International Review of Business Research Papers
Vol. 7. No. 5. September 2011. Pp.168-183

An Economical Multi-Criteria Decision-Making Process for Supplier Selection

Neda Javanmardi *[a], Amin kaboli [b], Iraj Mahdavi [a] and Babak Shirazi [a]

Supplier selection has become an important part of supply chain management, which has, as one of its principal goals, the cultivation of long-term relationships with a few reliable suppliers. The 'process of elimination' that is often currently used for the achieving of this goal involves criteria so various and so voluminous as to be detrimentally time-consuming and impractical. In this paper, a new approach for effective supplier selection is developed, based on the principle component analysis (PCA) and the TOPSIS algorithm. The proposed procedure consists of two main parts: 1) Reducing supplier selection criteria to the most important ones by filtering out the parameters that don't impact the final decision significantly, and 2.) Categorizing suppliers based on this newly reduced set of criteria. In most of the models proposed in current literature on the subject, criteria weights were determined by experts. In this paper we will propose a highly systematic way which will greatly decrease the probability of human error. For this purpose, principle component analysis is utilized to weigh all criteria and reduce them to the most important ones. TOPSIS algorithm is also applied to rank suppliers from best-to-worst. It is our hope that this reduced set of criteria will prove to be less complicated and much more economical in terms of time and cost.

Field of Research: Supplier selection, Multi-criteria decision making (MCDM), Principal Component Analysis (PCA).

1. Introduction and Literature Review

Outsourcing is one of the most important aspects of production, which consists of subcontracting a process, such as product design or manufacturing, to another company. For outsourcing to be successful, two vital steps must be taken: identifying the appropriate processes to be outsourced and selecting suitable suppliers to perform them. Outsourcing decisions are not only related to the materials and components of a product, they are also applied to non-manufacturing activities such as support services. For many organizations, the potential number of outsourcing decisions is enormous. Typically, manufacturing companies have hundreds of components that can either be made in-house or outsourced (Tayles & Colin 2001). Hence, selecting a wrong supplier can have far-reaching impact on a company, while an appropriate choice can open new windows of opportunity.

Supplier selection and evaluation is a complex problem. There is an abundance of researches in this area, such as that of (Weber et al 1991; Degraeve et al 2000; De Boer et al 2009; Ho et al 2009). Prior to the early 1970s, supplier selection had been

[a] Department of Industrial Engineering, College of Technology, Mazandaran University of Science & Technology, Babol, Iran.
[b] EPFL, Laboratory for Production Management and Processes, CH-1015 Lausanne, Switzerland.

done largely on the basis of obtaining the best price and taking into account a few other factors, such as quality and delivery. In most cases, a significant number of important factors were taking into account, such as: delivery reliability, technical capability, cost-effectiveness and the financial stability of the supplier (Ford et al 1993).Proper attention to these factors will help avoid some of the pitfalls of the classic 'make-or-buy' approach, which uses cost alone as the deciding factor (Humphreys et al 2000; Dickson 1998).

Another research on the importance of supplier evaluation includes works by (Banker & Khosla 1995; Dobler et al 1990). Banker and Khosla have identified supplier evaluation and justification as an important part of operations management. They advocate such strategic practices and standards as: total quality management, zero defect, process improvement, statistical process control, and continuous process improvement, which should result in an increase in quality and a cost reduction (De Ron 1998; Lederer & Rhee 1995; Tham 1998).

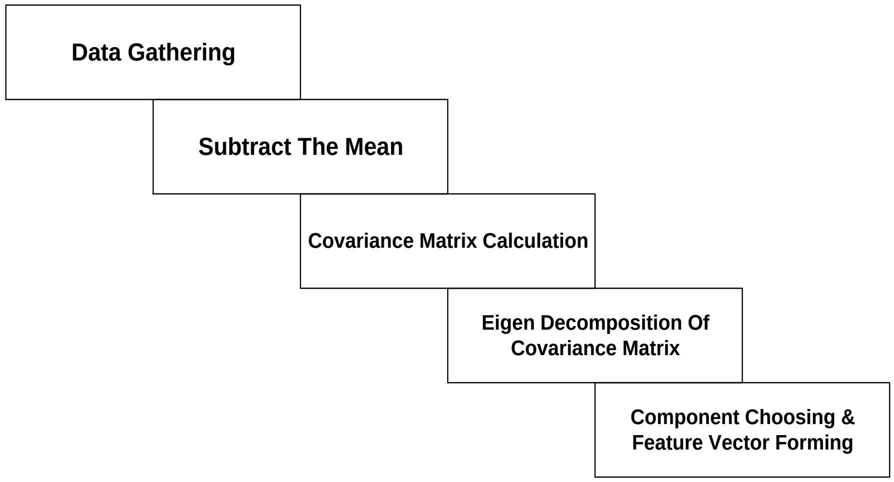
Another work in this area belongs to (Talliri & Narasimhan 2008) who propose an objective framework involving multiple strategic and operational factors in the evaluation process. In their work, suppliers are categorized according to their performance, which assists managers in identifying candidates for long-term strategic partnerships, supplier development programs, and pruning. They also investigate the differences among supplier groups and propose improvement strategies for suppliers with ineffective performance.

