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SUPPLIER SELECTION FOR VENDOR MANAGED INVENTORY: AN INTEGRATED FUZZY DECISION APPROACH

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Abstract

Vendor Managed Inventory (VMI) is a useful inventory management strategy, allowing a vendor (supplier) to access its retailer's inventory level. Effective selection of appropriate VMI suppliers can enhance supply chain integration and inventory control capability, reduce inventory cost, and improve customer service level. This research develops a systematic VMI supplier selection approach from VMI functional analysis, supplier evaluation factor construction, to optimal VMI supplier selection. The proposed method first uses the value engineering and fuzzy Analytic Hierarchy Process (AHP) to obtain weights of VMI primary and secondary functions. Fuzzy quality function deployment (QFD) approach is then used to derive weights of evaluation factors. Finally, a fuzzy multiple-criteria decision-making (MCDM) is designed to select the best VMI supplier. An electronic original-equipment manufacturer (OEM) company in southern Taiwan is employed to evaluate the applicability of the proposed approach. The results validate that the proposed method can serve as an effective tool for selecting VMI supplier.

Key words: vendor managed inventory, supplier selection, value engineering, Fuzzy AHP, fuzzy QFD, fuzzy MCDM

Introduction

To mitigate the bullwhip effect in supply chain, enterprises have adopted some useful strategies, such as vendor managed inventory (VMI), third party logistics, and distributor integration, which all aim to lower inventory cost and improve customer service level. Among these strategies, VMI can alleviate the bullwhip effect effectively, lower inventory cost, improve supplier service quality, and improve all-around service level (Ru et al., 2018). In VMI, suppliers (vendors) manage the inventory so that they have to know the inventory condition and sale information of enterprises (retailers) to formulate appropriate replenishment strategy, control inventory level, and track transaction dynamics. Accordingly, they can notify the enterprises (retailers) about the shipping information on time and grasp the right opportunity to respond to market change and consumer demand rapidly (Yan et al., 2019).

Under the VMI mechanism, a supplier plays a very important role. Researchers (e.g., Tao et al., 2019; Kadiyala et al., 2020) indicated that the selected suppliers are willing to coordinate with the sourcing demands of enterprises, lower raw material cost, aid in enterprise operation, and improve competence. Hence, it is very important for an enterprise to select its VMI suppliers. Recently, there are numerous researches on supplier selection. For example, Shakourloo et al. (2016) implemented a two-phase supplier selection model for closed loop supply chain by using fuzzy AHP and MOLP methods. Bai et al. (2017) established a hybrid multicriteria supplier selection for green supply chain by using rough set theory, VIKOR, and fuzzy C-means methods. They also evaluated the feasibility of the method in a large chemical company. Amindoust (2018) presented a fuzzy-DEA model in supplier selection process using alpha-cut approach. An application of supplying automotive parts company was presented to show the practicality of this model. Based on interval-valued fuzzy group decision-making, Foroozesh et al. (2018) introduced a new FMEA model. A real case study for manufacturing services was given and solved by their model to demonstrate its capability in the S-SCM environment. Nguyen and Chen (2018) presented a two-stage stochastic programming model to deal with supplier selection for biomass supply chain in the uncertain environment. The applicability of their method was well-performed by numerical studies. Alizadeh and Yousefi (2019) provided an integrated framework for supplier selection problem by using Taguchi loss function, fuzzy cognitive map, hybrid learning algorithm, and goal programming methods. A paint and coating company was employed to examine the effectiveness of their approach. Diba and Xie (2019) developed a new synthetic GRA model to select the best supplier for a milk company in Senegal. Their model was applied to estimate the sustainability level of the company's suppliers. Gupta et al. (2019) proposed a multicriteria decision-making based framework for green supplier selection using an integrated fuzzy AHP with three techniques. They applied the method to a real case study in automotive industry, verifying the applicability of this new technique. Radulescu and Radulescu (2020) combined a group decision method and multi-objective model for supplier selection. A case study connected with the purchase of certain medical devices was conducted and the related results were validated. Rouyendegh et al. (2020) developed an intuitionistic fuzzy TOPSIS method to evaluate green suppliers and criteria conveniently. Their method was effective to select more suitable supplier, and their method can be applied to similar problems.

