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A THREE-PHASE MULTICRITERIA METHOD TO THE SUPPLIER SELECTION PROBLEM

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This paper describes a new multi-criteria method to solve the general supplier selection problem. The supplier selection problem is complicated and risky, owing to a variety of qualitative and quantitative factors affecting the decision-making process. For this matter, we present a unique three-phase methodology to reduce the base of potential suppliers to a manageable number and optimize the allocation of orders by means of multi-criteria techniques, namely ideal solution approach, Analytical Hierarchy Process (AHP) and Goal Programming (GP). Finally, a real-life example is provided to illustrate how the method can be used in practice.

Significance: For those companies where the number of potential suppliers is large, the procurement decision process becomes increasingly complicated. In response to this, in this paper we present an appropriate method to simplify the final selection of suppliers.

Keywords: Supplier Selection, Analytical Hierarchy Process, Goal Programming.

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1. INTRODUCTION AND OVERVIEW

One of the most important strategic decisions in a company is the purchasing strategy. In most industries the cost of raw materials and component parts represents the main cost of a product. For instance, in high technology firms, purchased materials and services account for up to 80% of the total product cost, as acknowledged by Weber et al. (1991). The identification, evaluation, and motivation of the right sources ensure that the firm will receive the proper quality, quantity, time, and price from its suppliers. Therefore, selecting the right suppliers becomes a critical activity within a company and consequently affects its efficiency and profitability.

The paper is divided as follows. Section 2 presents a brief literature review. Section 3 presents our proposed methodology for supplier selection along with a numerical example that illustrates each one of the phases involved in this methodology. Section 4 presents a real application of the goal programming model (Phase 3) along with an analysis of the results. Sections 5 presents some important managerial implications and conclusions derived from current research. The above statistics indicate the disparity that exists in employment rates between the disabled and non-disabled and also within the various groups among the disabled. Further, from figures 2 and 3, it can be also inferred that there exists a strong relationship between the employment of an individual and his reliance on disability benefits via SSDI and/or SSI, his/her economic well-being (in terms of each group's annual median earnings). This has been observed particularly in the case of individuals with sensory disabilities who had higher employment rates, better economic well-being and higher median earnings (shown in figures 1,2, and 3), compared to the other groups and hence lesser reliance on the disability benefits through SSDI and/or SSI. This implies that individuals with disabilities can function better in the society when they can make avail of the employment opportunities.

2. LITERATURE REVIEW

As mentioned above, several factors and criteria affect the supplier selection problem, namely price, quality, technical capabilities, and service, among others. For example, Stamm and Golhar (1993), and Ellram (1990) identified 13 and 18 criteria, respectively, for supplier selection. An important review of these criteria is presented by Weber et al. (1991). Table 1 presents the top fifteen supplier selection criteria analyzed in their article (in order of relevance).

There has been a comprehensive effort to develop decision methods and techniques for the supplier selection which consider some of these different factors and criteria. Several decision making steps prior to the ultimate choice of suppliers have been identified in the literature. De Boer et al. (2001) divided these steps as follows: (1) problem definition, (2) formulation of criteria, (3) qualification, and (4) final choice.

Table 1: Supplier Selection Criteria

Rank	Criteria
1	Net Price
2	Delivery
3	Quality
4	Production facilities and capabilities
5	Geographical location
6	Technical capability
7	Management and organization
8	Reputation and position in industry
9	Financial position
10	Performance history
11	Repair service
12	Attitude
13	Packaging ability
14	Operational controls
15	Training aids

In terms of models for ***problem definition and formulation of criteria*** there has been very limited research. An example is the work by Vokurka et al. (1996), in which they developed an expert system that covers multiple phases in the supplier selection process, including the formulation of supplier selection criteria.

Different methods exist for ***pre-qualification of suitable suppliers.*** Important ones are: Categorical Methods, Data Envelopment Analysis (DEA), and Cluster Analysis (CA). Timmerman (1986) discussed the categorical method thoroughly, Weber and Ellram (1992) presented DEA, and Holt (1998) discussed the concept of CA along with its fundamental benefits.

The majority of the decision models or methodologies developed for supplier selection fall into the ***final choice phase.*** A common classification of these methodologies includes weighting models, statistical approaches, and mathematical programming models.

By far, the most utilized approach in practice has been the *weighting models*. These models place a numerical weight on each criterion (typically subjectively determined) and provide a total score for each vendor by summing up the vendor's performance on the criteria multiplied by these weights. Although these approaches are very simple, they heavily depend on human judgment and proper scaling of criteria values. They also assume a linear value function which is not true in practice. An example is the Cost Ratio method presented by Timmerman (1986).

Very few *statistical approaches* have been published to date. An example in this category is the work by Ding et al. (2005). Their approach uses discrete-event simulation for performance evaluation of a supplier portfolio and a genetic algorithm (GA) for optimum portfolio identification based on performance measures estimated by the simulation.

Several *mathematical programming models* have been proposed to solve the final choice problem. Most of these models include approaches with a single objective such as cost minimization or profit maximization. Some of the techniques applied to these methods are linear and non-linear programming, mixed integer programming, goal programming, and multi-objective programming. Moore and Fearon (1973) stated that price, quality and delivery are important criteria for supplier selection. They discussed the use of linear programming in the decision making. Anthony and Buffa (1977) developed a single objective linear programming model to support strategic purchasing scheduling (SPS). The linear model minimized the total cost by considering limitations on purchasing budget, supplier capacity and buyer's demand. Narasimhan and Stoynoff (1986) applied a single objective, mixed integer programming model to a large manufacturing firm in the Midwest, to optimize the allocation procurement for a group of suppliers. Pan (1989) proposed multiple sourcing for improving the reliability of supply for critical materials, in which more than one supplier is used and the demand is split between them. The author used a single objective linear programming model to choose the best suppliers based on three criteria: price, quality, and service. Ghoudsypour and O'Brien (2001) applied a mixed integer non-linear programming model to select and properly allocate orders to suppliers. In this model, they took into account ordering, holding, and purchasing costs.