Onuh and Kara have developed a supplier evaluation approach based on the Analytic Network Process (ANP). In this model the technique for ordering performance by similarity to ideal solution (TOPSIS) methods under the fuzzy environment is used where the vagueness and subjectivity are handled with linguistic terms parameterized by triangular fuzzy numbers (Semih et al 2008).
An interactive group decision-making methodology is proposed by Kahraman and Engine, using multiple criteria to select/rank IS providers. In this approach, a consensus of group preferences is used as a measure of reliability and overall group satisfaction. The Spearman coefficients for both aggregated rank order and each DM's rank order have also been calculated.

The group and the individual evaluations are gathered through a fuzzy TOPSIS approach. Sensitivity analysis was also provided to see the effects of parameter changes on the final decision (Cengiz 2008).

An effective approach which can be used in supplier selection and evaluation problems is Principal Component Analysis (PCA) which has received much less attention in current research. PCA is a useful statistical technique that has found application in fields such as face recognition and image processing for instance it's a common technique for finding patterns in data of high dimensions. The other main advantage of PCA used in this research is that, by finding these patterns in the data, data can be compressed, i.e. by reducing the number of dimensions, without much loss of information. Fig.1 briefly shows Principal Component Analysis steps.

Fig.1: Principal Component Analysis steps.



All of the researchers mentioned above have tried to establish different criteria for choosing the best suppliers, and most of these criteria have been selected and weighted by experts. In this paper, a new method is proposed using the PCA approach to reduce the number of criteria and use only the best in order to save time and money. Furthermore, this approach will be used to find the number of criteria—with probability of error clearly specified—that should be sufficient for the purpose of ranking suppliers. The paper is organized as follows: In section 2 the proposed model for sorting suppliers and reducing the number of criteria to the most important ones will be explained. Section 3 illustrates the application of the model for a tele-communications company. Concluding remarks will be given in Section 4. Finally, future works are suggested in section 5.

2. Methodology

Supplier selection is one of the most important activities in the supply chain. Because of this, companies should pay attention to this problem from different aspects and evaluate suppliers with various criteria. Information for these criteria must be gathered from many sources. To accomplish this task, we propose a new methodology for reducing the various criteria to a manageable number, and rating suppliers according to quality. The algorithm for this process is shown in fig.2.

First all criteria germane to the selection should be determined and related information for these criteria should be gathered from the various suppliers. They will then be inserted into the matrix $m \times n$, where m is the number of criteria and n is the number of suppliers.

For calculating a covariance matrix, since access to Probability Destiny Function (PDF) is difficult and the number of potential suppliers is more than 20, the Law of Large Number (L.L.N) can be used as formula (1).

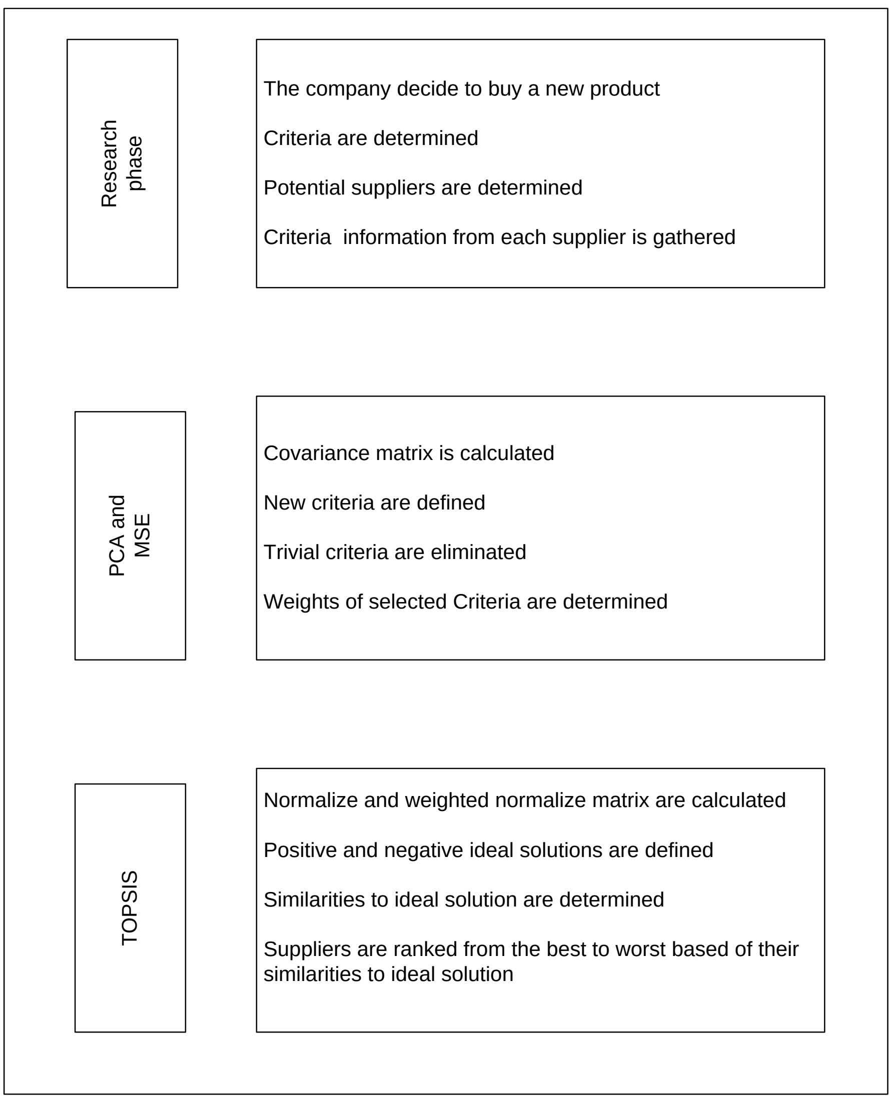
$$L.L.N \Rightarrow \frac{1}{K}\sum_{i=1}^{K}(x_i - m_{x_i})(x_i - m_{x_i})^T \rightarrow C_{xx}$$
$$K \rightarrow \infty \tag{1}$$

