerating MCSs can provide better results than other well-known approaches for MOCO.

Introduction

In Multi-Objective Combinatorial Optimization (MOCO) applications such as scheduling [6] or green computing [17], there is more than one objective to be optimized, but there is no pre-defined hierarchy among the objective functions. Hence, there may exist multiple optimal solutions, known as Pareto optimal solutions, each of them favoring certain objectives at the expense of others. Several approaches have been proposed [7] that try to identify the Pareto front, i.e., all Pareto optimal solutions. However, this is known to be very hard for large MOCO instances. Given a time limit, most algorithms for MOCO are just able to provide an approximation to the Pareto front.

Recently, several new constraint-based algorithms have been proposed to identify Minimal Correction Subsets (MCS) of propositional formulas. Moreover, it is well-known that MCSs provide an approximation for single-objective optimization problems. In this paper, we review the notion of an MCS of a propositional formula and describe how MCS enumeration can be used to find the Pareto front of MOCO instances.

This paper is a brief presentation of the authors previous works [12, 13, 14] and organized as follows. Section 2 starts by defining Propositional Satisfiability (SAT), pseudo-Boolean Optimization (PBO) and MOCO. Next, we present MCSs and describe how MCS enumeration can be used to find the Pareto front of MOCO instances. Experimental results showing the effectiveness of the proposed technique are presented in section 4. Finally, the paper concludes in section 5.

Preliminaries

This section starts by describing Pseudo-Boolean Optimization (PBO) and Multi-Objective Combinatorial Optimization (MOCO). Next, Minimal Correction Subsets (MCSs) are defined. Finally, we review how MCSs can be used to find solutions for PBO and MOCO problems.

Pseudo-Boolean Optimization

Let $X = \{x_1, \dots, x_n\}$ be a set of n Boolean variables. A literal is either a variable x_i or its complement $\neg x_i$. If a literal $l_i = x_i$ and x_i is assigned value 1 or $l_i = \neg x_i$ and x_i is assigned value 0, then the literal is said to be true. Otherwise, the literal is said to be false. A propositional clause is a disjunction of literals and a propositional formula in Conjunctive Normal Form (CNF) is a conjunction of clauses. A clause is said to be unsatisfied if all its literals are assigned value 0, and it is said to be satisfied if at least one of its literals is assigned value 1.

A CNF formula is said to be satisfied if all clauses are satisfied. If there is no assignment that satisfies a CNF formula, then we say that the formula is unsatisfiable.

Given a CNF formula φ defined over a set X of n Boolean variables, the propositional Satisfiability (SAT) problem can be defined as finding an assignment to all variables such that φ is satisfied, or prove that there is no assignment that satisfies φ.

Given a set of m literals $l_1, \dots, l_m$ and their respective coefficients $w_1, \dots, w_m \in \mathbb{N}$, a Pseudo-Boolean (PB) expression is a weighted sum of literals of the form $\sum w_i l_i$. Given an integer $k \in \mathbb{N}$, a linear PB constraint has the form:

$$\sum w_i l_i \bowtie \text{k}, \qquad \text{k} \in \{\leq, =, \geq\} \qquad (1)$$

The Pseudo-Boolean Satisfiability (PBS) problem is a generalization of the SAT problem where constraints can be any PB constraint instead of just clauses. Note that propositional clauses are special cases of PB constraints. For example, clause $(l_1 \vee, \dots, \vee\, l_m)$ is equivalent to $\sum w_i l_i > 1$. In this paper, for ease of explanation, we use the set notation on formulas. Hence, a formula is represented as set of constraints, meaning a conjunction of constraints.

Consider a set $F = \{c_1, \dots, c_m\}$ of m PB constraints and a cost function f defined over a set of X Boolean variables. The Pseudo-Boolean Optimization (PBO) [3] problem consists of finding an assignment $\alpha: X \rightarrow \{0,1\}$ that satisfies all constraints in F, denoted $\alpha(F) = 1$, and minimizes the value of f, denoted $f(\alpha)$. If F is unsatisfiable, then $\alpha(F) = 0$ for any assignment α. Analogously, given a PB constraint c, $\alpha(c) = 1$ $(\alpha(c) = 0)$ denotes that α satisfies (does not satisfy) c.

Example 1. Consider a PBO instance defined over $X = \{x_1, x_2, x_3\}$ where $F = \{(x_1 + x_2 + x_3 \geq 2)\}$ is the set of PB constraints and $f(X) = 4x_1 + 2x_2 + 3x_3$ is the cost function. In this case, $\alpha = \{(x_1, 0), (x_2, 1), (x_3, 1)\}$ is an optimal assignment with a cost of 5. All other assignments to X either do not satisfy F, or result in a higher value of $f(X)$.

Multi-Objective Combinatorial Optimization

A MOCO [15] instance can be defined as a pair of two sets: a set $F = \{c_1, \dots, c_m\}$ of constraints that must be satisfied and a

Algorithm 1. CLD algorithm for computing an MCS of a PB formula [9]

Input: F

1 $S \leftarrow \emptyset$
2 $C \leftarrow F$
3 $status \leftarrow SAT$
4 while ($status = SAT$) do
5 $\quad D \leftarrow (\vee_{\{c \in C\}} c)$
6 $\quad (status, \alpha) \leftarrow$ PBS($S \cup \{D\}$)
7 $\quad$ if ($status = SAT$) then
8 $\quad\quad S \leftarrow S \cup \bigcup_{\{c \in C, \alpha(c)=1\}} \{c\}$
9 $\quad\quad C \leftarrow F \setminus S$
10 $\quad$ end
11 end
12 return C

set $O = \{f_1, \dots, f_k\}$ of cost functions to minimize. In this work, we focus on the special case where $c_1, \dots, c_m$ are PB constraints and $f_1, \dots, f_k$ are linear PB expressions over a set X of Boolean variables.

Given two complete assignments α, α' such that $\alpha \neq \alpha'$ and $\alpha(F) = \alpha'(F) = 1$, we say that α dominates α', written $\alpha \prec \alpha'$, if and only if, $\forall f \in O: f(\alpha) \leq f(\alpha')$ and $\exists f' \in O: f'(\alpha) < f'(\alpha')$. α is said to be Pareto optimal if, and only if, no other complete assignment α'' exists such that $\alpha''(F) = 1$ and $\alpha'' \prec \alpha$. In MOCO, the goal is to find the set of Pareto optimal solutions, also referred to as Pareto front.

Table 1. Satisfiable assignments and respective costs for the instance in example 2

x_1	x_2	x_3	$2x_1 + x_2$	$2 \neg x_2 + 2x_3$
0	**1**	**1**	**1**	**2**
1	0	1	2	4
1	**1**	**0**	**3**	**0**
1	1	1	3	2

Example 2. Let $F = \{(x_1 + x_2 + x_3 \leq 2)\}$ be the set of constraints and $O = \{(2x_1 + x_2), (2 \neg x_2 + 2x_3)\}$ the set of cost functions of a MOCO instance. The costs for each possible satisfiable assignment to F are shown in Table 1. The lines that correspond to Pareto optimal solutions are highlighted in bold, while the others are dominated. For example, $\{(x_1, 1), (x_2, 0), (x_3, 1)\}$ is not Pareto optimal because it is dominated by $\{(x_1, 0), (x_2, 1), (x_3, 1)\}$.

Solving MOCO with Minimal Correction Subsets

This section starts by defining a Minimal Correction Subset (MCS) of an unsatisfiable formula. Next, we describe how an MCS approximates a single-objective optimization problem. Finally, an algorithm to solve MOCO using MCSs is proposed.

Let F be an unsatisfiable set of PB constraints. A Minimal Correction Subset (MCS) of F is a subset $C \subseteq F$ such that $F \setminus C$ is satisfiable and C is minimal, i.e., $(F \setminus C) \cup \{c\}$ is unsatisfiable for all $c \in C$.

Example 3. Consider the unsatisfiable set of PB constraints $F = \{(x_1 + x_2 = 1), (x_1 \geq 1), (x_2 \geq 1)\}$. F has three MCSs $C_1 = \{(x_1 \geq 1)\}$, $C_2 = \{(x_2 \geq 1)\}$ and $C_3 = \{(x_1 + x_2 = 1)\}$.

