A Case Study of Supplier Evaluation Based on Internal and External Metrics Using Decision-Matrix

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Abstract

Most supplier selection decisions are made subjectively by purchasing personnel or through referrals, although a few are analyzed and made based on internal information. In this study, we develop a supplier recommendation framework to aid supplier selection by integrating internal and external data. To compute the decision matrix and to determine the recommended order of suppliers, TOPSIS is used with a mixture of objective and subjective weighting techniques. A case study of an assembly plant in northern Taiwan was used to validate the proposed method with colleagues from the factory. As a result of the analysis, it was shown that the framework developed in this study meets the information needs of industry buyers in selecting suppliers, especially when companies do not have enough information about suppliers at the outset to assist them in making decisions.

Keywords: Supplier selection, web crawlers, decision matrix, recommendation decisions

1. Introduction

With US-China trade and COVID-19, companies are not only affected by global supply chains, raw materials, and manpower. The business decision-making process must be minimized to minimize the threat of material supply chain impacting the supply chain. The importance of risk management cannot be overstated, especially when managing suppliers. Hence, companies must actively address the issue of risk distribution with a more comprehensive evaluation model. In today's manufacturing industry, finding the right supplier is a significant challenge, and the right supplier is one of the necessary conditions for successful development. Finding the wrong supplier will result in various undesirable factors, including poor quality materials, suppliers failing to deliver on time, and poor after-sales service. These factors will directly affect the enterprise and indirectly adversely affect consumers and other factors. Companies often evaluate suppliers using the QCDS four indicators to avoid these undesirable factors (Chien, Chen, Trappey, & Trappey, 2022).

A supplier should be selected based on the specific situation and using an appropriate method. There are four types of selection methods: intuitive judgment, assessment selection, tender selection, and negotiation selection. For future growth in competitive industries, evaluating the right supplier is essential for maintaining a long-term relationship, leading technology, significant capital, and ensuring a competitive edge. In each industry, decision-makers can use the standard selection model as a reference when developing preferred suppliers to provide objective and practical supplier selection. Analytical methods are used in the majority of supplier selection studies. However, there are still uncertainties, and different selection methods may lead to different rankings (Benyoucef, Ding, & Xie, 2003; Vonderembse, & Tracey, 1999).

The evaluation of suppliers is an uninterrupted process of supplier assessment. The evaluation/selection of suppliers constitutes a complex multi-criteria decision-making (MCDM) problem with many suppliers and various criteria involved. The MCDM approach is divided into two categories: discrete problems handled by multiple attribute decision-making (MADM) or general MCDM, and continuous problems handled by multiple objective decision-making (MODM) techniques (Zakeri, Ecer, Konstantas, & Cheikhrouhou, 2021; Jiang, Liang, & Sun, 2015). There have been several MCDM techniques developed over the years that use different algorithms and concepts to provide solutions. AHP was first proposed by Saaty (1971; 1988), TOPSIS was originally proposed by Hwang, and Yoon, (1981). ANP was proposed by Saaty (1996) and VIKOR by Fontela, and Gabus (1976). According to their performance in evaluating alternatives or criteria, MCDM methods can be divided into two categories: weighting methods and ranking methods. Previous studies on supplier selection have primarily utilized indicators derived from internal company data, employing multi-criteria decision-making (MCDM) techniques to rank suppliers. However, these data are biased toward the historical transactions between the company and the supplier and do not consider the company's situation. Therefore, it is crucial to supplement the supplier management process with external data to mitigate risk exposure. Although this area of research has been relatively lacking in the past, some external factors can be considered when selecting suppliers, such as market trends, supplier reputation, and regulatory compliance, among others, to enhance risk management in the supplier selection process.

This study aims to develop a systematic supplier evaluation mechanism based on the internal ERP system's quality, cost, delivery, and service data and external information (e.g., financial reports). It is critical to include external indicators to avoid the loss of quality costs and internal processing costs (e.g., inspection costs, stocking costs, and failure costs), as this may result in a positive gross profit but a negative net operating profit. Alternatively, poor liquidity may force the company to make a mistaken decision, leading to bankruptcy and the inability to supply goods.

