An Improved Multi-Choice Goal Programming Approach for Supplier Selection Problems

O. Jadidi [a], S. Cavalieri [b], S. Zolfaghari [c,*]

[a] *Department of Business Administration, Bergamo University, Via Dei Caniana 2, Bergamo BG, Italy*

[b] *Department of Engineering, Bergamo University, Viale Marconi 5, Dalmine BG, Italy*

[c] *Department of Mechanical and Industrial Engineering, Ryerson University, Toronto, ON, Canada M5B 2K3*

ABSTRACT

In this study, a supplier selection problem is first modeled as a multi-objective optimization problem with three minimization objectives: price, rejects and lead-time. In reality, the objectives may have different relative weights. In addition, due to uncertainty/imprecision, it may be easier for decision makers to determine an interval goal or aspiration level for every objective, instead of a single one. Also, the decision makers may have other preferences such as the purchasing cost not significantly exceeding the budget. For this purpose, a new Multi-Choice Goal Programming (MCGP) approach is proposed. One of the main advantages of the proposed model is that it provides the decision makers with more control over their preferences. Finally, an illustrative example demonstrates the effectiveness of our proposed model.

Keywords: Supplier selection; Multi-objective optimization; Multi-choice goal programming.

[*] Corresponding author. Tel. : 416 979 5000 x7735; fax: 416 979 5265.
E-mail address: zolfaghari@ryerson.ca (S. Zolfaghari).

1. Introduction

Today companies need to take advantage of any opportunity to increase their ability for competing with their rivals. They should fulfill the expectations of their customers for acquiring a high quality and low price product with a short lead-time delivery. It is also notable that for most industries up to 70% of the product cost comes from raw materials and component parts [1]. In such an environment, suppliers play a very important role for the companies. When suppliers can provide companies with low price and high quality raw materials (or component parts) in a timely manner, the companies can also do so for their customers. As a result, different criteria such as price, quality and delivery should be considered at the time of evaluating suppliers [2,3]. Depending on the companies' strategy on purchasing, the supplier selection criteria may have different priorities [4].

Our study assumes that buyers have pre-evaluated all suppliers according to some criteria (such as financial strength, performance history, technical capability, geographical location, etc.) and now they need to further assess the pre-approved suppliers for order allocation based on some quantitative criteria such as price, quality and lead time. The order allocation exercise may result in either a *single sourcing scenario* if the best supplier has enough capacity to fulfill the buyer's demand, or a *multi-sourcing scenario* when the capacity limitation becomes an issue. The most suitable tool for Decision Makers (DMs) to formulate multi-supplier selection problem is mathematical programming [5]. Therefore, supplier selection problem (SSP) can be modeled as a multi-objective optimization problem subject to some constraints such as suppliers' capacity, buyer's demand, etc.

For multi-objective problems, the ideal solution for the DMs is to have the optimal objective values for each and every objective. However, this may not happen in reality due to conflicts among objectives. Popular approaches for solving multi-objective problems in the literature can be categorized into two main groups: (1) fuzzy goal programming, and (2) the general goal programming approaches. In the first group, the DMs allow the objectives to take any value between their minimum and maximum possible values, and then try to come as close to their best point as possible: For minimization objectives, the minimum and maximum possible values can be called respectively the positive ideal solution (PIS) and the negative ideal solution (NIS). Kumar et al. [6] formulated a mixed integer goal programming for SSPs including three objectives: cost, quality and delivery, that are subject to some constraints. They adopted the max–min approach proposed by Zimmermann [7] to solve the multi-objective model. Wadhwa and Ravindran [8] modeled the SSP as a multi-objective programming problem, in which price, lead-time and rejects were considered as the three conflicting criteria. They presented and compared several multi-objective optimization methods, including weighted objective method, goal programming (GP) method, and compromise programming, in order to solve their multi-objective problem. By the weighted objective and compromise programming, the DMs do not need to determine a specific goal or aspiration level for the objectives. Throughout this paper, goal and aspiration level are used interchangeably. Amid et al. [9,10] formulated a multi-objective model for SSPs including three objectives: cost, quality and delivery under the influence of capacity and demand requirement constraints. They adopted a weighted additive method, proposed by Tiwari et al. [11], to solve their model. In another study, Amid et al. [12] used a weighted max–min approach, proposed by Lin [13], for solving a multi-objective SSP with the three objectives: cost, quality and delivery subject to suppliers' capacity and market demand. Amin and Zhang [14] developed an integrated multi-objective model for SSP and order allocation, and then employed the compromise programming approach for solving the multi-objective model. Shaw et al. [15] proposed an integration of the fuzzy-AHP and fuzzy multi-objective linear programming for SSP and order allocation, in which purchasing costs, rejects and lead time were considered as some of the main objectives. Similar to Amid et al. [9,10], Shaw et al. [15] used the model of Tiwari et al. [11] to solve their multi-objective model. Lin [16] developed an integrated fuzzy multi-objective linear programming model for SSP and order allocation, and then proposed a two-phase approach, based on Zimmermann [7] and Chen and Chou [17] to solve the fuzzy multi-objective model. Nazari-Shirkouhi et al. [18] developed a fuzzy goal programming approach for solving a fuzzy multi-objective multi-product SSP with multi-price level, in which cost, quality and delivery were their three key objectives.

In the second group, the general goal programming approach, the DM determines a specific goal for every objective and then tries to achieve the goal as much as possible. Ustun and Demirtas [19] proposed an integrated multi-period multi-objective model for SSP and order allocation, in which ε-constraint method, a reservation level driven Tchebycheff procedure (RLTP) and preemptive goal programming were used to solve the multi-objective model. In another study, Ustun and Demirtas [20] defined an additive achievement function by combining min–max goal programming (MGP) and weighted goal programming (WGP) for their multi-objective problem.