There are several algorithms described in the literature for finding MCSs [1, 5, 9, 10]. For the purpose of this work, the state-of-the-art CLD algorithm was used [9]. CLD’s pseudo-code is presented in algorithm 1. The algorithm starts by initializing the sets S and C of satisfied and not satisfied PB constraints respectively (lines 1 and 2). Initially, all constraints are considered as not satisfied. Then, the CLD algorithm repeatedly checks if it is possible to satisfy at least one of the constraints in C, while satisfying all constraints in S (lines 5 and 6). If so, then sets S and C are updated accordingly (lines 8 and 9). If not, then C is an MCS and is returned by the algorithm (line 12).

MCSs for Pseudo-Boolean Optimization

One can extend the definition of MCS to an unsatisfiable formula F such that $F = F_H \cup F_S$ where the subset F_H of F is denoted as hard, while the remaining constraints F_S are deemed as soft. In this case, a subset $C \subseteq F_S$ is an MCS of F if, and only if, $F_H \cup (F_S \setminus C)$ is satisfiable and $F_H \cup (F_S \setminus C) \cup \{c\}$ is unsatisfiable for all $c \in C$. Observe that in this case, the correction to formula F is done solely by identifying a minimal subset of soft constraints from F_S such that $F_H \cup (F_S \setminus C)$ is satisfiable. Note also that algorithm 1 could be trivially adapted to this case by initializing S to F_H and C to F_S in the first two lines.

MCSs can be used to find approximate solutions of PBO instances. Let F be the set of constraints and $f(X) = \sum w_i \cdot l_i$ the cost function of a PBO instance. Let $L(f)$ be the set of all literals in f and $L^{\neg}(f)$ the set of clauses built from the negation of the literals in $L(f)$, i.e., $L^{\neg}(f) = \bigcup_{\{l \in L(f)\}} \{(\neg l\_i)\}$. Applying an MCS algorithm to a formula $F_{\_PBO} = F_H \cup F_S$ where $F_H = F$ and $F_S = L^{\neg}(f)$, produces an MCS C of $L^{\neg}(f)$. We abuse notation and denote as $f(C)$ the cost of C, defined as:

$$f(C) = \textstyle\sum_{(\neg l_i) \in C} w_i \qquad (2)$$

Any assignment that satisfies $F \cup L^{\neg}(f) \setminus C$ will have a cost of $f(C)$, which provides an approximation to the optimum of the PBO instance. Actually, the PBO problem can be reduced to finding the MCS $C \subseteq L^{\neg}(f)$ that minimizes $f(C)$ [2].

MCSs for Multi-Objective Optimization

MCSs can also be used to find the Pareto front of MOCO instances. Let F be the constraint set and O the set of objective functions to minimize of a MOCO instance. Let $L^{\neg}(f_i)$ denote the set of clauses built from the negation of the literals in $f_i \in O$. Therefore, one can built a formula $F_{MOCO} = F_H \cup F_S$ where $F_H = F$ and $F_S = \bigcup_{\{f_i \in O\}} L^{\neg}(f_i)$. Next, an MCS enumerator can be applied to F_{MOCO} and enumerate all MCSs. Note that for each MCS there is a satisfiable assignment of the problem variables that satisfies all constraints, except the MCS constraints. As a result, the Pareto front of the MOCO instance can be determined by analyzing the solutions of the MCSs of F_{MOCO} and excluding the dominated solutions. We refer to Terra-Neves et al. [12] for a formal proof of the correction of this method.

Example 4. Consider $F = \{(x_1 + x_2 + x_3 \geq 2)\}$ and $O = \{(2x_1 + x_2), (2\neg x_2 + 2x_3)\}$ from example 2. In this case, we have $L^{\neg}(O) = \{(\neg x_1), (\neg x_2), (x_2), (\neg x_3)\}$. As a result, there are three MCSs: $C_1 = \{(\neg x_2), (\neg x_1)\}$, $C_2 = \{(\neg x_2), (\neg x_3)\}$ and $C_3 = \{(\neg x_1), (x_2), (\neg x_3)\}$ with costs (3, 0), (1, 2) and (2, 4), respectively. Observe that these MCSs include all the Pareto optimal assignments highlighted in table 1.

Experimental Results

In this section, the performance of the MCS enumeration approach for MOCO is evaluated on instances of the Virtual Machine Consolidation (VMC) problem. In VMC, we have several servers with fixed resource capacities and Virtual Machines (VMs) with requirements of those same resources. Each VM must be placed in some server, but server capacities cannot be exceeded and some VMs cannot be placed in the same server. There exists an initial placement, i.e., a VM can be associated with an initial server, incurring a migration cost if the VM is placed in a different one. A migration budget constraint can be used to enforce an upper limit on the migration costs, and is specified as a percentile bp of the total memory capacity of the servers. The goal is to find a placement for all VMs that satisfies the constraints and simultaneously minimizes (1) energy consumption in the data center, (2) migration costs and (3) resource wastage. The latter is a measure of the imbalance of server resource usage.
A detailed description of the VMC problem and the MOCO formulation can be found in the literature [12, 17]. The evaluation is performed on publicly available VMC benchmarks[2], based on subsets of workload traces randomly selected from the Google Cluster Data project[3].
Currently, there is no solver that is able to enumerate the Pareto front for these VMC instances. Hence, we evaluate the quality of the approximations to the Pareto front that the algorithms provide within a time limit of 1800 seconds. For that, we use the Hypervolume (HV) quality indicator [18]. Larger values of HV mean that the solution set is composed of solutions of better quality and/or diversity.

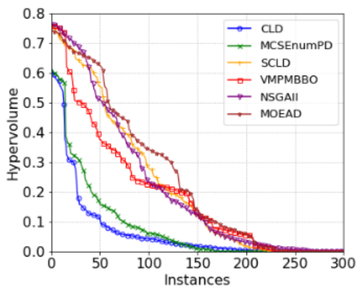

Fig. 1. HV Distribution (bp=100%)

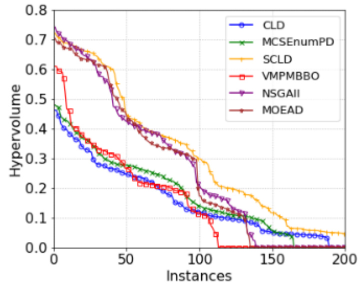

Fig. 2. HV Distribution (bp=5%)

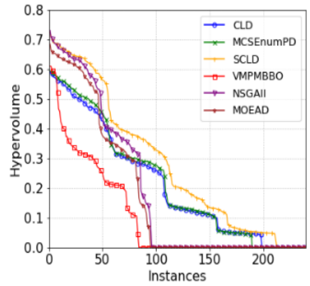

Fig. 3. HV Distribution (bp=1%)

In our approach, any MCS algorithm can be used. In this evaluation, CLD solver corresponds to using the ClauseD (CLD) algorithm [9], while SCLD uses a stratification technique [14]. The MCSEnumPD variant incorporates an MCS diversification technique [13].
We compare MCS-based algorithms with the VMPMBBO [17] algorithm for VMC and with the general-purpose evolutionary algorithms NSGAII [4] and MOEAD [16]. VMPMBBO and NSGAII were configured as suggested in the literature [17, 12, 13]. The only difference is in how we encoded the individuals in NSGAII's population. In this work, the regular integer encoding is used instead of the binary integer encoding, since it produces better results on the VMC problem. Further details on encodings for evolutionary algorithms can be found in the literature [11]. MOEAD was configured with crossover and mutation rates of 0.8 and 0.05 respectively, a population size of 100, a neighborhood size of 20, a 0.9 probability of crossover with individuals from the neighborhood and a maximum of 2 individuals that can be replaced by a single offspring. All algorithms are implemented in Java and Sat4j-PB v.2.3.4 [8] is used as satisfiability checker[4].
Each algorithm was run with a memory limit of 4 GB and a time limit of 1800 seconds. Stochastic algorithms were executed with 10 different seeds for each instance, and the analysis is performed using the median values over all executions. Finally, it was observed that algorithms with better performance have lower standard deviation values than algorithms with worse performance.
Figure 1 shows the hypervolume distributions of each algorithm for VMC instances with bp = 100%. Observe that stratification technique (see [14] for details) used in SCLD allows a huge performance improvement when compared with other constraint-based algorithms for MOCO,

