An Interactive Methodology for the Web-based GDSS

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Abstract

This research suggests an interactive methodology for multiple objective linear programming problems to help the group select a compromising solution in the World Wide Web environment. Our methodology lessens the burden of group decision makers, which is one of necessary conditions of the web environment. Only the partial weak order of variables and objectives from the group decision makers are enough for searching the best compromising solution. For such a purpose, we expand the Dror and Gass algorithm to the group decision context. And we suggest the system architecture of a web-based GDSS for the implementation of our methodology.

Keywords: Web-based GDSS, Multiple objective decision making, Group Decision Making, Interactive algorithm, Weak order preference.

1. Introduction

Formally, a multiobjective linear programming (MOLP) model is stated as follows;

> *Maximize* $\mathbf{Cx}$, *subject to* $\mathbf{x} \in \mathbf{S}$,
> where $S = \{\mathbf{x} \in \mathbf{R}^n \mid \mathbf{Ax} = \mathbf{b}, \mathbf{x} \geq \mathbf{0}\}$, $\mathbf{A}$, $\mathbf{C}$ are $m \times n$ and $k \times n$ matrices respectively and $\mathbf{b} \in \mathbf{R}^n$.

The optimization is expressed in terms of vector valued objective function $\mathbf{Cx}$ and a feasible set defined by $\mathbf{S}$. The solution set to the problem is the set of all efficient solutions. This solution set is usually very large and the purpose of existing interactive MOLP decision support system is to aid the decision maker (DM) in locating and selecting the most preferred solution from the set of efficient solutions. A variety of MOLP procedures have been proposed in their literature. However, up to date, the development of effective MOLP solution procedures remains a most challenging research area (Sun et al. 2000). Surveys of several of these procedures can be found in (Steuer 1986).

Nowadays, managers are increasingly faced with the task of making complex decisions in rapidly changing organizational environments, and spend much of their time in decision related meetings. Managers balancing tradeoffs between objectives are even more important in groups than for individuals, because conflicting objectives and opposing viewpoints are inevitably going to exist. In group situations, multiple individual interpretations of the best solution must be aggregated into the best single group interpretations. Because each DM evaluates alternative solutions based on his/her frame of preference, the individual judgments of the best solution may not coincide (Lewis and Butler 1993; Davey and Olson 1998).

Although several researchers have designed methods to aid decision making among groups, their research has focused only on comparative study of the proposed methods without consideration for system implementation. Two key forces are currently having a profound impact on managerial decision making; (1) a move toward more team-based organizations which necessitates an increased use of group decision making methods, and (2) advancements in electronic communication (World Wide Web etc.) and computing which increases the geographical and temporal dispersion of organizational members.

A net result of these two key forces is an increased reliance on technology-assisted group decision support methods to facilitate rapid decision in organizations in setting where work force is geographically, or temporally despersed (Slevin et al. 1998; Nikos and Costas 1997).

Dror and Gass (1987) suggested an interactive scheme that requires only partially ordered set of the variables and objectives involved, and does not require that the DM has an ability to directly evaluate trade-offs at a given point. The Dror-Gass methodology uses a DM's expressed weak order preference on decision variables and another on objectives. The simplicity of Dror-Gass methodology does not require much burden of decision maker, so we extend the Dror-Gass methodology for solving group decision making problems in client-server environment. Compared with other interactive approaches, our methodology relies on only weak order-typed preference information of group DMs. And the methodology was designed to avoid any assumptions about the shape or existence of the DMs' utility function and

Group's utility function. It is also designed to simplify as much as possible the input preference requirements of the DM. Our suggested methodology compares intermediate solutions based on the weak order-typed preference of group DMs. For the minimal assumptions this methodology makes, we suggested an aggregation method of individual DM's weak order preference. The aggregation methods is modified from weak ranking method of Cook and Kress (1990).

The overall procedure of our suggested methodology is as follows: First, each DM uses weak order information to represent DM's preference about objectives and decision variables. The weak order-typed preferences are aggregated into group's one. We attempt to exploit this weak order information in the search for the best group's compromising solution. Second, the group DMs must rank the order of objectives to be improved at next stage. Then our procedure determines group order of objectives and finds out their preferred solution. Finally, the iteration is continued until predefined stopping conditions are satisfied. The methodology is explained step by step with an illustrative example. Furthermore, we suggest the system architecture of a web-based GDSS for implementing our methodology.

2. Backgrounds

2.1 Multiobjective Decision Making in Group Decision Support

In the past few decades, a lot of multiobjective decision making (MODM) methods, specially interactive MOLP methods, have been developed to solve conflicting preferences among objectives for single decision maker (Steuer 1986). With these techniques, the DM sequentially evaluates a limited number of solutions in order to direct movement through objective space toward a good solution. The interactive evaluation process continues until the DM expresses satisfaction with a solution. These interactive methods offer significant benefits because the DM provides only local preference information regarding a small number of solutions at a time.