Despite the multiple criteria nature of the problem, very little work has been devoted to the study of the supplier selection problem by using multi-criteria techniques such as goal programming, multi-objective programming, or other similar approaches. For example, Weber and Current (1993) used multi-objective linear programming for supplier selection with aggregate price, quality and late delivery as objectives.

As noted in the literature review most attention has been paid to the final choice phase in the supplier selection process. However, the quality of the final choice largely depends on the quality of the steps prior to that phase. To our knowledge, there has not been an integrated approach involving all the phases in supplier selection. The importance of this paper is that it considers the various phases of the supplier selection process and presents an efficient methodology that integrates them. The advantages of the integrated approach are that the decision makers (DM) can (1) reduce a large number of suppliers into a manageable one and (2) make the final choice and order allocation by means of multicriteria techniques. To reduce the large number of potential suppliers we use the ideal solution approach and AHP techniques, whereas the order allocation is made by means of goal programming. Unlike most mathematical programming models, goal programming provides the DM with enough flexibility to set target levels on the different criteria and obtain the best compromise solution that comes as close as possible to each one of the targets.

3. THE THREE-PHASE MULTICRITERIA METHODOLOGY FOR SUPPLIER SELECTION

The integrated methodology presented in this paper first screens an initial list of potential suppliers and reduces it to a manageable number. This makes it easier for companies to analyze a short list of suppliers in detail. Then our methodology allocates the proper order quantities to the different suppliers in order to comply with some pre-specified goals set by the Purchasing Department. These goals, in turn, depend upon some specific criteria, related to the supplier selection process and defined by the purchasing function; e.g. quality, minimum cost, service levels, etc. The benefits of this methodology become evident when a company wants to choose just a few suppliers from a list of a large number of potential suppliers.

The Three-Phase approach uses the L_2 metric to screen an initial list of suppliers; then, the Analytical Hierarchy Process (AHP) is utilized to determine the weights of both, qualitative and quantitative criteria in a very powerful and easy way. For a complete tutorial on AHP, readers may refer to Saaty (1994). Another important tool implemented in our approach is Goal Programming (GP). Section 3.3 shows how a GP model can be built to solve the supplier selection problem.

In general, our model can be applied to companies in any type of industry. For illustrative purposes, the methodology was applied to a manufacturing facility located in Tijuana, Mexico. Because of confidentiality issues, the data used in this paper have been disguised. The criteria and goals shown do reflect the actual procedure developed jointly with the Purchasing Manager of this company.

3.1 Phase 1: Screening Process with an Lp Metric

The first phase in our methodology requires that the company define the criteria that will be used to select their suppliers. The set of criteria chosen is unique to every company and component/product, though they all reflect several similarities. As we have already mentioned, the purpose of using an L_p metric in this phase is to reduce the initial list of suppliers with minimal effort. A short manageable list is not only easy to handle but will allow us to efficiently collect detailed data on the suppliers and apply AHP in Phase 2. The technical details on how to implement the L_p metric (Phase 1) are described next and summarized in Figure 1.

The L_p metric represents the distance between two vectors x, y with the same number of elements. One of the most commonly used L_p metrics is the L_2 metric, which measures the Euclidean distance between vectors. The ranking of alternatives is done by calculating the L_2 metric between the ideal solution and each vector representing the supplier's ratings for the criteria. Mathematically, this is computed as follows:

$$\|x-y\|_2=\sqrt{\sum_{i=1}^{n}|x_i-y_i|^2} \qquad \ldots \qquad (1)$$

The algorithm for this phase is described next:

STEP 1. Define the ideal value for each criterion and sub-criterion. The ideal value represents the best value attainable for each criterion/subcriterion from the list of potential suppliers.

STEP 2. Use these values to form the ideal vector (denoted by **y)** as in Table 2.

STEP 3. Use the L_2 metric to measure how "*close*" the rating vector $\mathbf{x_i}$ for each supplier matches the ideal supplier vector **y** (Table 3).

In case the different criteria and sub-criteria chosen are not measured using the same scale, i.e. 0-1, 0-10, 0-100, the initial list of criteria values of the suppliers must be normalized before computing the L_2 metric. To normalize the data it must be recognized whether each criterion is improved when minimized or maximized. Once this is established, one of the following two equations is used to normalize the data:

$$\text{If Minimized, use } \frac{H_j-f_{ij}}{R_j}\text{; otherwise use } \frac{f_{ij}-L_j}{R_j}$$

where H_j is the maximum value for the j^{th} criterion, L_j is the minimum value, f_{ij} is the score of the i^{th} supplier for the j^{th} criterion and R_j represents the corresponding range, $H_j - L_j$. Scores that represent or match the ideal value get a normalized value of one, while the lowest scores get a normalized value of zero. Table 4 shows the normalized data for Table 3. Note that this normalization method converts all criteria to maximization. Hence the ideal values are all ones.