2 `http://sat.inesc-id.pt/dome`
3 `http://code.google.com/p/googleclusterdata/`

4 Source code available at `http://gitlab.ow2.org/sat4j/moco`

CLD and MCSEnumPD. Moreover, considering the hypervolume indicator, SCLD is competitive with stochastic algorithms NSGAII, MOEAD and VMPMBBO for these instances.
Figures 2 and 3 present the results when migration budgets of VMC instances are constrained to 5% and 1%. Observe that NSGAII's, MOEAD's and VMPMBBO's performance degrades considerably as the budget decreases because these algorithms have a much harder time dealing with more tightly constrained instances. On the other hand, constraint-based methods for MOCO thrive in such scenarios. Nevertheless, note that SCLD is still able to improve considerably on both CLD and MCSEnumPD. Overall, SCLD is the first constraint-based algorithm to be competitive with stochastic approaches for the VMC instances where $bp = 100\%$, and is the best performing algorithm when $bp \leq 5\%$.

Conclusions

Stochastic methods for solving MOCO formulations are unsuitable for hard constrained problems. On the other hand, constraint-based methods are able to quickly satisfy tightly constrained problems, but have a harder time producing good quality approximations. Nevertheless, this paper shows that for some classes of benchmark instances, constraint-based methods using Minimal Correction Subsets (MCSs) are able to find better approximations of the Pareto front within a given time limit.
It has been proved that the enumeration of MCSs allows to completely identify the Pareto front of MOCO instances. Despite the early success of this approach, several other constraint-based algorithms based on iterative calls to a constraint solver should be devised. The goal is to use the effectiveness of constraint solving in order to build a new generation of MOCO solvers.

Acknowledgments

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MCDA Research Groups

About the 90th meeting of the EWG-MCDA

The 90th meeting of the EURO WG MCDA was held in the Brest Campus of the Technological University IMT Atlantique from 26 to 28 September 2019. The main topic of this meeting was “MCDA for a sustainable development of the ocean”. As usual, the meeting covered cutting edge research issues in the area of Multi-Criteria Decision Aiding, as well as innovative applications of MCDA for a sustainable management and development of the ocean.

Brest is the most western city of continental France, and everything in Brest revolves around the ocean. The Brest campus of IMT Atlantique is probably one of the most beautiful Campuses in Europe, as it it overlooks the ocean in a green setting. The main topic was therefore very appropriate for this 90th meeting. The scientific committee received 24 abstract submissions. The program was divided into 8 sessions. During the opening session, Christian Person, the deputy director for research and innovation of IMT Atlantique, presented the university’s activities and how they contribute to the fields of new technologies, energy, health and artificial intelligence. Then, the Bernard Roy award was bestowed to Miłosz Kadziński. It is a recognition conferred to a researcher under 40 years old for an outstanding contribution to the methodology and/or applications of Multi-Criteria Decision Aiding. The next session was dedicated to the main topic of the meeting and gave researchers the opportunity to present applications and software contributing to a sustainable development of the ocean. The last session of this first day concerned applications of MCDA. On Friday, the meeting started with a session on theoretical contributions, before switching to a session on software innovations. After lunch, a session dedicated to the life of the group opened the afternoon discussions. Then, a round table was organized to bring together industrialists and academics around the theme of decision aiding for activities related to the sea. The industrialists were Naval Group, Shom and France Energies Marines, whereas the academics were Vincent Mousseau, Marc Pirlot and Roman Słowiński. After presentations of the major challenges facing industrialists, the discussion focused on concrete problems related to the type of decision aiding models to be taken into account to solve these challenges, the consideration of uncertainty in the data and in the models, and the differences between machine learning algorithms and those of MCDA. Finally, the last session of the meeting was dedicated to theoretical aspects of MCDA.

The social events of the meeting included a banquet on Thursday evening. It was held in a restaurant in the marina of Brest, facing the Brest bay. On Saturday morning, the participants had the opportunity to walk for 2 hours in the city of Brest and discover the main attractions of this port city. Then they boarded a boat, which took them on a tour of the harbor, while offering them a typical Brest lunch, consisting of oysters, pâté, wine and local strawberry dessert.

The meeting was also co-organised and co-located with the 16th Decision Deck Workshop, which took place on 25 September 2019. This workshop was an opportunity to present the latest advances in terms of decision aiding software, the application of these software to real cases, as well as discussions on data formats for multi-criteria decision aiding problems.

Patrick Meyer

Meeting Program

Thursday, September 26, 2019

Time	Sessions	Talk/Articles submitted to discussion
11:00-12:00	Registration	
12:00-13:00	Lunch	
13:00-13:30	Opening session	
13:30-14:00	Bernard Roy award	
14:00-15:30	Decision aiding for a sustainable development of the ocean Chairman: Mehrdad Mohammadi	Willingness to pay for cleaning up the Great Pacific Garbage Patch: can spatial visualization help in choice experiments? *Valentina Ferretti, Yasmean Luk*
		Supporting decision makers facing spatial decision problems: deSEAsion *Son Duy Dao, Antoine Mallégol, Patrick Meyer, Mehrdad Mohammadi, Sophie Loyer*
		A Multi-Methodological Evaluation Approach for Naples Port-City Sustainable Development *Maria Cerreta, Giuliano Poli, Stefania Regalbuto*
	Articles submitted for discussion	The valuation of ecosystem services in the Venice lagoon: a multicriteria approach *Chiara D'Alpaos, Andrea D'Alpaos*
15:00-16:00	Coffee break	
16:00-17:30	Applications of MCDA to	Multiple criteria decision analysis to compare hypotheses of adaptive reuse

Thursday, September 26, 2019

Time	Sessions	Talk/Articles submitted to discussion
	real-life problems Chairman: *Salvatore Greco*	for an iconic historical building *Francesca Abastante, Isabella M. Lami, Beatrice Mecca, Salvatore Corrente, Salvatore Greco*
		Multiple criteria classification of soldiers into the Portuguese Army Special Forces units *Ana Sara Costa, José Rui Figueira, José Borbinha*
		Financial rating with ordinal classification based on the hierarchical SMAA Choquet integral approach *Sally Giuseppe Arcidiacono, Salvatore Corrente a, Salvatore Greco*
	Articles submitted for discussion	A Bi-Objective Programming for the Household Waste Collection and Transportation Problem *Haifa Jemmali, Hatem Masri, Mejdi Agroubi, Fouad Ben Abdelaziz*
		Bio-Waste Collection in Normandy: Multi-Modal Transportation Simulation Model *Xu Yiyi, Mhammed Sahnoun, Fouad Ben Abdelaziz*
		Multi Objective Optimization For Food Supply Chain Under Stochastic Demand *Samatthachai Yamsa-Ard, Fouad Ben Abdelaziz*
		Multi-Objective Optimal Design of Produced Water Treatment System *Mariam Falahi, Vivek Dua, Eric S. Fraga*
19:30-23:00	Banquet	Restaurant L'Épuisette, Fresh and Home-made foods.

