Using a Product Life Cycle Cost Model to Solve Supplier Selection Problems in a Sustainable, Resilient Supply Chain

Yu-Jwo Tao 1,2,3, Yi-Shyuan Lin 1, Hsuan-Shih Lee 4,5, Guo-Ya Gan 6 and Chang-Shu Tu 7,*

1 Graduate Institute of Technological & Vocational Education, National Taipei University of Technology, Taipei 10608, Taiwan; ta794260@gmail.com (Y.-J.T.); yishyuan@ntut.edu.tw (Y.-S.L.)
2 Department of Business, National Open University, Taipei 10607, Taiwan
3 Department of Business Administration, National Taiwan University of Science and Technology, Taipei 10607, Taiwan
4 Department of Shipping and Transportation Management, National Taiwan Ocean University, Pei-Ning Road, Keelung 202, Taiwan; hslee@email.ntou.edu.tw
5 Department of Information Management, Ming Chuan University, Taipei 11103, Taiwan.
6 College of Auditing and Evaluation, Nanjing Audit University, Nanjing 211815, China; ganguoya@foxmail.com
7 Department of Information Management, Chang Gung University, KweiShan, Taoyuan City 33302, Taiwan

* Correspondence: long_tree@msa.hinet.net; Tel.: +886-0927351833

Abstract: Supplier selection constitutes a crucial component of manufacturing procurement. We developed a product life cycle cost (PLCC) model to support Taiwanese light-emitting diode (LED) manufacturers in capacity planning for sustainable and resilient supply chain (SC) management. For firms, supply chain PLCC (SCPLCC) is a key consideration, but relevant evidence is scarce. We applied two types of goal programming, namely multiobjective linear programming and revised multichoice goal programming (RMCGP), to develop a PLCC-based model that minimizes net costs, rejections, and late deliveries. Moreover, we constructed a decision-making tool for application to a case of SC sustainable procurement management in a high-tech Taiwanese LED company. Managers can resolve relevant problems by employing the two approaches of the SCPLCC model with various parameters. The implementation of RMCGP with weighted linear goal programming sensitivity analysis produced sufficient findings, according to a study of five models for practical implications. The primary findings of the current model assist business decision-makers in minimizing PLCC, reducing PLCC cost, minimizing net cost, number of rejections, number of late deliveries, achieving PLCC goals, and selecting the best supplier in the context of sustainable SC development.

Keywords: supplier selection; product life cycle cost; geometric mean weighting; penalty weighting; multiobjective linear programming; revised multichoice goal programming

1. Introduction

Because of the globalization of commercial markets and improvements in information technology, a well-constructed supply chain management (SCM) system is an instrumental tool for gaining competitive advantage [1,2]. In higher SC levels, supplier selection constitutes an integral component of manufacturing procurement and a pivotal industrial activity [3–5]. With the growing globalization of industry, SCM has become an increasingly multifaceted undertaking. SCM is an essential element of most businesses and is critical to corporate success and customer satisfaction. SCs represent the pathway between suppliers and buyers, customers, or consumers [6].

The primary goal of a manufacturing company is to make the correct product in the correct amount for the correct customer in a timely manner. Purchasing companies de-
mand advanced buyer interactions with their suppliers for a respectful relationship between the two parties.

Sustainability in industry has emerged as a crucial strategy that expands beyond organizational boundaries to include the entire SC. Concerns regarding SC resilience have also arisen. Research on the intersection between the sustainability and resilience of SCs is nascent and is a consequence of their mutual effects. However, confusion regarding concepts, measurements, and implementation methods of sustainable and resilient SCs remains.

Some life cycle studies have compared the environmental sustainability of organic and nonorganic pork SCs. The present study investigated how overall food SC performance depends on the performance of partners in a sustainable and energy-efficient SC [7–9].

A light-emitting diode (LED) is a semiconductor device that emits light through the recombination of electrons with electron holes within the apparatus. LEDs are a green technology with high potential for reducing global CO2 emissions. McKinsey stated that the overall market share of LED manufacturers was likely to increase after 2012, with global annual revenues projected to reach €37 billion by 2016 and €64 billion by 2020. Fortune Business Insights reported that the value of the global lighting market reached an estimated US$118.33 billion in 2019 and is projected to reach US$163.72 billion by 2027 [10,11]. Using white LED lighting technology, according to the optoelectronics industry development organization (OIDA), may cut CO2 emissions by 2.5 billion tons per year globally.

The LED industry is a prominent example of sustainability and resilience concepts in SCM. Although the industry is highly competitive and dynamic, its products are resource and emission intensive in both the production and use phases. In the context of climate change, the growing focus placed on sustainability represents a response to demands for carbon emission reductions. Resilience constitutes a response to climate adaptation challenges. Sustainable SCM (SSCM) has been employed for objectives concerning climate-related adaptation. The basic concepts of resilience SCM (RSCM) are derived from the characteristic elements of resilience theory. Despite the increasing relevance of SSCM and RSCM to enterprises with respect to addressing climate change concerns, studies have largely neglected the need for the systematic integration of the two paradigms [12–16].

Resilience is key to the ability of organizations to effect positive change and overcome various challenges, even in crisis situations. The extent of an organization’s ability to respond to various disturbances depends on that organization’s objectives and level of maturity in crisis management. In human resource management, organizational resilience is acknowledged as a multidisciplinary, multidimensional quality. Suryaningtyas et al. [7] reported a positive association between organizational resilience and organizational performance. For general managers, this suggests that organizational resilience should be continually applied both operationally and strategically to maintain a company’s sustainability.

To choose suppliers and distribute resources in the food industry, Kaviani et al. [17] develop a combined intuitionistic fuzzy analytic hierarchy process and fuzzy multi-objective optimization approach. Noppasorn et al. [18] provided a Fuzzy Programming approach for optimizing multi-objective Aggregate Production Planning problems in uncertain situations.

We developed a product life cycle cost (PLCC) model to support Taiwanese LED manufacturers in capacity planning for sustainable and resilient SCM. Taiwan has a unique political and economic environment. The present PLCC-based model integrates SSCM and RSCM, thus allowing for high degrees of flexibility and efficiency. In applying this model, LED firms can employ technologies that provide decision-makers with strategic guidance with regard to examining and comparing various alternative sustainability strategies.
Although SCPLCC is a vital corporate consideration, relevant evidence is limited. SCPLCC has become associated with deciding how one supplier should be selected from various alternatives. The supplier base must be optimized to identify high-performing suppliers in SCs. Approaches for solving SCPLCC-related problems have been discussed. Details are provided as follows.

Few attempts have been made to incorporate information vagueness into the SCPLCC problem. The multiobjective linear programming (MOLP) model can account for the variation in or imprecision of a decision-maker’s aspiration level (intermediate control variables), thus establishing a more certain key point for decision-making policy [17]19. Herein, we implemented a fuzzy MOLP model and a revised multichoice goal programming (RMCGP) model. The application of weighted linear goal programming (WLGP) to the RMCGP model produced adequate results in a scenario involving the PLCC of a high-tech company.

We extended the work of Amid et al. [19] and referenced a study by Wang [5] to solve the PLCC problem. To solve the SCPLCC problem, we modified a sample data set of auto part manufacturers from a study by Kumar et al. [20]. For sustainable buying, we used real-world data from LED companies [21].

Third, to solve the SCPLCC problem, we incorporated geometric mean weighting into the MOLP and RMCGP models such that the decision-maker can understand differences between assigning and not assigning all objectives and constraints in an SC decision of equal importance [22]. Our SCPLCC model can help decision-makers optimize supplier selection and prioritization; moreover, it can enable purchasing managers to enhance SC performance through the fulfilment of PLCC goals and minimization of net costs, rejections, and late deliveries. Managers can resolve relevant problems by employing the two approaches of the SCPLCC model with various parameters [22].

To close the theory–practice gap, we integrated experiential information and the opinions of practitioners in considering industrial SCs. By proposing a novel PLCC framework encompassing aspects of both resilience and sustainability, we extended existing conceptual frameworks on SSCM and RSCM. We considered climate change the most critical environmental concern that warrants SCM responses in terms of both sustainability and resilience through climate change mitigation and adaptation measures, respectively. We selected the LED industry as the study subject because it contributes substantially to climate change and is vulnerable to its adverse effects (because of the globalized and highly complex SC).

