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A Brief Survey of Multicriteria Decision Making Methods and Software Systems*

Vassil Vassilev, Krassimira Genova, Mariyana Vassileva

Institute of Information Technologies, 1113 Sofia

Abstarct: *A short review is made in this paper of multicriteria analysis and multicriteria optimization methods, and software systems developed by now. There are also given some typical applications of these methods and systems.*

Keywords**:** *multicriteria analysis, multicriteria optimization, decision support systems*.

Introduction

Different tasks in planning, control, analysis and monitoring in economy, transport, industrial production, education, ecology and other spheres can be reduced to multicriteria decision making problems. Multicriteria decision making problems can be divided into two separate classes depending on their formal statement. In the first class of problems a finite number of alternatives are explicitly given in a tabular form. These problems are called discrete multicriteria decision making problems or multicriteria analysis problems. In the second class a finite number of explicitly set constraints in the form of functions define an infinite number of feasible alternatives. These problems are called continuous multicriteria decision making problems or multicriteria optimization problems.

In multicriteria analysis and multicriteria optimization problems several criteria are simultaneously optimized in the feasible set of alternatives. In the general case there does not exist one alternative, which optimizes all the criteria. There is a set of alternatives however, characterized by the following: each improvement in the value of one criterion leads to deterioration in the value of at least one other criterion. This

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set of alternatives is called a set of the non-dominating or Pareto optimal alternatives (solutions). Each alternative in this set could be a solution of the multicriteria problem. In order to select one alternative, it is necessary to have additional information set by the so-called decision maker (DM). The information that the DM provides reflects his/her global preferences with respect to the quality of the alternative sought.

The multicriteria analysis problems can be divided into three types: problems of multicriteria choice, problems of multicriteria ranking and problems of multicriteria sorting. Many real life problems in management practice may be formulated as problems of choice, ranking or sorting of resources, strategies, projects, offers, policies, credits, products, innovations, designs, costs, profits, portfolios, etc. (Belton [6], Beinat and Nijkamp [5], Holbourn [28], Paschetta and Tsoukias [60], Kelley et al. [37], Ananda and Herath [2], Srdjevic et al. [68], Mustajoki et al. [53]).The multicriteria optimization problems are only problems of multicriteria choice. Many real life problems in planning, control and industrial production may be formulated as problems of multicriteria choice (Korhonen [42], Joos (1999), Rajesh et al. [62], Ehrgott and Ryan [20], Thibault et al. [72], Hamalainen et al. [26], Kaleta et al. [34], Vera et al. [81]).

Different methods have been developed to solve multicriteria analysis problems. A great number of the methods developed up to now, can be grouped in three separate classes (Vincke [83]). The first class of methods (Dyer [19]) includes the multiattribute utility (value) theory methods (value tradeoff method (Keeney and Raiffa [36]), UTA method (Beuthe and Scannella [9]), MACBETH method (Bana e Costa and Chagas [3]), direct weighting method (Von Winterfeldt and Edwards [84])) etc.), AHP weighting methods (Saaty [64]). There are differences in the way in which the DM's global preferences are aggregated in the two subclasses of these methods. In the first one a generalized functional criterion is directly synthesized, whereas in the second subclass (weighting methods) it could be said that such a criterion (additive form) is indirectly synthesized. The two subclasses of methods are based on the assumption that there does not exist limited comparability among the alternatives. The DM's preferences are sufficient for the comparison of two alternatives, using two binary relations only: a strict preference relation P (irreflexive, asymmetric and transitive) and an indifference relation I (reflexive, symmetric and transitive).

The second class of methods are called outranking methods (ELECTRE methods (Roy [63]), PROMETHEE methods (Brans and Mareschal [10]); TACTIC method (Vansnick [73]) etc.) and they are based on the assumption that there exists limited comparability among the alternatives. In these methods one (or several outranking relation(s)) are first built to aggregate DM's global preferences, after which this outranking relation is used to assist the DM in solving the multiple criteria decision analysis problem. Four binary relations are used when comparing two alternatives: the indifference I (reflexive and symmetric), the weak preference Q (irreflexive and anti-symmetric), the strict preference P (irreflexive and anti-symmetric), and the incomparability R (irreflexive and symmetric). The outranking relation covers these four relations. In most of the outranking methods it is assumed that the DM is often unable or unwilling to make explicit distinctions among these four relations, hence the DM selects to specify some preference information about inter- and intra-criteria. While the inter-criteria information is expressed in the form of weights and veto thresholds, the intra-criteria information is usually expressed in the form of indifference and preference thresholds.