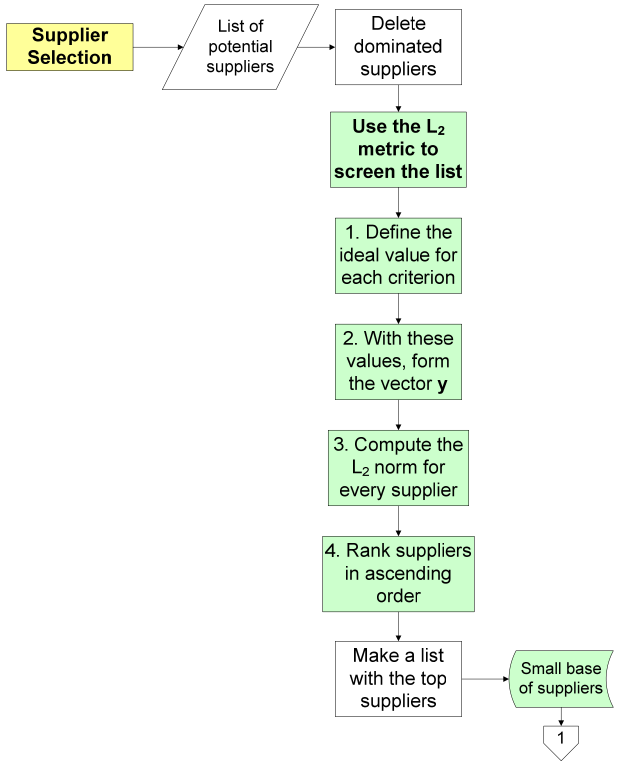

Figure 1: Phase 1 – Screening the Initial List of Suppliers

Table 2: Ideal values for each criterion

	Ideal Values						
	Price ($)	C_{pk} (index)	Defective Parts (ppm)	Flexibility (%)	Service (%)	Distance (km)	Leadtime (hrs/part)
Ideal Vector y	40	2.00	3.4	25	100	5	0.05

Table 3: Initial Supplier Data

	List of Potential Suppliers						
Supplier	Price ($)	C_{pk} (index)	Defective Parts(ppm)	Flexibility (%)	Service (%)	Distance (km)	Leadtime (hrs/part)
1	50	0.95	105,650	10	75	500	0.25
2	80	2.00	3.4	0	100	1,500	0.60
3	45	0.83	158,650	25	65	50	0.20
4	60	1.00	66,800	15	85	5,000	0.80
5	40	1.17	22,750	18	90	9,500	0.95
6	60	1.50	1,350	5	99	7,250	0.50
7	65	1.33	6,200	0	100	10	0.10
8	70	1.50	1,350	0	50	15,000	1.50
9	45	1.00	66,800	5	80	7,500	1.75
10	70	1.25	12,225	10	85	12,500	2.00

11	75	0.83	158,650	15	75	1,345	1.25
12	65	1.00	66,800	0	80	6,680	1.15
13	80	1.33	6,200	0	85	5,000	1.00
14	75	1.15	22,750	2	87	16,000	0.90
15	70	1.33	6,200	5	86	17,000	0.95
16	70	1.05	44,500	0	65	1,860	1.50
17	85	1.25	12,225	5	70	1,789	1.45
18	65	0.95	105,650	0	77	1,775	0.90
19	55	0.83	158,650	10	89	2,500	0.75
20	80	1.25	12,225	10	85	12,500	1.50
21	85	0.83	158,650	0	50	17,500	2.00

Table 4: Normalized Supplier Data

	List of Potential Suppliers						
Supplier	Price ($)	C_{pk} (index)	Defective Parts(ppm)	Flexibility (%)	Service (%)	Distance (km)	Leadtime (hrs/part)
1	0.78	0.10	0.33	0.40	0.50	0.97	0.90
2	0.11	1.00	1.00	0.00	1.00	0.91	0.72
3	0.89	0.00	0.00	1.00	0.30	1.00	0.92
4	0.56	0.15	0.58	0.60	0.70	0.71	0.62
5	1.00	0.29	0.86	0.72	0.80	0.46	0.54
6	0.56	0.57	0.99	0.20	0.98	0.59	0.77
7	0.44	0.43	0.96	0.00	1.00	1.00	0.97
8	0.33	0.57	0.99	0.00	0.00	0.14	0.26
9	0.89	0.15	0.58	0.20	0.60	0.57	0.13
10	0.33	0.36	0.92	0.40	0.70	0.29	0.00
11	0.22	0.00	0.00	0.60	0.50	0.92	0.38
12	0.44	0.15	0.58	0.00	0.60	0.62	0.44
13	0.11	0.43	0.96	0.00	0.70	0.71	0.51
14	0.22	0.27	0.86	0.08	0.74	0.09	0.56
15	0.33	0.43	0.96	0.20	0.72	0.03	0.54
16	0.33	0.19	0.72	0.00	0.30	0.89	0.26
17	0.00	0.36	0.92	0.20	0.40	0.90	0.28
18	0.44	0.10	0.33	0.00	0.54	0.90	0.56
19	0.67	0.00	0.00	0.40	0.78	0.86	0.64
20	0.11	0.36	0.92	0.40	0.70	0.29	0.26
21	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Sometimes it is easy to identify *dominated alternatives*, i.e. alternatives (suppliers) whose individual scores are less than or equal to the criterion scores for another alternative (supplier). The dominated alternatives are obviously not good choices; hence they can be eliminated from the analysis. To compute the L_2 metric use Equation 1.

STEP 4. Rank the suppliers by ordering them in ascending order; i.e., the supplier with the smallest L_2 value should be ranked as # 1 and so on (See Table 5). Pre-select the list of suppliers to a short list for further consideration based on their ranking (e.g. the top 5, top 10, etc).

For illustration, we choose the first seven suppliers for further consideration. The number of selected suppliers is up to the decision maker (DM), but generally this number should be less than 10. The data for the top ranked suppliers will be used in later sections in Phases 2 and 3.

Table 5: Ranking Ordering of Suppliers Based on L_2 Value

Supplier	L_2 value	Rank	Supplier	L_2 value	Rank
1	1.92	#6	**11**	3.40	#19
2	1.88	#5	**12**	2.84	#14
3	2.51	#7	**13**	2.53	#8
4	1.58	#3	**14**	3.09	#17
5	1.15	#1	**15**	2.65	#9
6	1.25	#2	**16**	3.24	#18
7	1.64	#4	**17**	2.94	#15
8	3.91	#20	**18**	2.97	#16
9	2.66	#10	**19**	2.67	#11
10	2.82	#13	**20**	2.72	#12

3.2 Phase 2: Criteria Weights and Ranking of Suppliers with AHP

The relevance of using AHP in this phase relies on the fact that many companies consider *exclusively* quantitative factors in their respective supplier selection analysis. It is precisely this technique that allows a company to involve the decision maker (DM) in the assessment of not only numerical but also intangible factors as well (e.g. supplier's prestige, financial stability, or the matureness of their quality management system).