The first goal programming was developed by Charnes and Cooper [1]. Most goal programming methods rely on mapping one goal to a single scalar aspiration level. However, one goal may map multiple choice aspiration levels [2]. Chang conceived multichoice goal programming (MCGP) to address such scenarios [2]. The two main characteristics of MCGP are as follows. First, the aspiration levels used in goal programming need not be scalars; they can be vectors. Second, in the problem formulation stage, the aspiration level should not be underestimated. Acknowledging the complexity of the multiplicative mixed binary terms employed in MCGP, Chang [4] devised an MCGP approach that obviates the need for such terms altogether. MCGP methods can be implemented to solve real-world decision-making problems.

Nasr et al. [23] demonstrated the applicability of a fuzzy goal programming technique in the garment manufacturing and distribution business through a case study. Beiki et al. [24] used a real-world case study of automotive manufacturing to apply the linguistic entropy weight approach and the multi-objective programming (MOP) method to the applicability of a sustainable supplier selection and order allocation issue.

The remainder of this paper is organized as follows: Section 2 presents a review of the literature on quantitative decision-making techniques concerning SCs. Section 3 introduces the explanation of the solution of the SCPLCC problem under the two present approaches. In Section 4, considering a Taiwanese LED firm, the problem-solving pro-
cess of the two goal programming approaches based on a sample data set of auto part manufacturers from a study by Kumar et al. [20] is described. In Section 5, conclusions are drawn regarding the SCCM-related advantages provided by these two approaches.

2. Literature Review

Criteria concerning SC selection and supplier ratings have been a research focus since the 1960s. In a review article, Dickson [25] compiled a list of more than 50 distinct factors meaningful to SCM. Various methods have been used in SC research, including linear weighting methods and mathematical programming models. For example, linear programming and goal programming, as multicriteria decision-making techniques, aim to facilitate decision-making by minimizing undesirable deviations in goal-related values.

In the present study, we classified studies on SCs according to whether they employed the qualitative factor approach or the integrated factor approach. Table 1 provides information on SC studies in which mathematical programming models were applied. SC models involve the use of diverse approaches, such as simple weighted scoring methods and compound mathematical programming techniques. The incorporation of multiple elements in the selection criteria is desirable and is often associated with high subjectivity in the decision-making process [26].

| Author(s)/Year       | Category       | Methods       | Cost | Rejection | Delivers | PLCC | Capacity | Budget |
|----------------------|----------------|---------------|------|-----------|----------|------|----------|--------|
| MO’ Ath et al. (2017)| Integrated     | WGP, LP       | ✓    | ✓         | ✓        | ✓    | ✓        |        |
| Umarusman (2018)     | Qualitative    | criterion     | ✓    | ✓         | ✓        | ✓    |          |        |
| Budzinski et al. (2019)| Integrated |              | ✓    |           |          |      |          |        |
| Ojo et al. (2020)    | Qualitative    | GP            | ✓    |           |          |      |          | ✓      |
| Hocine et al. (2020) | Integrated     | WA-F MCGP     | ✓    |           |          |      |          | ✓      |
| Hardy et al. (2020)  | Qualitative    | GP            | ✓    |           |          |      |          | ✓      |
| Al-Huaain et al. (2020)| Qualitative |              | ✓    |           |          |      |          | ✓      |
| Bibhas and Sushil (2020)| Qualitative | Game Theoretic| ✓    |           |          |      | ✓        |        |
| Biswarup and Bibhas (2021)| Qualitative | Game Theoretic| ✓    |           |          |      | ✓        |        |
| Bahareh et al. (2021)| Qualitative    | FGP           | ✓    |           |          |      |          | ✓      |
Few studies have considered fuzziness in the analysis of SCPLCC data. Kumar et al. [39] presented a fuzzy goal programming model that minimizes the total tolerable weight variations of variables. In the present study, we employed two fuzzy programming approaches.

3. Methods

Zimmermann [40] used the approach of Bellman and Zadeh [41] and reformulated a linear programming problem with a fuzzy goal and fuzzy restrictions such that it could be solved as a conventional linear programming problem. Indexes, decision variables, and parameters were accounted for in the construction of an enriched multiobjective linear programming model in compliance with a set of assumptions, which are listed as follows.

(i) Assumptions
(ii) Only one item is purchased from one supplier.
(iii) Quantity discounts are not considered.
(iv) The suppliers have an adequate supply of the item.

The lead time and demand of the item are constant and known with confidence.
The indexes, parameters, and decision variables of the SCPLCC model are defined in Table 2.

Table 2. Definitions of indexes, parameters, and decision variables.

| Index | Description |
|-------|-------------|
| i     | Key index for supplier, for all \(i = 1, 2...n\) |
| j     | Key index for objectives function, for all \(j = 1, 2...J\) |
| k     | Key index for constraints, for all \(k = 1, 2...K\) |
| \(x_i\) | Order quantity given to the supplier \(i\) |
| \(D\) | Aggregate demand of the item over a fixed planning period |
| \(n\) | Number of suppliers competing for selection |
| \(p_i\) | Price of a unit item of ordered quantity \(x_i\) to supplier \(i\) |
| \(R_i\) | Percentage of the rejected units delivered by supplier \(i\) |
| \(L_i\) | Percentage of the units delivered late by supplier \(i\) |
| \(C_i\) | PLCC cost for supplier \(i\) |
| \(\tilde{U}_i\) | Upper limit of the quantity available for supplier \(i\) |
| \(r_i\) | Vendor rating value for supplier \(i\) |
| \(P\) | Least total purchasing value that a vendor can have |
| \(f_i\) | Supplier quota flexibility for supplier \(i\) |
| \(F\) | Least value of flexibility in supply quota that a supplier should have |
| \(B_i\) | Budget constraint allocated to each supplier |

Note: Fuzzy parameters are indicated by a tilde.
Model: SCPLCC problem.
We formulate the multiobjective SCPLCC problem with four fuzzy objectives and fuzzy crisp constraints as follows.

Minimize:  \[ Z_1 = \sum_{i=1}^{n} p_{i} x_{i} \]  (1)

Minimize  \[ Z_2 = \sum_{i=1}^{n} r_{i} x_{i} \]  (2)

Minimize  \[ Z_3 = \sum_{i=1}^{n} l_{i} x_{i} \]  (3)

Minimize  \[ Z_4 = \sum_{i=1}^{n} c_{i} x_{i} \]  (4)

The problem is subject to the following constraints:

\[ \sum_{i=1}^{n} x_{i} \geq D \] (aggregate demand constraint)  (5)

\[ x_{i} \leq U_{i} \quad \forall \quad i = 1, 2, \ldots, n \] (capacity constraint)  (6)

\[ \sum_{i=1}^{n} p_{i} x_{i} \geq P \quad i = 1, 2, \ldots, n \] (total items purchasing constraint for supplier \( i \))  (7)

\[ \sum_{i=1}^{n} f_{i} x_{i} \leq F \quad i = 1, 2, \ldots, n \] (Supplier quota flexibility for supplier \( i \))  (8)

\[ p_{i} x_{i} \leq B_{i} \quad i = 1, 2, \ldots, n \] (budget constraint)  (9)

\[ x_{i} \geq 0, i = 1, 2, \ldots, n \] (non-negativity constraint)  (10)

3.1. Key Elements of Objectives or Constraints of the SCPLCC Model

This model has four main fuzzy objectives: minimizing the total net cost, minimizing rejected items, minimizing late deliveries, and realizing the supplier’s goal regarding the PLCC. The aggregate demand constraint ensures that the item is available in the required quantity over a fixed planning period. The supplier production capacity constraint limits the supply on the basis of the uncertain aggregate demand being set at 10% of the deterministic model. The budget constraint means that no one supplier can exceed its budget. The nonnegativity constraint prohibits negative orders. In general, the tilde (\( \sim \)) indicates that a situation is fuzzy. In the present model, both the objective functions and demand constraints are fuzzy parameters [15,22].