However, researches related to the use of MODM in group decision support, although considered to have great potential, fell behind (Davey and Olson 1998). Several researchers have designed few methods to aid decision making among groups.

A study by Rao and Jarvenpaa (1991) highlighted a group decision support system frame work for addressing multiple DMs multiobjective problems. Wendell (1980) developed a theoretic approach for the bi-criterion case which allows progressive articulation of DM preferences. NEGO (Kersten 1985) formulates a goal programming model to find the decision that is closest to the feasible ideal of the group. Korhonen et al. (1986) adapted the well-known Zionts and Wallenious (1976) interactive single DM MOLP technique to a multiple DM situation using the implicit weights obtained from group selection of a given set of extreme points. The quasisatisficing framework SCDAS (Lewandowski 1989) supports discrete choice problems through the use of aspiration level, while Wang and Sen (1989) presented a procedure requiring explicit estimation of the individual and aggregate utility functions in order to aid group members in consensus seeking by combining MOLP with the Delphi technique. Franz, Reeves, and Gonzalez (1992) proposed three decision-making procedures based on the SIMOLP methodology (Reeves and Franz 1985) for facilitating a group of DMs in reaching a collectively acceptable solution to a MOLP problem. Iz and Krajewski (1992) proposed three group decision making procedures, each of which extends the well-known MOLP method for single DMs to group decsion making, by augmenting with a preference aggregation component in order to capture the preferences of multiple decision makers. The three extended single DM MOLP methods are GNS based on the weighted-sum approach, GSM based on the STEP method, and GGPM using the sequential goal programming method. Lewis and Butler (1993) also suggested and evaluated the interactive multiple objective, multiple DM decision procedures which combines the SIMOLP and/or Tchebycheff MOLP (Steuer and Choo 1983) optimization methods with a preference ranking tool (Cook and Kress 1985) and a consensus ranking heuristic (Beck and Lin 1983).

2.2 Dror-Gass Interactive Algorithm for a Single DM

Dror-Gass algorithm (Dror and Gass 1987) requires only partial ordered set of the variables and objectives involved, and does not require that the DM has an ability to directly evaluate trade-offs at a given point. The weak order preference structure is the primary mechanism by which initial solutions are located for evaluating by the DM. For seven variables like x_1, x_2 ... x_7, if DM classifies the variables three classes $\{x_1, x_3\}$, $\{x_2, x_5, x_7\}$, $\{x_4, x_6\}$, then rank 3, 2, and 1 are given to each class according to DM's preferences. Weak order of variables, and that of objectives (in the similar way) are enough for the representation of DM's preferences. Dror-Gass algorithm was developed for a single decision maker, but it is explained in brief for the understanding of our methodology.

The Dror-Gass methodology is basically composed of the following steps.

Step 1. The weak order *PV* and *PO* on a problem's variables and objectives are determined in the problem's modeling stage by the DM.

Step 2. Obtain an initial candidate solution W_o, which is efficent, basic and with (locally) highest preference value.

Step 3. Present W_0 to the DM. If it is satisfactory, stop. The search is completed, and the present solution W_0 is optimal. Otherwise, DM indicates the following information.

(3.1) The objective DM is most dissatisfied with, and the direction of DM's dissatisfaction. DM has an option to indicate more than one unsatisfactory objective value.

(3.2) The DM has an option of changing the weak order of variables and/or objectives. In this case, return to step 2.

Step 4. Obtain a new candidate solution whch improves (if possible) the values of the objectives indicated in step 3.1, while at the same time (locally) maximizing the preference value of the new solution. Set the new solution to be W_o, and return to Step 1.

The characteristics of Dror-Gass methodology is summarized as follows:

First, a more preferred solution is one which involves more of the preferred variables in its basis. Therefore, it makes us evaluate the solutions only by rank sum of variables in its basis.

Second, given that weak orders of variables and objectives are set, they express the DMs' preferences respectively. The additional information required from the DM at each interactive step is minimal in the sense that he should only indicate acceptance, or, rejection. In the case of rejection, DM should indicate the objective which has the most dissatisfying value and whether this value is too low or too high.

Third, it was designed to avoid any assumptions about the shape or existence of the DMs' value function or utility function. And they need as much as possible the simplified input preference requirements of the DM, so any DM can use the methodology with ease even when he has no knowledge about MOLP.

For more about this, please refer (Dror and Gass 1987; Dror, Gass, and Yellin 1988).