In this formula x_i is the realization of criteria suggested by each supplier, m is the mean of each criterion.

Since the criteria do bear correlation with each other, the importance of each one cannot be independently calculated; thus new uncorrelated criteria must be defined, based on a linear combination of main criteria, as in formula (2):

$$y_{m\times 1} = \Phi_{m\times m}{}^{T} x_{m\times 1} \tag{2}$$

Fig.2: An integrated supplier selection algorithm



$\Phi_{m \times m}$ is matrix of the eigenvectors of the covariance matrix for the main criteria, and since eigenvectors are orthonormal, $\Phi^T \Phi = I$. New criteria are uncorrelated which is proved in formula (3):

$$\begin{aligned} C_{yy} &\overset{(1)}{=} E\{yy^T\} = E\{(\Phi^T x)(\Phi^T x)^T\} \\ &\overset{(2)}{=} \Phi^T E\{xx^T\}\Phi = \Phi^T C_{xx}\Phi \overset{(3)}{=} \Phi^T(\Phi\Lambda\Phi^T)\Phi \\ &\overset{(4)}{=} \Lambda \end{aligned} \tag{3}$$

(1): definition of covariance matrix.

(2): Φ is deterministic.

(3): definition of eigenvalue-eigenvector decomposition.

(4): Φ is orthonormal matrix.

The covariance matrix of new criteria is a matrix of eigenvalues of main criteria (which is a diagonal matrix), therefore new criteria are uncorrelated.
After calculation of covariance matrix of main criteria, the matrix is decomposed by eigenvector-eigenvalue decomposition which is shown in formula (4).

$$C_{xx} = \Phi\Lambda\Phi^T \tag{4}$$

Further, all eigenvalues are sorted in descending order as: (5)

$$\lambda_1 \succ \lambda_2 \succ \lambda_3 \ldots \succ \lambda_m \tag{5}$$

By using MSE criterion, the most important new eigenvalues are chosen as: (6)

$$\begin{aligned} MSE &= \frac{\sum_{i=k+1}^{m} \lambda_i}{\sum_{i=1}^{m} \lambda_i} \\ MSE &\le \zeta \end{aligned} \tag{6}$$

k is the number of maintained criteria.

Corresponding eigenvectors of eliminated eigenvalues are removed from eigenvector matrix, and new eigenvector matrix is constructed under the symbol $\tilde{\Phi}$.
Now reduced new criteria based on a new eigenvector is defined as (7):

$$\tilde{y}_{k \times 1} = \tilde{\Phi}_{k \times m}{}^{T} x_{m \times 1} \tag{7}$$

- New criteria are not only uncorrelated but also the number of them is reduced.
- New criteria, in fact, are linear combination of main criteria.

The importance of each main criterion in new criteria is corresponding to amount of elements in each eigenvector ($\tilde{\Phi}_{m,j}$) and its correspondent eigenvalue (λ_m). Therefore, by finding the maximum elements in each eigenvector, the most important main criteria are found, maintained and remaining elements are removed. Until now, in most research models, the weights of criteria were evaluated by experts but, in this paper, a new method is proposed for determining these weights without subjective human judgment. The weights of selected main criteria are calculated and normalized as (8),

$$\hat{w}_m = \lambda_m w_c ,\qquad w_m = \frac{\hat{w}_m}{\sum_{i=1}^{L} \hat{w}_i} \tag{8}$$

w_c is maximum element in the selected eigenvector and λ_m is correspondent eigenvalue.