Demirtas and Ustun [21] also employed WGP for solving their multi-objective SSP and order allocation. Jolai et al. [22] proposed an integrated multi-objective mixed integer linear programming model for SSP and order allocation, and used WGP for solving their model. Jadidi et al. [23] proposed a new goal programming approach for both deterministic and fuzzy multi-objective models that guarantees the achieved objectives to be consistent with their goals. They also applied the proposed model to multi-objective SSP. In real situations, however, the DMs may not always have precise data and information related to their criteria. Therefore, it may be difficult for them to specify an exact goal for every objective. Thus, the general goal programming approach becomes less favorable unless the DMs are allowed to choose more than one goal or aspiration level for each objective. This can be done either by choosing multiple aspiration levels for each objective or by specifying a range of values instead of a single aspiration level. Chang [24] proposed a new technique so-called multi-choice goal programming (MCGP) approach enabling DMs to determine multiple aspiration levels for every objective. Tabrizi [25] extended the model proposed by Chang [24] to solve fuzzy MCGP problems considering imprecise aspiration levels. In the original MCGP model [24], multiplicative terms of binary variables were used to express multiple discrete goals that resulted in an increase in the complexity of the model. To overcome this complexity, Chang [26] revised the original MCGP approach and instead of the multiple discrete aspiration levels, proposed a range for each aspiration level. Subsequently, Liao and Kao [27, 28], Chang et al. [29], Chang et al. [30] and Rouyendegh and Saputro [31] used the revised MCGP approach for SSP. In addition, Ustun [32] extended the revised model of Chang [26] to propose an alternative MCGP formulation based on the conic scalarizing function. However, Chang [33] argued that the revised MCGP model is not able to fully consider the DMs' preference value, and therefore, added general utility functions to this approach in order to maximize the DMs' expected utility.

In the approaches developed by Chang [26, 33], an interval (upper and lower bounds) is introduced for each objective's aspiration level, in which the aspiration level is a continuous decision variable that is able to move between the upper and lower bounds. The MCGP models aim at driving (1) the aspiration levels towards their lower bounds for minimization objectives (or upper bounds for maximization objectives), and (2) the achieved objectives towards their aspiration levels. The mechanism of Chang [26, 33] models is somewhat similar to the general goal programming approach: derive the achieved objective towards the aspiration level as much as possible. However, the DMs may be concerned with making the achieved objectives closer to their PIS values [23]. The DMs may also prefer that if an achieved objective cannot stay within the interval, it would remain in a close proximity to the interval limits. In situations where the aspiration level interval is selected at its minimum position (i.e., the lower bound is at PIS), the upper bound may be defined as a critical point from which the achieved objective should not be significantly exceeded. In this paper, we look at the MCGP from this angle that gives the DMs more control on both the inside and the outside of the interval aspiration level. If an objective can stay within the interval, it can be driven towards the lower bound (PIS); at the same time, if another objective stays outside the interval (due to conflicting objectives), it should be kept not too far from its upper bound. The previous MCGP approaches have not been designed for such conditions, and here we try to address this kind of problems. The new MCGP approach of this paper is an extension of the weighted additive method (a fuzzy multi-objective method) proposed by Tiwari et al. [11].

We present the rest of the paper as follows. Section 2 formulates the SSP by multi-objective mathematical programming and then introduces the model by the goal programming and the MCGP approaches [24, 26, 33]. The new MCGP is proposed in section 3, followed by an illustrative example in section 4. Finally, concluding remarks are presented in section 5.

2. Multi-objective supplier selection model

As shown by the literature, the most important criteria for SSP are purchasing cost, rejects and lead-time [6,8,9,10,12]. Here, we model a single item SSP in which a set of approved suppliers having limitation on their production capacity should satisfy the buyer's expectations on these three criteria and the demand, which is assumed to be known. The notations of the multi-objective problem are presented as follows:

k	index for objectives, k=1, 2, …, K
n	number of suppliers
X_i	number of units ordered to supplier i
V_i	capacity of supplier i
C_i	unit purchasing price from supplier i
q_i	expected defect rate of supplier i

F_i	percentage of items delivered late by supplier *i*
$f_k(X)$	objective *k*
D	demand

The multi-objective SSP is formulated as follows:

Model 1:

$$\text{Min } f_1(X) = \sum_{i=1}^{n} C_i X_i \tag{1.1}$$

$$\text{Min } f_2(X) = \sum_{i=1}^{n} q_i X_i \tag{1.2}$$

$$\text{Min } f_3(X) = \sum_{i=1}^{n} F_i X_i \tag{1.3}$$

Subject to:

$$\sum_{i=1}^{n} X_i = D \tag{1.4}$$

$$X_i \leq V_i \qquad i = 1, 2, \ldots, n \tag{1.5}$$

$$X_i \geq 0 \qquad i = 1, 2, \ldots, n. \tag{1.6}$$

Eq. (1.1), Eq. (1.2) and Eq. (1.3) minimize the three criteria: purchasing cost, rejects and late deliveries, respectively. Constraints (1.4) and (1.5) consider the buyer's demand and the suppliers' capacity, respectively.