Friday, September 27, 2019

Time	Sessions	Talk/Articles submitted to discussion
8:30-9:00	Coffee welcome	
9:00-10:30	Theoretical contributions to MCDA Chairman: Thibaut Lust	Active Preference Elicitation by Bayesian Updating on Optimality Polyhedra *Nadjet Bourdache, Patrice Perny, Olivier Spanjaard*
		Experimental analysis of greedy strategies to minimize pairwise comparisons in multicriteria decision aiding *Nawal Benabbou, Thibaut Lust, Lucie*

Friday, September 27, 2019

Time	Sessions	Talk/Articles submitted to discussion
		Galand
		Reference-based multiple criteria ranking-sorting *Philipe Fortemps, Vincent Mousseau, Marc Pirlot*
	Articles submitted for discussion	Combining MCDA and Machine Learning methods for Clustering Customers' Data *Alkaios Sakellaris, Konstantina G. Miteloudi, Nikolaos Matsatsinis*
		Post Factum Stepwise Benchmarking Model for Sorting *Miłosz Kadziński, Maciej Uniejewski, Mladen Stamenkovic*
10:30-11:00	Coffee break	
11:00-12:00	Software & Applications Chairman: Aida Valls	A tool for assisting in the definition of the parameters of the ELECTRE-III-H method *Jordi Pascual-Fontanilles, Antonio Moreno, Aida Valls*
		A multi-criteria decision-aiding approach to designing sustainable marine itineraries *Olga Porro, Núria Agell, Mónica Sánchez, Mar Vila*
12:00-13:00	Lunch	
13:30-14:00	Life of the group	
14:00-16:00	Round table: Decision Aiding and the Ocean	Naval Group: *Estelle Chauveau* Shom: *Sophie Loyer* France Energies Marines: *Nicolas Germain*
16:00-16:30	Coffee break	
16:30-18:00	Theoretical contributions to MCDA Chairman: *José Rui Figueira*	A new scaling MCDA procedure putting together pairwise comparison tables and the deck of cards method *Salvatore Corrente, José Rui Figueira, Salvatore Greco*
		Comparison of decisional maps on different territories *Amina Meghiche, Moncef Abbas, Philippe Fortemps, Marc Pirlot*
		Preference learning within non-additive aggregation MCDA methods *Abdelhak Imoussaten, Jacky Montmain*
	Articles submitted for discussion	Fuzzy-Rough Hybridization for Rule Representation of Preferences *Marko Palangetić, Chris Cornelis, Salvatore Greco, Roman Słowiński*
		Lexicographic Max-Min and

Friday, September 27, 2019

Time	Sessions	Talk/Articles submitted to discussion
		Approximated Compensatory Models for Equitable Multiple Criteria Optimization *Wlodzimierz Ogryczak*
		Preference estimation in large-group scarce-information context *Mohammad Ghaderi*

Persons and Facts

At the INFORMS Conference in Seattle (October 20-23,2019) that gathered a record number of participants (7300), **Roman Słowiński** was awarded the INFORMS Fellow degree. This is the highest honor of INFORMS, which annually awards only one percentile of its members with the Fellow degree. 12 people entered the Fellows Class of 2019: https://connect.informs.org/communities/community-home/digestviewer/viewthread?MessageKey=1c7fbcc4-cfc5-49d4-864d-39c2e6b835af&CommunityKey=1d5653fa-85c8-46b3-8176-869b140e5e3c&tab=digestviewer#bm1c7fbcc4-cfc5-49d4-864d-39c2e6b835af

Results of elections of the MCDM Society (2019)

Dear members of the International Society on Multiple Criteria Decision Making, as you know, we conducted the election of officers for the society at the beginning of October. The results are now known, and I'd like to inform you about the new officers.

President elect: Jose Rui Figueira
Vice President Finance: Birsen Karpak
Members of the Executive Committee: Carlos Coello Coello, Michalis Doumpos, Caroline Mota, Francisco Ruiz

Their names will appear on the society website soon. I would like to take this opportunity to congratulate all elected officers, and I am looking forward to working with them over the next four years. I would also like to thank you as members for participating in the election.

Best regards
Matthias Ehrgott
President of the Society

Nomination de C. Zopounidis comme docteur honoris causa de l'Ecole d'économie de Macédoine occidentale

Le Département d'administration et de gestion des entreprises de l'École d'économie de l'Université de Macédoine occidentale a approuvé la nomination du professeur-universitaire Konstantinos Zopounidis comme docteur honoris causa. L'Université de Macédoine occidentale est la huitième université du pays en terme de nombre d'étudiants et compte 28 départements. L'école d'économie se compose de 9 départements dans trois villes de Macédoine occidentale : Grevena, Kastoria, Kozani.

Le professeur Zopounidis est membre de deux académies, l'Académie royale européenne des docteurs (dont neuf de ses membres ont reçu le prix Nobel d'économie), docteur honoris causa de l'Université Aristote de Thessalonique, titulaire du prix Edgeworth-Pareto, la plus haute distinction accordée par la Société internationale pour des critères multiples à des chercheurs ou praticiens. Il est également titulaire de distinctions majeures de la Société hellénique pour la recherche opérationnelle (médaille d'or) ; Audencia Business School ; Ecole Supérieure de Paris ; MAICH ; la Société mathématique hellénique ; tandis qu'en 2016, l'Université technique de Crète lui a donné le prix d'excellence pour sa carrière et sa contribution à la Recherche. Il a également reçu un certain nombre de prix pour la mise en œuvre de son travail scientifique aux entreprises et à la société par les Chambres de commerce d'Héraklion, du Pirée et de La Canée et la Banque coopérative de La Canée.

Au cours de sa longue carrière, il a supervisé avec succès un grand nombre de thèses de doctorat, dont plusieurs ont mené à des nominations comme professeurs d'université ainsi qu'à des postes de direction dans des organisations et des entreprises. Son énorme travail académique est classé à Google Scholar avec 15421 références, un h-index de 68 et il est classé dans le 1% des auteurs scientifiques les plus actifs du monde.

INFORMS annual conference notes

Dear Members of the MCDM Community,

last week some of us attended the INFORMS annual conference in Seattle. We had an MCDM cluster that consisted of 10 sessions, including the Junior Researcher Best Paper Award finalists' session. The three finalists in 2019 were Brian Dandurand, with the paper Quadratic Scalarization For Decomposed Multiobjective Optimization, OR Spectrum 2016 Milosz Kadzinski, with the paper Heuristics For Prioritizing Pair-wise Elicitation Questions With Additive Multi-attribute Value Models, Omega 2017 Taewoo Lee, with the paper Trade-off Preservation in Inverse Multi-objective Convex Optimization, EJOR 2018.

I congratulate all finalists and the winner of the 2019 award, Milosz Kadzinski. As I will be responsible for administering the application process in 2020, I would like to remind all young researchers to consider being nominated for the next edition, which will be presented during the annual INFORMS meeting in National Harbor, Maryland, USA. The details about the award can be found at https://connect.informs.org/multiple-criteria-decision-making/awards/new-item2. The deadline for application is February 1, 2020 and I will be posting an invitation with details early in the year.

Serpil Sayın

Software

Plotting multi-objective linear/integer programming models in R

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The R package gMOIP can make 2D and 3D plots of the polytope of a linear programming (LP), integer linear programming (ILP) model, or mixed integer linear programming (MILP) model with 2 or 3 variables, including integer points, ranges and iso profit curve. Moreover you can also make a plot of the bi-objective criterion space and the non-dominated (Pareto) set for bi-objective LP/ILP/MILP programming models. Figures can be prepared for LaTeX and can automatically be transformed to TikZ using package tikzDevice.

You can install the latest stable release from CRAN:

```
install.packages("gMOIP")
library(gMOIP)
```

Alternatively (recommended), install the latest development version from GitHub:

```
install.packages("devtools")
devtools::install_github("relund/gMOIP",build_vignettes
= TRUE)
library(gMOIP)
```

Let us have a look at some examples.