Nevertheless, most of these studies focus on general supplier selection or supplier selection in one enterprise/industry. Few studies concentrate on the topic of VMI supplier selection. In VMI, inventory is managed by suppliers. It is different from the general logistics suppliers in terms of nature and function. The mechanism and function of VMI should be carefully examined when determining the selection factors. In addition, the VMI supplier selection process mainly relies on subjective judgment and evaluation from experience and intelligence of decision analysts in enterprises. The evaluation values may have high uncertainty and fuzzy characteristics. To effectively solve the two issues, this study applies the fuzzy set theory to develop an integrated VMI supplier selection approach from VMI functional analysis, supplier evaluation factor construction, to optimal VMI supplier selection. Moreover, we take an electronic OEM factory in southern Taiwan to analyze the selection of the suitable VMI supplier.

Fuzzy Number

The fuzzy set theory, introduced by Zadeh (1965), is aimed to deal with subjective, vague, or imprecise information. Hence, these imprecise or vague values can be precisely quantified by fuzzy sets.

Let X be a collection of objects, called the universe, whose elements are denoted by x. A fuzzy set $\tilde{A}$ in X is defined by a membership function $\mu_{\tilde{A}}(x)$, which maps each element x in X into a real number in the interval [0, 1]. Triangular fuzzy number (TFN) is a widely used type of fuzzy set since it can be easily handled arithmetically and interpreted intuitively. Therefore, TFNs are selected to develop the proposed method. A TFN $\tilde{A}$, denoted as $\tilde{A} = (a, b, c)$, where $a \le b \le c$, has the triangular-shape membership function:

$$\mu_{\tilde{A}}(x) = \begin{cases} (x-a)/(b-a), & a \le x \le b, \\ (c-x)/(c-b), & b \le x \le c, \\ 0, & \text{otherwise} \end{cases}$$

where b denotes the element with the largest membership value, a and c denote the lower and upper values of the support of $\tilde{A}$, respectively.

Let two positive TFNs, $\tilde{A}$ and $\tilde{B}$, be (a_1, b_1, c_1) and (a_2, b_2, c_2), respectively. Some arithmetic operations of $\tilde{A}$ and $\tilde{B}$ can be defined as follows:

$$\tilde{A}+\tilde{B}=(a_1+a_2,\ b_1+b_2,\ c_1+c_2),$$
$$\tilde{A}-\tilde{B}=(a_1-c_2,\ b_1-b_2,\ c_1-a_2),$$
$$\tilde{A}\times\tilde{B}=(a_1\cdot a_2,\ b_1\cdot b_2,\ c_1\cdot c_2),$$
$$\tilde{A}/\tilde{B}=(a_1/c_2,\ b_1/b_2,\ c_1/a_2),$$
$$k>0,\ k\cdot\tilde{A}=(ka_1,\ kb_1,\ kc_1).$$

The algebraic operations of TFNS are used to derive the fuzzy sets in the proposed method.

Research Method

The proposed integrated VMI selection method can be divided into three stages as follows: (1) VMI functional analysis: Functional analysis in value engineering is used to divide VMI functions into primary and secondary functions, and build VMI function hierarchical structure, then apply fuzzy AHP to obtain weights of primary and secondary functions. (2) Quality function deployment: Secondary functions are not appropriate to act as evaluation factors for supplier selection. Hence, this study will take secondary functions and supplier evaluation factors collected from literatures, as customer requirements and design parameters in quality function deployment (QFD) respectively, then use fuzzy QFD method to obtain the weights of supplier evaluation factors. (3) VMI supplier selection: According to evaluation factors and qualified suppliers, decision analysts can assess every supplier's performance in each evaluation factor, and build a decision matrix, then use the proposed MCDM approach to select the best suitable VMI supplier. In the following sections, each stage is explained in detail.