Figure 2 shows a typical example of the criteria used for supplier selection. The structure given by Figure 2 will be shown to be very useful when we perform AHP to compute the criteria weights.

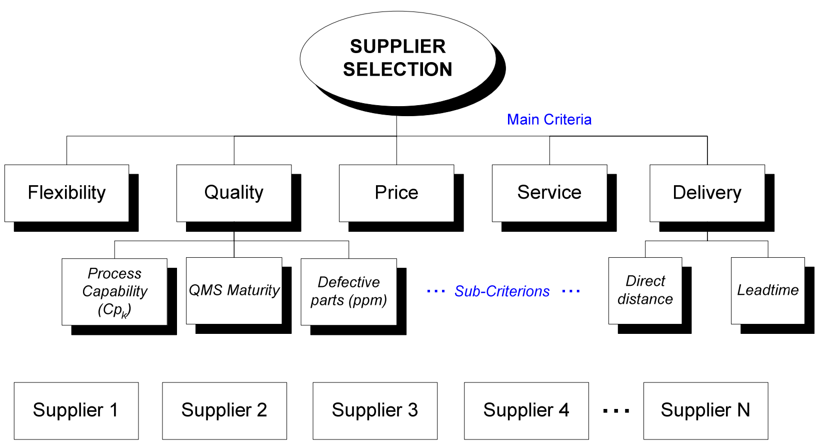

Figure 2: Supplier Selection Criteria

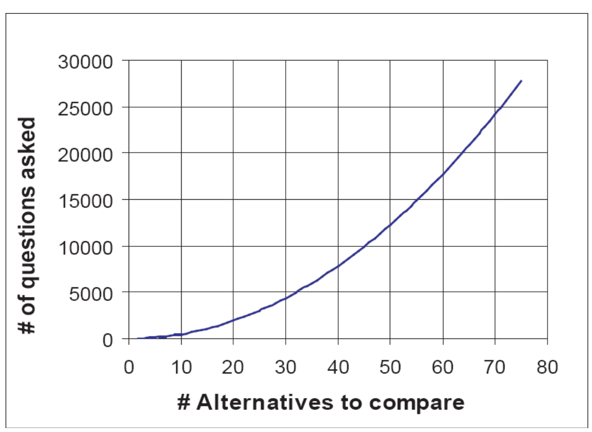

Figure 3: Growth in the Number of Questions

The value of **Phase 1** becomes obvious when AHP is implemented in **Phase 2** because AHP can be a tedious and inefficient process for ranking more than 10 suppliers. AHP requires a number of pair-wise comparison questions between criteria/sub-criteria and between alternatives. Figure 3 shows how the number of questions to be answered by the DM increases when using AHP; this number exceeds 500 questions for more than 10 alternatives (suppliers) and nine criteria.

Figure 4 summarizes the steps for Phase 2. The two outputs from this phase consist of the weights for the criteria and a list of suppliers with their respective total scores. This output will be used in Phase 3, during the formulation of the GP model.

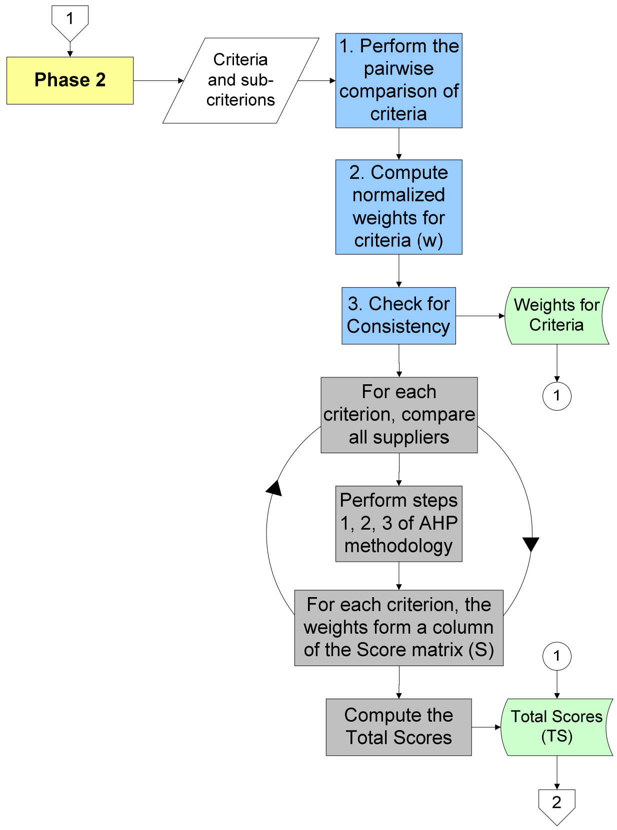

Figure 4: Phase 2 – Defining the Weights with AHP and Supplier Screening

3.2.1 AHP Algorithm

This section summarizes the basic blocks in the AHP algorithm. The figures and tables shown were used to develop the example in this paper. AHP uses a rating scale, shown in Table 6, for the pairwise comparison questions.

Table 6: Rating Scale for Pairwise Comparison

Degree of Importance	**Definition**
1	Equal Importance
3	Weak importance of one over another
5	Essential or Strong Importance
7	Demonstrated importance
9	Absolute importance
2, 4, 6, 8	Intermediate values between the two adjacent judgments

STEP 1. Do a pairwise comparison of the main criteria using the scale in Table 6. Form the matrix $A_{nxn} = \lfloor a_{ij} \rfloor$, where the a_{ij} entry represents the relative importance of criterion 'i' with regard to criterion 'j'. Let $a_{ii} = 1 \; \forall i$ and $a_{ji} = 1/a_{ij}$. This is shown in Table 7.