2.1. The Weighted Goal Programming (WGP) approach

Since the previous MCGP approaches [24, 26, 33] were developed based on WGP, the above multi-objective model is first introduced using WGP. In the WGP, proposed by Charnes and Cooper [34], DMs first determine the aspiration level (f_k^*) for every objective, and then try to minimize deviations between the aspiration levels and the achievements as follows:

Model 2:

$$\text{Min. } \sum_{k=1}^{3} w_k (d_k^- + d_k^+) \tag{2.1}$$

Subject to:

$$f_k(X) + d_k^- - d_k^+ = f_k^* \qquad k=1,2,3 \tag{2.2}$$

$$d_k^- . d_k^+ = 0 \qquad k=1,2,3 \tag{2.3}$$

$$d_k^-, d_k^+ \geq 0 \qquad k=1,2,3 \tag{2.4}$$

and the constraints of (1.4), (1.5) and (1.6).

where d_k^- and d_k^+ are negative and positive goal deviations, respectively, and w_k is the relative importance of the k^{th} objective.

2.2. The original MCGP approach

Chang [24] argued that due to uncertainty/imprecision, the DMs may prefer to set multiple aspiration levels for every objective. Since the above WGP approach has not been designed for this purpose, Chang [24] proposed the MCGP approach as follows:

Model 3:

$$\text{Min. } \sum_{k=1}^{3} w_k (d_k^- + d_k^+) \tag{3.1}$$

Subject to:

$$f_k(X) + d_k^- - d_k^+ = \sum_{j=1}^{J} f_{kj}^* S_{kj}(B) \quad k=1,2,3 \tag{3.2}$$

$$d_k^- . d_k^+ = 0 \quad k=1,2,3 \tag{3.3}$$

$$d_k^-, d_k^+ \geq 0 \quad k=1,2,3 \tag{3.4}$$

$$S_{kj}(B) \in R_k(x) \quad k=1,2,3 \tag{3.5}$$

and the constraints of (1.4), (1.5) and (1.6).

where f_{kj}^* ($k = 1,2,3$ and $j = 1,2,\ldots,J$) is the j^{th} aspiration level of the k^{th} objective, $f_{k,j-1}^* \leq f_{kj}^* \leq f_{k,j+1}^*$, and $S_{kj}(B)$ represents a function of binary serial numbers that is defined according to the number of goals for each objective and based on resource limitations $R_k(x)$. The main role of $S_{kj}(B)$ is to ensure that each objective chooses only one of the multiple goals. Interested readers are referred to Chang [24] for further discussions on $S_{kj}(B)$.

2.3. The revised MCGP approach

According to Chang's [24] model, Chang [26] discussed that the multiplicative terms of binary variables that are used to express multiple aspiration levels increase the complexity of the model. To address this issue, Chang [26] proposed a revised MCGP approach as follows:

Model 4:

$$\text{Min.} \sum_{k=1}^{3} [w_k^d (d_k^- + d_k^+) + w_k^e (e_k^- + e_k^+)] \tag{4.1}$$

Subject to:

$$f_k(X) + d_k^- - d_k^+ = y_k \quad k=1,2,3 \tag{4.2}$$

$y_k + e_k^- - e_k^+ = f_{k,min}$ $\quad k$=1,2,3 $\quad$ (4.3)

$f_{k,min} \leq y_k \leq f_{k,max}$ $\quad k$=1,2,3 $\quad$ (4.4)

$d_k^-.d_k^+ = 0$ $\quad k$=1,2,3 $\quad$ (4.5)

$e_k^-.e_k^+ = 0$ $\quad k$=1,2,3 $\quad$ (4.6)

$d_k^-, d_k^+, e_k^-, e_k^+ \geq 0$ $\quad k$=1,2,3 $\quad$ (4.7)

and the constraints of (1.4), (1.5) and (1.6).

where $f_{k,min}$ and $f_{k,max}$ are the range of k^{th} aspiration level, y_k, which is the continuous decision variable. d_k^+ and d_k^- are respectively the positive and negative deviations of $f_k(X)$ from y_k. e_k^+ and e_k^- are the positive and negative deviations of y_k from $f_{k,min}$. Lastly, w_k^d and w_k^e are the relative importance connecting (d_k^+, d_k^-) and (e_k^+, e_k^-), respectively.

For SSP, deviations may have different units that cause unintentional bias among the objectives. Some techniques that aim to transferring different units of the deviations to a common unit in order to remove the incommensurability were reviewed by Tamiz et al. [35]. Here, we normalize the deviations of the Chang's [26] model as follows:

$$\text{Min.} \sum_{k=1}^{3} [w_k^d \frac{(d_k^+ + d_k^-)}{(f_k^- - f_k^+)} + w_k^e \frac{(e_k^+ + e_k^-)}{(f_{k,max} - f_{k,min})}]$$

where $f_k^+ = \left\{\min_X f_k(X)\right\} \ \forall\, k$, and $f_k^- = \left\{\max_X f_k(X)\right\} \ \forall\, k$.

From here on, we refer to the normalized revised MCGP (Model 4) as *NR-MCGP*.