Thus, this study uses crawler technology to collect decision matrices based on essential factors in public financial reports. It compares the results obtained from TOPSIS techniques based on entropy weighting, combined weighting, and subjective weighting. A case study of an assembly plant in northern Taiwan was used to validate the proposed method with colleagues from the factory. Applying the analyzed results, purchasing and supplier management units should be able to prevent risks associated with the purchase of recommended suppliers.

2. Methodology

Figure 1 shows the proposed framework of this study.

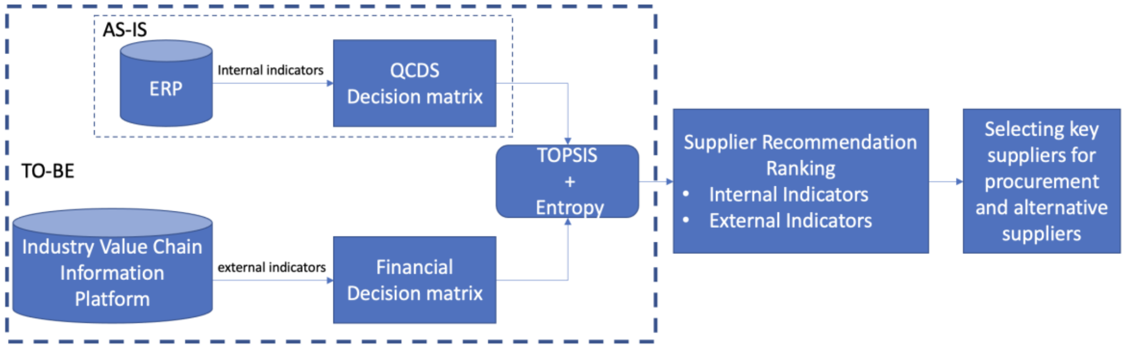

Figure 1: Research Framework of this Study

2.1 Web Crawler

A web crawler is a program that automatically collects a large number of web pages according to the http protocol and some well-defined crawling strategies (Huang, & Zhao, 2009). The use of web crawlers has expanded to many fields, including search engines, web data mining, and business intelligence (Batsakis, Petrakis, & Milios, 2009; Bedi, Thukral, & Banati, 2013). From the Industry Value Chain Information Platform (https://ic.tpex.org.tw/index.php), Figure 2 shows financial information about some suppliers. Figure 3 shows the Python code for crawling the Industry Value Chain Information Platform's data.

2.2 Internal and External Indicators

This study used the most commonly used QCDS in practice as internal indicators. Quality: The quality of a product, and if that quality is stable, is essential; Cost: The lower the cost, the lower the price, and the stronger the company's competitiveness; Delivery: Whether the order will be delivered on time within the delivery period, as well as whether the urgent order will be delivered on time; Service: During the cooperation process, effective communication and after-sales service are essential. Regarding case manufacturers, Q consists mainly of five items: Lot reject rate (LRR), Incoming Quality Control (ICQ), Supplier Corrective Action Report (SCAR), Shipment hold, and Defect material defect rate (DMDA); C consists of Cost Down. D consists of On Time Delivery Rate, and S is composed of three items: Pull in Achievement, Push Out Achievement, and Response Time/Cooperativeness/Aggressiveness.

Mainly financial indicators are used as external indicators. To examine the supplier's operations, we use the following relationships.

- Net profit = effective output - operating expenses
- Inventory turnover = operating cost ÷ average inventory：A reasonable inventory turnover rate represents a company's effi-

cient use of capital and short-term solid solvency.

- Operating cash flow to debt ratio = annual operating cash flow/end of period debt：The operating cash inflow is too low, and the cash generated from profits is insufficient to cover current liabilities.
- Gross profit margin = (operating revenue - operating costs) / operating revenue x 100%

The higher the gross margin, the higher the ability of the company to "create added value"!