The interactive algorithms (VIMDA method (K o r h o n e n [41], aspiration-level method (L o t f i et al. [45], InterQuad method (S u n and S t e u e r [71], LBS method (J a s z k i e w i c z and S l o w i n s k i [32], RNIM method (N a r u l a et al. [55] etc.) belong to the methods of the third group. They are "optimizationally motivated" and are oriented to solve multicriteria analysis problems with a large number of alternatives and a small number of criteria. The first and the second methods use the first type of DM's preference model and the DM must define the desired or acceptable values of the criteria at every iteration. The fourth and the fifth methods use the second DM's preference model and the DM has to give not only the desired or acceptable values of the criteria but also inter- and intra-criteria information at every iteration.

There are two main approaches in solving multicriteria optimization problems: a scalarizing approach (M i e t t i n e n [48]) and an approximation approach (E h r g o t t and W i e c e k [21]). The major representatives of the scalarizing approach are the interactive algorithms (W i e r z b i c k i [85])), S a w a r a g i et al. [65], S t e u e r [70], G a r d i n e r and V a n d e r p o o t e n [23], M i e t t i n e n [48], M i e t t i n e n and M a k e l a [50]). Multicriteria optimization problems are treated in these algorithms as a decision making problem and the emphasis is put on the real participation of the DM in the process of their solution. The interactive methods are the most developed and widespread due to their basic advantages – a small part of the Pareto optimal solutions must be generated and evaluated by the DM; in the process of solving the multicriteria problem, the DM is able to learn with respect to the problem; the DM can change his/her preferences in the process of problem solution; the DM feels more confident in his/her preferences concerning the final solution. Each interactive algorithm consists usually of two procedures – an optimization and an evaluating one, which are cyclically repeated until the stopping conditions are met. In the evaluating procedure the DM evaluates the current Pareto optimal solution (solutions), either approving it as the final (the most preferred) solution or setting his/her preferences about the search for a new solution. On the basis of these preferences a scalarizing problem is stated and solved in the optimization procedure and with its help a new Pareto optimal solution (solutions) is obtained, which is presented to the DM for evaluation and choice. The main property of every scalarizing problem is that each optimal solution it has, is a Pareto (weak Pareto) optimal solution of the corresponding multicriteria optimization problem. The scalarizing problem is a single-criterion optimization problem, which enables the use of the theory and methods of single-criterion optimization. Each one of the interactive methods developed up to now for solving different classes of multicriteria optimization problems has its advantages and shortcomings, connected mainly with the way and type of the information derived by the DM, which is reflecting his/her global and local preferences, the type and ways of solution of the scalarizing problems, and also with the type of the information given by the DM. The interactive algorithms are especially appropriate for solving linear and convex non-linear multicriteria optimization problems, in which the time for scalarizing problems solution (the time for a new solution expecting) does not play an important role. In NP-problems (integer, discrete, combinatory and non-convex non-linear problems), this time may become considerable and hence hamper the work of the DM. Different strategies are suggested that deal with the time of expecting a new solution for evaluation for some of these problems, like the multicriteria linear integer problems in (N a r u l a and Va s s i l e v [54], K a r a i v a n o v a et al. [35], V a s s i l e v a [78]). In the learning phase the DM is presented at a given iteration not an integer Pareto optimal (weak Pareto optimal) solution, but an approximate Pareto optimal (weak Pareto optimal) solution or a Pareto optimal solution of the relaxation problem (in case of a continuous linear problem). The interactive methods of the reference point (direction) and the classification-oriented interactive methods (M i e t t i n e n [48]) are the most widely spread interactive methods solving multicriteria optimization problems. Though the interactive methods of the reference point are still dominating, the classification-oriented interactive methods enable the better solution of some chief problems in the dialogue with the DM, relating to his/her preferences defining, and also concerning the time of waiting for new non-dominated solutions that are evaluated and selected.

