GENERALIZED MULTICRITERIA OPTIMIZATION SOFTWARE SYSTEM MKO-2

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Abstract: The paper describes a generalized multicriteria decision support system, called MKO-2, which is designed to model and solve linear and linear integer multicriteria optimization problems. The system implements the innovative generalized classification-based interactive algorithm for multicriteria optimization with variable scalarizations and parameterizations, which is applicable for different types of multicriteria optimization problems (i.e., linear, nonlinear, mixed variables) as well as for different ways of defining preferences by the decision maker. It can apply different scalarizing problems and strategies in the search for new Pareto optimal solutions. The class of the problems solved, the structure, the functions and the user interface of the MKO-2 system are described in the paper. The graphical user interface of MKO-2 system enables decision makers with different degrees of qualification concerning methods and software tools to operate easily with the system. It can be used both for education and for solving real-life problems. Because of its nature, MKO-2 system applies specific expert knowledge of the field of multicriteria optimization and knowledge-based (expert) subsystems, explicitly representing specific domain knowledge, as well as specific MO solving knowledge, can be included in it concerning different levels of expertise.

1 INTRODUCTION

Different problems of planning, control, analysis and monitoring in economy, transport, industrial production, education, ecology and other spheres may be reduced to decision making problems at many criteria. These problems can be divided in two separate classes depending on their formal statement (Miettinen, 1999). One of these classes consists of the problems of multicriteria optimization (MO), in which a finite number of explicitly set constraints (in the form of set of functions) define an infinite number of feasible alternatives. These problems are also called continuous multicriteria decision making problems. Several criteria (or objective functions) are simultaneously optimized in the feasible set of solutions (or alternatives) in MO problems. In the general case, there is no single solution that optimizes all the criteria. Instead, there is a set of solutions where improvement in the value of one criterion leads to deterioration in the value of at least another criterion. This set is known as a Pareto optimal set. Any element of this set could be the final solution of the MO problem. In order to select the final solution, additional information is necessary and it is supplied by the so-called decision maker (DM). The information that the DM gives reflects his/her global preferences with respect to the quality of the solution obtained. Generally, MO has to combine two aspects: optimization and decision support.

One of the main approaches in solving MO problems is the scalarizing approach. The major representatives of this approach are the interactive algorithms (Miettinen, 1999). Scalarization means transformation of the MO problem into one or

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several single-criterion optimization problems, called scalarizing problems (SPs) with the following main property: each optimal solution generated is a Pareto or weakly Pareto optimal solution of the original MO problem. The SPs are the basis, on which different interactive MO methods are developed. They define the type of information, which the DM has to set, and also the type and number of the Pareto optimal obtained as well as the type of the MO problem (linear, non-linear, mixed variables, etc.) that can be solved.

Up to now, a large variety of SPs have been suggested and a number of interactive algorithms have been developed based on them. The different algorithms give different kind of information to the DM and provide different possibilities for the DM to control and stop the solution process.

The interactive MO algorithms use different SPs (Miettinen, 1999, Vassileva et al., 2005) like the Weighted SP (Gass and Saaty, 1955), the SP of ε – Constraint Method (Haimes et al., 1971), the SP STEM (Benayoun et al., 1971), the Chebyshev SP (Steur and Choo, 1983), the SP STOM (Nakayama and Sawaragi, 1984), the SP of the Reference Point (Wierzbicki, 1980), the SP GUESS (Buchanan, 1997), the SP of the Modified Reference Point (Vassilev et al., 2001), the SP of the External Reference Direction (Korhonen, 1997), the SP of the Reference Direction (Vassilev and Narula, 1993), the SP of the Internal Reference Direction (Narula et al., 1994), the Classification-based SP NIMBUS (Miettinen, 1999, Miettinen and Makela, 2006), the Classification-based SP DALDI (Vassileva, 2000). In the Weighted SP the DM defines his/her preferences by the values of the criteria weights, while in the SP of ε-constraint Method – by the selection of one function for optimization and defining the lower or upper bounds of change of the remaining criteria. In the SP of the Reference Point the so called reference point is determined by the aspiration levels of the criteria and these levels are the ones that the DM wishes or agrees to be obtained in the new solution. Actually, these aspiration levels of the criteria are parameters in all of the SPs of the reference point. In all of the classification-based SPs not only the aspiration levels could be parameters of the problem, but also the directions and intervals of alteration in the criteria values that the DM wishes or agrees to be obtained in the new Pareto optimal solution. Such parameters of a classification-based SP could also be the values of the criteria in the currently obtained solution. By setting desired or acceptable alterations in the values of the criteria in the currently obtained solution in the classification-based SPs, the DM indirectly classifies the separate criteria in different groups.