3. Methodology

3.1 Overall Flow of Methodology

Dror-Gass algorithm uses individual DM's weak order preference information on decision variables and objective functions, and so our suggested algorithm. However, if our methodology is applicable for the group decision making, it is necessary to develop an aggregation procedure which combines each DM's weak order information to the group's one. For this purpose, we suggest a weak-order raking method. Given the group's aggregated weak order preference information, the search process to find a group's compromising solution is similar to Dror-Gass algorithm except that our procedure needs a stopping rule and our procedure is processed in the client/server environment. In this research, instead of suggesting one stopping rule, we illustrate the characteristics of each stopping rule through simulation analysis. Overall flow of our suggested methodology is shown at the following Figure 1. Next section describes the aggregation process for the group's weak order information, and detailed description of the methodology is explained step by step at the following.

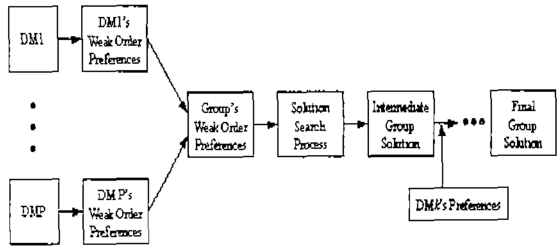

Figure 1. Overall flow

3.2 Group Preference Aggregation Scheme

We use only weak orders of decision variables and objectives as input of DM's preferences. In this framework, we integrate DM's weak orders to get the group's collective preference. Our suggested aggregation process is composed of three phases: Phase I is to obtain group's preferences of decision variables based on individual DM's preferences. Phase II is to obtain group's composite preference rank based on group's preferences of decision variables. Group's composite preference rank is used to select group's compromising solution among adjacent efficient extreme points. Phase III is to get group's preferences of objective functions.

Phase I. Group's preferences of decision variables.

Step 1: At first each DM's weak order preference is obtained according to Dror-Gass's individual preference ranking scheme (for more detailed description see in (Dror and Gass 1987)).

For an illustrative purpose, consider the example of three decision makers denoted as DM1, DM2, and DM3, and six decision variables, x_1, x_2, x_3, x_4, x_5, x_6. Based on Dror-Gass's preference ranking scheme, it is assumed that each DM's weak order preference is given as follows.

DM1: $x_1 \prec x_2 \prec x_4 \prec x_3 \prec x_5, x_6.$

DM2: $x_3 \prec x_2 \prec x_5 \prec x_1, x_6 \prec x_4.$

DM3: $x_6 \prec x_5 \prec x_4 \prec x_1 \prec x_2 \prec x_3.$

In DM1's preference, x_5 and x_6 are in the same class, so their rank is same.

Step 2: From the result of each DM's preference class, it is obtained a pairwise comparison matrix $\mathbf{A}_k = (a_{ij})$, where $k = 1, \ldots, p$ and p is the number of DMs.

$$a_{ij} = \begin{cases} 1, & \text{if variable } x_i \text{ is preferred to variable } x_j \\ 0.5, & \text{if variable } x_i \text{ and variable } x_j \text{ are indifferent} \\ 0, & \text{if variable } x_j \text{ is preferred to variable } x_i \end{cases}$$

Compared with Dror-Gass algorithm, we use Kendall scores method to rank the variables based on their preference records. The Kendal scores method amounts simply to determining the row sums of matrix $\mathbf{A}_k$, $PV_{k,i}$, where i = 1, ..., n, and n is the number of decision variables. $PV_{k,i}$ means preference rank of decision variables of DM k. In the illustrative example, $\mathbf{A}_1$ and $PV_{1,i}$ are as follows. $\mathbf{A}_2$ and $\mathbf{A}_3$ are obtained similarly.

$$\mathbf{A}_1 = \begin{array}{c|ccccccc} & x_1 & x_2 & x_3 & x_4 & x_5 & x_6 & PV_{1,i} \\ \hline x_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ x_2 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ x_3 & 1 & 1 & 0 & 1 & 0 & 0 & 3 \\ x_4 & 1 & 1 & 0 & 0 & 0 & 0 & 2 \\ x_5 & 1 & 1 & 1 & 1 & 0 & 0.5 & 4.5 \\ x_6 & 1 & 1 & 1 & 1 & 0.5 & 0 & 4.5 \end{array}$$

Step 3: Group's aggregated preference rank of decision variable, GPV_i is defined as the sum of individual DM's preference rank, $PV_{k,i}$.

$$GPV_i = \sum_k PV_{k,i}.$$

If individual DM has different weights, weight multiplied score sum becomes GPV_i. In this research, we assumed that every DM has equal weight. If DMs have different weights, GPV_i becomes the weighted average of $PV_{k,i}$. In the illustrative example, group's aggregated preference rank of decision variable, GPV_i, is as follows; $GPV_1 = 6.5$, $GPV_2 = 6.0$, $GPV_3 = 8.0$, $GPV_4 = 9.0$, $GPV_5 = 7.5$, $GPV_6 = 8.0$. Based on above group's rank, group's preference is represented as follows, $x_2 \prec x_1 \prec x_5 \prec x_3, x_6 \prec x_4$. Please compare this result with those of individual DMs in step 1.