A variety of methods to approximate the set of Pareto optimal solutions of different types have been proposed (K o s t r e v a et al. [43], M a t e o s and R i o s [47], B e n s o n [8], D e b (2001), C o e l l o et al. [15], S c h a n d l et al. [66], E h r g o t t and W i e c e k [21]). A big majority of the methods are iterative and produce points or objects approximating this set. Some methods (E h r g o t t and W i e c e k [21]) are exactly equipped with theoretical proofs for correctness and optimality while some other methods (C o e l l o et al. [15]) are heuristic and often theoretically unsupported. For a majority of multicriteria optimization problems it is not easy to obtain an exact description of the set of Pareto optimal solutions that typically includes a very large or infinite number of points. Even if it is theoretically possible to find these points exactly, this is often computationally challenging and expensive and therefore usually abandoned. For some problems, finding elements of the solution set is even impossible due to numerical complexity of resulting optimization problems.

The main representatives of the heuristic methods are the multicriteria genetic (evolutionary) methods (C o e l l o et al. [15], D e b [16], J a s z k i e w i c z [30], V e l d h u i z e n and L a m o n t [80], F o n s e c a and F l e m i n g [22], G o l d b e r g [24]). The multicriteria optimization problem is treated in these methods rather as a vector optimization problem, than as a decision making problem and the stress is placed on the determination of a subset of potential Pareto optimal solutions, which approximates well enough the whole Pareto optimal set. This is achieved, supporting a population of candidates for the approximating subset during the whole process of optimization. This population is improved at each iteration with the help of different operators, modeling the basic processes of biologic genetics such as selection, recombination and mutation. Different modifications of these operators are used in various genetic methods and different population models also for improving the convergence to a Pareto optimal set. Different spreading mechanisms are utilized in improving the current population, which ensures good approximation of the entire Pareto optimal set.

The genetic methods are methods with a built-in parallelism, which enables the overcoming of numerous difficulties in solving single- or multicriteria combinatory and non-convex non-linear problems, difficulties, connected with the presence of a set of local optima, a set of solutions, etc. The main disadvantages of these methods are related to the incomplete use of the specifics of the problems being solved, with the necessity for relatively powerful computing resources, with the lack of optimality conditions. The research activity in overcoming some of these difficulties is quite large. Some hybrid genetic methods (I s h i b u c h i and M u r a t a [29], K n o w l e s and C o r n e [39], J a s z k i e w i c z [30]) are already developed, which use the specifics of the problems being solved in the local improvement of the populations, the procedures for new solutions selection are improved, and new mechanisms are included in populations spreading.

The solutions obtained with the help of the genetic methods, are near Pareto optimal solutions. Besides this, during the process of defining the approximating set, the DM is isolated and he/she is provided with a large set of solutions for evaluation and choice towards the end (this is a comparatively hard problem of multicriteria analysis). A great part of these solutions are not necessary to the DM, at that the most preferred solution may be even not shown.

The developed systems supporting the solution of multicriteria analysis and multicriteria optimization problems may be classified in three groups: commercial, research or teaching and experimental (for new methods testing). Sometimes it is difficult to make a clear distinction between these groups. A number of experimental software systems can be successfully applied for research and learning purposes. The realization and documentation of some research or learning software systems is very well accomplished, but they are offered free, without any commercial purpose. The status of the multicriteria decision support systems until 1996 is discussed in (Wiestroffer and Narula [86]).

The software systems supporting the solution of multicriteria analysis problems can be divided in two classes – software systems with general purpose and problem-oriented software systems. The general-purpose software systems aid the solution of different multicriteria analysis problems by different decision makers. One method or several methods from one and the same group are usually realized in them for solving multicriteria analysis problems. This is due to the following two reasons:

– in the methods from the different groups, different types of procedures are used to get information from the DM, which leads to considerable difficulties in the realization of appropriate user's interface modules in the software systems;

– the designers of the software systems are usually interested in the realization of their own method (methods) or have distinct preferences towards methods from one and the same group.

The general-purpose software systems developed (VIMDA (Korhonen [41]), Expert Choice (Saaty [64]), HIVIEW (Peterson [61]), PROMCALC and GAIA (Brans and Mareschal [10]), ELECTRE III-IV (Roy [63]), MACBETH (Bana e Costa and Vansnick [4]), VIP (Dias and Climaco [17]), PREFDIS (Zopounidis and Doumpos [90]), Decision Lab (Brans and Mareschal [11]), Web-HIPRE (Mustajoki and Hamalainen [52]), IRIS (Dias and Mousseau [18]), IDS (Xu and Yang [87]), MultiChoice (Vassilev et al. [74]), knowCube (Hanne and Trinkaus [27])) realize one method or several methods from one and the same group.