Table 7: Pairwise Comparison Matrix

	Quality	***Delivery***	***Criteria*** ***Flexibility***	***Service***	***Price***
Quality	1	3	3	5	1
Delivery	0.333333	1	1	3	1
Flexibility	0.333333	1	1	3	0.333333
Service	0.2	0.333333	0.333333	1	0.2
Price	1	1	3	5	1

STEP 2. Compute the normalized weights for the main criteria from matrix A. The most common way to do this is by normalizing each column with the L_1 norm. Using the following formulas, we can get the results displayed in Table 8:

$$\text{Compute } r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}, \text{ then average the } r_{ij} \text{ values to get the weights, } w_i = \frac{\sum_j r_{ij}}{n}.$$

Table 8: Normalized Matrix

	Quality	***Delivery***	***Criteria*** ***Flexibility***	***Service***	***Price***	***Weights***
Quality	0.348837	0.473684	0.360000	0.294118	0.283019	0.351932
Delivery	0.116279	0.157895	0.120000	0.176471	0.283019	0.170733
Flexibility	0.116279	0.157895	0.120000	0.176471	0.094340	0.132997
Service	0.069767	0.052632	0.040000	0.058824	0.056604	0.055565
Price	0.348837	0.157895	0.360000	0.294118	0.283019	0.288774

Steps 1 and 2 are continuously performed throughout every sub-level of criteria and sub-criteria. As shown in Figure 5, we would first determine the weights for the five main criteria, and then we would proceed to compare the two sub-levels of Quality and Delivery separately. The final weight of a sub-criterion is the product of the weights along the corresponding branch.

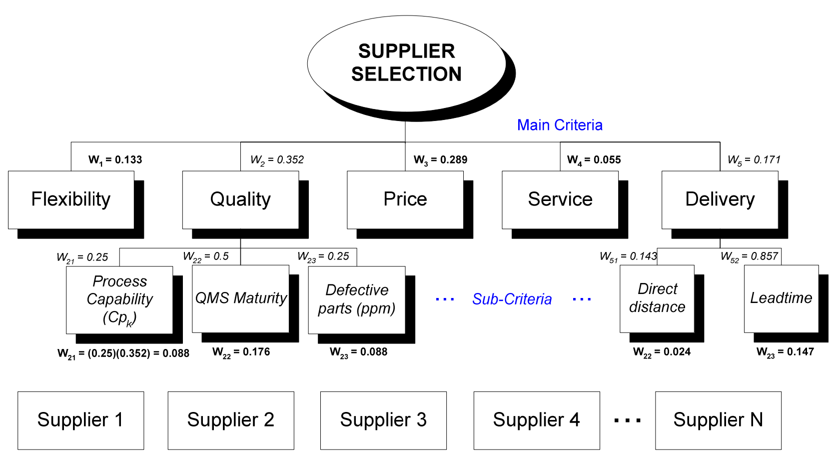

Figure 5: Supplier Selection Criteria Weights

STEP 3. Check for consistency of the pairwise comparison matrix, using the Consistency Index (*CI)* and Consistency Ratio (*CR*). AHP has a procedure to check the consistency of the DM's responses. If the DM is perfectly consistent then, A (before normalization) has the following property:

$$A \cdot \vec{w} = \begin{bmatrix} 1 & w_1/w_2 & \cdots & w_1/w_n \\ w_2/w_1 & 1 & \cdots & w_2/w_n \\ \vdots & \vdots & \ddots & \vdots \\ w_n/w_1 & w_n/w_2 & \cdots & 1 \end{bmatrix} \cdot \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} = n\vec{w}.$$

If A is perfectly consistent then $\lambda_{\max} = n$; also $\lambda_{\max} \geq n$, where $\lambda_{\max} = \text{Average}\left[A_{1\bullet} \cdot w/w_1,\ \ A_{2\bullet} \cdot w/w_2,\ \ \cdots,\ \ A_{n\bullet} \cdot w/w_n\right]$. To measure the degree of inconsistency, we can use the following indicators: ***Consistency Index*** (***CI***) and the ***Consistency Ratio*** (***CR***).

$$CI = \frac{\lambda_{\max} - n}{n-1};\quad CR = \frac{CI}{RI},$$

where *RI* is a random index, obtained from Table 9. If *CR* < 0.1, accept the pairwise comparison matrix.

Table 9: Random Index (RI) Values (Saaty (1994))

n	2	3	4	5	6	7	8	9	10
RI	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

Finally, for our example, the respective computations lead to the results shown in Figure 6.

A x w	**(A x w)/w$_i$**
1.829720	5.1990786
0.876509	5.1338128
0.683994	5.1429332
0.284949	5.1281943
1.488255	5.1537058
λmax	5.1515449

Consistency Index:	0.037886
Consistency Ratio:	0.034132

Figure 6: Consistency Ratio and Consistency Index

At this point, we should have a small list of suppliers available and proceed to rank all the suppliers by comparing the suppliers with regard to each criterion using AHP. The weights computed for each criterion form a column of the Score matrix (*S*). The Total Scores (*TS*) of the suppliers is determined by Equation 2, where *w* corresponds to the criteria weights previously computed.

$$TS = [S \times w] \qquad \ldots \qquad (2)$$

The suppliers are ranked based on their *TS* values (higher the better).

3.3 Phase 3: Allocation of Orders with a Preemptive GP Model

The model described in this phase is used to allocate the right quantities to be purchased from each supplier. Therefore, ***model variables*** are the planned purchases from each vendor.

As mentioned before, we make use of goal programming (GP) as an appropriate technique. In goal programming, all the objectives are assigned target levels for achievement and a relative priority on achieving these levels. GP treats these targets as goals to aspire for and not as absolute constraints. There are two types of goal programming: preemptive and non-preemptive. In the preemptive case, goals at higher priority must be satisfied as far as possible before lower priority goals are even considered. Therefore, the problem reduces to a sequence of single-objective optimization problems. In the non-preemptive case, different weights are assigned to each goal turning the problem into a single-objective optimization problem, consequently assuming a linear utility function. Since the nature of the Supplier Selection problem suggests that the utility function is nonlinear, implementing a non-preemptive GP model might not be very realistic; therefore we propose a preemptive GP model to emulate the behavior of such utility functions.