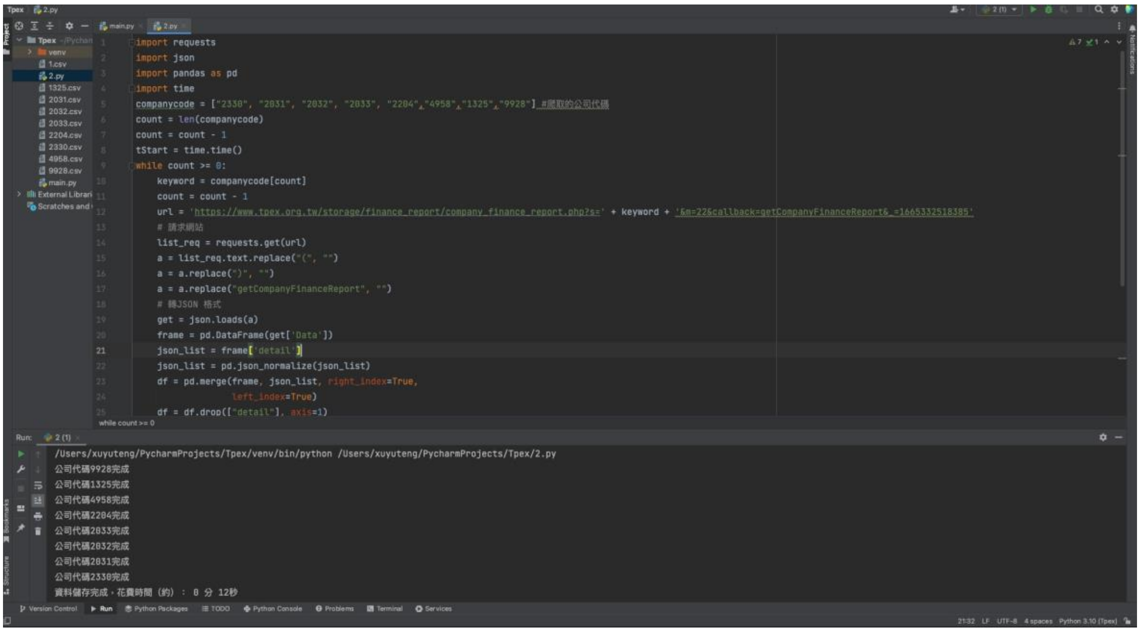

Figure 2: Python Code of the Web Crawler

Figure 3: Industry Value Chain Information Platform

2.3 Decision Matrix Analysis

This study applies TOPSIS to evaluate suppliers using a decision matrix built from internal and external indicators. TOPSIS evaluates solutions from two perspectives: a positive ideal solution and a negative ideal solution. Therefore, it avoids the disadvantage of ignoring different needs and provides the best solution. In this study, subjective weights were provided by the panel of experts, while objective weights were calculated using the Entropy technique. The TOPSIS analysis proceeds as follows:

Step 1: Establish a normalized evaluation matrix.

First, relevant experts are invited to score the evaluation indicators (including qualitative and quantitative ones). Then the scoring results are expressed in the mathematical matrix, and the characteristic matrix is established as follows.

$$D = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1jn} \\ \vdots & & & & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & & & & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} = \begin{bmatrix} D_1(x_1) \\ \vdots \\ D_i(x_j) \\ \vdots \\ D_m(x_n) \end{bmatrix}$$

$$= [X_1(x_1), \cdots, X_j(x_i), \cdots, X_n(x_m)]$$

Using the n evaluation criteria, m evaluation samples are evaluated to create the original matrix. Because different units are used in the original data, the evaluation matrix must be normalized to ensure that each X evaluation criterion has a consistent and objective basis for comparison, of which r is the normalized matrix.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}}}, i = 1,2, \dots, m, j = 1,2, \dots, n$$

Step 2: Establish a normalized weighted matrix.

In this study, we used the entropy technique to calculate the weight. For each evaluation criterion $C_1, C_2 \dots, C_n$, the entropy weights and weights for each criterion are calculated. In this model, the entropy value of the j-th criterion is the uncertainty of the degree of information conveyed by the j-th attribute, assuming that the maximum degree is 1.

$$e_j = \frac{1}{ln\,(m)} \sum_{j=1}^{n} (r_{ij})(\ln r_{ij}),\ i = 1,2, \dots, m, j = 1,2, \dots, n$$

Next, the objective weight between attributes, w_j, is calculated. The purpose of calculating the weight of a criterion is to measure the degree of certainty of the information that can be conveyed by the criterion at the time, so the uncertainty of the ability to convey each criterion must be deducted from the calculation, so the degree of certainty of the decision to convey information by the criterion is (1-e_j)and the weight is w_j.

$$w_j = \frac{1-e_j}{\sum_{j=1}^{n} 1-e_j}$$

These weighted ratings are combined to form the normalized weighted matrix V.