A bi-objective model with two variables

We define a function for grouping plots of the solution and criterion space into one figure (you may just use functions plotPolytope and plotCriterion2D for single plots):

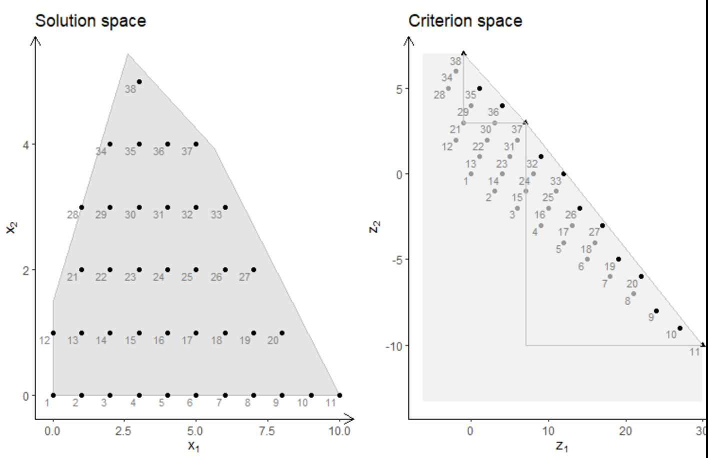
```
library("gridExtra")  # to combine two plots into one
plotBiObj2D <- function(A, b, obj,
   type = rep("c", ncol(A)),
   crit = "max",
   faces = rep("c", ncol(A)),
   plotFaces = TRUE,
   plotFeasible = TRUE,
   plotOptimum = FALSE,
   labels = "numb",
   addTriangles = TRUE,
   addHull = TRUE)
{
   p1 <- plotPolytope(A, b, type = type, crit = crit, fa
ces = faces, plotFaces = plotFaces,
                      plotFeasible = plotFeasible, plotO
ptimum = plotOptimum, labels = labels) +
      ggplot2::ggtitle("Solution space")
   p2 <- plotCriterion2D(A, b, obj, type = type, crit =
crit, addTriangles = addTriangles,
                         addHull = addHull, plotFeasible
= plotFeasible, labels = labels) +
      ggplot2::ggtitle("Criterion space")
   gridExtra::grid.arrange(p1, p2, nrow = 1)
}
```

Let us define the constraints:

```
A <- matrix(c(-3,2,2,4,9,10), ncol = 2, byrow = TRUE)
b <- c(3,27,90)
```

First let us have a look at an ILP model (maximize):

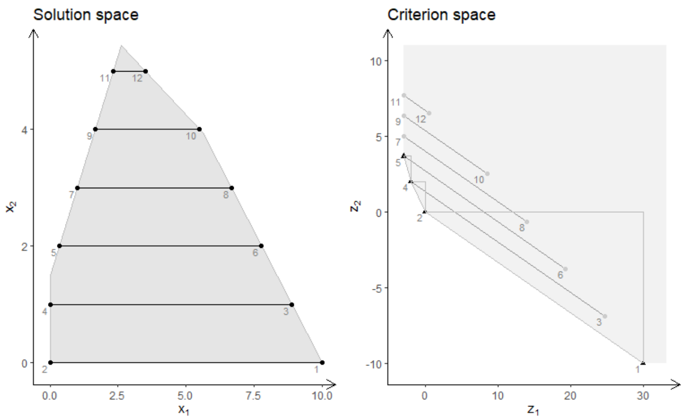
```
obj <- matrix(c(3, -1, -2, 2), nrow = 2)
plotBiObj2D(A, b, obj, type = rep("i", ncol(A)))
```



Note the non-dominated set consists of all points in black (with shape supported extreme = triangle, supported non-extreme = round, unsupported = round (not on the border)). The triangles drawn using the extreme non-dominated points illustrate areas where unsupported non-dominated points may be found. A point in the solution space is identified in the criterion space using the same number.

A MILP model (x_2 integer - minimize):

```
obj <- matrix(c(3, -1, -2, 2), nrow = 2)
plotBiObj2D(A, b, obj, type = c("c", "i"), crit = "min")
```



Note the solution space now consists to segments and hence the non-dominated set may consist of points and segments (open and closed). Note these segments are not highlighted in the current version of gMOIP.

A bi-objective model with three variables

We define functions for plotting the solution and criterion space:

```
plotSol <- function(A, b, type = rep("c", ncol(A)),
                    faces = rep("c", ncol(A)),
                    plotFaces = TRUE, labels = "numb")
{
   loadView(v = view, close = F, zoom = 0.75)
   plotPolytope(A, b, type = type, faces = faces, labels = labels, plotFaces = plotFaces,
                argsTitle3d = list(main = "Solution space"))
}

plotCrit <- function(A, b, obj, crit = "min", type = rep("c", ncol(A)), addTriangles = TRUE,
                     labels = "numb")
{
   plotCriterion2D(A, b, obj, type = type, crit = crit, addTriangles = addTriangles,
                   labels = labels) +
      ggplot2::ggtitle("Criterion space")
}
```

We define the model with three variables:

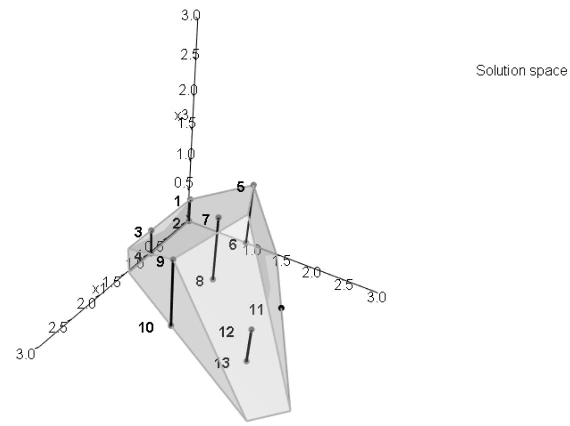
```
Ab <- matrix( c(
   1, 1, 2, 5,
   2, -1, 0, 3,
   -1, 2, 1, 3,
   0, -3, 5, 2
), nc = 4, byrow = TRUE)
A <- Ab[,1:3]
b <- Ab[,4]
obj <- matrix(c(1, -6, 3, -4, 1, 6), nrow = 2)
```

We load the preferred view angle for the 3D window:

```
view <- matrix( c(-0.452365815639496, -0.446501553058624, 0.77201122045517, 0, 0.886364221572876,
                  -0.320795893669128, 0.333835482597351, 0, 0.0986008867621422, 0.835299551486969,
                  0.540881276130676, 0, 0, 0, 0, 1), nc = 4)
loadView(v = view)
```

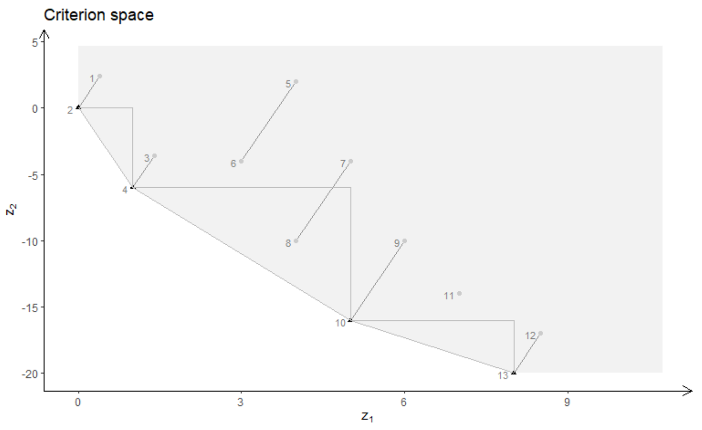
MILP model with variable 1 and 2 integer (solution space):

```
plotSol(A, b, type = c("i","i","c"))
```



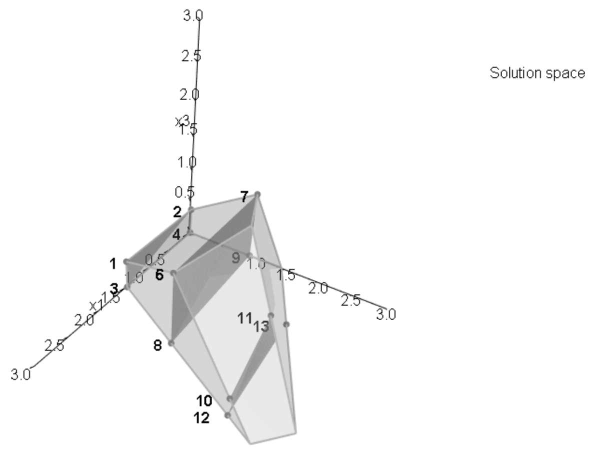
MILP model with variable 1 and 2 integer (criterion space):

```
plotCrit(A, b, obj, type = c("i","i","c"))
```