Among the well-known decision support systems (DSSs), which support the solving of MO problems, are the following systems: VIG, NIMBUS, DIDAS, CAMOS, LBS, DINAS, ADBASE, MOLP-16, MONP-16 and MOIP (Miettinen, 1999, Vassilev et al., 1997, Wiestroffer and Narula, 1997). Each multicriteria DSS contains control modules, interface modules and optimization modules. The optimization modules realize different multicriteria and single-criterion algorithms. In most of the MO DSSs developed up to now, basic attention is paid to the MO interactive algorithms. Two types of MO interactive algorithms are included in the well-known MO DSSs. The first type comprises interactive algorithms of the reference point and the reference direction (as in the systems DIDAS, VIG, CAMOS, DINAS and LBS). The second type includes classification-based algorithms (as in NIMBUS, MOLP-16, MONP-16 and MOIP).

The new programming languages and operating systems make possible the considerable improvement of the control modules and interface modules of MO DSSs. The description of DM's local preferences and the generating of new solutions for evaluation however depend to a higher degree on the type of the MO and single-criterion optimization algorithms included in the system. As shown in (Miettinen, 1999), the major part of the MO DSSs, developed up to now, include MO methods of the reference point and the reference direction, and they are intended to solve continuous MO problems. This has significantly influenced the design of these systems with respect to the input data entry, the interactive solution of MO problems and the visualization of the current and final results.

The paper describes the basic elements of the developed generalized MO DSS, called MKO-2, which supports the solving of linear and linear integer MO problems. The proposed generalized classification-based interactive algorithm, called GENWS-IM, which is the basis of the system, uses the scalarizing approach for solving MO problems and allows the DM to define not only the aspiration levels at each iteration, as it is in most of the classification-based MO interactive algorithms known up to now, but also to set aspiration intervals and aspiration directions of change in the values of some or of all the criteria. Such kind of generalized MO DSS that implements generalized MO interactive methods, based on the scalarizing approach, is an innovative one in the field of MO. In distinction with the traditional one-method MO

DSSs, the MKO-2 system can be used successfully both for education and for solution of real-life problems, not only with the help of one particular MO method but combining different MO methods. In this way, the MKO-2 DSS can be used not only for direct solving of MO problems but also for comparing and analyzing different solutions of given MO problem using different preference information, set by the DM, and different MO interactive methods. Thereby, this generalized MO DSS enables the DM to be more confident of the solving process and more satisfied by the final solution of the MO problem being solved. Because of its nature, such kind of MO DSS applies specific expert knowledge of the MO field and, therefore, knowledge-based (expert) subsystems, explicitly representing specific domain knowledge, as well as specific MO solving knowledge, can be included in it concerning different levels of expertise (i.e., recommendations like what kind of preference information and interactive methods to be used by the DM for solving the corresponding classes of MO problems).

The rest of the paper is organized as follows. The second section describes the proposed generalizing classification-based scalarization problem, called GENWS. The generalized classification-based interactive algorithm GENWS-IM is described in the third section and the MO DSS MKO-2 is stated in the fourth section. Finally, the conclusions are given in the last section.

2 GENERALIZED SCALARIZING PROBLEM GENWS

The general MO problem of can be stated as follows:

$$\text{maximize } \{ f_k(x),\ k \in K \}$$
$$\text{subject to } x \in X,$$

where $f_k(x): R^n \rightarrow R$, $k \in K = \{1, 2, \ldots, p\}$ are different criteria (or objective functions) which have to be simultaneously maximized.

The solution $x \in X$ is a Pareto optimal solution of the MO problem if there does not exist another solution $\bar{x} \in X$, for which is valid $f_k(\bar{x}) \geq f_k(x)$, for every $k \in K$ and $f_k(\bar{x}) > f_k(x)$ for at least one index $k \in K$. Furthermore, the solution $x \in X$ is a weakly Pareto optimal solution of the MO problem if there does not exist another $\bar{x} \in X$, for which is valid $f_k(\bar{x}) > f_k(x)$, for every $k \in K$. The vector $z = f(x) = (f_1(x), \ldots, f_p(x))^T \in Z$ is a (weakly) Pareto optimal solution in the criteria space if $x \in X$ is a (weakly) Pareto optimal solution in the decision space. A reference point (Wierzbicki, 1980) or a reference vector is a vector that consists of desirable or aspiration values set by the DM for each criterion. These aspiration values may be achievable or not.