Phase II: Group's composite preference rank of efficient basic solutions.

Our suggested algorithm finds a group compromising solution among adjacent efficient extreme points using group's preference rank. Group's composite preference rank of solution, $\mathbf{X}^j$ is defined as follows;

$$\mathrm{GR}(\mathbf{X}^j) = \sum_{i \in \text{basis of solution } \mathbf{X}^j} GPV_i$$

To find a next group compromising solution, we should calculate group's composite preference rank of each adjacent efficient basic solution. In the illustrative example, let $\mathbf{X}^1 = (0, 1, 2, 0, 0, 1)^T$ to be one of the adjacent efficient basic solutions of current solution. Then $GR(\mathbf{X}^1) = GPV_2 + GPV_3 + GPV_6 = 6 + 8 + 8 = 22$. Among adjacent efficient basic solutions, the solution with the highest group's composite preference rank is selected as a new candidate solution.

Phase III. Group's preferences of objective functions to improve most.

This preference measure is used in order to determine which objectives to improve further in our proposed algorithm.

Step 1: Each DM represents one or more objectives with which DM is dissatisfied using weak order-typed information. For an illustrative example, it is assumed that there are six objectives and DM1 is most dissatisfied with the value of f_2 and next that of f_1. DM2 and DM3 represent also the following weak order information.

DM1: $f_1 \prec f_2$
DM2: $f_2 \prec f_3 \prec f_1$
DM3: f_2

The preference of unidentified objectives is lower than that of identified ones, and the preferences among unidentified ones are assumed to be equal. Therefore, each DM's preference of objectives is represented as follows:

DM1: $f_3, f_4, f_5, f_6 \prec f_1 \prec f_2$.
DM2: $f_4, f_5, f_6 \prec f_2 \prec f_3 \prec f_1$.
DM3: $f_1, f_3, f_4, f_5, f_6 \prec f_2$.

Step 2: From the result of each DM's preference class, it is obtained pairwise comparison matrix $\mathbf{B}_k = (b_{ij})$, where k = 1, ..., p and p is the number of DMs.

$$b_{ij} = \begin{cases} 1, & \text{if variable } f_i \text{ is preferred to variable } f_j \\ 0.5, & \text{if variable } f_i \text{ and variable } f_j \text{ are indifferent} \\ 0, & \text{if variable } f_j \text{ is preferred to variable } f_i. \end{cases}$$

$PO_{k,i}$ means preference rank of objective f_i of DM k. In the illustrative example, $\mathbf{B}_1$ and $PO_{k,i}$ are obtained as follows. $\mathbf{B}_2$ and $\mathbf{B}_3$ may be obtained similarly.

$$\mathbf{B}_1 = \begin{array}{c|ccccccc} & f_1 & f_2 & f_3 & F_4 & f_5 & f_6 & PO_{1,i} \\ \hline f_1 & 0 & 0 & 1 & 1 & 1 & 1 & 4 \\ f_2 & 1 & 0 & 1 & 1 & 1 & 1 & 5 \\ f_3 & 0 & 0 & 0 & 0.5 & 0.5 & 0.5 & 1.5 \\ f_4 & 0 & 0 & 0.5 & 0 & 0.5 & 0.5 & 1.5 \\ f_5 & 0 & 0 & 0.5 & 0.5 & 0 & 0.5 & 1.5 \\ f_6 & 0 & 0 & 0.5 & 0.5 & 0.5 & 0 & 1.5 \end{array}$$

Step 3: Group's aggregated preference rank of objective function, GPO_i is defined as the sum of individual DM's preference rank, $PO_{k,i}$.

$$GPO_i = \sum_k PO_{k,i}.$$

In the illustrative example, group's aggregated preference rank of objective functions, GPO_i, is as follows; GPO_1 = 11, GPO_2 = 13, GPO_3 = 7.5, GPO_4 = 4.5, GPO_5 = 4.5, GPO_6 = 4.5. Based on group's rank, group's preference may be represented as follows: $f_4, f_5, f_6 \prec f_3 \prec f_1 \prec f_2$.
Please compare this result with those of individual DM's in step 1.

Our procedure is suggested for group decision making in client/server environment. So each step of the procedure is processed at two areas, client system and server system. Client systems give intermediate results to each DM, receive DM's response, and transfer each DM's response into server system. Most part of our suggested procedure is processed at server system area. Please refer Cho and Kim (2000) for a more detail about the algorithm.