Depending on the objectives and restrictions and on whether the weights are equal or unequal, the fuzzy decision is either symmetric or asymmetric, respectively [22,40]. This problem is defined as the following membership function:

\[ \mu_{d}(x) = \min(\mu_{g}(x), \mu_{s}(x)). \]

A general linear MOLP model for supplier selection involving the minimization \((Z_1, Z_2, Z_3, Z_4)\) and maximization \((Z_2)\) of the fuzzy and crisp constraints of the objective function is expressed as follows [22]:

\[ Z_1 = Z_3 = Z_4 = \sum_{i=1}^{n} c_{k} x_{i}, \quad k = 1, 2, 3, 4 \]

\[ Z_2 = \sum_{i=1}^{n} c_{t} x_{i}, \quad t = 2, \text{ for maximization of the fuzzy and crisp constraints of the objective function.} \]
such that \( \sum_{i=1}^{n} a_{ir} x_i \geq d_r, \ r = 1, 2, \ldots, m \) for fuzzy restrictions (capacity constraints 1–4),
\[ \sum_{i=1}^{n} b_{is} x_i \geq d_s, \ s = 1, 2, \ldots, m \] for crisp restrictions (budget constraints 1–4), and
\[ x_i \geq 0, \text{ where } i = 1, 2, \ldots, m. \]

In fuzzy linear programming, objectives and restrictions are treated the same because they are defined through an individual membership function. Figure 1 presents the fuzzy objective functions and constraints of the SCPLCC problem.

The membership function \((Z_k)\) and maximization goals \((Z_l)\) are expressed as

\[
\mu_{zk}(x) = \begin{cases} 
1 & \text{for } Z_k \leq Z_k^- \\
\frac{f_{\mu_{zk}}}{(Z_k^+ - Z_k^-)} & \text{for } Z_k^- \leq Z_k(x) \leq Z_k^+ \\
0 & \text{for } Z_k \leq Z_k^+ 
\end{cases} \quad (k = 1, 2, \ldots, p)
\]

\[
\mu_{zl}(x) = \begin{cases} 
1 & \text{for } Z_l \geq Z_l^- \\
\frac{f_{\mu_{zl}}}{(Z_l^+ - Z_l^-)} & \text{for } Z_l^- \leq Z_l(x) \leq Z_l^+ \\
0 & \text{for } Z_l \leq Z_l^+ 
\end{cases} \quad (l = p + 1, p + 2, \ldots, q)
\]

where \(Z_k^-\) and \(Z_l^-\) can be obtained by solving the multiobjective problem by considering only one objective at a time; \(Z_k^+\) is the maximum value (i.e., the least optimal solution) of the negative objective \(Z_k^-\), and \(Z_l^-\) is the minimum value (i.e., the least optimal solution) of the positive objective function \(Z_l^+\) [20,42,43].

**Figure 1.** Presentation of the objective function as a fuzzy number: (a) minimum \(Z_k^-\) and (b) maximum \(Z_l^-\).
3.2. Solving the SCPLCC Problem through the Weighted Additive Approach

The weighted additive (WA) model, which is convex, enables decision-makers to select different weights according to specific purposes.

When the SCPLCC problem is solved, the weights of the membership functions of the objectives and constraints are calculated according to a supertransitive approximation; thus, these weights are assigned separately. In Equations (13)–(19), $\alpha_j$ is the weighting coefficient that indicates the relative importance of the fuzzy goals and fuzzy restrictions.

The following crisp simplex objective programming function is the same as that of the fuzzy model.

$$\text{Max } \sum_{j=1}^{s} \alpha_j \lambda^*$$  \hspace{1cm} (13)

$$\lambda_j \leq \mu_{g_j}(x) \quad j = 1, 2, \ldots, q, \text{ for all objective functions}$$  \hspace{1cm} (14)

$$\gamma_r \leq \mu_{h_r}(x) \quad r = 1, 2, \ldots, h, \text{ for all constraints}$$  \hspace{1cm} (15)

$$g_m(x) \leq b_m, \quad m = 1, \ldots, p,$$  \hspace{1cm} (16)

$$\lambda \in [0, 1]$$  \hspace{1cm} (17)

$$\sum_{j=1}^{s} \alpha_j = 1, \quad \alpha_j \geq 0,$$  \hspace{1cm} (18)

$$x_i \geq 0, \quad i = 1, 2, \ldots, n.$$  \hspace{1cm} (19)

Refer to the study by Amid et al. [19] for a more detailed discussion of this model.

Weighted Max–Min Approach

Lin [44] devised and provided a proof for a weighted max–min approach that can capture an ideal resolution within a feasible area such that the ratio of the achievement level is as close to the ratio of the weight as possible. Lin noted that the WA model of Tiwari et al. [45] yields objectives involving heavy weights with relatively greater achievement values. However, the proportion of the achievement levels is not essentially the same as that of the objective weights [20,44,46]. To solve the present SCPLCC problem, the following equations corresponding to Lin’s weighted max–min model were employed [20]:

$$\text{Max } \lambda$$  \hspace{1cm} (20)
subject to
\[ w_j \lambda \leq \mu_{y_j}(x) \quad j = 1, 2, \ldots q, \] for all objection functions
\[ y_r \leq \mu_{b_r}(x) \quad r = 1, 2, \ldots h, \] for all constraints
\[ g_m(x) \leq b_m, \quad m = 1, \ldots p, \]
\[ \lambda \in [0, 1] \]
\[ \sum_{j=1}^{s} \alpha_j = 1, \quad \alpha_j \geq 0, \]
\[ x_i \geq 0, \quad i = 1, 2, \ldots n. \]

See Amid et al. [20] for a more detailed description of this model.

3.3. Revised MCGP Approach for Solving the SCPLCC Problem

We employed the RMCGP achievement function model developed by Chang [47]. Two RMCGP achievement function models were implemented. Details are presented as follows.

Specifically, the type I model is used for the scenario in which “more is better” (i.e., where achievement is the upper bound):

Minimize \[ \sum_{i=1}^{n} \left[ w_i (d_i^+ + d_i^-) + \alpha_i (e_i^+ + e_i^-) \right] \]

Subject to
\[ f_i(X)b_i - d_i^+ + d_i^- = b_i y_i \quad i = 1, 2, \ldots n, \]
\[ y_i + e_i^+ + e_i^- = g_{i,\text{max}} \quad i = 1, 2, \ldots n, \]
\[ g_{i,\text{min}} y_i \leq g_{i,\text{max}} \]
\[ d_i^+, d_i^-, e_i^+, e_i^- \geq 0, \quad i = 1, 2, \ldots n, \]

Here, \( X \in F \), where \( F \) is a feasible set and \( X \) is unrestricted in sign.

Note that \( b \in [0, 1] \) is a control variable attached to \( f_i(X) - y_i \), which can be either achieved or released in Equation (27). In terms of real conditions, \( b \) is subject to some constraints in guiding the relationships between the objectives of the SCPLCC model.

The type II model is used in the scenario in which “less is better” (i.e., where achievement is the lower bound):

Minimize \[ \sum_{i=1}^{n} \left[ w_i (d_i^- + d_i^+) + \alpha_i (e_i^- + e_i^+) \right] \]
Subject to
\begin{align*}
f_i(X) & - d_i^+ + d_i^- = b_i y_i \quad i = 1, 2, \ldots, n, \quad (31) \\
y_i - e_i^+ + e_i^- = g_{i,\text{min}} \quad i = 1, 2, \ldots, n, \quad (32) \\
g_{i,\text{min}} y_i & \leq g_{i,\text{max}} \quad (33) \\
d_i^+, d_i^-, e_i^+, e_i^- & \geq 0, \quad i = 1, 2, \ldots, n, \quad (34)
\end{align*}

Here, \( X \in F \), where \( F \) is a feasible set and \( X \) is unrestricted in sign.