The advantages of using goal programming are that (1) it allows the firm to set planning goals related to the supplier selection criteria and policies, (2) GP also lets the company assign priorities on these goals, reflecting their relative importance, and (3) setting goals allows a company to control the deviation from targets and achieve tradeoffs for goals in conflict.

It is important to note that since "*purchasing decisions*" usually span the long-term, these are made once for a given demand over some period of time. In this case, the demand is considered to be sufficient to satisfy the market over a period of one year; decisions are made as to allocate the right amount within the set of selected suppliers to fulfill this demand.

3.3.1 Goal Constraints

Goal constraints must be developed together with management and must be defined according to the company's main goals. In our case, the constraints were derived from the Scorecard used in the Supplier's Evaluation process. Some constraints had to be redefined or changed to meet the model's specific needs. Table 10 presents the notation and terminology used.

Table 10: Problem Notation

n	Number of suppliers
X_i	Ordered quantity from i^{th} supplier
D	Annual demand
C_i	Capacity of i^{th} supplier
TS_i	Total score of i^{th} supplier
L_i	Company's required leadtime for the i^{th} supplier
l_i	Time required by i^{th} supplier to procure one unit of product
$\overline{C}_{pk}$	Company's required level of C_{pk}
C_{pi}	C_{pk} of i^{th} supplier
q_i	Defects of i^{th} supplier (in parts per million)
SL	Service level required
S_i	Service level of i^{th} supplier
F	Level of flexibility required
Δ_i	Flexibility level of i^{th} supplier
P_i	Price of i^{th} supplier
Z_i	Distance from i^{th} supplier to buyer
Y_i	1, if an order is allocated to i^{th} supplier; 0, otherwise
d^+	Amount of deviation above the goal
d^-	Amount of deviation below the goal

The goal constraints included in the model along with their formulation are introduced next.

Weighted Value of Purchase – WVP. In this goal constraint, the total scores obtained in Phase 2 form the coefficients TS_i for each supplier. The aim is to maximize the total WVP. In other words, the total scores indicate particular preferences of the DM when comparing the suppliers with respect to the criteria. We then try to maximize the number of units allocated to suppliers with higher total scores. In general, WVP is maximized by setting an ideal value (*M*) to the goal constraint and trying to minimize the underachievement d_1^- as much as possible.

$$\sum_{i=1}^{n} TS_i X_i + d_1^- - d_1^+ = M. \qquad \dots \qquad (3)$$

***Distance goal**.* Globalization seems to be changing paradigms in industry with international suppliers. Unfortunately there is still a strong negative correlation between quick delivery and distance. JIT requires that ideally suppliers should be close to the buyer; as a matter of fact several companies keep as many suppliers as possible to a distance where they can supply any order within minutes. The following constraint minimizes the total distance to the suppliers selected. The distance is minimized by setting an ideal goal of zero, and by minimizing the overachievement d_2^+.

$$\sum_{i=1}^{n} Z_i Y_i + d_2^- - d_2^+ = 0. \qquad \dots \qquad (4)$$

Process Capability (C_{pk}). Current Six Sigma trends motivate companies to ensure certain quality level throughout the value stream. Consequently, it is logical to avoid as much as possible, suppliers that do not meet a specific quality level. This constraint is strictly on the average, hence the restriction does not discriminate any supplier for not achieving this goal, but it does select a group of suppliers satisfying such constraint. For our example, this index represents the supplier's sigma level with respect to a critical quality feature, given the respective LSL (Lower Specification Limit) and USL (Upper Specification Limit) provided by the company. The objective is established as to minimize d_3^-, the underachievement of C_{pk}.

$$\sum_{i=1}^{n} C_{pi} Y_i + d_3^- - d_3^+ = \overline{C}_{pk} \sum_{i=1}^{n} Y_i. \qquad \dots \qquad (5)$$

Flexibility goal. One of the most important competitive advantages of world class companies is their ability to satisfy a dynamic demand. Flexibility allows a company to expand its capacity and respond to changes in demand. Hence, we must try to select suppliers that maximize the company's flexibility. The objective of this goal is to minimize d_4^-, the underachievement of a flexibility level required by the purchaser.

$$\sum_{i=1}^{n} \Delta_i Y_i + d_4^- - d_4^+ = F \sum_{i=1}^{n} Y_i. \qquad \dots \qquad (6)$$

Quality – Defective parts per million (ppm). This goal constraint was chosen to minimize the defective percentage rate of our suppliers. It is known that there is a direct relationship between C_{pk} and ppm, but we are distinguishing it by considering ppm in a more general sense; i.e., considering not only as defective products, those who do not meet the company's specifications for a certain critical quality feature, but for any non-conformance issue that may appear. The objective of this goal is set to minimize d_5^+, the overachievement of defective parts.

$$\sum_{i=1}^{n} q_i Y_i + d_5^- - d_5^+ = 0. \qquad \dots \qquad (7)$$

Service level goal. With the increasing importance in keeping a performance indicator to monitor service satisfaction, most of the companies keep track of their supplier service level. It is a prudent choice to keep suppliers that provide an average satisfaction level (*SL*). The service level required is kept at an optimal value by minimizing d_6^-.

$$\sum_{i=1}^{n} S_i Y_i + d_6^- - d_6^+ = SL \sum_{i=1}^{n} Y_i. \qquad \dots \qquad (8)$$

Purchasing expenses. We want to avoid purchasing from suppliers with the highest prices. When we talk about prices we are assuming that this cost reflects the total cost in the buyer's location warehouse, including cost of distance for freight, and broker costs as well. This constraint minimizes the purchasing expenses made by the company, according to the orders placed and the individual price (total cost) offered by every supplier. The objective in this case, is to minimize the overachievement (d_7^+) of an unrealistic target of zero cost.