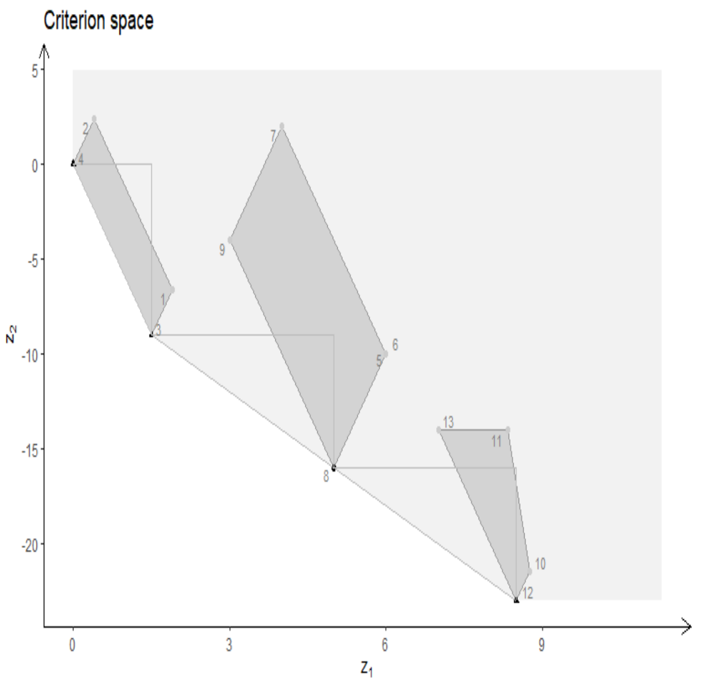
MILP model with variable 2 integer (solution space):

```
plotSol(A, b, type = c("c","i","c"))
```



MILP model with variable 2 integer (criterion space):

```
plotCrit(A, b, obj, type = c("c","i","c"))
```



For more examples see the package vignettes.

LaTeX support

You may create a TikZ file of the plot for LaTeX using

```
library(tikzDevice)
tikz(file = "plot_polytope.tex", standAlone=F, width = 7, height = 6)
plotPolytope(A, b, obj, type = rep("i", ncol(A)))
dev.off()
```

Forthcoming meetings

- 10-12/1/2020

Winter School on Machine Learning – WISMAL 2020
Las Palmas de Gran Canaria, Spain
http://appis.webhosting.rug.nl/2020/wismal-2020/

- 12-17/1/2020

Low-Rank Models 2020: Optimization, approximation, and applications in data science
Villars-sur-Ollon, Switzerland
https://www.unige.ch/math/folks/sutti/LowRank2020/index.html

- 13-17/1/2020

6th International Winter School on Big Data - BigDat 2020
Ancona, Italy
http://bigdat2020.irdta.eu/

- 19-24/1/2020

Winter School on Optimization and Operations Research
Zinal, Switzerland
http://transp-or.epfl.ch/zinal/

- 20-24/1/2020

Winter School Netopt2020
Estoril, Portugal
http://netopt2020.campus.ciencias.ulisboa.pt/

- 30-31/1/2020

ORBEL 34. 34th conference of ORBEL, the Belgian Operational Research (OR) Society
Centrale Lille, France
https://www.orbel.be/orbel34/

- 5-7/2/2020

4th AIRO Young Workshop
Bolzano, Italy
http://www.airoyoung.org/

- 9/2020-13/2/2019

Discrete Choice Analysis: Predicting Individual Behavior and Market Demand
EPFL, Lausanne, Switzerland
http://transp-or.epfl.ch/dca/

- 17-19/2/2020

OLA'2020 International Conference on Optimization and Learning: Challenges and Applications
Cadiz, Spain
http://ola2020.sciencesconf.org/

- 19-21/2/2020

ROADEF 2020
Montpellier, France
https://roadef2020.sciencesconf.org/

- 4-6/3/2020

SIGOPT 2020 International Conference on Optimization
Dortmund, Germany
http://www.wiwi.tu-dortmund.de/sigopt/

- 15-17/3/2020

8th INFORMS Optimization Society Conference
Greenville, SC, USA
https://cecas.clemson.edu/informs-conference/

- 19-20/3/2020

3rd conference of the EURO Working Group on the Practice of Operations Research
Berlin, Germany
https://www.euro-online.org/websites/or-in-practice/events/

- 21-22/3/2020

ISMSI 2020 International Conference on Intelligent Systems, Metaheuristics & Swarm Intelligence
Thimphu, Bhutan
http://www.ismsi.org/index.html

- 15-17/4/2020

EvoCOP 2020 - The 20th European Conference on Evolutionary Computation in Combinatorial Optimisation
Seville, Spain
http://www.evostar.org/2020/

- 15-17/4/2020

PMS 2020 17th International Workshop on Project Management and Scheduling
Toulouse, France
https://pms2020.sciencesconf.org/

- 22-24/4/2020

17th Meeting of the EWG on cutting and packing (ESICUP)
Toledo, Spain
https://www.euro-online.org/websites/esicup/17th-esicup-meeting/

- April 2020

91st Meeting of EURO Working Group on MCDA
Ispra, Italy
http://www.cs.put.poznan.pl/ewgmcda/

- 26-28/4/2020

2020 INFORMS Conference on Business Analytics & Operations Research
Gaylord Rockies, Aurora, Colorado, USA
https://www.informs.org/Meetings-Conferences/INFORMS-Conference-Calendar

- 5-7/5/2020

SIAM Conference on Mathematics of Data Science
Cincinnati, Ohio, USA

https://www.siam.org/Conferences/CM/Conference/mds20

- 18-21/5/2020

2020 MIP Workshop feat. DANniversary
DIMACS, Rutgers University, New Brunswick, New Jersey
https://sites.google.com/view/mipworkshop2020/home?authuser=0

- 26-29/5/2020

CPAIOR 2020
Vienna, Austria
https://cpaior2020.dbai.tuwien.ac.at/

- 27-29/5/2020

ICDSST 2020- EWG-DSS 6th International Conference on Decision Support System Technology
Zaragoza, Spain
https://icdsst2020.wordpress.com/

- 4-6/6/2020

The ECCO XXXIII 2020 Conference
St. Petersburg, Russia
https://ecco2020.euro-online.org/

- 8-10/6/2020

Conference on Integer Programming and Combinatorial Optimization IPCO XXI
London, UK
http://www.lse.ac.uk/IPCO-2020

- 8-10/6/2020

IWOCA 2020 - 31st International Workshop on Combinatorial Algorithms
Bordeaux, France
https://iwoca2020.labri.fr/10-12/6/2020

- 1-3/7/2020

EUROPT 2020 - 18th Workshop on Advances in Continuous Optimization
Toulouse, France
http://europt2020.recherche.enac.fr/

- 6-17/7/2020

EURO PhD School on MCDA/MCDM
Ankara, Turkey
http://mcdm.metu.edu.tr/

- 6-10/7/2020

International Conference "Mathematical Optimization Theory and Operations Research" (MOTOR 2020)
Novosibirsk Scientific Center, Russia
http://math.nsc.ru/conference/motor/2020

- 8-12/7/2020

2020 Genetic and Evolutionary Computation Conference (GECCO 2020)
Cancun, Mexico
http://gecco-2020.sigevo.org/

- 10-19/7/2020

EURO PhD School on Data Driven Decision Making and Optimization
Seville, Spain
https://www.imus.us.es/eps-data-optimization

- 19-25/7/2020

EURO PhD School on Sustainable Supply Chains
Lisbon, Portugal
http://epsinssc.tecnico.ulisboa.pt/

- 27-29/7/2020

OPTIMIZATION 2020
Aveiro, Portugal
https://optimization2020.web.ua.pt/

- 27-31/7/2020

MESS 2020 - Metaheuristics Summer School ~ Learning & Optimization from Big Data
Catania, Italy
https://www.ANTs-lab.it/mess2020/

- 21-26/7/2020

IFORS 2020
Seoul, South Korea
http://www.ifors2020.kr

- 31/8-2/9/2020

CLAIO 2020
Madrid, Spain
http://www.claio2020.com

- 14-18/9/2020

12th International Conference on Parametric Optimization and Related Topics (paraoptXII)
Augsburg, Germany
https://www.uni-augsburg.de/de/fakultaet/mntf/math/prof/opt/team/duer/paraopt/