VMI Functional Analysis

In value engineering, the function refers to one attribute satisfying one specific demand of analysis object, and is divided into primary function and secondary function. Primary functions are functions in immediate relation to analysis object, while secondary functions are subfunctions to enhance primary functions. Hence, this study uses the functional analysis in value engineering to obtain primary and secondary functions in VMI mechanism. Some research (Torres and Garcia-Diaz, 2018; Li et al., 2019) has focused on functions required by VMI. By reviewing related literature and analyzing the company's VMI mechanisms and functions, decision analysts can acquire primary and secondary functions in VMI mechanism and build a VMI function hierarchical structure.

According to the function hierarchical structure, this study employs fuzzy AHP to calculate weights of primary and secondary functions. First, decision analysts employ linguistic variables to represent relative importance between primary functions, and the corresponding triangular fuzzy numbers can be used to build fuzzy positive reciprocal matrix **E** by means of the equation below:

$$\mathbf{E}=\left[\tilde{e}_{ij}\right]_{n\times n},\tilde{e}_{ij}=1,\forall i=j,$$
$$\tilde{e}_{ij}=\frac{1}{\tilde{e}_{ji}},\forall i,j=1,2,...n \tag{1}$$

where $\tilde{e}_{ij}$: importance of primary function i relative to primary function j, represented by TFN $\left({}_{L}e_{ij},{}_{M}e_{ij},{}_{U}e_{ij}\right)$.

Weight of every primary function in fuzzy positive reciprocal matrix is calculated by following equation:

$$\tilde{W}_i=\sum_{j=1}^{n}\tilde{e}_{ij}\times\left(\sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{e}_{ij}\right)^{-1},\ i,j=1,2,...n \tag{2}$$

where $\tilde{W}_i$: fuzzy weight of primary function i, $\tilde{W}_i=\left({}_{L}W_i,{}_{M}W_i,{}_{U}W_i\right)$.

To assure the assessed values in fuzzy positive reciprocal matrix are consistent, the Lambda-Max method proposed by Csutora and Buckley (2001) is adopted for consistency test. The consistency index (CI) and consistency ratio (CR) equations are provided as follows:

$$\begin{aligned}\lambda_{\max}&=\frac{1}{n}\left(\sum_{i=1}^{n}\frac{{}_{M}e_{ij}\cdot{}_{M}W_i}{{}_{M}W_i}\right)\\ CI&=\frac{\lambda_{\max}-n}{n-1}\\ CR&=\frac{CI}{RI}\end{aligned} \tag{3}$$

where $\lambda_{\max}$: maximal eigenvalue of the matrix. RI: random index.

When CR ≤ 0.1, it indicates that evaluation values given by decision analysts are consistency; when CR>0.1, it indicates that evaluation values are no consistency, and have to be reevaluated by decision analysts.

Similarly, decision analysts can construct several fuzzy positive reciprocal matrices for secondary functions related to each primary function. Further, they can use Eqs. (1)-(3) to calculate weights of secondary functions. Then, weights of secondary functions are multiplied by the weight of the related primary function to determine final weights of secondary functions.

Quality Function Deployment

In VMI analysis, the common secondary functions are often abstract, unquantifiable, and immeasurable. Hence, it is difficult for decision analysts to evaluate the performance of secondary functions directly. Therefore, this study intends to transform the secondary functions into quantifiable and measurable evaluation factors for subsequent supplier selection. There are some researches on supplier selection criteria, such as Bai et al. (2017), Gupta et al. (2019), and Rouyendegh et al. (2020). After reviewing related literature and examining the company's VMI mechanisms, decision analysts can find suitable evaluation factors for VMI supplier selection.

Based on VMI secondary functions and supplier selection evaluation factors, decision analysts can build a QFD table. QFD was designed to improve product quality and functions in product development. It allows personnel in different departments to communicate and translate customer requirements into design parameters and then identify the important design parameters. Here, VMI secondary functions can be deemed customer requirements in QFD, and evaluation factors can be deemed design parameters. Thus, decision analysts can evaluate the relationship level between secondary functions and evaluation factors and build a relationship matrix. Further, a fuzzy QFD approach is designed to calculate weights of evaluation factors. Here, this study adopts independent counting method to calculate weight of every evaluation factor by using following equation:

$$C\tilde{W}_j = \sum_{i=1}^{s} (\tilde{W}_i \times \tilde{R}_{ij}) \tag{4}$$

where $C\tilde{W}_j$: weight of evaluation factor j, j =1, 2, …, n. $\tilde{W}_i^*$: weight of secondary function i, i =1, 2, …, s. $\tilde{R}_{ij}$: relationship between secondary function i and evaluation factor j.