4. An Illustrative Example

The illustrative problem for our suggested interactive procedure is a restatement of a problem taken from Steuer (1986), which has a three-objective linear programming model with five variables. The numerical expression is as follows :

$$\mathbf{C} = \begin{bmatrix} 1 & 3 & -2 & 0 & 1 \\ 3 & -1 & 0 & 3 & 1 \\ 1 & 0 & 2 & 0 & 3 \end{bmatrix}$$

$$\mathbf{A} = \begin{bmatrix} 2 & 4 & 0 & 0 & 3 \\ 0 & 0 & 2 & 5 & 4 \\ 5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 \\ 5 & 5 & 2 & 0 & 0 \end{bmatrix}$$

$$\mathbf{b} = \begin{bmatrix} 27 \\ 35 \\ 26 \\ 24 \\ 36 \end{bmatrix}$$

The above numerical representation is expressed as the following matrix formulation:

$$\begin{aligned} &\max\ \ \mathbf{Cx}, \\ &\text{s.t.}\ \ \ \mathbf{Ax} \le \mathbf{b};\ \mathbf{x} \ge 0. \end{aligned}$$

For the simplicity of our illustration, it is assumed that 3 DMs attend in the group decision making procedure. Furthermore, as a majority rule, a half satisfaction rule is used. Figure 2 shows the set of efficient basic vectors (solutions) together with the connected graph of those vectors. The variables right of each vector represent basic variables composing the vector, and the numbers below the basic variable set show the values of three objective functions. In Figure 2, $\mathbf{X}^0$, $\mathbf{X}^9$ and $\mathbf{X}^{11}$ are ideal solutions. Please notify that $\mathbf{X}^0$ is not a basic efficient solution. The weak orders on variables and objectives that each DM sends to server system, are summarized at Table 1.

Table 1. Weak order preference

	DM1	DM2	DM3
Variables	$x_4,x_5 \prec x_1,x_2,x_3$	$x_1,x_2,x_3 \prec x_4,x_5$	$x_2 \prec x_3,x_5 \prec x_1,x_4$
Objectives	$f_1,f_2 \prec f_3$	$f_2,f_3 \prec f_4$	$f_1,f_3 \prec f_2$

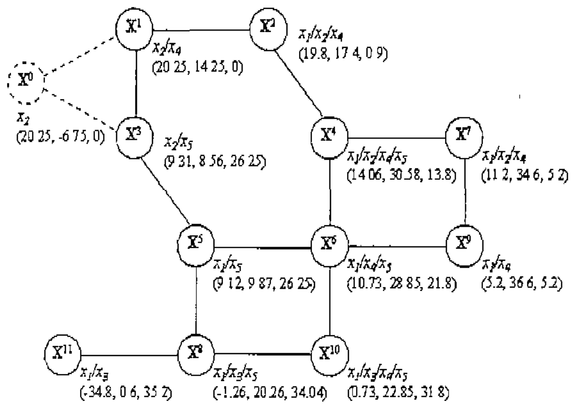

Figure 2. Basic efficient solutions

According to the preference ranking scheme of Dror-Gass (1987), the resulting equivalence classes for the variables of each DM are as follows:

DM1 : $x_4 \prec x_5 \prec x_1, x_3 \prec x_2$
DM2 : $x_2, \prec x_1, x_3 \prec x_4 \prec x_5$
DM3 : $x_2 \prec x_3 \prec x_5 \prec x_1, x_4$

Based on our suggested aggregation method of Phase I of section 2, we get the pairwise comparision matrix $\mathbf{A}_k$ as follows :

$A_1 =$

	x_1	x_2	x_3	x_4	x_5	$PV_{1,i}$
x_1	0	1	0.5	0	0	1.5
x_2	0	0	0	0	0	0
x_3	0.5	1	0	0	0	1.5
x_4	1	1	1	0	1	4
x_5	1	1	1	0	0	3

$A_2 =$

	x_1	x_2	x_3	x_4	x_5	$PV_{2,i}$
x_1	0	0	0.5	1	1	2.5
x_2	1	0	1	1	1	4
x_3	0.5	0	0	1	1	2.5
x_4	0	0	0	0	1	1
x_5	0	0	0	0	0	0

$A_3 =$

	x_1	x_2	x_3	x_4	x_5	$PV_{3,i}$
x_1	0	0	0	0.5	0	0.5
x_2	1	0	1	1	1	4
x_3	1	0	0	1	1	3
x_4	0.5	0	0	0	0	0.5
x_5	1	0	0	1	0	2

Based on preference rank of decision variables of three DMs, GPV_i, the group's aggregated preference rank of variable i, is as follows :

$GPV_1 = 4.5$
$GPV_2 = 8.0$
$GPV_3 = 7.0$
$GPV_4 = 5.5$
$GPV_5 = 5.0$

The group preference ranks of three ideal solutions are as follows :
$GR(\mathbf{X}^0) = GPV_2 = 8.0$
$GR(\mathbf{X}^9) = GPV_1 + GPV_4 = 10.0$
$GR(\mathbf{X}^{11}) = GPV_1 + GPV_3 = 11.5$