The definitions given in the definition of the type I model apply to the variables. All mixed-integer terms in Equations (27) and (29) can be easily linearized through the approach developed by Chang [47]. As presented in Equations (27), (29) and (30), no selection limitations were imposed on a specific objective, but some dependent relationships were observable between goals. Thus, we can add the auxiliary constraint \( b_i \leq b_{i+1} + b_{i+2} \) to the RMCGP achievement function model, where \( b_i, b_{i+1}, \) and \( b_{i+2} \) are binary variables. Therefore, if \( b_i = 1, b_{i+1} \) or \( b_{i+2} \) must also equal 1. In other words, if goal 1 has been accomplished, then either goal 2 or goal 3 must have also been accomplished. Chang [47] presented a case regarding the managerial implications of these restrictions.

3.4. Process of SCPLCC Problem Resolution

A comprehensive solution to the SCPLCC problem was obtained through the following steps.

Step 1: Construct the model of the SCPLCC problem.

Step 2: Solve the MOLP problem through geometric mean weighting and obtain the lower and upper bounds (i.e., the max and min) of the ideal value of the four objectives, respectively.

Step 3: Replicate the procedure for each remaining objective. Define the lower and upper bounds of the optimal values for each objective according to the set of constraints.

Step 4: Process these values as the lower and upper bounds of the ideal values for the crisp construction of the SCPLCC problem.

Step 5: For each objective function, find a lower bound and an upper bound matching the established resolutions for each goal. Let \( Z_j^- \) and \( Z_j^+ \) denote the lower and upper bounds of the \( j \)th objective goal \( Z_j \), respectively [20].

Step 6: For each objective function, find the membership function in relation to Equations (11) and (12).

Step 7: Subject the criteria to geometric mean weighting.

Step 8: Establish and solve the corresponding WA model for the SCPLCC problem in relation to Equations (13)–(19).

Step 9: Establish and solve the corresponding max–min model for the SCPLCC problem in relation to Equations (20)–(25).

Step 10: Implement RMCGP through the geometric-mean-weighted and no-penalty-weighted construction of the fuzzy optimization problem, as expressed in Equations (27) and (30).

Step 11: Implement RMCGP through the geometric-mean-weighted and penalty-weighted construction of the fuzzy optimization problem, as presented in Equations (27) and (34).
Step 12: Solve the RMCGP model through the geometric-mean-weighted and penalty-weighted goal programming construction of the fuzzy optimization SCPLCC problem. Subsequently, compare the results obtained under the two goal programming approaches. Figure 2 shows a schematic representation of the entire methodology (MOLP and RMCGP) used to address the SCPLCC procurement challenge.

**Figure 2.** Graphic representation of the whole process.

### 4. Practical Example

The company on which the SCPLCC model was tested is part of a multinational group in the LED research and development sector. Specifically, the firm manufactures
parts for made-to-order electric lights. External purchases accounted for more than 75% of the total annual costs of the company. The manager of the LED firm formed a team to propose three prospective providers. This group included managers from buying, marketing, quality control, manufacturing, engineering, and research and development.

Members of the team convened multiple sessions to develop profiles for competing providers and assembled a preliminary list of three companies for evaluation purposes [21]. The management is concerned with improving the efficiency of the purchasing process and optimizing the company’s sourcing strategies. The managers believe that evaluating and certifying their vendors is essential for achieving inventory reduction and shortening the time to market. They had been instructed to develop longer-term trust-based relationships with a smaller group of vendors. In response, a team was formed to recommend three or four suitable vendors. The team consisted of managers from the purchasing, marketing, quality control, production, engineering, and research and development departments. The team convened several meetings to create profiles for the evaluation of three initial candidate vendors. An SCPLCC problem model was developed for vendor selection and quota allocation under the consideration of uncertain environmental conditions. Four main objective functions were investigated: (1) minimizing net cost, (2) minimizing net rejections, (3) minimizing late deliveries, and (4) minimizing PLCC. All four functions were under practical constraints regarding item demand, vendor capacity limitations, and vendor budgets, among other factors. The price quoted $P$, percentage of rejections $R$, on a scale from 0 to 1, percentage of late deliveries $L$, the PLCC (designated as $C$), suppliers’ cost capacity $U$, suppliers’ quota flexibility $F$ on a scale from 0 to 1, the vendors’ ratings $r$, on a scale from 0 to 1, and suppliers’ budget allocation $B$ were considered. Profiles of the three suppliers are presented in Table 3.

| Supplier no. | $P$ ($\) | $R$ (%) | $L$ (%) | $C$ ($) | $U$ (Units) | $r$ | $F$ | $B$ ($) |
|--------------|---------|---------|---------|---------|-------------|-----|-----|--------|
| 1            | 3       | 0.05    | 0.04    | 1.92    | 5000        | 0.88| 0.02| 25,000 |
| 2            | 2       | 0.03    | 0.02    | 1.04    | 15,000      | 0.91| 0.01| 100,000|
| 3            | 6       | 0.02    | 0.08    | 3.94    | 6000        | 0.97| 0.06| 35,000 |

In this case demonstration, the linear membership function was employed to fuzzy the right-hand side of the restrictions in the preceding SCPLCC model. The net cost, rejections, late deliveries, and supplier capacity at the lowest and highest levels of the membership function must be defined according to Equations (11) and (12). The fuzzy parameters’ uncertainty level was assumed to be 10% of that of the deterministic model. The values corresponding to the lowest and highest aspiration levels of the membership functions are listed in Table 4.
Table 4. Limiting values in the membership functions of net cost, rejections, late deliveries, PLCC, vendor capacities, and budget information.

|                                | (Min.) \( \mu = 1 \) | (Min.) \( \mu = 0 \) |
|--------------------------------|------------------------|------------------------|
| Net cost objective goal        | 57,000                 | 71,833                 |
| Rejection objective goal       | 413                    | 521                    |
| Late deliveries objective goal | 604                    | 816                    |
| Product life cycle cost        | 10,000                 | 90,000                 |
| Capacity constraints           |                        |                        |
| Supplier 1                    | 5000                   | 5500                   |
| Supplier 2                    | 15,000                 | 16,500                 |
| Supplier 3                    | 6000                   | 6600                   |
| Budget constraints             |                        |                        |
| Supplier 1                    | 25,000                 | 27,500                 |
| Supplier 2                    | 100,000                | 110,000                |
| Supplier 3                    | 35,000                 | 38,500                 |

4.1. Application of the WA Approach to a Numerical Example

We examined a numerical example through the WA approach employed by Tiwari et al. [45]. Before solving the problem, we first determined the weights of four goals and six restrictions through supertransitive approximation. The following binary comparison matrix was assumed to consist of the obtained net cost, rejections, late deliveries, PLCC, supplier 1 constraints, supplier 2 constraints, and supplier 3 constraints:

\[
A = \begin{pmatrix}
\text{Net cost} \\
\text{Rejection} \\
\text{Late deliveries} \\
\text{Product lifecycle cost} \\
\text{Vendor 1 capacity} \\
\text{Vendor 2 capacity} \\
\text{Vendor 3 capacity} \\
\text{Vendor 1 budget constraints} \\
\text{Vendor 2 budget constraints} \\
\text{Vendor 3 budget constraints}
\end{pmatrix}
\]
Supertransitive approximation [48] was conducted to generate the comparison matrix, and the following weights were obtained [9]:

\[ w_1 = 0.2958, \quad w_2 = 0.0579, \quad w_3 = 0.0863, \quad w_4 = 0.0365, \quad w_5 = 0.1291, \quad w_6 = 0.1254, \quad w_7 = 0.0392, \quad w_8 = 0.0199, \quad w_9 = 0.0151, \quad \text{and} \quad w_{10} = 0.1949. \]

### 4.1.1. Solving the SCPLCC Problem through the WA Approach

For this SCPLCC example, the optimal quota allocations (i.e., the purchasing orders), production capacity limitations, and budget restrictions were obtained through Zimmermann’s WA method [49], as shown in Equations (13)–(19). This SCPLCC problem can now be reformulated as the following program:

Maximize \[ 0.2958 \lambda_1^* + 0.0579 \lambda_2^* + 0.0863 \lambda_3^* + 0.0365 \lambda_4^* + 0.1291 \lambda_5^* + 0.1254 \lambda_6^* + 0.0392 \lambda_7^* + 0.0199 \lambda_8^* + 0.0151 \lambda_9^* + 0.1949 \lambda_{10}^* \]

Subject to

\[
\begin{align*}
\lambda_1^* & \leq \frac{(71833 - (3 x_1 + 2 x_2 + 6 x_3))}{(71833 - 57000)} \\
\lambda_2^* & \leq \frac{(521 - (0.05 x_1 + 0.03 x_2 + 0.01 x_3))}{(521 - 413)} \\
\lambda_3^* & \leq \frac{(816 - (0.04 x_1 + 0.02 x_2 + 0.08 x_3))}{(816 - 604)} \\
\lambda_4^* & \leq \frac{(90000 - (1.92 x_1 + 1.04 x_2 + 3.94 x_3))}{(90000 - 10000)} \\
\mu_1^* & \leq \frac{(71833 - (3 x_1 + 2 x_2 + 6 x_3))}{(71833 - 57000)} \\
\mu_2^* & \leq \frac{(521 - (0.05 x_1 + 0.03 x_2 + 0.01 x_3))}{(521 - 413)} \\
\mu_3^* & \leq \frac{(816 - (0.04 x_1 + 0.02 x_2 + 0.08 x_3))}{(816 - 604)} \\
\mu_4^* & \leq \frac{(90000 - (1.92 x_1 + 1.04 x_2 + 3.94 x_3))}{(90000 - 10000)} \\
Z_1 & = 3 x_1 + 2 x_2 + 6 x_3 \\
Z_2 & = 0.05 x_1 + 0.03 x_2 + 0.01 x_3 \\
Z_3 & = 0.04 x_1 + 0.02 x_2 + 0.08 x_3 \\
Z_4 & = 1.92 x_1 + 1.04 x_2 + 3.94 x_3 \\
x_1 + x_2 + x_3 & = 20000 \\
\lambda_5^* & \leq \frac{(5500 - x_1)}{(5500 - 5000)} \\
\lambda_6^* & \leq \frac{(16500 - x_2)}{(16500 - 15000)}
\end{align*}
\]
The numerical example of the SCPLCC problem was solved using LINGO software (2002) Chicago, IL, USA [50]:

\[
\begin{align*}
    x_1 &= 240 \quad x_2 = 15,570 \quad x_3 = 4190 \quad \mu_1 = 0 \quad \mu_2 = 0 \quad \mu_3 = 0 \\
    \mu_4 = 0 \quad \mu_5 = 0 \quad \mu_6 = 0.3066 \quad \mu_7 = 0.0011 \\
    z_1 &= 57,000 \quad z_2 = 521 \quad z_3 = 656.20 \quad z_4 = 33,162.20.
\end{align*}
\]

4.1.2. Solving the SCPLCC Example through the Weighted Max–Min Approach

The optimal quota allocations (i.e., the purchasing orders), production capacity limitations, and budget constraints were obtained using the weighted max–min approach developed by Lin [44], as expressed in Equations (20)–(26). This SCPLCC problem can now be reformulated as the following program:

Maximize \( \lambda \)

Subject to

\[
\begin{align*}
    0.2958 \lambda &\leq (71833 - (3x_1 + 2x_2 + 6x_3))/ (71833 - 57000) \\
    0.0579 \lambda &\leq (521 - (0.05x_1 + 0.03x_2 + 0.01x_3))/ (521 - 413) \\
    0.0863 \lambda &\leq (816 - (0.04x_1 + 0.02x_2 + 0.08x_3))/ (816 - 604) \\
    0.0363 \lambda &\leq (90000 - (1.92x_1 + 1.04x_2 + 3.94x_3))/ (90000 - 10000) \\
    0.2958 \mu &\leq (71833 - (3x_1 + 2x_2 + 6x_3))/ (71833 - 57000) \\
    0.0579 \mu &\leq (521 - (0.05x_1 + 0.03x_2 + 0.01x_3))/ (521 - 413) \\
    0.0863 \mu &\leq (816 - (0.04x_1 + 0.02x_2 + 0.08x_3))/ (816 - 604) \\
    0.0363 \mu &\leq (90000 - (1.92x_1 + 1.04x_2 + 3.94x_3))/ (90000 - 10000) \\
    Z_1 &= 3x_1 + 2x_2 + 6x_3 \\
    Z_2 &= 0.05x_1 + 0.03x_2 + 0.01x_3 \\
    Z_3 &= 0.04x_1 + 0.02x_2 + 0.08x_3 \\
    Z_4 &= 1.92x_1 + 1.04x_2 + 3.94x_3 \\
    x_1 + x_2 + x_3 &= 20000 \\
    0.1291 \lambda &\leq (5500 - x_1)/ (5500 - 5000)
\end{align*}
\]
where \( x_i \geq 0 \) and \( i = 1, 2, \) and 3

The numerical example of the SCPLCC problem was solved using LINGO software (2002):
\[
\begin{align*}
    x_1 &= 0 \\
    x_2 &= 15,750 \\
    x_3 &= 4250 \\
    \lambda &= 0.9595 \\
    \mu_1 &= 0 \\
    \mu_2 &= 0 \\
    \mu_3 &= 0 \\
    \mu_4 &= 0 \\
    \mu_5 &= 0 \\
    \mu_6 &= 0 \\
    \mu_7 &= 0.3066 \\
    \mu_8 &= 1 \\
    \mu_9 &= 1 \\
    \mu_{10} &= 0.0011 \\
    z_1 &= 57,000 \\
    z_2 &= 515 \\
    z_3 &= 655 \\
    z_4 &= 33,125.
\end{align*}
\]

4.1.3. Solving the SCPLCC Example by Using the RMCGP Approach

We now consider an RMCGP problem with goals and constraints that cannot be solved under current goal programming methods. The optimal quota allocations (i.e., the purchasing orders), supplier production capacity, and financial budget constraints were considered. This SCPLCC problem was then formulated as follows:

Main goals (with each goal designated as \( G \)):
\[
\begin{align*}
    (G_1) & : \quad 3x_1 + 2x_2 + 6x_3 = 57,000 \quad (G_{1, \text{MIN}}) \text{ or } 71,833 \quad (G_{1, \text{MAX}}) \\
    (G_2) & : \quad 0.05x_1 + 0.03x_2 + 0.01x_3 = 413 \quad (G_{2, \text{MIN}}) \text{ or } 521 \quad (G_{2, \text{MAX}}) \\
    (G_3) & : \quad 0.04x_1 + 0.02x_2 + 0.08x_3 = 604 \quad (G_{3, \text{MIN}}) \text{ or } 816 \quad (G_{3, \text{MAX}}) \\
    (G_4) & : \quad 1.92x_1 + 1.04x_2 + 3.94x_3 = 10,000 \quad (G_{4, \text{MIN}}) \text{ or } 90,000 \quad (G_{4, \text{MAX}}) \\
\end{align*}
\]

Capacity constraints:
\[
\begin{align*}
    (G_5) & : \quad x_1 = 5000 \quad (G_{5, \text{MIN}}) \text{ or } 5500 \quad (G_{5, \text{MAX}}) \quad (X_1, \text{ production capacity of supplier 1}) \\
    (G_6) & : \quad x_2 = 15,000 \quad (G_{6, \text{MIN}}) \text{ or } 165,000 \quad (G_{6, \text{MAX}}) \quad (X_2, \text{ production capacity of supplier 2}) \\
    (G_7) & : \quad x_3 = 6,000 \quad (G_{7, \text{MIN}}) \text{ or } 165,000 \quad (G_{7, \text{MAX}}) \quad (X_3, \text{ production capacity of supplier 3}) \\
    x_1 + x_2 + x_3 &= 20,000 \quad (\text{Constraint of total demand}) \\
\end{align*}
\]