An important concept in many interactive methods is classification of criteria into classes, where the DM studies the criteria values at the current solution and expresses hopes of what kind of values he/she wishes to obtain (Miettinen, 1999, Narula and Vassilev, 1994). An example of classification can be given as follows as assigning the criteria into the following classes: $K^{\geq}$, a set of criteria, the current values of which the DM wishes to improve up to a given or desired levels; $K^{>}$, a set of criteria, the current values of which the DM wishes to improve; $K^{\leq}$, a set of criteria, the current values of which the DM agrees to be deteriorated till given acceptable levels; $K^{<}$, a set of criteria, the current values of which the DM agrees to be deteriorated; $K^{=}$, a set of criteria, the current values of which the DM does not wish to be deteriorated; $K^{><}$, a set of criteria, the values of which the DM allows to vary within a given interval; K^{0}, a set of criteria, for which the DM has no explicit preferences about the criteria values alteration.

Now we can formulate the generalized SP GENWS (Vassileva et al., 2005) where the starting point for the classification is assumed to be the current (weakly) Pareto optimal solution and the problem is of the form

$$\text{minimize } S(x) =$$

$$\Big\{ \max_{k \in K^{\geq}} \left[F_k^1 - f_k(x) \right] G_k^1 \ R_1 \max_{k \in K^{\leq}} \left[F_k^2 - f_k(x) \right] G_k^2 \ R_2 \qquad (1)$$

$$\max_{k \in K^{<}} \left[F_k^3 - f_k(x) \right] G_k^3 R_3 \max_{k \in K^{>}} \left[F_k^4 - f_k(x) \right] G_k^4 \Big\} +$$

$$\sum_{k \in K^0} \left[F_k^5 - f_k(x) \right] G_k^5$$

subject to

$$f_k(x) \geq z_k^c, k \in K^{>} \cup K^{=}, \tag{2}$$

$$C_k \geq f_k(x) \geq E_k, k \in K^{\geq}, \tag{3}$$

$$f_k(x) \geq z_k^c - D_k, k \in K^{\leq}, \tag{4}$$

$$z_k^c - t_k^- \leq f_k(x) \leq z_k^c + t_k^+, k \in K^{><}, \tag{5}$$

$$x \in X, \tag{6}$$

where: $G_k^1, G_k^2, G_k^3, G_k^4, G_k^5$ are scaling, normalizing or weighting coefficients; C_k, D_k, E_k are parameters ($D_k > 0$; $E_k \leq z_k^c \leq C_k$); $F_k^1, F_k^2, F_k^3, F_k^4, F_k^5$ are parameters, connected with aspiration, current and other levels of the criteria values; R_1, R_2, R_3 are equal to the arithmetic operation "+" or to the separator " , " ; t_k^- and t_k^+ are the upper and lower limit of the acceptable for the DM interval of alteration of the criterion with an index $k \in K^{><}$ (t_k^->0; t_k^+>0); z_k^c is the value of the *k-th* criterion with an index in the current preferred solution.

It is proved in (Vassileva et al., 2005) that the solutions obtained by solving the generalized SP GENWS are always (weakly) Pareto optimal.

Altering some parameters of the generalized SP GENWS (Vassileva et al., 2005), the following thirteen, known in the literature, SPs, which were introduced in Section 1, can be obtained: the Weighted SP, SP of ε–constraint Method, Chebyshev SP, SP STEM, SP STOM, SP of the Reference Point, SP GUESS, SP of the Modified Reference Point, SP of the External Reference Direction, SP of the Reference Direction, SP of the Internal Reference Direction, Classification-based SP NIMBUS, and Classification-based SP DALDI.

3 GENERALIZED INTERACTIVE METHOD GENWS-IM

On the basis of the generalized classification-based SP GENWS, a generalized classification-based interactive algorithm for solving MO problems with variable scalarizations and parameterizations, called GENWS-IM, is designed, having the following characteristics:

- the DM may set his/her preferences with the help of the criteria weights, ε – constraints, desired and acceptable levels of change of the criteria values, desired and acceptable levels, directions and intervals of alteration in the criteria values, etc.;
- during the process of the MO problems solving, the DM may change the way of presenting his/her preferences;
- starting from one and the same current Pareto optimal solution and applying different SPs, the DM may obtain different new Pareto optimal solutions at given iteration, and this opportunity is especially useful in education and in comparison of different SPs.

The most wide-spread interactive algorithms for solving MO problems are the algorithms of the reference point, the algorithms of the reference direction and the classification-based algorithms. GENWS-IM interactive algorithm is an algorithm with variable scalarizations and parameterizations and it is a generalization of a large number of the above mentioned algorithms. This generalization is with regard to the classes of the problems solved, the type of defined preferences, the number and type of the scalarizing problems used, as well as the strategies utilized in the search for new Pareto optimal solutions.

4 GENERALIZED MULTICIRETIRA OPTIMIZATION SOFTWARE SYSTEM MKO-2

The MO DSS MKO-2, developed on the GENWS-IM, has a graphical interface in relation both to the classes of the MO problems being solved and to the possibilities for setting the DM's preferences.