The ideal solution with the highest group preference rank is $\mathbf{X}^{11}$, and its group preference rank is 11.5. The server searches the neighborhood of $\mathbf{X}^{11}$, that has a higher group preference rank by calling the 'Edge' algorithm of step 4. At figure 3, there is only one neighboring basic efficient solution, $\mathbf{X}^8$, of which the group preference rank, $GR(\mathbf{X}^8)$ is 16.5. Denote this solution as an initial candidate solution, $\mathbf{W}^0$ (4.83, 0, 5.94, 0, 5.78). For this initial candidate solution, we have the following values for the three objective functions:
$f_1(\mathbf{W}^0) = -1.26$
$f_2(\mathbf{W}^0) = 20.26$
$f_3(\mathbf{W}^0) = 34.04$

The solution is presented to all DMs according to step 5. Each DM is asked to judge it, taking a vote whether the current solution is satisfactory or not. The response of each DM is transferred and aggregated at server system. Group DMs responses are summarized and the agreed ratio is calculated. All DMs are not satisfied at the current solution, so the agreed ratio is zero. At step 8, objectives which each DM would like to improve most is represented as follows:
DM1: f_2
DM2: f_2, f_1 ($f_1 \prec f_2$)
DM3: f_3

Based on Phase III (group's preferences of objective functions to improve most) of section 2, the server computes group's aggregated preference rank of objective function.
$GPO_1 = 2$
$GPO_2 = 4.5$
$GPO_3 = 2.5$

Now the server finds an adjacent solution, $\mathbf{X}^{10}$, as a new candidate solution $\mathbf{W}^1$ (5.2, 0, 5.0, 0.57, 5.53).
$f_1(\mathbf{W}^1) = 0.73$
$f_2(\mathbf{W}^1) = 22.85$
$f_3(\mathbf{W}^1) = 31.8$

The solution $\mathbf{W}^1$ increased significantly the value of the objective f_2. The value of f_1 is also increased, but that of f_1 is reduced.

When this solution is presented to group DMs, DM3 is satisfied, but DM1 and DM2 are not satisfied and they want to increase the value of f_2 continually. The server finds an adjacent solution, $\mathbf{X}^6$, as a new candidate solution $\mathbf{W}^2$ (5.2, 0, 0, 2.57, 5.53).
$f_1(\mathbf{W}^2) = 10.73$
$f_2(\mathbf{W}^2) = 28.85$
$f_3(\mathbf{W}^2) = 21.8$

DMs' responses are that DM1 is satisfied at $\mathbf{W}^2$, but DM2 and DM3 are not satisfied and furthermore, they want to increase the value of f_3. A new efficient solution $\mathbf{X}^5$, as a new candidate solution $\mathbf{W}^3$ (0.38, 0, 0, 0, 8.75).
$f_1(\mathbf{W}^3) = 9.12$
$f_2(\mathbf{W}^3) = 9.87$
$f_3(\mathbf{W}^3) = 26.25$

At this point, DM2 and DM3 are still concerned with the value of f_3, and request the improvement of it. The adjacent solution $\mathbf{W}^4$ that improves the value of f_3 most is $\mathbf{X}^8$. But $\mathbf{W}^4$ is equal to $\mathbf{W}^0$. Thus, a cycle has occurred. The server has to examine the cycle and suggests a compromise solution according to step 12. As you can see in figure 3, the cycle sequence $\mathbf{W}^0 \rightarrow \mathbf{W}^1 \rightarrow \mathbf{W}^2 \rightarrow \mathbf{W}^3 \rightarrow \mathbf{W}^0$ belongs to one efficient face, allowing a compromise solution to be generated. The compromise solution is obtained as a weighted linear sum of the solutions in the cycle. The weights are normalized and directly proportional to the group preference ranks of the solutions in the cycle. The corresponding group preference ranks of the solutions in the cycle are as follows: $GR(\mathbf{W}^0) = 16.5$, $GR(\mathbf{W}^1) = 22$, $GR(\mathbf{W}^2) = 15$, $GR(\mathbf{W}^3) = 9.5$.
The resulting compromise solution $\mathbf{W}^c$ has the following values :
$\mathbf{W}^c$ (4.376, 0, 3.302, 0.811, 6.081)
$f_1(\mathbf{W}^c) = 3.85$
$f_2(\mathbf{W}^c) = 21.64$
$f_3(\mathbf{W}^c) = 29.22$

5. System Architecture

5.1 Introduction

In this section, we will describe a web-based group decision support system, namely **GroupDecision.Net**, which is developed to evaluate three proposed methods in a field experiment with human participants under distributed group decision environment.