As evaluation factors may interact with each other, this study also considers the correlation between evaluation factors for more accurate calculation. Hence, factor weights obtained in Eq. (4) are adjusted. The weights of adjusted evaluation factors, $C\tilde{W}_j^*$, are calculated by using following equation:

$$C\tilde{W}_j^* = C\tilde{W}_j + \frac{1}{n-1} \sum_{i \neq j, j=1}^{n} (C\tilde{W}_j \times \tilde{r}_{ij}) \tag{5}$$

where $C\tilde{W}_j^*$: weight of evaluation factor j after adjusted. $\tilde{r}_{ij}$: correlation degree of evaluation factor i with evaluation factor j, $i \neq j$.

VMI Supplier Selection

Decision analysts give proper linguistic evaluation value to each qualified supplier for each evaluation factor, transform linguistic evaluation values into corresponding fuzzy numbers, and build a fuzzy decision matrix as follows:

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_r \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{r1} & \tilde{x}_{r2} & \cdots & \tilde{x}_{rn} \end{bmatrix} \end{array}$$

where A_i : supplier candidate i, i = 1, 2, …, r. C_j : evaluation factor j, j = 1, 2, …, n. $\tilde{x}_{ij}$: evaluation value of supplier i in terms of evaluation factor j.

From the above fuzzy decision matrix, the ideal value of each evaluation factor, $\tilde{x}_j^*$, is found, where the ideal value can be defined as the highest triangular fuzzy number (1, 1, 1). Then, unsatisfactory index $\tilde{D}_{ij}$ of each evaluation value $\tilde{x}_{ij}$ is calculated in following equation:

$$\tilde{D}_{ij} = \tilde{x}_j^* - \tilde{x}_{ij} = (1,1,1) - \tilde{x}_{ij} \tag{6}$$

where $\tilde{D}_{ij}$: unsatisfactory index of supplier i in evaluation factor j.

According to unsatisfactory index $\tilde{D}_{ij}$, we can build unsatisfactory matrix $\mathbf{D}=\left[\tilde{D}_{ij}\right]_{r\times n}$.

As evaluation factor weights vary, this study introduces weight of each evaluation factor into unsatisfactory matrix in following equation

$$\tilde{F}_{ij}=C\tilde{W}_j^{*}\times\tilde{D}_{ij} \tag{7}$$

where $\tilde{F}_{ij}$: unsatisfactory weight of supplier i in evaluation factor j.

According to Eq. (7), we can build unsatisfactory weight matrix $\mathbf{F}=\left[\tilde{F}_{ij}\right]_{r\times n}$.

Furthermore, this study adopts fuzzy ranking method, proposed by Deng et al. (2006), to rank unsatisfactory weights of all suppliers in each evaluation factor. Assume ranking result as follows:

$$\begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array}\begin{array}{c} \begin{array}{cccc} 1st & 2nd & \cdots & rth \end{array} \\ \begin{bmatrix} A_2 & A_r & \cdots & A_1 \\ A_r & A_1 & \cdots & A_2 \\ \vdots & \vdots & \ddots & \vdots \\ A_1 & A_2 & \cdots & A_r \end{bmatrix} \end{array}$$

Taking evaluation factor C_1 for example, supplier A_2's unsatisfactory degree ranks the first, supplier A_r's unsatisfactory degree ranks the second, and supplier A_1's unsatisfactory degree ranks the rth. Then transform every supplier in this rank matrix into corresponding unsatisfactory weight to build unsatisfactory weight rank matrix as follows:

$$\begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array}\begin{array}{c} \begin{array}{cccc} 1st & 2nd & \cdots & rth \end{array} \\ \begin{bmatrix} \tilde{F}_{21} & \tilde{F}_{r1} & \cdots & \tilde{F}_{11} \\ \tilde{F}_{r2} & \tilde{F}_{12} & \cdots & \tilde{F}_{22} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{F}_{1n} & \tilde{F}_{2n} & \cdots & \tilde{F}_{rn} \end{bmatrix} \end{array}$$