2.4. The MCGP approach considering utility function

Chang [33] argued that the *NR-MCGP* model cannot consider the DMs' preference value, and therefore, he added a general utility function to the revised approach in order to maximize the DMs' expected utility. Chang [33] considered linear and S-shape utility functions. In this paper, we only review the linear utility function; however, the discussion can be extended to the S-shape utility function as well. The new model of Chang [33] is presented as follows:

Model 5:

$$\text{Min.} \sum_{k=1}^{3} [w_k^d (d_k^- + d_k^+) + w_k^\delta \delta_k^-] \tag{5.1}$$

Subject to:

$$\lambda_k \le \frac{f_{k,max} - y_k}{f_{k,max} - f_{k,min}} \qquad k=1,2,3 \tag{5.2}$$

$$f_k(X) + d_k^- - d_k^+ = y_k \qquad k=1,2,3 \tag{5.3}$$

$$\lambda_k + \delta_k^- = 1 \qquad k=1,2,3 \tag{5.4}$$

$$f_{k,min} \le y_k \le f_{k,max} \qquad k=1,2,3 \tag{5.5}$$

$$d_k^- . d_k^+ = 0 \qquad k=1,2,3 \tag{5.6}$$

$$d_k^-, d_k^+, \delta_k^-, \lambda_k \ge 0 \qquad k=1,2,3 \tag{5.7}$$

and the constraints of (1.4), (1.5) and (1.6).

where δ_k^- represents the normalized deviation of y_k from $f_{k,min}$, w_k^δ is the weight associated with δ_k^-, and λ_k is the utility value. Other variables are defined as before.

If needed, the objective function of Chang [33] can be also normalized as follows:

$$\text{Min.} \sum_{k=1}^{3} [w_k^d \frac{(d_k^- + d_k^+)}{(f_k^- - f_k^+)} + w_k^\delta \delta_k^-]$$

where δ_k^- does not need to be normalized because $0 \le \delta_k^- \le 1 \; \forall k$.

From here on, we refer to the above MCGP that considers the utility function (Model 5) as *MCGP-U*. In the following section, we propose a new version of the MCGP model that we call, the *New-MCGP*.

3. The *New-MCGP* approach

In addition to the significant improvement on the original MCGP, the *NR-MCGP* and *MCGP-U* models contribute to the general goal programming approach by considering an interval goal instead of a single goal. By regulating w_k^d in both methods, the achieved objective, $f_k(X)$, is driven towards the aspiration level, y_k, that is bounded within the interval goal, $[f_{k,min}, f_{k,max}]$. At the same time, y_k is also driven towards $f_{k,min}$ by adjusting w_k^δ in *MCGP-U* (or w_k^e in *NR-MCGP*). However, it might be worthwhile to consider the MCGP from a different angle: (1) setting the lower bound, $f_{k,min}$, at the PIS, f_k^+, which may be the DMs' preference [23], and (2) considering the upper bound, $f_{k,max}$, as a critical point so that the achieved objective should not significantly exceed it. For example, manufacturers such as Toyota and Honda, before selecting their suppliers, may determine the maximum price of components and raw materials that they can afford to pay [36] (i.e., they predetermine the maximum purchasing cost). In this case, the predetermined cost can be considered as a critical point. In other words, if an objective stays within the interval goal, $[f_{k,min}, f_{k,max}]$, the lower bound, $f_{k,min}$, should be considered as a pivot point which magnetizes the objective towards itself. If at the same time another objective falls outside the interval goal (due to conflicting objectives), the upper bound, $f_{k,max}$, should be considered as a new pivot point which keeps the objective as close as possible to itself. The structure of the two previous methods does not support this type of conditions while it may happen in reality.

In order to address such conditions in SSP, we propose a *New-MCGP* approach inspired by the fuzzy model of Tiwari et al. [11]. This new approach will pay special attention to $f_{k,min}$ and $f_{k,max}$ as two pivot points that enables the DMs to have control on both the inside and the outside of the interval. Applying the original Tiwari et al. [11] approach to Model 1 results in:

Model 6:

$$\text{Max.} \sum_{k=1}^{3} w_k \alpha_k \tag{6.1}$$

Subject to:

$$\frac{f_k^- - f_k(X)}{f_k^- - f_k^+} = \alpha_k \qquad k=1,2,3 \tag{6.2}$$

$$0 \leq \alpha_k \leq 1 \qquad k=1,2,3 \tag{6.3}$$

and the constraints of (1.4), (1.5) and (1.6).

where α_k is a continuous coefficient, $0 \leq \alpha_k \leq 1$, that represents the normalized distance of the achieved objective from f_k^-. Constraint (6.2) can be rewritten as:

$$f_k(X) = \alpha_k f_k^+ + (1 - \alpha_k) f_k^- \qquad k=1,2,3 \tag{6.2a}$$

As the range for each aspiration level $[f_{k,min}, f_{k,max}]$ is decided by the DMs, here we propose that the lower bound of the range, $f_{k,min}$, be set equal to f_k^+, while the upper bound, $f_{k,max}$, can be less than or equal to f_k^-. The rationalization for this suggestion is that in a minimization problem, the DMs would normally prefer the lowest value for the objective. As a result, the range

$[f_k^+, f_k^-]$ is divided into two sub-ranges of $[f_{k,min}, f_{k,max}]$ and $[f_{k,max}, f_k^-]$ that we call, the *more desirable range* (MDR), and the *less desirable range* (LDR).

We also propose that α_k be the normalized distance of the achieved objective *k* from $f_{k,max}$ so that by maximizing this coefficient, we approach to $f_{k,min}$. Therefore, Eq. (6.2) can be written as:

$$\alpha_k = \frac{f_{k,max} - f_k(X)}{f_{k,max} - f_{k,min}} \qquad k=1,2,3$$

Realizing that by moving the upper limit of α_k to $f_{k,max}$ the range for each objective is tightened; therefore, we allow the achieved objective to take a value outside this tightened range subject to penalty. We do so by introducing another variable, β_k, that represents the normalized distance of the achieved objective *k* from $f_{k,max}$ when it is greater than $f_{k,max}$. Thus:

$$\beta_k = \frac{f_k(X) - f_{k,max}}{f_k^- - f_{k,max}} \qquad k=1,2,3$$

As both α_k and β_k determine the position of a single objective *k*, only one of them can be non-zero. Therefore, we employ a binary variable, y_k, as follows:

$$\alpha_k \leq y_k < 1 + \alpha_k \qquad k=1,2,3$$
$$\beta_k + y_k \leq 1 \qquad k=1,2,3$$
$$y_k \in \{0, 1\} \qquad k=1,2,3$$
$$0 \leq \alpha_k, \beta_k \leq 1 \qquad k=1,2,3$$

when $\alpha_k > 0$ then $y_k = 1$ that results in $\beta_k = 0$; when $\alpha_k = 0$ then $y_k = 0$ that allows β_k to assume any value between 0 and 1.