$$\sum_{i=1}^{n} P_i X_i + d_7^- - d_7^+ = 0. \qquad \dots \qquad (9)$$

Leadtime goal. Take l_i to be the production rate at which an order can be satisfied by the i^{th} supplier. Therefore, the time it takes the supplier to fulfill an order is directly proportional to this variable. The company, usually has a maximum allowed leadtime for every single supplier (L_i), usually being more strict with local suppliers. There will be at most 'n' constraints of this type. The objective is established as to minimize d_8^+ , the overachievement of L_i .

$$l_i X_i + d_8^- - d_8^+ = L_i, \ i = 1,2,...,n. \quad \ldots \quad (10)$$

3.3.2 Real Constraints

The following two constraints must be always satisfied. Equation 11 implies that the orders placed over a given period must satisfy the demand. Equation 12 refers to the fact that a particular order can not exceed the corresponding capacity of that supplier.

$$\sum_{i=1}^{n} X_i = D, \quad \ldots \quad (11)$$

$$X_i \le C_i, \ \ i = 1,2,...,n. \quad \ldots \quad (12)$$

Figure 7 summarizes the steps for Phase 3. The two outputs from this phase consist of the goal priorities and the GP model.

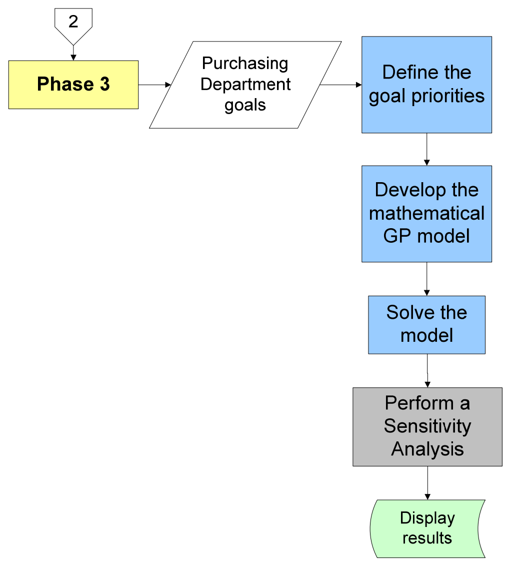

Figure 7: Phase 3 – Goal Programming

4. APPLICATION AND ANALYSIS

In this section, we present the application of the GP model along with an analysis of the results. It is important to note that this analysis is performed on the top seven suppliers obtained in Phase 1 (Section 3.1). For this application a preemptive GP model is considered, as explained before. The specific goal priorities used in this model are presented in Table 11. This priority structure is defined by the company and reflects the importance given (by the DM) to the different criteria considered in the supplier selection process.

Based on this priority structure, we obtain the objective function as presented in Equation 13.

$$\text{Min} \quad Z = P_1(d_1^-) + P_2(d_2^+) + P_3(d_3^+) + P_4(d_4^-) + P_5(d_5^+ + d_6^+ + d_7^+ + d_8^+ + d_9^+ + d_{10}^+ + d_{11}^+) + P_6(d_{12}^-) + P_7(d_{13}^-) + P_8(d_{14}^+) \quad \ldots \quad (13)$$

In order to test the model, different profiles (characterizations) for each supplier are proposed. These profiles represent characteristics of each supplier with respect to each criterion. The data for the illustrative example corresponding to each supplier is provided in Table 12.

Supplier 1: supplier 1 offers a low price for the product and a relatively bad performance in all the remaining criteria.
Supplier 2: supplier 2 provides an excellent service. It also offers products with superior quality but at a high price.
Supplier 3: supplier 3 presents an excellent flexibility but at the expense of low quality.
Supplier 4: supplier 4 offers an average performance in all criteria.

Table 11: GP Model Priorities

Priority	Goal Constraint	Deviational Variables
1: P_1	Weighted value of purchase	d_1^-
2: P_2	Purchasing expenses	d_2^+
3: P_3	Quality (ppm)	d_3^+
4: P_4	Flexibility	d_4^-
5: P_5	Leadtime	$d_5^+, d_6^+, d_7^+, d_8^+, d_9^+, d_{10}^+, d_{11}^+$
6: P_6	Service Level	d_{12}^-
7: P_7	Process Capability (C_{pk})	d_{13}^-
8: P_8	Distance	d_{14}^+

Supplier 5: supplier 5 stands out for its very low price, although it is far away in terms of travel distance.
Supplier 6: supplier 6 also offers an average performance but, unlike supplier 4, its service level is nearly perfect. Also, in terms of quality level (ppm), supplier 6 offers a higher level than supplier 4.
Supplier 7: supplier 7 maintains the shortest leadtime of all suppliers (given its proximity to the purchasing company); it also provides an excellent service; however, it offers poor technical capability.

Table 12: Input Model Data

	Criteria						
Supplier's Profile	Price ($)	C_{pk} (index)	Defective Parts(ppm)	Flexibility (%)	Service (%)	Distance (km)	Leadtime (hrs/part)
Supplier 1	50	0.95	105,650	10	75	500	0.25
Supplier 2	80	2.00	3.4	0	100	1,500	0.60
Supplier 3	45	0.83	158,650	25	65	50	0.20
Supplier 4	60	1.00	66,800	15	85	5,000	0.80
Supplier 5	40	1.17	22,750	18	90	9,500	0.95
Supplier 6	60	1.50	1,350	5	99	7,250	0.50
Supplier 7	65	1.33	6,200	0	100	10	0.10

In addition, a constant yearly demand (D) of 13,000 units is considered. One supplier or a combination of them must satisfy this demand in its entirety.

4.1 Computational Results

On this final stage, the results obtained with the preemptive GP model are presented. All results were generated using the optimization software `LINDO`. In particular, the '*preemptive goal*' option available in this software is applied in solving the model. This option solves preemptive (lexicographic) goal programs sequentially by priority. Table 13 shows the final allocation quantities for each supplier.