Based on unsatisfactory weight rank matrix, sum unsatisfactory weights of each supplier under all ranks to get final rating matrix. For example, the final weight of supplier A_1 with unsatisfactory degree ranked the first ($\tilde{AD}_{11}$) equals to total of all unsatisfactory weights of supplier A_1 ranked the first in unsatisfactory weight rank matrix, and the rest of suppliers can be done in a similar way. The final rating matrix is as follows:

$$\begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_r \end{array}\begin{array}{c} \begin{array}{cccc} 1st & 2nd & \cdots & rth \end{array} \\ \begin{bmatrix} \tilde{AD}_{11} & \tilde{AD}_{12} & \cdots & \tilde{AD}_{1r} \\ \tilde{AD}_{21} & \tilde{AD}_{22} & \cdots & \tilde{AD}_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{AD}_{r1} & \tilde{AD}_{r2} & \cdots & \tilde{AD}_{rr} \end{bmatrix} \end{array}$$

where $\tilde{AD}_{ij}$: unsatisfactory weight of supplier A_i at rank j.

By using the linear assignment principle, the above final rating matrix can be transformed into fuzzy linear assignment model as follows:

$$
\begin{aligned}
&Min \quad \sum_{i=1}^{r}\sum_{j=1}^{r}\tilde{AD}_{ij}\, t_{ij} \\
&S.T. \\
&\quad \sum_{i=1}^{r} t_{ij} = 1, \qquad j = 1,2,..,r \\
&\quad \sum_{j=1}^{r} t_{ij} = 1, \qquad i = 1,2,..,r \\
&\quad \forall t_{ij} = 0 \;\; or \; 1
\end{aligned}
\tag{8}
$$

When $t_{ij} = 1$, supplier A_i is assigned to rank j; if $t_{ij} = 0$, then supplier A_i will not assigned to rank j.

There are many methods of solving fuzzy linear programming with different applicable scopes. As to this fuzzy linear assignment model, its objective function is fuzzy number, but all coefficients in constraints are crisp values. Therefore, this study adopts the method proposed by Li and Yang (2004) to solve above fuzzy linear assignment problem. According to their method, fuzzy linear assignment model is transformed as follows:

$$
\begin{aligned}
&Min \quad \sum_{i=1}^{r}\sum_{j=1}^{r}[{}_{M}AD_{ij} - \alpha({}_{M}AD_{ij} - {}_{L}AD_{ij})]t_{ij} \\
&S.T. \\
&\quad \sum_{i=1}^{r} t_{ij} = 1, \qquad j = 1,2,..,r \\
&\quad \sum_{j=1}^{r} t_{ij} = 1, \qquad i = 1,2,..,r \\
&\quad \alpha \in [0,1] \\
&\quad \forall t_{ij} = 0 \;\; or \; 1
\end{aligned}
\tag{9}
$$

The mathematical model can be solved by using mathematical programming software (e.g., LINGO) so as to find the best VMI supplier.

A Case Study

This section introduces a large electronics OEM company in southern Taiwan, as an example of selecting its VMI suppliers by using the proposed method. This company specializes in electronics manufacturing industry, including computer, telecommunication, and consumer electronic products. Most of the products are exported to mainland China, Japan, the U.S., and European countries. This study takes the outsourcing engineering plastic material of the company as an example to demonstrate the process of applying the proposed method to select appropriate VMI supplier.

Supplier Selection Process for the Case Company

The case company formed a VMI supplier selection team consisting of a warehouse controller, a logistics manager, a production scheduler, a process engineer, and an information management director. Then, the team conducted VMI function analysis to acquire primary and secondary functions. After reviewing related literature and analyzing company's VMI mechanism and functions, the team summarized 4 primary functions (PF_1 - PF_4) and 12 secondary functions (SF_1 – SF_{12}) through team discussion. The VMI function hierarchical structure is shown in Figure 1.