The problem-oriented multicriteria analysis software systems are included in other information-control systems and serve to support the solution of one or several types of specific multicriteria analysis problems. In this connection problem-oriented user's interface is usually realized in them and methods from different groups of multicriteria analysis methods are included in some of these systems. Some representatives of the problem-oriented software systems are the following: the FINCLAS system – for financial classification problems (Zopounidis and Doumpos [88]), the Investor system – for portfolio selection and composition (Zopounidis and Doumpos [89]), the Agland Decision system – for agricultural property (Parsons [59]), the DESYRE system –for rehabilitation of contaminated sites (Carlon et al. [12]), the

MultCSync system -for incorporating multiple criteria in conservation planning (Moffett et al. [51])).

The software systems developed to aid the multicriteria optimization problems solution can be divided also into two groups: software systems of general purpose and problem-oriented software systems.The software systems of general purpose serve to aid the solution of different multicriteria optimization problems by different DMs. Usually one method is realized in them to solve the multicriteria problems. This is due to the following reasons:

- the different methods are intended to solve different types of multicriteria optimization problems (linear, non-linear, discrete, continuous, network, etc.);
- different types of procedures are used in the different methods to derive and set information by and to the DM, which causes considerable difficulties in the realization of user-friendly interface modules;
- different strategies are used in the different methods that learn the DM and different ways to decrease the time for scalarizing problems solution;
- usually the developers of the software systems are interested in the realization of their own method.

Some well-known general-purpose software systems, which solve problems of multicriteria optimization, are the systems VIG (Korhonen [40]), CAMOS (Osyczka [58]), DIDAS (Lewandowski and Wierzbicki, Eds., [44]), DINAS (Ogryczak et al. [57]), MOLP-16 (Vassilev et al. [76]), MONP-16 (Vassilev et al. [76]), LBS (Jaszkiewicz and Slowinski [31]), SOMMIX (Climaco et al. [13]), MOIP (Vassilev et al. [77]), NIMBUS (Miettinen and Makela [49]), MOLIP (Vassilev et al. [75], NLPJOB (Schittkowski [67]), MOMILP (Alves and Climaco [1]) and NBI package for Matlab (**http://www.owlnet.rice.edu/~indra/NBIhomepage.html**). Some of them, as the systems DIDAS, VIG, CAMOS, DINAS and LBS, realize the interactive methods of the reference point and of the reference direction (Wierzbicki [85], (Korhonen [40]). The second type, as the systems NIMBUS, MOLP-16, MONP-16, MOIP and MOLIP, realize the classification-oriented interactive methods (Benayoun et al. [7], Miettinen [48], Narula and Vassilev [54], Vassileva et al. [79]).

The problem-oriented multicriteria optimization systems are included in other information-control systems and serve to aid the solution of one or several types of various multicriteria optimization problems and most frequently problem-oriented user's interface is implemented in them. In some of these systems more than one method for solving the multicriteria optimization problems is realized. The following two systems are very interesting: ADELAIS system – for Portfolio Selection (Zopounidis et al. [91]) and Multicriteria DSS – for River Water-Quality Planning (Lotov et al. [46].

In the class of multicriteria optimization software systems the software systems, which implement different multicriteria evolutionary methods (algorithms) must also be included. Although they do not guarantee obtaining accurate solutions they can successfully find approximations of the sets of the Pareto optimal solutions of discrete, combinatorial and non-convex non-linear multicriteria problems. There are many similar software systems developed. Some of them are the following: PAES system (Knowles and Corne [38]), NSGM system (Srinivas and Deb [69]), MOSES system (Coello and Christiansen [14]), MOEA toolbox for MATLAB (**http://vlab.ee.nus.edu.sg/~kctan/moea.htm**), Finally, it is important to be consider some Web-based group decision and negotiations software system, as DECISIONARIUM system (H a m a l a i n e n [25])), INSPARE system (V e t s c h e r a et al.[82]), htmAthena negotiator (**www.athenasoft.org/sub/software.htmAthena**), etc.

Conclusion

Although the survey made is brief it gives a relatively good idea about the state of the art of modern methods, software systems, and applications of the multicriteria decision making. The results achieved and the modern information and communications technologies are a good ground for the future development of this scientific area.

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