As it can be seen, suppliers 2 and 4 were not chosen. In particular, they both possess the lowest Total Score values (TS_i) for the first priority (*WVP*). Moreover, Supplier 2 offers the highest price among all suppliers. This makes it less likely to be chosen given the priority structure, on which '*Purchasing Expenses*' is defined as the second most important criterion to consider. In the case of Supplier 4, although it offers an average performance on all criteria, its performance is surpassed by other suppliers.

Another important result is the achieved levels for each criterion. These results are summarized in Table 14. Based on the results, only the leadtime goal was fully achieved. That is, suppliers 1, 3, 5, 6, and 7 loosely fulfilled the levels set by the company as goals in terms of total leadtime (hrs). The rest of the goals are partially achieved with respect to the corresponding deviational variables and target levels initially set by the DM.

Table 13: Orders Allocated (in units) to Each Supplier

Supplier	Quantity
1	2,200
2	-
3	3,000
4	-
5	3,200
6	1,500
7	3,100
Total Cost	$665,500.00

Table 14: Goal Achievements

Criteria	Achievements
Weighted value of purchase	7,719.00
Purchasing expenses ($)	665,500.00
Quality level (ppm)	73,650
Flexibility achieved (%)	11.60
Leadtime underachievement (hrs)	200.00
Service Level achieved (%)	85.80
Process Capability achieved (C_{pk})	1.15
Average distance (km)	3,462.00

4.4.1 Sensitivity Analysis

As part of the analysis performed, several scenarios were analyzed. Each scenario defines a different priority structure with respect to the criteria. Scenarios are evaluated to check the robustness of the response for the GP model. The scenarios are described in Table 15. The first scenario corresponds to the priority structure originally defined by the DM, while the rest of them reflect situations where price may not be as important and leadtime or distance are crucial, etc.

Table 15: Analysis of Scenarios

	P r I o r i t i e s							
Scenario	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
1	WVP	P.Exp.	Quality	Flexib.	Leadtime	Service	P.Cap.	Distance
2	P.Exp.	Quality	Flexib.	Leadtime	Service	P.Cap.	WVP	Distance
3	P.Exp.	Quality	WVP	Leadtime	P.Cap.	Distance	Flexib.	Service
4	Flexib.	Leadtime	Service	Quality	Distance	P.Exp.	P.Cap.	WVP
5	Service	WVP	Quality	Distance	Leadtime	Flexib.	P.Cap.	P.Exp.
6	Distance	P.Cap.	Service	Leadtime	Flexib.	Quality	P.Exp.	WVP
7	Quality	Flexib.	Leadtime	P.Cap.	P.Exp.	WVP	Service	Distance
8	Leadtime	Distance	Flexib.	P.Exp.	Quality	Service	WVP	P.Cap.

It is worthwhile to mention that there are a total of 8!, or equivalently 40,320 different scenarios, many of them providing the exact same answer. Only a few of them were chosen, for being considered as representative of actual scenarios in industry. The results displayed in Table 16 show the allocation of orders under each scenario. We can see that there are several solutions, but they are all in the same form as the original solution for Scenario 1. In general, there seems to be a tendency to choose Suppliers 1, 3, 5, 6 and 7. Order quantities don't seem to vary that much and actually a more careful analysis on the deviational variables shows that the priorities are optimized to similar values for all solutions.

Table 16: Allocation for the Different Scenarios

	Supplier						
Scenario	X_1	X_2	X_3	X_4	X_5	X_6	X_7
1	2,200	-	3,000	-	3,200	1,500	3,100
2	2,200	-	3,000	400	3,200	4,200	-
3	2,200	-	3,000	400	3,200	4,200	-
4	2,200	-	2,400	1,240	3,160	4,000	-
5	-	-	3,000	-	3,200	3,700	3,100
6	2,200	3,200	3,000	1,900	-	-	2,700
7	-	2,900	-	-	3,200	4,200	2,700
8	2,200	1,700	2,400	-	-	4,000	2,700

The solutions presented in Table 13 could be shown to the DM along with information regarding the achieved values for each priority (as in Table 14). This should provide the DM with a good vision of possible alternatives for the final decision.

5. MANAGERIAL IMPLICATIONS AND CONCLUSIONS

The Three-Phase integrated methodology presented herein allows managers to make sound decisions with respect to supplier selection. In particular, Phase 1 offers an easy way to screen a large number of potential suppliers to a manageable number. Then, the advantage of AHP (in Phase 2) is that it can help managers in formulating decisions concerning the impact of alternative suppliers based on the multiple criteria of the organization. It also provides a strategic approach to evaluate alternatives. AHP is very useful for managerial decision making because it is flexible enough to accommodate a *larger set of evaluation criteria*. This enables managers to make sound selections based on both qualitative and quantitative criteria.

In Phase 3, managers can evaluate the impact of changing business conditions (e.g., increase service level, change the required flexibility, leadtime, etc.) and obtain the proper allocation of orders to each supplier by means of goal programming, which unlike other mathematical programming approaches, allows managers to consider different criteria levels of achievement and give their respective priority with certain flexibility. Different criteria and goal constraints can be introduced to account for specific needs of a company. In summary, use of this methodology can facilitate the supplier selection and the purchasing problems.

In conclusion, supplier selection is an essential part of the purchasing process. The objective is to find the optimal set of suppliers offering the best goods with respect to a company's specific criteria. Companies must consider multiple criteria in their attempts to differentiate between products offered by potential suppliers. In this research, we have considered both quantitative and qualitative criteria and introduced an approach to first, reduce the base of suppliers, rank the supplier selection criteria in order of importance, and then, to allocate orders to each supplier from the reduced base of potential suppliers. Specific criteria and goal constraints were defined in conjunction with the Purchasing Department of a particular manufacturing company. Results provide important insights into the Three-Phase methodology presented in this research.

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BIOGRAPHICAL SKETCH

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