- October 2020

92nd Meeting of EURO Working Group on MCDA
Budapest, Hungary
http://www.cs.put.poznan.pl/ewgmcda/

- 8-11/11/2020

2020 INFORMS Annual Meeting National Harbor
Gaylord National Resort and Convention Center, Maryland, USA
https://www.informs.org/

- April 2021

93rd Meeting of EURO Working Group on MCDA
Cracow, Poland
http://www.cs.put.poznan.pl/ewgmcda/

- 11-13/4/2021

2021 INFORMS Business Analytics Conference
Hyatt Regency Grand Cypress, Orlando, Florida, USA

https://www.informs.org/Meetings-Conferences/INFORMS-Conference-Calendar

- 11-14/7/2021

EURO 2021
Athens, Greece
https://www.euro-online.org

- September 2021

94th Meeting of EURO Working Group on MCDA
Belgrade, Serbia
http://www.cs.put.poznan.pl/ewgmcda/

- April 2022

95th Meeting of EURO Working Group on MCDA
Agios Nikolaos, Greece
http://www.cs.put.poznan.pl/ewgmcda/

- September 2022

96th Meeting of EURO Working Group on MCDA
Jaén, Spain
http://www.cs.put.poznan.pl/ewgmcda/

Seminars

SEMINAIRE «Aide à la décision»

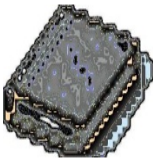
Responsable: Daniel VANDERPOOTEN
(le mardi de 13h45 à 15h15 salles à préciser)

Au choix des intervenants, les séances du séminaire sont de trois types. Type 1 : tutoriel, Type 2 : exposé de recherche, Type 3 : présentation mixte incluant une partie tutoriel et une partie recherche.

Prochaines reunions

22 octobre 2019	Conférence de **Sébastien Konieczny** CRIL, CNRS *Coscinus exploiter les données de DBLP pour analyser la recherche en informatique* (Présentation de Type 3)
12 novembre 2019	Conférence de **Michael Poss** LIRMM, Université de Montpellier, CNRS *Robust bin packing with budgeted uncertainty* (Présentation de Type 3)
10 décembre 2019	Conférence de **Evgeny Gurevsky** LS2N, Université de Nantes *Some new results for combinatorial problems with risk functions and controllable data* (Présentation de Type 2)
21 janvier 2020	Conférence de **Vincent T'kindt** LIFA, Polytech Tours *La RO ou l'art de bien optimiser* (Présentation de Type 1)

Web site for Annoucements and Call for Papers:
www.cs.put.poznan.pl/ewgmcda



Books

Multi-Objective Optimization in Theory and Practice II: Metaheuristic Algorithms

by **André Keller** (Author)

Multi-Objective Optimization in Theory and Practice is a simplified two-part approach to multi-objective optimization (MOO) problems.

This second part focuses on the use of metaheuristic algorithms in more challenging practical cases. The book includes ten chapters that cover several advanced MOO techniques. These include the determination of Pareto-optimal sets of solutions, metaheuristic algorithms, genetic search algorithms and evolution strategies, decomposition algorithms, hybridization of different metaheuristics, and many-objective (more than three objectives) optimization and parallel computation. The final section of the book presents information about the design and types of fifty test problems for which the Pareto-optimal front is approximated. For each of them, the package NSGA-II is used to approximate the Pareto-optimal front.

It is an essential handbook for students and teachers involved in advanced optimization courses in engineering, information science and mathematics degree programs.

Announcements and Call for Papers

Special Issue on Multiple Criteria Sorting methods of the Journal of Multi-Criteria Decision Analysis (a Wiley publication)

Guest editors:
Thierry **Marchant** (Ghent University, Belgium), Marc **Pirlot** (University of Mons, Belgium)

Submission deadline:
November 30, 2019

Recent years have seen a flourishing interest in multiple criteria sorting models, i.e., models for assigning alternatives to predefined ordered categories while respecting the preference order on the criteria scales. This special issue will publish original research papers on the following subjects:

- new multiple criteria sorting methods or variants of older ones, duly justified and/or empirically tested ;
- innovative and/or well-justified applications of multiple criteria sorting methods in real case studies;
- algorithms for learning and methods for eliciting the parameters of multiple criteria sorting methods; the proposed algorithms and methods should be well-justified and tested; the complexity of the algorithms should be studied;
- theoretical investigations of the properties of multiple criteria sorting methods and axiomatic characterization of such methods.

Papers in the same vein, on related methods such as multiple criteria classification or clustering, will also be considered.
The papers must conform with the Editorial Policy of the Journal of Multi-Criteria Decision Analysis (see https://onlinelibrary.wiley.com/page/journal/10991360/ homepage/productinformation.html).
This special issue is linked with but not restricted to papers presented at the Interna- tional Conference on Multiple Criteria Decision Making MCDM2019, held in Istanbul, Turkey, June 16-21, 2019.
Submission: Authors should prepare their paper following the Instructions to Authors available on the Internet site of the journal. They must submit it via the Journal of Multi- Criteria Decision Analysis online submission site https://mc.manuscriptcentral.com/ mcda, by November 30, 2019. When submitting, it is important to check the box in-dicating the submission is for a special issue, and to indicate the topic of the issue as “MCDM 2019-Sorting methods”.
The papers will undergo a thorough refereeing process, like papers submitted to regular issues.
The Journal of Multi-Criteria Decision Analysis is indexed in Scopus and the Emerging Sources Citation Index of the Web of Science (Clarivate Analytics).
For more information about this special issue, please contact the guest editors at the following e-mail addresses: Thierry Marchant (thierry.marchant@UGent.be) or Marc Pirlot (marc.pirlot@umons.ac.be).

2020 EURO PhD Summer School on MCDA/MCDM

The 2020 EURO PhD Summer School on MCDA/MCDM is going to take place in Ankara, Turkey, on July 6-17, 2020. PhD students interested in getting an in-depth understanding of the theoretical and applied aspects of MCDA/MCDM, interacting with the best scholars in the area, and conducting hands-on exercises/cases are welcome to apply. Although the priority is for PhD students, a limited number of Master’s students may also be admitted. Approximately 50 students will be admitted to the summer school.
There will be lectures on state-of-the-art multiple criteria methods, applications, and software. Teams of students will be formed to work on several case studies and will present their work at the end of the summer school. The students will be staying in a dormitory of the Middle East Technical University (METU) and interacting with each other throughout the summer school. This is a great opportunity for PhD students to network among themselves and with the lecturers and collaborate for years to come. Many of the current well-known scholars in the area have attended past summer schools.
In addition to the unique academic program, the summer schools are a lot of fun. There are social activities throughout and the students will enjoy spending time together. Many long-lasting friendships have been formed in past summer schools.
The lectures will be held at the Industrial Engineering Department of METU. All meals will be provided and the activities of the social program will also be covered. Thanks to the financial support from the Association of European Operational Research Societies (EURO) and the International Society on MCDM, we are able to keep the registration costs low. There will also be an opportunity to apply for partial support for the registration cost for those who have limited funds, especially from developing countries. METU is located on a beautiful, forested campus in the west side of Ankara (https://www.metu.edu.tr). Ankara, located in central Anatolia, is the capital of Turkey. It connects east and west parts of the country, and is the second largest city of Turkey. The city has great museums including Museum of Anatolian Civilizations which was elected as The Museum of the Year in Europe in 1997. Please check the following link for more information about Ankara https://www.goturkeytourism.com/destinations-turkey/ankara-city-in-turkey.html.