Budget constraints:
\[
\begin{align*}
    (G_8) & : \quad 3x_1 = 25,000 \quad (G_{8, \text{MIN}}) \text{ or } 27,500 \quad (G_{8, \text{MAX}}) \quad (X_1, \text{ budget constraint of vendor 1}) \\
    (G_9) & : \quad 2x_2 = 100,000 \quad (G_{9, \text{MIN}}) \text{ or } 110,000 \quad (G_{9, \text{MAX}}) \quad (X_2, \text{ budget constraint of vendor 2}) \\
    (G_{10}) & : \quad 6x_3 = 35,000 \quad (G_{10, \text{MIN}}) \text{ or } 110,000 \quad (G_{10, \text{MAX}}) \quad (X_3, \text{ budget constraint of vendor 3}) \\
\end{align*}
\]

Through an RMCGP approach involving no penalty weighting [47] combined with geometric mean weighting [22,47], this SCPLCC problem was rewritten as the following program:

\[
\begin{align*}
\text{Min} &= 0.2958(d_1^+ + e_1^-) + 0.0579(d_2^+ + e_2^-) + 0.0863(d_3^+ + e_3^-) + 0.0368(d_4^+ + e_4^-) \\
&+ 0.1291(d_5^+ + e_5^-) + 0.1254(d_6^+ + e_6^-) + 0.0392(d_7^+ + e_7^-) \\
&+ 0.0199(d_8^+ + e_8^-) + 0.0153(d_9^+ + e_9^-) + 0.1949(d_{10}^+ + e_{10}^-) \\
\text{s.t.} & \\
(3.1x_1 + 2x_2 + 7x_3)b_1 - d_1^+ + d_1^- &= y_1b_1 \quad \text{for the net cost goal, with a lower value being more desirable} \\
y_1 - e_1^+ + e_1^- &= 57000 \quad \text{represents } |y_1 - G_{1,\text{MIN}}|, \\
\text{where } 57000 \leq y_1 \leq 71833.
\end{align*}
\]
(0.05 x₁ + 0.03 x₂ + 0.01 x₃) b₂ - d₃₁ + d₅₂ = y₂ b₂ represents the rejection goal, with a lower value being more desirable; \( y₂ - \epsilon₂^₁ + \epsilon₂^₂ = 413 \) represents \( y₂ - g₂, min \), where \( 413 \leq y₂ \leq 521 \)

(0.04 x₁ + 0.02 x₂ + 0.08 x₃) b₅ - d₃₁ + d₃₅ = y₃ b₅ corresponds to the goal of minimizing late deliveries goal, with a lower value being more desirable. \( y₃ - \epsilon₃^₁ + \epsilon₃^₅ = 604 \) represents \( y₃ - \epsilon₃, min \), where \( 604 \leq y₃ \leq 816 \)

(1.92 x₁ + 1.04 x₂ + 3.94 x₃) b₄ - d₄₁ + d₄₅ = y₄ b₄ corresponds to the PLCC goal, with a lower value being more desirable. \( y₄ - \epsilon₄^₁ + \epsilon₄^₅ = 10000 \) represents \( y₄ - \epsilon₄, min \), where \( 10000 \leq y₄ \leq 90000 \)

\( x₁ b₅ - d₅₁ + d₅₃ = y₅ b₅ \) is the capacity constraint goal of supplier 1, with a lower value being more desirable. \( y₅ - \epsilon₅^₁ + \epsilon₅^₃ = 5000 \) represents \( y₅ - \epsilon₅, min \), where \( 5000 \leq y₅ \leq 5500 \)

\( x₂ b₆ - d₆₁ + d₆₅ = y₆ b₆ \) is the capacity constraint goal of supplier 2, with a lower value being more desirable. \( y₆ - \epsilon₆^₁ + \epsilon₆^₅ = 15000 \) represents \( y₆ - \epsilon₆, min \), where \( 15000 \leq y₆ \leq 16500 \)

\( x₃ b₇ - d₇₁ + d₇₅ = y₇ b₇ \) is the capacity constraint goal of supplier 3, with a lower value being more desirable. \( y₇ - \epsilon₇^₁ + \epsilon₇^₅ = 6000 \) represents \( y₇ - \epsilon₇, min \), where \( 6000 \leq y₇ \leq 6600 \)

\( 3 x₁ b₈ - d₈₁ + d₈₅ = y₈ b₄ \) is the budget constraint goal of supplier 1, with a lower value being more desirable. \( y₈ - \epsilon₈^₁ + \epsilon₈^₅ = 25000 \) represents \( y₈ - \epsilon₈, min \), where \( 25000 \leq y₈ \leq 27500 \)

\( 2 x₂ b₉ - d₉₁ + d₉₅ = y₉ b₄ \) is the budget constraint goal of supplier 1, with a lower value being more desirable. \( y₉ - \epsilon₉^₁ + \epsilon₉^₅ = 10000 \) represents \( y₉ - \epsilon₉, min \), where \( 10000 \leq y₉ \leq 110000 \)

\( 6 x₃ b₁₀ - d₁₀₁ + d₁₀₅ = y₁₀ b₁₀ \) is the budget constraint goal of supplier 1, with a lower value being more desirable. \( y₁₀ - \epsilon₁₀^₁ + \epsilon₁₀^₅ = 35000 \) represents \( y₁₀ - \epsilon₁₀, min \), where \( 35000 \leq y₁₀ \leq 38500 \)

In this program, \( b₁ = b₂ + b₃ + b₄ + b₅ + b₆ + b₇ + b₈ + b₉ + b₁₀ \) so that the net cost, rejection, and late delivery goals, as well as zero, are achieved.
Moreover, \( b_2 + b_3 + b_4 + b_5 + b_6 + b_7 + b_8 + b_9 + b_{10} = 1 \); this addition of auxiliary constraints can force the net cost goal such that the lower-bound goal is achieved and either the rejection goal or the late delivery goal is achieved.

\[
\begin{align*}
Z_1 &= 3x_1 + 2x_2 + 6x_3 \\
Z_2 &= 0.05x_1 + 0.03x_2 + 0.01x_3 \\
Z_3 &= 0.04x_1 + 0.02x_2 + 0.08x_3 \\
Z_4 &= 1.92x_1 + 1.04x_2 + 3.94x_3 \\
x_1 + x_2 + x_3 &= 20000 \\
0.88x_1 + 0.91x_2 + 0.97x_3 &\geq 18400 \\
0.02x_1 + 0.01x_2 + 0.06x_3 &\leq 600 \\
x_i &\geq 0 \quad \text{and} \quad i = 1, 2, 3. \\
d_i^l, d_i^r, e_i^l, e_i^r &\geq 0 \quad (i = 1, 2…10) \\
b_i &\geq 0 \quad (i = 1, 2,…, 10) \text{ are binary variable.}
\end{align*}
\]

The numerical example of the SCPLCC problem was solved using LINGO software [50]:

\[
\begin{align*}
x_1 &= 5000 & x_2 &= 9166.67 & x_3 &= 5833.33 & y_1 &= 57,000 & y_2 &= 410 & y_3 &= 604 \\
y_4 &= 10,000 & y_5 &= 5000 & y_6 &= 15,000 & y_7 &= 6000 & y_8 &= 25,000 & y_9 &= 100,000 & y_{10} &= 35,000 & b_1 &= 1 & b_2 &= 0 & b_3 &= 0 & b_4 &= 0 & b_5 &= 1 & b_6 &= 0 & b_7 &= 0 & b_8 &= 1 & b_9 &= 0 & b_{10} &= 0 \\
z_1 &= 68,383.33 & z_2 &= 583.33 & z_3 &= 850 & z_4 &= 42,116.67
\end{align*}
\]

In sum, the RMCGP method involving geometric mean weighting and no penalty weighting solved the SCPLCC problem.