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1jn} \\ v_{21} & v_{22} & \cdots & v_{2jn} \\ \cdots & \cdots & \cdots & \cdots \\ v_{m1} & v_{m2} & \cdots & v_{mjn} \end{bmatrix}$$

$$v_{ij} = w_j r_{ij}, i = 1,2, \dots, m, j = 1,2 \dots, n$$

Step 3: Determine the positive and negative ideal solutions.

The positive ideal solution A* and the negative ideal solution A- are determined according to the normalized weighted value v_{ij}

$$A^* = [v_1^*, v_2^*, \dots, v_J^*], A^- = [v_1^-, v_2^-, \dots, v_J^-]$$

where

$$v_j^* = \begin{cases} max\ v_{ij}, & \text{if } j \text{ is as benefit attrubure} \\ min\ v_{ij}, & \text{if } j \text{ is as cost attrubure} \end{cases}$$

$$v_j^- = \begin{cases} min\ v_{ij}, & \text{if } j \text{ is as benefit attrubure} \\ max\ v_{ij}, & \text{if } j \text{ is as cost attrubure} \end{cases}$$

Step 4: Determine the distances between a solution scheme to the positive and negative ideal solutions.

The distance scale, i.e., the distance from each target to the positive ideal solution and negative ideal solution, can be calculated from the n-dimensional Euclidean distance. The distance from the target to the positive ideal solution A* is S*, and the distance to the negative ideal solution A- is S-.

$$S^* = \sqrt{\sum_{j=1}^{n} (V_{ij} - v_j^*)^2},\ S^- = \sqrt{\sum_{j=1}^{n} (V_{ij} - v_j^-)^2}$$

$$i = 1,2 \cdots, m$$

where, $v_j^*$and v_j^- are the distance from the j-th target to the optimal target and the worst target, respectively, v_{ij} is the weight normalization value of the j-th evaluation index for the i-th target. S* is the closeness of each evaluation target to the optimal target, the smaller the value of S*, the closer the evaluation target is to the ideal target, the better the solution.

Step 5: Determine the relative proximity of the solution scheme relative to the ideal solution.

$$C_i^* = \frac{S_i^-}{(S_i^* + S_i^-)}, i = 1,2 \cdots, m$$

when $C_i^* = 0$ and $A_i = A^-$, which means the goal is the worst goal; when $C_i^* = 1$, $A_i = A^*$, which means the goal is the best goal. Optimal and inferior objectives are unlikely to exist in the actual multi-objective decision.

Step 6: Sort the calculated values C* from highest to lowest in order to select the best solution.

Based on C*, evaluation targets are ranked from smallest to largest. The larger the C* value, the better the evaluation target, and the target with the highest C* value is the best evaluation target.

3. Case Study and Analysis Results

During the epidemic, there were unscheduled work stoppages worldwide, especially in mainland China, where government clearances and work stoppages were frequent, and material shortages and port congestion posed a massive challenge to the entire supply chain. For a customized product to be certified as a qualified supplier takes a lot of time and money. Supplier management in the past was based on internal data and the degree of cooperation with suppliers, but now, external data is needed to enhance the risk management part.

An ERP system was used to compile the data corresponding to the QCDS to develop a decision matrix. Next, TOPSIS was used to rank suppliers based on weights calculated by Entropy and the results are shown in Table 1. The weights of QCDS are 0.55, 0.1, 0.2 and 0.15, respectively.