Figure 1 illustrates the relationship between α_k and β_k. If the achieved objective $f_k(X)$ falls within the MDR (e.g., point 1), then $\alpha_k > 0$. However, if it falls outside (e.g., point 2), then $\beta_k > 0$. While the aim is to obtain a value within the range and as close as possible to the lower bound $f_{k,min}$, the model allows the objective to take a value outside the range subject to penalty in order to avoid infeasible solutions. Therefore, the objective of the new model is to maximize α_k and to minimize β_k.

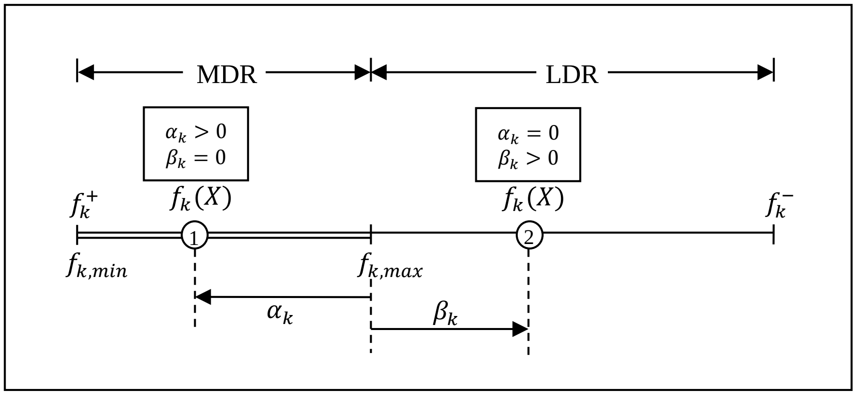

Fig. 1. The relationships among model parameters.

Using these new variables, we can re-write Eq. (6.2a) as follows:

$$f_k(X) = \alpha_k f_{k,min} + (1-\alpha_k) f_{k,max} + \beta_k (f_k^- - f_{k,max}) \qquad k=1,2,3 \qquad (6.2b)$$

Therefore, the *New-MCGP* approach for the multi-objective SSP of Model 1 is formulated as follows:

Model 7:

$$\text{Max.} \sum_{k=1}^{3} (w_k^{\alpha} \alpha_k - w_k^{\beta} \beta_k) \qquad (7.1)$$

Subject to:

$$f_k(X) = \alpha_k f_{k,min} + (1-\alpha_k) f_{k,max} + \beta_k (f_k^- - f_{k,max}) \qquad k=1,2,3 \qquad (7.2)$$

$$\alpha_k \leq y_k < 1 + \alpha_k \qquad k=1,2,3 \qquad (7.3)$$

$$\beta_k + y_k \leq 1 \qquad k=1,2,3 \qquad (7.4)$$

$$y_k \in \{0, 1\} \qquad k=1,2,3 \qquad (7.5)$$

$$0 \leq \alpha_k, \beta_k \leq 1 \qquad k=1,2,3 \qquad (7.6)$$

and the constraints of (1.4), (1.5) and (1.6).

As illustrated in Figure 1, the *New-MCGP* approach enables DMs to have control on both the MDR and the LDR. This will increase the effectiveness of the *New-MCGP* by involving some certain DMs' preferences.

The *New-MCGP* approach guarantees a feasible solution as $f_k(X)$ moves between its minimum, f_k^+, and maximum, f_k^-, values. Furthermore, since $0 \leq \alpha_k, \beta_k \leq 1$, it can facilitate the DMs' preference modeling by eliminating the incommensurability caused by scale differences among objectives.

Discussion on $f_{k,max}$:

Since $f_{k,max}$ is a user-selected parameter, it is worthwhile to have some guidelines for choosing an appropriate value for this parameter. The purpose of $f_{k,min}$ and $f_{k,max}$ is to determine a focus area between f_k^+ and f_k^-. As we make $f_{k,min} = f_k^+$, $f_{k,max}$ divides the range of f_k^+ and f_k^- into two sections: (1) more desirable one (MDR) that is on the left side of $f_{k,max}$, and (2) less desirable one (LDR) that is between $f_{k,max}$ and f_k^-. One consideration in determining $f_{k,max}$ is whether the objectives are conflicting or not. In case of conflicting objectives, it is recommended that if one $f_{k,max}$ is close to f_k^-, the other $f_{k,max}$ must be chosen relatively close to f_k^+. In other words, if the range of one objective $[f_{k,min}, f_{k,max}]$ is chosen tightly, the range for the other objective should be chosen wider to allow more movement for conflicting objectives. In the following example, the first and second objectives are in conflict, and since the range of first objective is chosen more tightly, the range for the second objective is not as tight as the first one (see Figure 2).

4. An illustrative example

The following numerical example is going to illustrate how the *New-MCGP* can solve multi-objective SSPs. This example considers a situation in which six suppliers, whose information is presented in Table 1, should meet the buyer's demand of 16 units.