### 4.1.4. Solving the SCPLCC Example through RMCGP, Geometric Mean Weighting, and Penalty Weighting

In this SCPLCC example, the optimal quota allocations (i.e., purchasing order), production capacity limitations, and budget constraints of the suppliers were determined through RMCGP with a penalty-weighted approach, as expressed in Equations (27) and (30). This SCPLCC problem can now be reformulated as the following program:

\[
\begin{align*}
\text{Min} &= 0.2958(5d_1^l + d_2^l + e_3^l) + 0.0579(4d_2^2 + d_3^2 + e_3^2) + 0.086(3d_3^2 + d_4^2 + e_3^2) \\
&+ 0.0365(2d_1^3 + d_4^3 + e_4^3) + 0.1291(d_5^3 + e_4^3) + 0.1254(d_6^3 + e_6^3) \\
&+ 0.0392(d_7^3 + e_6^3) + 0.0199(d_8^3 + e_6^3) + 0.0151(d_9^3 + e_9^3) + 0.1949(d_{10}^3 + e_{10}^3) \\
\text{s.t.} \\
&3.1x_1 + 2x_2 + 7x_3 \leq 57000 \\
&y_1 - e_1^2 + e_1^3 \leq 57000 \\
&57000 \leq y_1 \leq 71833 \\
&(0.05x_1 + 0.03x_2 + 0.01x_3) \leq b_2 - d_3^2 + d_5^2 \leq y_2b_2 \\
&y_2 - e_1^2 + e_1^3 \leq 413 \\
&413 \leq y_2 \leq 521 \\
&(0.04x_1 + 0.02x_2 + 0.08x_3) \leq b_3 - d_2^2 + d_7^2 \leq y_3b_3 \\
&y_3 - e_1^2 + e_1^3 \leq 604 \\
&604 \leq y_3 \leq 816 \\
&(1.92x_1 + 1.04x_2 + 3.94x_3) \leq b_4 - d_1^2 + d_4^2 \leq y_4b_4 \\
&y_4 - e_1^2 + e_1^3 \leq 10000 \\
&10000 \leq y_4 \leq 90000 \\
&y_5 - e_1^2 + e_1^3 \leq 15000 \\
&x_1b_5 - d_2^2 + d_5^2 \leq y_5b_5 \\
&5000 \leq y_5 \leq 5500 \\
&y_6 - e_1^2 + e_1^3 \leq 15000 \\
&x_2b_6 - d_2^2 + d_6^2 \leq y_6b_6
\end{align*}
\]
The numerical example of the SCPLCC problem was solved using LINGO software [50]:

\[ x_1 = 0 \quad x_2 = 15,750 \quad x_3 = 4250 \quad y_1 = 57,000 \quad y_2 = 410 \quad y_3 = 604 \]
\[ y_4 = 10,000 \quad y_5 = 5000 \quad y_6 = 15,000 \quad y_7 = 6000 \quad y_8 = 25,000 \quad y_9 = 100,000 \]
\[ y_{10} = 35,000 \quad b_1 = 1 \quad b_2 = 0 \quad b_3 = 0 \quad b_4 = 0 \quad b_5 = 0 \]
\[ b_6 = 1 \quad b_7 = 0 \quad b_8 = 0 \quad b_9 = 0 \quad b_{10} = 0 \]
\[ z_1 = 57,000 \quad z_2 = 515 \quad z_3 = 655 \quad z_4 = 33,125. \]

The results demonstrated that RMCGP with geometric mean weighting and penalty weighting was a suitable approach for solving the SCPLCC problem.

4.1.5. RMCGP with Mean Weighting, Penalty Weighting, and WLGP

To verify the RMCGP SCPLCC model problem, we modified the model through mean-weighted–penalty-weighted linear goal programming. The objective function was expressed as an equation presented in a study [13]:

\[
\min \quad \frac{\theta_1}{T_1} d_{n1} + \frac{\theta_2}{T_2} d_{p1} + \frac{\theta_3}{T_3} d_{m1} + \frac{\theta_4}{T_4} d_{n4} + \frac{\theta_5}{T_5} d_{p5} + \frac{\theta_6}{T_6} d_{p6} + \frac{\theta_7}{T_7} d_{n7} + \frac{\theta_8}{T_8} d_{n8} + \frac{\theta_9}{T_9} d_{n9} + \frac{\theta_{10}}{T_{10}} d_{n10}
\]

where

\[ \theta_i = i^{th} \text{ weighted geometric mean}; \, i = 1, 2, 3...10 \]
\[ \theta_1 = 0.2958; \quad \theta_2 = 0.0579; \quad \theta_3 = 0.0863; \quad \theta_4 = 0.0365; \quad \theta_5 = 0.1291; \quad \theta_6 = 0.1254; \quad \theta_7 = 0.0392; \]
\[ \theta_8 = 0.0199; \quad \theta_9 = 0.0151; \text{ and } \theta_{10} = 0.1949. \]
\[ T_i = \text{ normalization constant of the } i^{th} \text{ goal}; \, i = 1, 2, 3...10 \]
\( T_1 = 57,000 \) (total net cost goal)
\( T_2 = 515 \) (total rejection goal)
\( T_3 = 655 \) (total late delivery goal)
\( T_4 = 33,125 \) (total PLCC goal)
\( T_5 = 5000 \) (total capacity constraint goal of supplier 1)
\( T_6 = 15,000 \) (total capacity constraint goal of supplier 2)
\( T_7 = 25,000 \) (total budget constraint goal of supplier 1)
\( T_8 = 100,000 \) (total budget constraint goal of supplier 2)
\( T_9 = 35,000 \) (total budget constraint goal of supplier 3)

Subsequently, the numerical example of the SCPLCC problem was solved using LINGO software [50]:

\[
\begin{align*}
    x_1 &= 1034, \quad x_2 = 15,000, \quad x_3 = 3965, \\
    y_1 &= 57,000, \quad y_2 = 604, \quad y_3 = 10,000, \quad y_6 = 15,000, \quad y_7 = 6000, \quad y_8 = 25,000, \quad y_9 = 100,000, \quad y_{10} = 35,000, \\
    z_1 &= 56,896.55, \quad z_2 = 541.37, \quad z_3 = 658.62, \quad z_4 = 332,107.
\end{align*}
\]

An RMCGP SCPLCC model to which WLGP was applied should yield similar results to an RMCGP SCPLCC model to which WLGP was applied. The results indicated that supplier 2 is the most suitable.

### 4.2. Summary of Results Obtained under All Approaches

Table 5 presents a summary of the results obtained under all goal programming approaches.

| Approach                        | Zimmermann’s Additive Weighted (FMOLP) | Lin’s Weighted Max-Min (FMOLP) | RMCGP with Mean Weighting NO Penalty-Weighted | RMCGP with Geometric Mean Weighting Penalty-Weighted | RMCGP with Geometric Mean Weighting Penalty-Weighted and WLGP |
|---------------------------------|----------------------------------------|--------------------------------|-----------------------------------------------|------------------------------------------------------|-------------------------------------------------------------|
| Objective                       |                                        |                                |                                               |                                                      |                                                             |
| Net cost \( z_1 \)              | 57,000                                 | 57,000                         | 68,383                                        | 57,000                                               | 56,896                                                      |
| Rejection \( z_2 \)             | 521                                    | 515                            | 583                                           | 515                                                  | 541                                                         |
| Late deliveries \( z_3 \)       | 656                                    | 655                            | 850                                           | 655                                                  | 658                                                         |
| Product Life cycle cost \( z_4 \) | 33,162                                | 33,125                         | 42,116                                        | 33,125                                               | 33,210                                                      |
| Order quantity \( x_1 \)        | 240                                    | 0                              | 15,000                                        | 0                                                    | 1034                                                        |
| Order quantity \( x_2 \)        | 15,570                                 | 15,750                         | 9166                                          | 15,750                                               | 15,000                                                      |
| Order quantity \( x_3 \)        | 4190                                   | 4250                           | 5833                                          | 4250                                                 | 3965                                                        |
| Capacity restrictions           |                                        |                                |                                               |                                                      |                                                             |
| Supplier 1                      | 5500                                   | 5500                           | 5000 \(y_5\)                                 | 5000 \(y_5\)                                         | 5000 \(y_5\)                                               |
| Supplier 2                      | 16,500                                 | 16,500                         | 15,000 \(y_6\)                               | 15,000 \(y_6\)                                       | 15,000 \(y_6\)                                             |
| Supplier 3                      | 6600                                   | 6600                           | 6000 \(y_7\)                                 | 6000 \(y_7\)                                         | 6000 \(y_7\)                                               |
| Budget restrictions             |                                        |                                |                                               |                                                      |                                                             |
| Supplier 1                      | 27,500                                 | 27,500                         | 25,000 \(y_8\)                               | 25,000 \(y_8\)                                       | 25,000 \(y_8\)                                             |
| Supplier 2                      | 110,000                                | 110,000                        | 100,000 \(y_9\)                              | 100,000 \(y_9\)                                      | 100,000                                                     |
4.3. Discussion of Results Obtained under the Two Approaches

Notably, the weighted max–min method developed by Lin [39] yielded the same solution to the SCPLCC problem as did the RMCGP method involving geometric mean weighting and penalty weighting.