Table 1: Supplier Recommendation Ranking Using Internal Metrics

Vendor Code	Q						C	D	S			Ranking
	Number of purchases	LRR	IQC	SCAR	Shipment hold	DMDA	Cost down	OTD	Pull in	Pull out	Responsiveness /service	
P15003	23	15	10	10	5	5	6	20	2.6	5	4	1
P9T001	225	15	10	10	5	5	4	18.8	4.1	5	4	2
PCM006	14	15	10	10	5	5	0	20	3.8	5	4	3
PER008	18	15	10	10	5	5	0	18.9	3.2	5	4	4

The Industry Value Chain Information Platform compiles financial reports using crawler technology as external indicators. In Table 2, TOPSIS was used to rank suppliers based on weights calculated by Entropy. The weights of QCDS are 0.25, 0.25, 0.56, and 0.19, respectively.

Table 2: Supplier Recommendation Ranking Using External Metrics

Vendor Code	Net profit margin after tax	Inventory turnover rate	Operating cash to current load ratio	Gross profit margin	Ranking
P15003	21.2	1.2	8.4	33.7	1
P9T001	1.3	2.4	5.2	19.9	4
PCM006	9.1	1.0	7.9	18.0	3
PER008	13.5	0.7	9.1	18.1	2

Tables 1 and 2 show that the recommended suppliers' results differ internally and externally, especially for suppliers P9T001 and PER008. The ranking is further influenced by the number of batches and quantities received. In terms of risk management, this area is not included. For example, the supplier of P9T001, which has an enormous delivery volume, should reasonably have a good financial report. However, he may accept small orders to receive orders, increase line and labor costs, or meet the delivery and increase internal failure costs, which are purely internal. It is recommended that users prioritize P15003, PCM006, or PER008 as the second backup in practice applications. Currently, only internal metrics are considered and not external metrics, which will result in higher risks in the future.

4. Conclusion

Identifying qualified suppliers is difficult for most companies at the beginning of the process. If the supplier interaction is too weak, only internal information is available, which does not provide timely feedback on financial gaps and significant changes in suppliers, especially in customized products whose lead time is over a month. Therefore, this study's most important feature is how to use the current crawling and textual exploration technologies to gather external data to address possible risks and complement the existing internal indicators to evaluate and select suppliers' shortcomings. The results obtained from the data-based framework were cross-validated with industry colleagues with experience in procurement. This study shows that the framework developed meets the information needs of industry buyers in supplier selection, especially when companies lack sufficient supplier information to support decision-making at the outset.

Regarding academic contributions, the study designed indicators mainly focused on incorporating external data to strengthen the TOPSIS ranking results with Entropy as the weight. This approach was superior to using only traditional internal indicators based on data from real-world settings. In terms of practical benefits, in the past, case manufacturers have used an empirical model for supplier selection. However, new employees do not have enough time to accumulate experience, leading to difficulty obtaining supplier information efficiently. This study developed a module on Excel that allows for quick calculation of recommended supplier rankings. The results can be used as a reference for inexperienced colleagues, and experienced colleagues can use the results to verify differences between supplier selection and previous practices. These differences can be used to adjust the recommendation model in the future. Furthermore, future research studies should combine different methods to serve as a reference for companies choosing suppliers and to expand the number of data evaluations.

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About Authors

Chien-Chih Wang is a professor of industrial engineering and management at the Ming Chi University of Technology. He received his B.S. in Applied Mathematics from National Chung Hsing University in 1992, his M.S. in Statistics from National Cheng Kung University in 1994, and his Ph.D. in Industrial Engineering and Management from Yuan Ze University in 2001. His recent research interests include Data analysis and intelligent decision-making, Process quality optimization, Lean six sigma management, Machine vision inspection and application, Service systems, and medical decision-making. He has received research support from the Ministry of Science and Technology of Taiwan and some companies in the industry. He has published over 70 articles in refereed journals. He is an active member of the Chinese Institute of Industrial Engineers (CIIE), the Chinese Society for Quality (CSQ), and the Chinese Society of Electronic Business Management (EBMS).

Ho-Wen Chiang is a master's industrial engineering and management student at the Ming Chi University of Technology. She is open-minded and always willing to consider new ideas, opinions, and arguments. In my past work experience, I have more than five years of experience in supplier management. In managing suppliers, academic knowledge can be applied to this field, which can help us make more realistic choices. I am also very grateful to Dr. Chien-Chih Wang for teaching me to use academic research to assist industry materials so that the industry can have different frameworks and selections.