Now that the most important criteria and their weights have been determined, a new decision matrix, $n \times k$, should be constructed, with n as the number of suppliers and k as the number of selected criteria. This, then, will be normalized as follows: (9).

$$r_{i,j} = \begin{cases} \dfrac{x_{ij}}{x_j^+} \\ \dfrac{x_j^-}{x_{ij}} \end{cases} \Rightarrow \quad D' = \begin{array}{c c} & \begin{array}{ccccc} X_1 & \cdots & X_j & \cdots & X_n \end{array} \\ \begin{array}{c} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} & \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & & \vdots & & \vdots \\ r_{i1} & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & & \vdots & & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix} \end{array} \tag{9}$$

The weighted normalized decision matrix is calculated as formula (10),

$$D' = \begin{array}{c c} & \begin{array}{ccccc} X_1 & \cdots & X_j & \cdots & X_n \end{array} \\ \begin{array}{c} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} & \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & & \vdots & & \vdots \\ r_{i1} & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & & \vdots & & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix} \end{array} \Rightarrow v_{ij} = r_{ij}.w_j \Rightarrow v = \begin{array}{c c} & \begin{array}{ccccc} X_1 & \cdots & X_j & \cdots & X_n \end{array} \\ \begin{array}{c} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} & \begin{bmatrix} v_{11} & \cdots & v_{1j} & \cdots & v_{1n} \\ \vdots & & \vdots & & \vdots \\ v_{i1} & \cdots & v_{ij} & \cdots & v_{in} \\ \vdots & & \vdots & & \vdots \\ v_{m1} & \cdots & v_{mj} & \cdots & v_{mn} \end{bmatrix} \end{array} \tag{10}$$

$$W = (w_1,...,w_j,...,w_n);$$

The positive ideal (A^+) and the negative ideal (A^-) solutions are identified by formula (11):

$$\begin{aligned} A^+ &= [v_1^+,\ldots,v_j^+,\ldots,v_n^+]; \qquad v_j^+ = \max_i \{v_{ij}\} \\ A^- &= [v_1^-,\ldots,v_j^-,\ldots,v_n^-]; \qquad v_j^- = \min_i \{v_{ij}\} \end{aligned} \tag{11}$$

And the similarities to ideal solutions for each supplier are determined by formula (12):

$$\left.\begin{aligned} S_i^+ &= \sum_{j=1}^{n} \left| v_{ij} - v_j^+ \right| = \sum_{j=1}^{n} D_{ij}^+ \\ S_i^- &= \sum_{j=1}^{n} \left| v_{ij} - v_j^- \right| = \sum_{j=1}^{n} D_{ij}^- \end{aligned}\right\} \Rightarrow C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-} \tag{12}$$

All suppliers are ranked in descending order from best to worst, from the biggest amount of C_i^+ to the smallest.

3. Findings

In this paper the data set for a large communication company, collected by (Talluri et al 2004), is used to rank suppliers. The data has been collected from 23 suppliers. Talluri and Narasimhan extracted eleven selected features containing both subjective and objective features. The selected features are as follows:

- Quality management practices and systems (QMP);
- Documentation and self-audit (SA);
- Process/manufacturing capability (PMC);
- Management of the firm (MGT);
- Design and development capabilities (DD);
- Cost reduction capability (CR);
- Quality;
- Price;
- Delivery;
- Cost reduction performance (CRP);
- Other

The main data matrix is shown in Table 1:

Table 1: Data Matrix Transpose

Supplier #	QMP	SA	PMC	MGT	DD	CR	Quality	Price	delivery	CRP	Other
1	0.9662	0.9742	1.0339	1.0808	1.1417	0.7839	0.6211	0.8922	0.1284	1.2107	0.6359
2	0.7054	1.0438	0.7500	0.8782	0.0000	0.8750	0.6932	0.8922	0.3855	0.0000	0.3179
3	0.5611	0.8947	0.7789	0.7205	0.8372	0.7404	1.0205	0.4341	1.5420	0.0000	1.2719
4	1.1272	1.0438	0.9520	0.9607	0.9661	1.1402	1.6639	1.1333	1.5420	1.2107	1.8019
5	1.1272	1.0438	1.1251	1.0808	1.2560	1.2115	0.9983	1.3503	1.1565	1.2107	0.9540
6	0.9877	1.0438	0.9376	1.0808	1.0466	0.9422	1.0426	1.3263	1.7990	2.4214	1.2719
7	0.8051	0.8351	1.0385	0.9607	1.2560	1.0768	1.2201	1.2056	0.7710	2.4214	1.2719
8	1.1809	1.0438	1.1251	1.0208	1.0627	1.0096	0.8429	1.1333	0.6424	1.2107	0.8479
9	1.2346	1.0438	1.1251	1.0808	1.2560	1.1442	0.6433	0.8922	0.3855	0.0000	0.5299
10	0.5904	1.0438	0.6058	0.7629	0.5796	0.4038	1.4419	0.4341	1.4135	0.0000	1.2719
11	0.8642	0.8118	0.8182	0.9536	0.9661	0.8076	0.4215	0.8922	1.0279	0.0000	0.8479
12	0.6441	0.8351	0.0227	1.0208	0.9661	1.0768	1.0205	1.3263	0.7710	1.2107	0.7418
13	1.2346	1.0438	1.1251	1.0808	1.2560	1.2115	0.5546	1.1092	1.0279	1.2107	1.1660
14	1.0662	1.0438	1.1251	1.0808	1.1593	1.2115	0.8208	0.8922	0.8994	1.2107	0.8479
15	1.0100	1.0438	0.8654	1.0208	0.7322	0.6815	1.2423	1.5674	1.4135	2.4214	1.2719
16	0.8978	0.9742	1.0385	1.0208	0.9420	0.8076	1.0205	0.8922	0.3855	0.0000	0.4240
17	1.1272	0.9742	1.0385	1.0208	1.2560	1.0768	1.0205	0.8681	0.7710	0.0000	0.5299
18	1.1809	1.0438	1.1251	1.0808	1.2660	1.2115	1.2201	0.2411	0.0000	0.0000	0.4240
19	1.0735	1.0438	1.1251	0.9007	1.1593	0.9422	1.1641	0.8922	1.4135	1.2107	1.0599
20	1.0735	1.0438	1.1251	1.0808	0.6762	1.1442	0.8429	1.0550	1.4135	1.2107	1.4839
21	1.2346	1.0438	1.1251	1.0133	1.2560	1.2115	0.7764	0.8922	1.0279	0.0000	0.9540
22	1.2346	1.0438	0.9520	1.0808	1.0466	1.2115	1.4642	1.3263	1.7990	2.4214	1.4839
23	1.0735	1.0438	1.0385	1.0172	0.8695	1.0768	1.2423	1.3503	1.2849	2.4214	1.5900

To calculate covariance matrix first all criteria should be zero mean. Table 2 shows means of criteria and Table 3 is the zero mean matrix.

Table 2: Means of Criteria

Mean	Criteria
1	**QMP**
1	**SA**
0.9564	**PMC**
1	**MGT**
0.9980	**DD**
0.9999	**CR**
0.9999	**Quality**
0.9999	**Price**
1	**Delivery**
1.0001	**CRP**
1	**Other**

Here the Singular Value Decomposition (SVD) method is used, instead of eigenvalue-eigenvector decomposition, to determine the singular values vector (Table 4) and eigenvectors matrix (Table 5).

Now the MSE method is used to specify the number of important criteria. In this paper 5% is determined for the margin of error as shown in Formula (13) and Fig.3.

$$MSE\{m = L\} \leq 5\% \tag{13}$$

The algorithm chooses the six largest eigenvalues and corresponding eigenvectors with less than 5% error, as shown in tables (6) and (7).

Table 3: Transpose of data matrix with mean of zero in every column

Supplier #	QMP	SA	PMC	MGT	DD	CR	Quality	Price	delivery	CRP	Other
1	-0.0338	-0.0258	0.0775	0.0808	0.1437	-0.2160	-0.3788	-0.1077	-0.8716	0.2106	-0.3641
2	-0.2946	0.0438	-0.2064	-0.1218	-0.9980	-0.1249	-0.3067	-0.1077	-0.6145	-1.0001	-0.6821
3	-0.4389	-0.1053	-0.1775	-0.2795	-0.1608	-0.2595	0.0206	-0.5658	0.5420	-1.0001	0.2719
4	0.1272	0.0438	-0.0044	-0.0393	-0.0319	0.1403	0.6640	0.1334	0.5420	0.2106	0.8019
5	0.1272	0.0438	0.1687	0.0808	0.2580	0.2116	-0.0016	0.3504	0.1565	0.2106	-0.0460
6	-0.0123	0.0438	-0.0188	0.0808	0.0486	-0.0577	0.0427	0.3264	0.7990	1.4213	0.2719
7	-0.1949	-0.1649	0.0821	-0.0393	0.2580	0.0769	0.2202	0.2057	-0.2290	1.4213	0.2719
8	0.1809	0.0438	0.1687	0.0208	0.0647	0.0097	-0.1570	0.1334	-0.3576	0.2106	-0.1521
9	0.2346	0.0438	0.1687	0.0808	0.2580	0.1443	-0.3566	-0.1077	-0.6145	-1.0001	-0.4701
10	-0.4096	0.0438	-0.3506	-0.2371	-0.4184	-0.5961	0.4420	-0.5658	0.4135	-0.0001	0.2719
11	-0.1358	-0.1882	-0.1382	-0.0464	-0.0319	-0.1923	-0.5784	-0.1077	0.0279	-1.0001	-0.1521
12	-0.3559	-0.1649	-0.9337	0.0208	-0.0319	0.0769	0.0206	0.3264	-0.2290	0.2106	-0.2582
13	0.2346	0.0438	0.1687	0.0808	0.2580	0.2116	-0.4453	0.1093	0.0279	0.2106	0.1660
14	0.0662	0.0438	0.1638	0.0808	0.1613	0.2116	-0.1791	-0.1077	-0.1006	0.2106	-0.1521
15	0.0100	0.0438	-0.0910	0.0208	-0.2658	-0.3184	0.2424	0.5675	0.4135	1.4213	0.2719
16	-0.1022	-0.0258	0.0821	0.0208	-0.0560	-0.1923	0.0206	-0.1077	-0.6145	-1.0001	-0.5760
17	0.1272	-0.0258	0.0821	0.0208	0.2580	0.0769	0.0206	-0.1318	-0.2290	-1.0001	-0.4701
18	0.1809	0.0438	0.1687	0.0808	0.2680	0.2116	0.2202	-0.7588	-1.0000	-0.0001	-0.5760
19	0.0735	0.0438	0.1687	-0.0993	0.1613	-0.0577	0.1642	-0.1077	0.4135	0.2106	0.0599
20	0.0735	0.0438	0.1687	0.0808	-0.3218	0.1443	-0.1570	0.0551	0.4135	0.2106	0.4839
21	0.2346	0.0438	0.1687	0.0133	0.2580	0.2116	-0.2235	-0.01077	0.0279	-1.0001	-0.0460
22	0.2346	0.0438	-0.0044	0.0808	0.0486	0.2116	0.4643	0.3264	0.7990	1.4213	0.4839
23	0.0735	0.0438	0.0821	0.0172	-0.1285	0.0769	0.2424	0.3504	0.2849	1.4213	0.5900