RMCGP involving geometric mean weighting and no penalty weighting revealed that the lower-bound order quantity of supplier 1 was 5000. This is attributable to the lack of penalty-weighted constraints. Moreover, \( b_1 = 1 \) and \( b_6 = 1 \) (Table 5).

RMCGP involving mean weighting and penalty weighting yielded \( b_1 = 1 \) and \( b_6 = 1 \), and the upper bound of the order quantity of supplier 1 exceeded 15,000; specifically, \( x_2 = 15,750 \). To ensure that the net cost rejection or late delivery goal is met, zero should be obtained (e.g., \( b_1 = 1 \) and \( b_6 = 1 \)), and the auxiliary constraints of \( b_i \) should be applied to the order quantity adjustment (Table 5).

To compare the results of the two verification approaches and increase the accuracy, we applied RMCGP with geometric mean weighting and penalty weighting. We also implemented a WLGP model. Figure 3 shows that the order quantity, net cost, rejections, late deliveries, PLCC, production capacity, and budget under the MCGP model approach were lower than those under the MOLP model approach. In sum, the RMCGP SCPLCC model yielded the same results as did the RMCGP with geometric mean weighting and penalty weighting and the WLGP model (refer to the results for the fifth model in Table 5).

![Figure 3. Results obtained using revised multichoice goal programming (RMCGP), multiobjective linear programming (MOLP) model approaches.](image)

4.4. Sensitivity Analysis

To test the RMCGP and the WLGP models using geometric mean weighting and penalty weighting, we employed a method presented by Ho [51]. Table 6 and Figure 4 demonstrate that if managers wish to diversify the supplier selection risk, deci-
sion-makers can set \( \lambda \) to 0 or 0.2 to divide low order quantities among the three suppliers. Otherwise, they can set \( \lambda \) to 0.8 or 1 to obtain relatively higher achievement levels.

Table 6. Sensitivity analysis results of the mean-weighted–penalty-weighted linear goal programming model.

|    | \( \lambda = 0 \) | \( \lambda = 0.2 \) | \( \lambda = 0.5 \) | \( \lambda = 0.8 \) | \( \lambda = 1 \) |
|----|-------------------|-------------------|-------------------|-------------------|-------------------|
| Z1 | 56,897            | 56,897            | 56,897            | 56,898            | 57,000            |
| Z2 | 541               | 541               | 541               | 540               | 515               |
| Z3 | 658               | 658               | 658               | 658               | 655               |
| Z4 | 33,210            | 33,209            | 33,209            | 33,208            | 33,125            |
| X1 | 1030              | 1029              | 1026              | 1013              | 0                 |
| X2 | 15,003            | 15,003            | 15,006            | 15,015            | 15,750            |
| X3 | 3966              | 3966              | 3967              | 3971              | 4250              |

Figure 4. Sensitivity analysis results of the WLGP model.

4.5. Discussion

A short review of the key results from the study is as follows. For the SCPLCC sustainable procurement challenge, the WLGP approach model and RMCGP with geometric mean weighting and penalty weighting are appropriate (from Table 6, we can discover \( z_2 \) order quantity value 15,750 is acceptable).

The two approaches to tackling the SCPLCC problem provided here can assist decision-makers in improving supplier selection and provide real-world consequences for the LED sector in terms of lowering PLCC costs, minimizing net costs, reducing rejections, and meeting PLCC objectives.

5. Conclusions and Managerial Implications

5.1. Conclusions

Because high-tech companies consider numerous factors (e.g., net cost, rejections, late deliveries, PLCC strategies), achieving only one objective is insufficient for PLCC reduction. SC models for solving this SCPLCC problem have seldom been investigated. In the present study, we solved the SCPLCC problem through two approaches, both of which employed geometric mean weighting. The results serve as a managerial reference for the examined company—specifically, for determining vendor quotas in SCM when
the capacities and budget constraints of each vendor are uncertain (given a lower or upper bound). The first approach, which considered the uncertainty of the fuzzy model, used a linear membership function, and the entire formulation was solved through a fuzzy multiobjective programming approach. The SCPLCC problem was then transformed through a weighted max–min method, as well as through the application of an AW MOLP model and a corresponding crisp, single-objective linear programming approach. The second approach, which involved RMCGP with geometric mean weighting and penalty weighting, emphasized the supply of a high-quality product and PLCC reduction. Furthermore, this approach guided the relationships between goals in the multiobjective problem.

5.2. Managerial Implications

Our study has the following managerial implications. First, the SCPLCC problem can easily be solved using commercially available linear programming software such as LINDO and LINGO.

Second, our solution to the SCPLCC problem is more comprehensive than that achieved through linear programming, conventional goal programming, and other deterministic methods applied when information vagueness is a concern. We transformed the SCPLCC problem into a weighted max–min fuzzy programming model with lower computational complexity, thus simplifying the application of fuzzy methodology [20].

Third, in real-world SCM scenarios, the provision of deterministic values of system parameters (e.g., production capacity and constraints) is unnecessary.

Fourth, our findings can assist managers of LED manufacturers in identifying associations between SSCM and RSCM, thereby facilitating informed decision-making in terms of both sustainability and resilience. We assert that transparency, as well as the consideration of the PLCC model in SCM and stakeholder engagement, can help firms gain competitive advantage. Our findings revealed several complementary and conflicting relationships among the formative elements of SSCM and RSCM. For example, flexibility enables sustainability in SCs but is at least partially discordant with long-term firm–supplier relationships. Our examination of a real-world case adds to the empirical evidence on the implementation of SSCM and RSCM. However, the generalizability of these results to other industries or regions is questionable given potential differences in managerial practices and other features.

Fifth, under the RMCGP approach [47], auxiliary constraints can inform between-goal relationships in multiobjective problems. Regarding the example of the SCPLCC problem, auxiliary constraints facilitated goal realization (e.g., through the adjustment of order quota allocation). RMCGP is relevant to managerial decision-making problems. We modified an RMCGP approach proposed by Chang [47] involving weighted goal programming to solve the SCPLCC problem, accounting for multiple target levels by employing the multiplicative terms of binary variables. Regarding the mapping of one goal to numerous aspiration levels, under certain conditions, decision-makers may base their decisions on a goal that can be achieved on various aspiration level [52]. According to Little [53], operational models are only useful if they are simple, robust, easily controllable, adaptive, easily communicated, and address essential SCPLCC issues. In particular, our SCPLCC model satisfies the first four criteria [27].

We tested our SCPLCC model on a Taiwanese LED company. Because having precise knowledge of all parameters is not required, high-tech companies can easily use our two goal-programming approaches to select suppliers in a fuzzy environment. The two present methods for solving the SCPLCC problem can help decision-makers optimize supplier selection. They also enable managers (including purchasing managers) to manage SC performance and SSCM goals on the basis of factors such as the net cost, number of rejections, number of late deliveries, and overarching PLCC goals.
5.3. Limitations

To validate the SCPLCC problem, overcome the shortcomings of the two goal programming approaches, and ensure accurate outcomes, we compared the models with the RMCGP and weighted goal programming approaches. However, should decision-makers employ a hybrid RMCGP method with a multicriteria decision-making approach, they may obtain unexpected or confusing results.

5.4. Future Directions

To solve SCPLCC problems in scenarios involving multiple suppliers, our SCPLCC models can be integrated with other goal programming approaches, including multicriteria decision-making approaches such as de novo programming, the rough set approach [54,55], or the neutrosophic set approach [56].

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