The existing group decision support systems(GDSS) designed to execute in the mainframe, DOS or the Windows version share weaknesses in common from the viewpoint of both the user and the developer of the system. As far as the user is concerned, the installation of compilers and the system itself is needed. Futher, they work only certain computer environments and operation systems. For the developer, the delivery of the updates of GDSS software is laborious. Keeping up separate versions for different environments also needs extra effort. Via the web, there is only one version of the software to updated and any client computer has the capabilities of a sever computer. Futher, the web provides a graphic user interface. No special tools, compiler or software besides a web browser are needed[Miettinen and Mäkelä, 2000]. Thus, we use the latest web technologies such as Java, RMI, and JFC in order to solve the problems of the existing GDSS, in the development of **GroupDecision.Net**. The characteristics of **GroupDecision.Net** can be described as following.

(1) Platform Independence and Network Mobility
The massive growth of the Internet and the World-Wide Web leads us to a completely new way of looking at development and distribution of software. In such environments, applications such as GDSS must be capable of executing on a variety of hardware architectures. Within this variety of hardware platforms, applications must execute atop a variety of operating systems and inter-operate with multiple programming language interfaces. Java technology is designed to support applications that will be deployed into heterogeneous network environments. To accommodate the diversity of operating environments, the Java Compiler product generates bytecodes - an architecture neutral intermediate format designed to transport code efficiently to multiple hardware and software platforms. The interpreted nature of Java technology solves both the binary distribution problem and the version problem. And also Applets, which we had used for developing client interfaces, are Java-supported dynamically loadable procedures that can run on Java-enabled Web browser [Sun Microsystems, 1996]. They require no installation, can be executed in any Java-enabled browser and run on most platforms. Advantages of using applets are numerous as this technique provides secure and heterogeneous software that can run on literally any computer connected to the Web. Therefore, **GroupDecision.Net** developed using Java technology can easily support decision making among group members who are working on heterogeneous platforms, without recompilation or porting of the programs.

(2) Distributed Object Computing
RMI(Remote Method Invocation) enables the programmer to create distributed Java technology-based to Java technology-based applications, in which the methods of remote Java objects can be invoked from other Java virtual machines, possibly on different hosts. A Java technology-based program can make a call on a remote object once it obtains a reference to the remote object, either by looking up the remote object in the bootstrap naming service provided by RMI or by receiving the reference as an argument or a return value. RMI provides a simple and direct model for distributed computation with Java objects. Because RMI is centered around Java, it brings the power of Java safety and portability to distributed computing. And also, RMI has several advantages over traditional RPC systems because it is part of Java's object oriented approach[Sun Microsystems, 1999]. In this research, we implement the distributed computing environments suitable to a group decision making using Java RMI with several advantages in developing the client/server systems.

(3) Simple and Easy User Interface
The Java Foundation Classes (JFC) are a comprehensive set of GUI components and services which dramatically simplify the development and deployment of commercial-quality desktop and Internet/Intranet applications. Java Foundation Classes extends the original AWT by adding a comprehensive set of graphical user interface class libraries that is completely portable and delivered as part of the Java platform. Since the JFC is core to the Java platform, it eliminates the need to download special classes at runtime and offer significant performance improvements[Sun Microsystems, 2000]. By implementing the user interface using the JFC, **GroupDecision.Net** which requires simple reactions from decision makers provide a simple and user-friendly decision environment to decision makers so that any decision makers with no specific MODM knowledge can be involved in a multiobjective group decision making.

5.2 Overall System Architecture

GroupDecision.Net consists of server components and a client interface each of which executes in the web server and in the web browser respectively. In the web server, there are DM(decision making) controller which controls and manages the whole group decision making process, GDM processor to support a group decision making, and IDM processor for supporting individual decision making. Each of them accesses database and uses modelbase. The client module running the web browser in the client(because it is implemented using Java applets) sends information from decision makers to the server, and then presents to each decision maker the results from server. Figure 3 shows the overall system architecture.

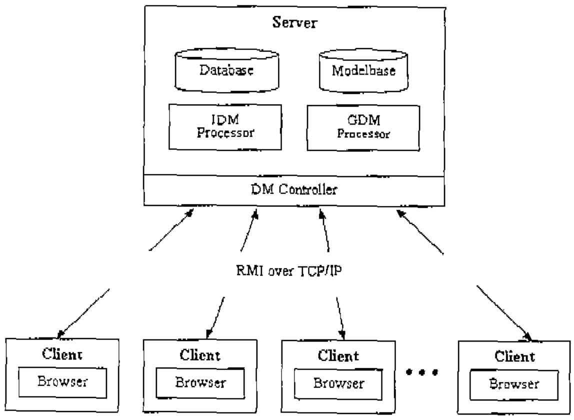

Figure 3. Overall system architecture

5.3 Server Components

The server of **GroupDecision.Net** consists of five components as shown in Figure 4 :

- DM controller
- GDM processor
- IDM processor
- Database
- Modelbase.