Important dates

- Application submission opening: September 1, 2019
- Deadline for Application: February 1, 2020
- Notification of Acceptance: February 15, 2020
- Early registration deadline: March 15, 2020
- Late registration deadline: April 15, 2020
- Beginning of the summer school: July 6, 2020

Lecturers (in alphabetical order)

1. Adiel T. de Almeida, Federal University of Pernambuco, Brazil
   Multi-attribute Utility Theory (MAUT), Multi-criteria Group Decision Making (MCGDM)
2. Matthias Ehrgott, Lancaster University, UK
   MCDA/M Community, Multiobjective Combinatorial Optimization
3. Jose Rui Figueira, Technical University of Lisbon, Portugal Outranking Methods, Robust Ordinal Regression
4. Carlos Fonseca, University of Coimbra, Portugal
   Evolutionary multiobjective optimization

5. Salvatore Greco, University of Catania, Italy Preference Modelling, Robust Ordinal Regression
6. Milosz Kadzinski, Poznan University of Technology, Poland Decision Deck
7. Gulsah Karakaya, Middle East Technical University, Turkey Case Work
8. Ralph L. Keeney, Duke University, USA
Value-Focused Thinking and Problem Structuring
9. Murat Koksalan, Middle East Technical University, Turkey
Interactive Methods of Multiobjective Optimization, Behavioral Aspects of Decision Making
10. Banu Lokman, University of Portsmouth, UK Case Work
11. Serpil Sayın, Koç University, Turkey Multiobjective Optimization Theory
12. Roman Slowinski, Poznan University of Technology, Poland Decision Rule Approach, "Meet the editor"
13. Jyrki Wallenius, Aalto University, Finland
Introduction to MCDA/MCDM, History and Traditions of MCDM
14. Constantin Zopounidis, Technical University of Crete, Greece MCDM in Finance

The most up-to-date information regarding the application process and all other developments about the summer will be available at http://mcdm.metu.edu.tr/en.
We look forward to an exciting summer school in Ankara!

Articles Harvest

(This section is prepared by Salvatore CORRENTE, salvatore.corrente@unict.it)

Abdallah, F., Tanougast, C., Kacem, I., Diou, C., Singer, D. (2019). Genetic algorithms for scheduling in a CPU/FPGA architecture with heterogeneous communication delays. Computers and Industrial Engineering, 137, 106006.
Abdel-Aal, M.A.M., Selim, S.Z. (2019). Robust optimization for selective newsvendor problem with uncertain demand. Computers and Industrial Engineering, 135, 838-854.
Abdi, A., Taghipour, S. (2019). Sustainable asset management: A repair-replacement decision model considering environmental impacts, maintenance quality, and risk. Computers and Industrial Engineering, 136, 117-134.
Adediran, T.V., Al-Bazi, A., dos Santos, L.E. (2019). Agent-based modelling and heuristic approach for solving complex OEM flow-shop productions under customer disruptions. Computers and Industrial Engineering, 133, 29-41.
Ahmadi-Javid, A., Fallah-Tafti, M. (2019). Portfolio optimization with entropic value-at-risk. European Journal of Operational Research, 279(1), 225-241.
Ahn, B.S., Kim, J.H., Lee, D.H. (2019). Extension of the aggregation of preference rankings using an optimistic-pessimistic approach. Computers and Industrial Engineering, 132, 433-438.
Aires, R.F.D.F., Ferreira, L. (2019). A new approach to avoid rank reversal cases in the TOPSIS method. Computers and Industrial Engineering, 132, 84-97.
Ajam, M., Akbari, V., Salman, F.S. (2019). Minimizing latency in post-disaster road clearance operations. European Journal of Operational Research, 277(3), 1098-1112.
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Akgül, A., Ulusam Seçkiner, S. (2019). Optimization of biomass to bioenergy supply chain with tri-generation and district heating and cooling network systems. Computers and Industrial Engineering, 137, 106017.
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Akram, M., Arshad, M. (2019). A Novel Trapezoidal Bipolar Fuzzy TOPSIS Method for Group Decision-Making. Group Decision and Negotiation, 28(3), 565-584.
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Algethami, H., Martínez-Gavara, A., Landa-Silva, D. (2019). Adaptive multiple crossover genetic algorithm to solve workforce scheduling and routing problem. Journal of Heuristics, 25(4-5), 753-792.
Alinaghian, M., Aghaie, M., Sabbagh, M.S. (2019). A mathematical model for location of temporary relief centers and dynamic routing of aerial rescue vehicles. Computers and Industrial Engineering, 131, 227-241.
Alizadeh, M., Amiri-Aref, M., Mustafee, N., Matilal, S. (2019). A robust stochastic Casualty Collection Points location problem. European Journal of Operational Research, 279(3), 965-983.
Alkaabneh, F., Diabat, A., Gao, H.O. (2020). Benders decomposition for the inventory vehicle routing problem with perishable products and environmental costs. Computers and Operations Research, 113, 104751.
Almaraj, I.I., Trafalis, T.B. (2019). An integrated multi-echelon robust closed- loop supply chain under imperfect quality production. International Journal of Production Economics, 218, 212-227.
Almoghathawi, Y., Barker, K. (2019). Component importance measures for interdependent infrastructure network resilience. Computers and Industrial Engineering, 133, 153-164.
Almohri, H., Chinnam, R.B., Colosimo, M. (2019). Data-driven analytics for benchmarking and optimizing the performance of automotive dealerships. International Journal of Production Economics, 213, 69-80.
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Aminifard, Z., Babaie-Kafaki, S. (2019). An optimal parameter choice for the Dai–Liao family of conjugate gradient methods by avoiding a direction of the maximum magnification by the search direction matrix. 4OR, 17(3), 317-330.

Aminzadegan, S., Tamannaei, M., Rasti-Barzoki, M. (2019). Multi-agent supply chain scheduling problem by considering resource allocation and transportation. Computers and Industrial Engineering, 137, 106003.

Amiri, A., Salari, M. (2019). Time-constrained maximal covering routing problem. OR Spectrum, 41(2), 415-468.

Andrejczuk, E., Bistaffa, F., Blum, C., Rodríguez-Aguilar, J.A., Sierra, C. (2019). Synergistic team composition: A computational approach to foster diversity in teams. Knowledge-Based Systems, 182, 104799.

Angel-Bello, F., Cardona-Valdés, Y., Álvarez, A. (2019). Mixed integer formulations for the multiple minimum latency problem. Operational Research, 19(2), 369-398.

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Aouad, A., Segev, D. (2019). The ordered k-median problem: surrogate models and approximation algorithms. Mathematical Programming, 177(1-2), 55-83.

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Arnold, F., Gendreau, M., Sörensen, K. (2019). Efficiently solving very large-scale routing problems. Computers and Operations Research, 107, 32-42.

Arram, A., Ayob, M. (2019). A novel multi-parent order crossover in genetic algorithm for combinatorial optimization problems. Computers and Industrial Engineering, 133, 267-274.

Arroyo-Cañada, F.-J., Gil-Lafuente, J. (2019). A fuzzy asymmetric TOPSIS model for optimizing investment in online advertising campaigns. Operational Research, 19(3), 701-716.

Arulselvan, A., Bley, A., Ljubić, I. (2019). The incremental connected facility location problem. Computers and Operations Research, 112, 104763.

Asgharizadeh, E., Taghizadeh Yazdi, M., Mohammadi Balani, A. (2019). An output-oriented classification of multiple attribute decision-making techniques based on fuzzy c-means clustering method. International Transactions in Operational Research, 26(6), 2476-2493.

Asian, S., Hafezalkotob, A., John, J.J. (2019). Sharing economy in organic food supply chains: A pathway to sustainable development. International Journal of Production Economics, 218, 322-338.

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Announcement:

The “Useful links” section of the group’s homepage

(www.cs.put.poznan.pl/ewgmcda)

is being enlarged. Contributions of URL links to societies, research groups and other links of interest are welcome.

A membership directory of the European Working Group on “Multiple Criteria Decision Aiding” is available at the same site. If you would like to be listed in this directory please send us your data (see examples already in the directory).

Contact: José Rui Figueira (figueira@ist.utl.pt)

Web site for the EURO Working Group “Multicriteria Aid for Decisions”

A World Wide Web site for the EURO Working Group on “Multicriteria Aid for Decisions” is already available at the URL:

http://www.cs.put.poznan.pl/ewgmcda/

Web site Editor: Milosz Kadzinski
(Milosz.Kadzinski@cs.put.poznan.pl)

This WWW site is aimed not just at making available the most relevant information contained in the Newsletter sections, but it also intends to become an online discussion forum, where other information and opinion articles could appear in order to create a more lively atmosphere within the group.

Groupe de Travail Européen “Aide Multicritère à la Décision” /
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