Table 1. The data for the numerical example

Supplier i	Price, C_i	Rejection Rate, q_i (%)	Late Delivery Rate, F_i (%)	Capacity, V_i
S1	3	0.40	0.25	5
S2	3.5	0.35	0.30	4
S3	4	0.30	0.15	3.5
S4	4.5	0.25	0.20	6
S5	5	0.20	0.40	5.5
S6	6	0.15	0.35	5

Using the above data, we can obtain f_1^+= 58.75, f_2^+= 0.03225, f_3^+= 0.03425, f_1^-= 82.25, f_2^-= 0.05325 and f_3^-= 0.05525. Furthermore, it can be seen that the first and second objectives are in conflict. That is, the suppliers with a better price have poor quality and vice versa. The third objective, while not directly in conflict with the other two objectives, shows the best delivery in mid range of price and quality.

Here, we assume there are three conditions that the DMs are going to incorporate in their decisions for suppliers' evaluation and order allocation:

Condition 1: $f_{k,min} = f_k^+$ and $f_{k,max} < f_k^-$, $\forall k$, so that $f_{1,max}$ =68, $f_{2,max}$ =0.0461 and $f_{3,max}$=0.04475. That is, each objective has a critical point, $f_{k,max}$ $\forall k$, and two ranges, MDR and LDR.

Condition 2: The second objective is more important than the first one: its achievement, $f_2(X)$, should be more preferable in MDR and as close as possible to $f_{2,min}$.

Condition 3: The first objective, while being less important than the second one, should not significantly exceed $f_{1,max}$: its achievement, $f_1(X)$, may be in the LDR but should be preferably close as possible to $f_{1,max}$.

Here, we apply the *New-MCGP* model to the above example.

The New-MCGP model:

We first set $f_{k,min}$ and $f_{k,max}$ $\forall k$ as defined in *Condition* 1. In order to consider *Condition* 2 (i.e., the second objective is the most important one), we should have $w_2^\alpha \gg w_1^\alpha$ which in turn will cause α_2 to increase and $f_2(X)$ to approach $f_{2,min}$. Since the first and second objectives are in conflict, $f_1(X)$ approaches f_1^-. For taking into account *Condition* 3 (i.e., the first objective should not significantly exceed $f_{1,max}$), we should have $w_2^\beta \ll w_1^\beta$ that causes β_1 to decrease and $f_1(X)$ to get far from f_1^- and towards $f_{1,max}$. As a result, the weights may be allocated as w_1^α=0.1, w_2^α=0.8, w_3^α=0.1, w_1^β=0.8, w_2^β=0.1 and w_3^β=0.1. We employ Solver in Excel to solve this problem by the *New-MCGP* model. The results are as follows:

$f_1(X)$ = 68 = $f_{1,max}$ that holds the second condition,

$f_2(X)$ = 0.044 (within MDR) that holds the first condition,

$f_3(X)$ = 0.039,

X_1=2.75, X_2=0, X_3=3.5, X_4=6, X_5=3.75, X_6=0, Here, we see that the first objective did not exceed $f_{1,max}$. As demonstrated here, the *New-MCGP* model allows the DMs to adjust w_k^α and w_k^β to move one objective closer to its $f_{k,min}$, and at the same time, to keep another objective not far from its $f_{k,max}$.

Analysis of weights:

The weights, w_k^α and w_k^β, are user-selected parameters by which the DMs can incorporate their strategies in SSP. For instance, if the strategy is to produce a high quality product, the weight of quality (rejects in this numerical example) should be higher than others. In this model, the more important objective is assigned a higher w_k^α that results in the objective to stay in MDR and to approach $f_{k,min}$. If the less important objective is in conflict with the first one, it may fall in LDR and far from $f_{k,max}$. In this case, we can assign a higher w_k^β to this objective so that it stays closer to $f_{k,max}$. When an equal value is assigned to all w_k^β, it means the DMs are not concerned with the objectives moving far from $f_{k,max}$. In order to investigate the effect of different weight values on the results, we gradually increase w_1^β. In Table 2, as we increase w_1^β from 0.33 to 0.80, we distribute the remaining values equally among the other two weights. We solve the model for different combinations of weights as presented in Table 2.

Table 2. The weight analysis for w_1^β.

$\boldsymbol{w_1^\beta}$	**0.33**	**0.60**	**0.80**
w_2^β	0.33	0.20	0.10
w_3^β	0.33	0.20	0.10
$f_1(X)$	82.00	76.45	68.00
$f_2(X)$	0.032	0.036	0.044
$f_3(X)$	0.050	0.045	0.039

Table 2 shows that as w_1^β increases from 0.33 to 0.80, $f_1(X)$ improves from f_1^- to $f_{1,max}$. The gain for the first objective comes at a slow loss for the second objective; i.e., $f_2(X)$ moves farther from $f_{1,min}$ but it does not surpass $f_{2,max}$. Figure 2 depicts the above analysis.