Table 4: Singular Values Vector

1.5072	0.7523	0.5371	0.3958	0.3101	0.2825	0.2254	0.1819	0.1208	0.0558	0.0504

Table 5: Eigenvectors Matrix

0.0373	0.1705	-0.4260	-0.0625	0.1436	-0.3425	-0.0973	0.0454	0.6112	-0.2478	0.4468
0.0097	-0.0012	-0.0725	0.0156	0.01907	-0.1685	-0.1264	-0.0769	0.3240	-0.2514	-0.8600
0.0090	0.1536	-0.4720	-0.0036	0.6494	0.0628	-0.2500	0.1521	-0.4760	0.1234	-0.0209
0.0252	0.1385	-0.0885	-0.0597	0.0324	-0.1247	0.0018	-0.0498	0.2996	0.9185	-0.1277
0.0227	0.2439	-0.5529	0.1557	-0.5972	0.4136	-0.1238	0.2022	-0.0109	-0.0519	-0.1529
0.0344	0.1801	-0.3339	-0.0527	-0.1700	-0.3998	0.4718	-0.5673	-0.3350	-0.0549	-0.0609
0.1322	-0.2400	-0.0129	0.8065	-0.1103	-0.4366	-0.2026	0.0982	-0.1217	0.0705	0.0331
0.2354	0.1544	0.1093	-0.4207	-0.2528	-0.5118	-0.0693	0.5750	-0.2459	-0.0268	-0.0963
0.3108	-0.6808	-0.2481	-0.3522	-0.1518	0.0035	-0.3857	-0.2771	-0.0468	0.0482	0.0344
0.8613	0.3520	0.1947	0.0997	0.0938	0.1872	-0.0516	-0.1877	0.0433	-0.0425	0.0318
0.2911	-0.4092	-0.2319	0.0620	0.1639	0.1278	0.6905	0.3892	0.1161	0.0313	-0.0659

Fig.3: Mean Square Error in base number of Eigenvalues

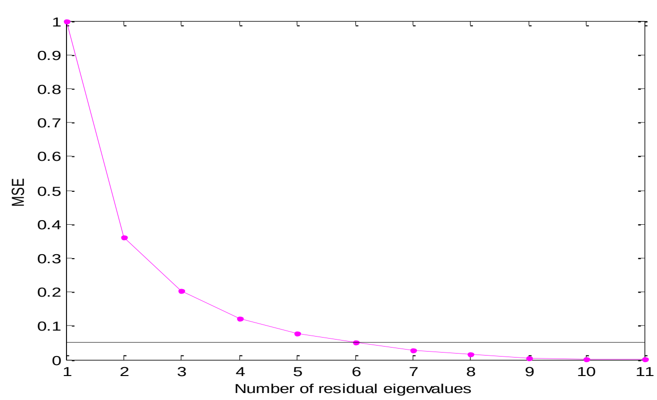


Table 6: Reduced Singular Values Vector

1.5072	0.7523	0.5371	0.3958	0.3101	0.2825

Table 7: Reduced Eigenvectors Matrix

0.0373	0.1705	-0.4260	-0.0625	0.1436	-0.3425
0.0097	-0.0012	-0.0725	0.0156	0.01907	-0.1685
0.0090	0.1536	-0.4720	-0.0036	0.6494	0.0628
0.0252	0.1385	-0.0885	-0.0597	0.0324	-0.1247
0.0227	0.2439	-0.5529	0.1557	-0.5972	0.4136
0.0344	0.1801	-0.3339	-0.0527	-0.1700	-0.3998
0.1322	-0.2400	-0.0129	0.8065	-0.1103	-0.4366
0.2354	0.1544	0.1093	-0.4207	-0.2528	-0.5118
0.3108	-0.6808	-0.2481	-0.3522	-0.1518	0.0035
0.8613	0.3520	0.1947	0.0997	0.0938	0.1872
0.2911	-0.4092	-0.2319	0.0620	0.1639	0.1278