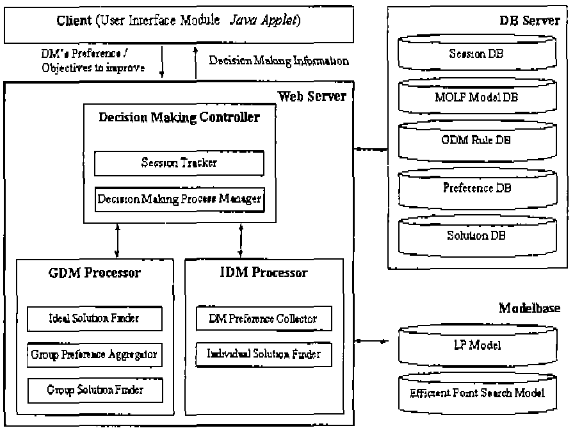

Figure 4. Components of the Server

(1) DM Controller
DM controller controls and manages the whole system. Interacting with the client through RMI interface, it collects and analyzes information from individual DMs and then activates GDM processor or IDM processor. The collected information are user login data, individual DM's preferences, individual DM's satisfactions and objectives to improve, etc. DM controller also is responsible to control the every step of a decision process and send to the client both process control information and decision making information generated from the IDM processor or the GDM processor. It is divided into session tracker and decision making process manager. The session tracker makes the user access environment such as session connection and error recovery so that each DM can conveniently involve in a group decision making. The decision making process manager performs the role to follows up every decision steps and to controls GDM processor an IDM processor, according to a predefined group decision procedure.

(2) GDM Controller
GDM controller performs the role to iteratively find a group solution through the interaction with DM controller and preference information from group members. It consists of ideal solution finder, group preference aggregator and group solution finder for implementing the proposed methodology.

(3) IDM Controller
IDM controller makes each individual DM to iteratively search a individual solution under control of DM controller. It is divided into DM preference collector and individual solution finder.
(4) Database
The database in WebDecision contains all data required for supporting group decision process and are retrieved through JDBC by other server components. JDBC technology is an API that provides universal data access from the Java programming language. It also provides cross-DBMS connectivity to a wide range of SQL databases.

(5) Modelbase
The role of modelbase is to provide methemetical programming algorithms to GDM processor and IDM processor for finding a efficient solution of MOLP model, iterativley. In order to solve a MOLP problem, a number of LP problems have to be solved. The efficient point search model modified from Ecker-Kouada's algorithm is frequently used to determine adjacent efficient basic solutions during the solution search process.

5.4 Client Interfaces

The client interface module performs the role to handle interactions between DMs and the server omponents through RMI and JDBC. By implementing the module as a Java applet, it can be invoked within a Java enabled web browser with no installation of a client program. As it requires few information from decision makers and displays various graphic information to decision makers, any decision makers with no specific MODM knowledge can easily be involved in a group decision. Given Figure 5 is some of the major screen shots to show the user interface and run-time characteristics of the system.

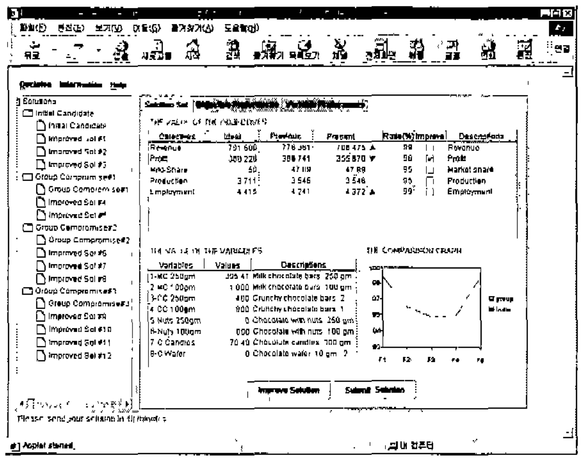

Figure 5. Interface screen for specifying objective(s) to improve

6. Conclusions

Multiobjective group decision support is conceived to be very difficult problem to search compromising solution under the conflicting criteria and conflicting decision makers. Generally, the search processes of existing methods are too complex for group decision makers to resolve their conflicting preferences. Furthermore, some existing methods need the shape of group utility functions, or others need too much information from group decision makers. To resolve these problems, we suggest methods to compromise conflicting preferences of group decision makers with less interaction with decision makers. Our methodology relies on only weak order-typed preference information of group decision makers about variables and about objectives. Further research should be done on the evaluation of our methodology in a computer simulation with hypothetical decision makers and in a field experiment with human participants for suggesting the most suitable method in given distributed group decision environment

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