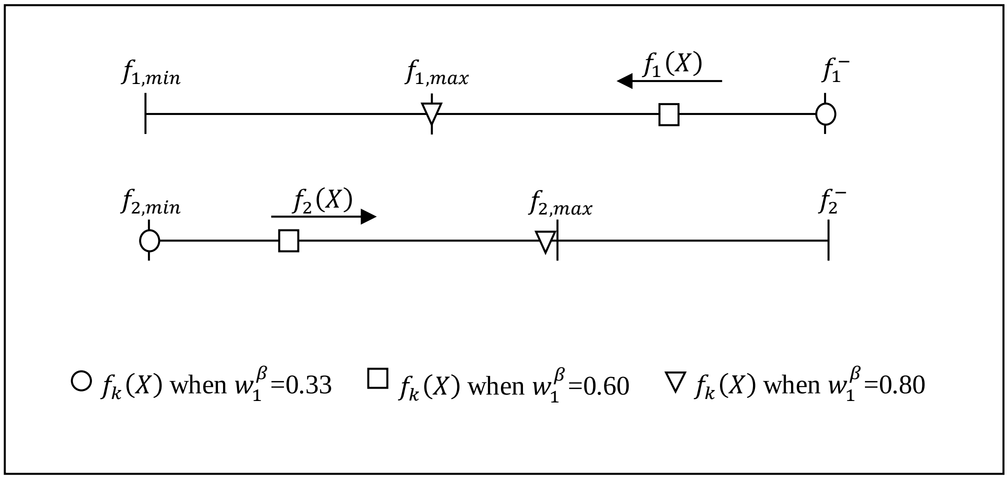

Fig. 2. The sensitivity of $f_1(X)$ and $f_2(X)$ to increased w_1^β and decreased w_2^β in the *New-MCGP*

This analysis shows that the *New-MCGP* enables DMs to better incorporate their preferences in the model for making a more desirable decision on supplier selection and order allocation. DMs are able to consider interval goals or aspiration levels, while also accurately taking into account their relative importance.

5. Operationalization of the proposed model

In reality, apart from the quantitative criteria, some of which were considered by the proposed multi-objective model, qualitative criteria also influence the SSP. However, multi-objective models cannot normally take into account the qualitative criteria, such as performance history, technical capability and geographical location. Multi-attribute decision making (MADM) techniques, such as analytic network process (ANP) and analytic hierarchy process (AHP), are able to consider both the qualitative and quantitative factors. Therefore, a two-stage process is developed for SSP in practice. The first stage is a tree-step procedure. In step 1, DMs select the criteria, and then, express their preferences on the criteria weight. In step 2, they evaluate and grade the suppliers for each criterion. Finally, a MADM technique is used to rank the suppliers based on the information gathered in the first two steps. In the second stage, the suppliers' score, obtained in the first stage, is used as one of the objectives of the multi-objective model. In this stage once again the DMs express their preferences on the criteria weight. By solving the multi-objective model, the optimum order allocation of each supplier is calculated.

The integration of ANP and the multi-objective model developed by Ustun and Demirtas [19, 20] and Demirtas and Ustun [21] is a real case of SSP that tells us how to operationalize our model. In fact, we can use our *New-MCGP* approach to solve the multi-objective model in their study.

6. Conclusions

In this paper, a single product supplier selection problem (SSP) was formulated as a multi-objective optimization model. It was assumed that: (1) the objectives can have different relative importance levels, and (2) it may be easier for decision makers to determine an interval goal or aspiration level for every objective. In order for these two assumptions to be incorporated into the solution methodology, the *New-MCGP* approach was then proposed. In comparison with the previous studies, we set the lower bound of the interval goal at the positive ideal solution (PIS) that drives the objective towards itself if it falls within the interval goal, and at the same time, set the upper bound as a magnetic point if the objective exceeds it. The numerical example illustrated that variation in priority of criteria will change the order quantities assigned to the suppliers. This means that our proposed model effectively incorporates DMs' preferences and conditions for SSP and order allocation by providing the DMs with control on both of the more desirable range (MDR) and the less desirable range (LDR).

As discussed in the introduction section, due to the imprecise data and information in real situations, determining an interval aspiration level for objectives makes the new approach one step closer to reality. In addition, this type of model can be used in situations, for example, when managers try to determine their maximum purchasing price for their components and raw materials before selecting their suppliers. Then, this maximum cost can be considered as the upper bound from which the achieved objective should not be significantly exceeded.

In this paper, we assumed that the demand and suppliers' capacities are known. However, these two parameters may be uncertain in practice. The study of SSP where the demand and suppliers' capacities are uncertain can be considered for direction in future research. In addition, the SSP can be integrated with the supply chain coordination. The supply chain coordination, which generally concentrates on inventory management, tries to improve the whole supply chain profitability by aligning the partners' strategies and goals. However, to the best of our knowledge, supplier selection studies have mainly considered the buyers' strategies and preferences rather than those of the entire supply chain. Taking supply chain coordination into account can open SSP up for further studies in the future.

Acknowledgements

The first author thanks the Università degli studi di Bergamo and Fondazione Italcementi for funding his doctoral studies. The authors are thankful of the editor and anonymous reviewers for their constructive comments.

References

[1] S.H. Ghodsypour, C. O'Brien, The total cost of logistics in supplier selection under conditions of multiple sourcing, multiple criteria and capacity constraint, Int. J. of Product. Econ. 73 (2001) 15–27.

[2] G.W. Dickson, An analysis of vendor selection: systems and decisions, J. of Purch. 1 (1966) 5–17.

[3] C.A. Weber, J.R. Current, W.C. Benton, Vendor selection criteria and methods, Eur. J. of Oper. Res. 50(1991) 2–18.

[4] G. Wang, S.H. Hang, J.P. Dismukes, Product-driven supply chain selection using integrated multi-criteria decision making methodology, Int. J. of Product. Econ. 91 (2004) 1–15.

[5] N. Aissaouia, M. Haouaria, E. Hassini, Supplier selection and order lot sizing modeling: A review, Comput. & Oper. Res. 34 (2007) 3516 – 3540.

[6] M. Kumar, P. Vrat, R. Shankar, A fuzzy goal programming approach for vendor selection problem in a supply chain, Comput. & Ind. Eng. 46 (2004) 69–85.