The most important main criteria correspond to the maximum absolute amount in each selected eigenvector as shown in table (8).

Table 8: Maximum absolute amount of eigenvectors and correspondent main criteria

PMC	DD	Quality	Price	delivery	CRP
0.8613	-0.6808	-0.5529	0.8065	0.6494	-0.5118

By maintaining only the data of selected criteria, a new data matrix is constituted (Table 9):

Table 9: Data Matrix for selected Criteria

Supplier #	PMC	DD	Quality	Price	delivery	CRP
1	0.0775	0.1437	-0.3788	-0.1077	-0.8716	0.2106
2	-0.2064	-0.9980	-0.3067	-0.1077	-0.6145	-1.0001
3	-0.1775	-0.1608	0.0206	-0.5658	0.5420	-1.0001
4	-0.0044	-0.0319	0.6640	0.1334	0.5420	0.2106
5	0.1687	0.2580	-0.0016	0.3504	0.1565	0.2106
6	-0.0188	0.0486	0.0427	0.3264	0.7990	1.4213
7	0.0821	0.2580	0.2202	0.2057	-0.2290	1.4213
8	0.1687	0.0647	-0.1570	0.1334	-0.3576	0.2106
9	0.1687	0.2580	-0.3566	-0.1077	-0.6145	-1.0001
10	-0.3506	-0.4184	0.4420	-0.5658	0.4135	-0.0001
11	-0.1382	-0.0319	-0.5784	-0.1077	0.0279	-1.0001
12	-0.9337	-0.0319	0.0206	0.3264	-0.2290	0.2106
13	0.1687	0.2580	-0.4453	0.1093	0.0279	0.2106
14	0.1638	0.1613	-0.1791	-0.1077	-0.1006	0.2106
15	-0.0910	-0.2658	0.2424	0.5675	0.4135	1.4213
16	0.0821	-0.0560	0.0206	-0.1077	-0.6145	-1.0001
17	0.0821	0.2580	0.0206	-0.1318	-0.2290	-1.0001
18	0.1687	0.2680	0.2202	-0.7588	-1.0000	-0.0001
19	0.1687	0.1613	0.1642	-0.1077	0.4135	0.2106
20	0.1687	-0.3218	-0.1570	0.0551	0.4135	0.2106
21	0.1687	0.2580	-0.2235	-0.01077	0.0279	-1.0001
22	-0.0044	0.0486	0.4643	0.3264	0.7990	1.4213
23	0.0821	-0.1285	0.2424	0.3504	0.2849	1.4213

Now, to use the TOPSIS algorithm, first weights should be calculated and normalized by formula (8). Normalized weights for selected criteria are shown in Table (10).

Table 10: Normalized Wight Matrix for selected criteria

Eigenvector	1	2	3	4	5	6
Normalized weight	0.8613	0.6808	0.5529	0.8065	0.6494	0.5118
row number	10	9	5	7	3	8
Name of the Criteria	CRP	Delivery	DD	Quality	PMC	Price

To test our method, the TOPSIS algorithm is applied: first to sort suppliers based on selected criteria and then again based on all criteria. Weights for all criteria are shown in Table (11).

Table 11: Wight Matrix for all criteria

Eigenvalue	1	2	3	4	5	6	7	8	9	10	11
Modulus of maximum amount weight	0.8613	0.6808	0.5529	0.8065	0.6494	0.5118	0.6905	0.5673	0.6112	0.5185	0.8600
Number of the line includes maximum amount	10	9	5	7	3	8	11	6*	1	4	2
Name of the Criteria	CRP	Delivery	DD	Quality	PMC	Price	Other	CR	QMP	MGT	SA

Maximum amount in this column is 0.5750, which is for the eighth criteria since it was chosen before the next maximum amount is selected.