MO DSS MKO-2 operates under the control of MS Windows operating system. This software system is designed to aid the solution of linear and linear integer MO problems. It may be used both for education and for solving real-life problems. MKO-2 system can also be extended to solve non-linear MO problems. For this purpose, some algorithms, solving non-linear continuous single-objective problems have to be included and new interface modules have to be added as well, connected with the solution of non-linear MO problems.

MO DSS MKO-2 consists of three main groups of modules – a control program, optimization modules and interface modules. The control program is integrated software environment for creation, processing and storing of files associated with

MKO-2, as well as for linking and execution of different types of software modules. The optimization modules realize the generalized interactive algorithm GENWS–IM for solving MO problems, two simplex algorithms for solving continuous single-criterion problems (Vanderbei, 1996), an algorithm of "Branches and Bounds" type for exact solution of linear integer single-criterion problems (Wolsey, 1998) and an algorithm for approximate solution of linear integer single-criterion problems (Vassilev and Genova, 1991). The interface modules provide the dialogue between the DM and the system during the entry and correction of the input data of the MO problems being solved, as well as during the interactive process of their solution. These modules enable the dynamic numerical and graphical visualization of the solving process parameters.

One of the main functions of MKO-2 system is to enable the extension of DM's possibilities to set his/her preferences in the terms of the criteria weights, ε – constraints, desired and acceptable levels of alteration in the criteria values, desired and acceptable directions of change of the criteria values, desired and acceptable levels, as well as directions and intervals of alteration of the criteria values. Thirteen SPs are generated in MKO-2 DSS in order to realize these possibilities. Depending on DM's preferences, these SPs are automatically generated by the generalized SP GENWS by changing its structure and parameters.

MO DSS MKO-2 system presents to the DM different windows intended for entry and correction of the MO problem's criteria and constraints, as well as for setting his/her preferences. The window, presented in figure 1, is the basic window of the editor for input data entry, called "MKO-2-Editor". It is used to set the data of a real-life MO linear integer problem for operative planning of the production program of a spinning department in a

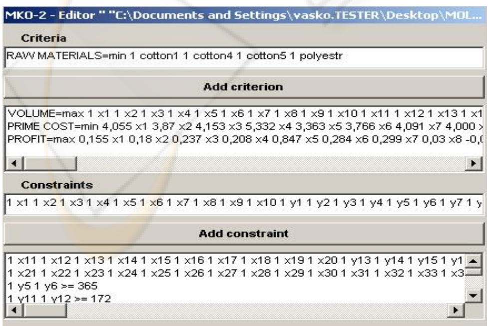

Figure 1: MKO-2 – Editor Main Window.

textile enterprise (Vassileva, 2006).

The window, presented in figure 2, is designed to identify the type of DM's preferences. The DM may select among five types of preferences and let assume that he/she has selected to set the preferences by aspiration levels (or reference point). In order to enter the different types of DM's preferences, different windows are used.

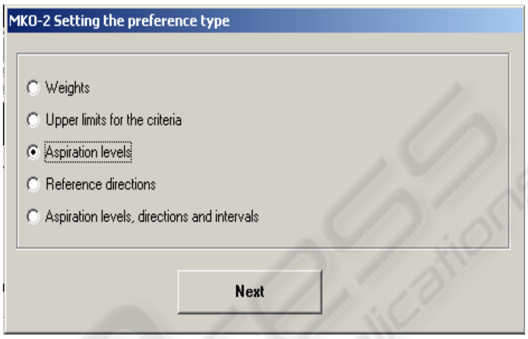

Figure 2: Type of the DM's Preferences.

5 CONCLUSIONS

The generalized MO DSS MKO-2 can be extended to model and solve not only linear and linear integer MO problems but also non-linear MO problems as well as a web-based version of the system can be developed.

The improved graphical user's interface of MKO-2 software system both to the classes of the MO problems solved and to the possibilities for setting DM's preferences, facilitates the operation of decision making persons of different qualification level relating to the optimization algorithms and software tools used. MKO-2 system is an innovative kind of DSS that implements generalized MO interactive method and can be used successfully both for education and for solution of real-life problems, not only with the help of one particular MO method but combining different MO methods. In addition to direct solving of MO problems the MKO-2 DSS can be used also for comparing and analyzing different solutions of given MO problem. Due to the fact that such kind of generalized MO DSS applies specific knowledge of the MO field, the future plans concerning the enhancement of the MKO-2 DSS comprise including of knowledge-based (expert) subsystems, explicitly representing specific domain knowledge, as well as specific MO solving knowledge. The aim of these subsystems is to analyze the information, supplied by the DM about different MO problems, as well as to provide this analysis and to recommend a course of DM's action. They will include, e.g., recommendations as what kind of preference information and interactive methods to be used for solving the corresponding classes of MO problems.

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