[7] H.J. Zimmermann, Fuzzy programming and linear programming with several objective functions, Fuzzy Sets and Syst. 1 (1978) 45–55.

[8] V. Wadhwa, A.R. Ravindran, Vendor selection in outsourcing, Comput. & Oper. Res. 34 (2007) 3725–3737.

[9] A. Amid, S.H. Ghodsypour, C. O'Brien, A fuzzy multiobjective linear model for supplier selection in a supply chain, Int. J. of Product. Econ. 104 (2006) 394–407.

[10] A. Amid, S.H. Ghodsypour, C. O'Brien, A weighted additive fuzzy multiobjective model for supplier selection in a supply chain under price breaks, Int. J. of Product. Econ. 121 (2009) 323–332.

[11] R.N. Tiwari, S. Dharmahr, J.R. Rao, Fuzzy goal programming - an additive model, Fuzzy Sets and Syst. 24 (1987) 27–34.

[12] A. Amid, S.H. Ghodsypour, C. O'Brien, A weighted max–min model for fuzzy multi-objective supplier selection in a supply chain, Int. J. of Product. Econ. 131 (2011) 139–145.

[13] C.C. Lin, A weighted max–min model for fuzzy goal programming, Fuzzy Sets and Syst. 142 (2004) 407–420.

[14] S.H. Amin, and G. Zhang, An integrated model for closed-loop supply chain configuration and supplier selection: Multi-objective approach, Expert Syst. with Appl. 39 (2012) 6782–6791.

[15] K. Shaw, R. Shankar, S.S. Yadav, L.S. Thakur, Supplier selection using fuzzy AHP and fuzzy multi-objective linear programming for developing low carbon supply chain, Expert Expert Syst. with Appl. 39 (2012) 8182–8192.

[16] R.H. Lin, An integrated model for supplier selection under a fuzzy situation, Int. J. of Product. Econ. 138 (2012) 55–61.

[17] H.K. Chen, H.W. Chou, 1996. Solving multi-objective linear programming problems-a generic approach, Fuzzy Sets and Syst. 82 (1), 35–38.

[18] S. Nazari-Shirkouhi, H. Shakouri, B. Javadi, A. Keramati, Supplier selection and order allocation problem using a two-phase fuzzy multi-objective linear programming, Appl. Math. Model. 37 (2013) 9308–9323.

[19] O. Ustun, E.A. Demirtas, An integrated multi-objective decision-making process for multi-period lot-sizing with supplier selection. Omega. 36 (2008) 509–521.

[20] O. Ustun, E.A. Demirtas, Multi-period lot-sizing with supplier selection using achievement scalarizing functions. Comput. & Ind. Eng. 54 (2008) 918–931.

[21] E.A. Demirtas, O. Ustun, Analytic network process and multi-period goal programming integration in purchasing decisions, Comput. & Ind. Eng. 56 (2009) 677–690.

[22] F. Jolai, S.A. Yazdian, K. Shahanaghi, M.A. Khojasteh, Integrating fuzzy TOPSIS and multi-period goal programming for purchasing multiple products from multiple suppliers. J. of Purch. and Supp. Manag. 17 (2011) 42–53.

[23] O. Jadidi, S. Zolfaghari, S. Cavalieri, A new normalized goal programming model for multi-objective problems: A case of supplier selection and order allocation. Int. J. of Product. Econ., 148 (2014) 158–165.

[24] C.T. Chang, Multi-choice goal programming, Omega. 35 (2007) 389–396.

[25] B.B Tabrizi, K. Shahanaghi, M.S. Jabalameli, Fuzzy multi-choice goal programming, Appl. Math. Model. 36 (2012) 1415–1420.

[26] C.T. Chang, Revised multi-choice goal programming, Appl. Math. Model. 32 (2008) 2587–2595.

[27] C.N. Liao, H.P. Kao, Supplier selection model using Taguchi loss function, analytical hierarchy process and multi-choice goal programming, Comput. & Ind. Eng. 58 (2010) 571–577.

[28] C.N. Liao, H.P. Kao, An integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management, Expert Syst. with Appl. 38 (2011) 10803–10811.

[29] C.T. Chang, C.Y. Ku, H.P. Ho, Fuzzy multi-choice goal programming for supplier selection, Int. J. of Oper. Res. And info. Syst. 1, (2010) 28–52.

[30] C.T. Chang, H.M. Chen, Z.Y. Zhuang, Integrated multi-choice goal programming and multi-segment goal programming for supplier selection considering imperfect-quality and price-quantity discounts in a multiple sourcing environment, Int. J. of Syst. Sci. 45 (2014) 1101–1111.

[31] B.D. Rouyendegh, T.E. Saputro, Supplier selection using integrated fuzzy TOPSIS and MCGP: a case study, Procedia Soc. Behav. Sci. 116 (2014) 3957–3970.

[32] O. Ustun, Multi-choice goal programming formulation based on the conic scalarizing function, Appl. Math. Model. 36 (2012) 974–988.

[33] C.T. Chang, Multi-choice goal programming with utility functions, Eur. J. of Oper. Res. 215 (2011) 439–445.

[34] A. Charnes, W.W. Cooper, Management model and industrial application of linear programming, Wiley, New York, 1961.

[35] M. Tamiz, D. Jones, C. Romero, Goal programming for decision making: An overview of the current state-of-the-art, Eur. J. of Oper. Res. 111 (1998) 569–581.

[36] J.K. Liker, T.Y. Choi, Building deep supplier relationships, Harvard Bus Rev 82 (2004) 104–113.