In Table 12 selected suppliers are shown in two positions, first by using all criteria and second by using selected ones:

Table 12: Sorting Suppliers from best to worst, using all Criteria and Selected Criteria

Suppliers (using all criteria)	22	15	6	23	7	4	19	20	5	13	14	12	8	1	3	10	21	11	17	9	18	16	2
Suppliers (using selected criteria)	22	15	6	23	7	4	19	20	5	13	14	12	8	1	3	10	21	11	17	9	18	16	2

4. Conclusion and Future Works

The supplier selection process is a technique for evaluating suitable companies to meet a particular need, and in order to narrow the field for such a selection, some evaluative criteria are needed. Gathering data for these criteria requires valuable resources. In this paper, an integrated algorithm for ranking suppliers is applied as follows: first Principal Component Analysis and Singular Value Decomposition are used to weight various criteria, so that probable human error can be significantly decreased. Secondly, by help of Mean Square Error, these criteria are further reduced to only the most important and viable ones. Lastly, the TOPSIS algorithm orders suppliers from best to worst. This algorithm has two main sections. In the first section, criteria are reduced to the most important ones; in the second, suppliers are ordered.

There are at least two occasions for applying such a process: 1.) when the number of potential suppliers is unmanageably high, in this situation the whole algorithm should be applied for an accidental sample set of potential suppliers to eliminate criteria with less importance, then data information can be gathered only for selected criteria for the rest of the potential suppliers and the algorithm continued. 2.) When potential suppliers must be evaluated short-term. Here for the first order the entire algorithm should be applied for all of potential suppliers to eliminate criteria with less importance, and then only these selected criteria can be used to rank these potential suppliers.

Here are some suggestions for future research on this subject. First, since in the proposed methodology all the inputs are ordinary or single-value numbers, further study can be based on the Fuzzy Set Theory (FST) so it can deal with fuzzy input data. Some criteria may be impractical to evaluate, information may be difficult to obtain, complex to analyze, or there may not be sufficient time to perform such evaluations. When the performance of alternative suppliers can only be approximated, Fuzzy Set Theory effectively helps to model uncertainty and imprecision in supplier selection problems.
Secondly, the proposed model can be implemented to reduce the number of criteria to most important ones in some other problems, to which MCDM approaches can be applied.

Thirdly, this method can be used when a systematic way is needed to determine the weight of criteria, rather than depending upon subjective human judgment.

References

Banker, RD, Khosla, IS 1995, ‘Economics of operations management: A research perspective’. *Journal of Operations Management*, vol. 12, pp. 423–425.

Cengiz, K, Orhan, E, Özgür, K & İhsan, K 2008, ‘Information systems outsourcing decisions using a group decision-making approach’. *Journal Engineering Applications of Artificial Intelligence*, vol. 22, pp. 832–841.

De Boer. L, Labro. E & Morlacchi, P 2009, ‘A review of methods supporting supplier selection.’ *European Journal of Operational Research*, vol. 125, pp. 34-58.

De Ron, AJ 1998, 'Sustainable production: The ultimate result of a continuous improvement'. *International Journal of Production Economics*, vol.56–57, pp. 99–110.

Degraeve, Z, Labro, E & Roodhooft, F 2000, 'An evaluation of supplier selection methods from a total cost of ownership perspective'*, European Journal of Operational Research*, vol. 125, pp.34-58.

Dickson, GW 1996, 'An analysis of vendor selection systems and decision'*, journal of purchasing*, vol. 2, no.1, pp. 5-17.

Dobler, DW, Burt, DN & Lee, L 1990, 'Purchasing and Materials Management'. McGraw-Hill, New York.

Ford, D, Cotton, B, Farmer, D, Gross, A & Wilkinson, I 1993, 'Make-or-buy decisions and their implications', Indust. *Marketing Mgmt*, vol. 22, pp. 207±214.

Ho, W, Xu, XK. & Dey, P 2009, 'Multi criteria decision making approaches for supplier evaluation and selection: A literature review', *European journal of Operational Research*. vol. 202, no.1, pp. 16-24.

Humphreys, PK, Lo, VH & McIvor, RT 2000, 'A decision support framework for strategic purchasing', *Journal of Materials Processing Technology*, vol.107, pp. 353±362.

Lederer, PJ, Rhee, SK 1995, 'Economics of total quality management.' *Journal of Operations Management*, vol.12, pp. 353–367.

Semih, O, Selin, S, K & Elif, I 2008, 'Long term supplier selection using a combined fuzzy MCDM approach: A case study for a telecommunication company', *Expert Systems with Applications*, vol. 36, pp. 3887-3895.

Talluri. S, Narasimhan. R 2004, 'A methodology for strategic sourcing'. *European Journal of Operational research*, vol. 154, pp. 236-250.

Talluri, S, Narasimhan, R 2008, in press. 'Vendor evaluation with performance variability: A max–min approach', *European Journal of Operational Research*.

Tayles, M, Colin Drury 2001, 'Moving from Make/Buy to Strategic Sourcing: The Outsource Decision Process', *Long Range Planning*, vol. 34, pp. 605–622.

Tham, WS 1988, 'Transactions of the American Association of Cost Engineers'. R.1.1.

Weber, CA, Current, JR & Benton, WC 1991, 'Vendor selection criteria and methods', *European Journal of Operation Research*, vol.50, pp. 2-18.