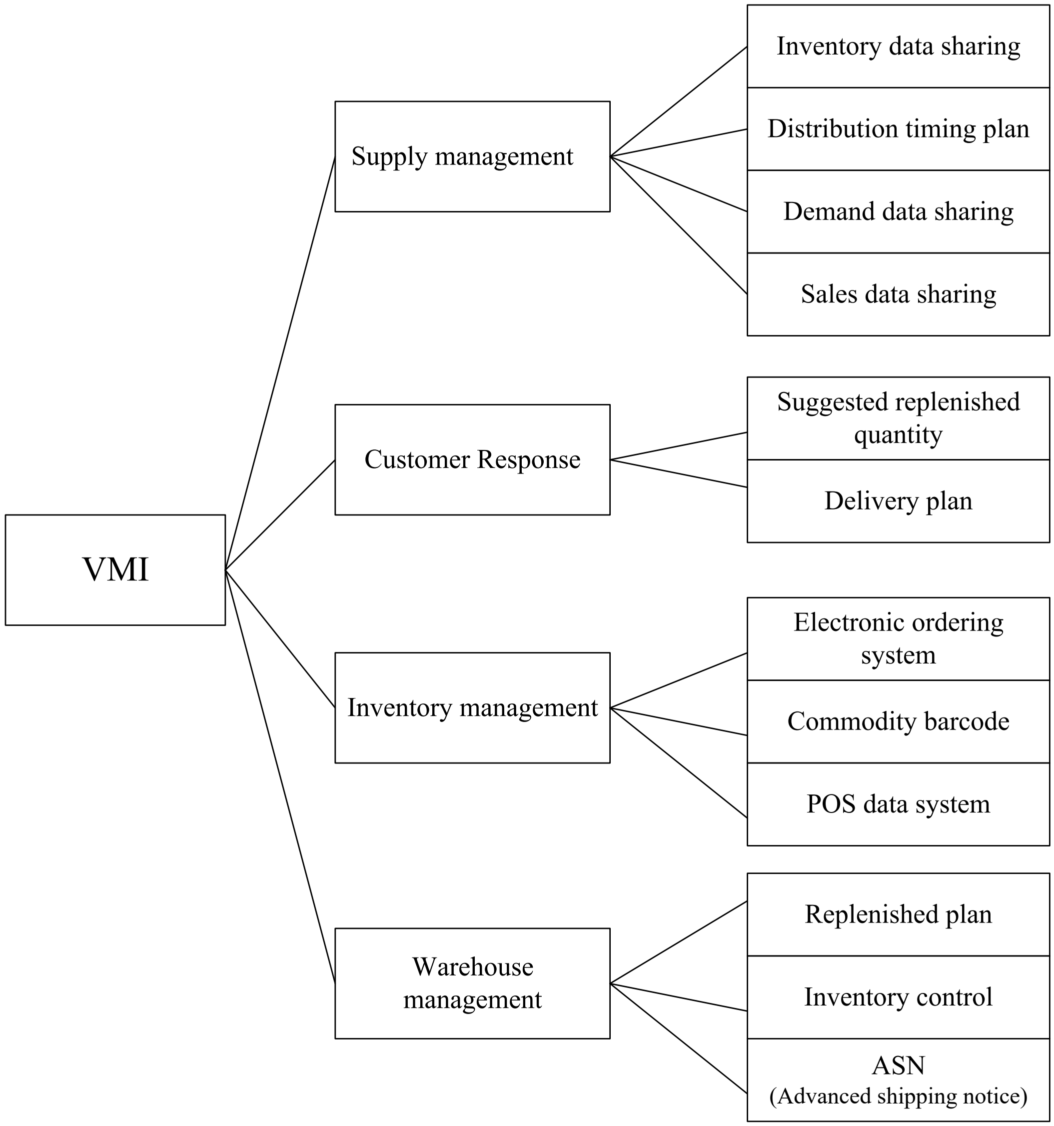


Figure 1. VMI function hierarchical structure.

Based on the VMI function hierarchical structure in Figure 1, the team collected members' opinions through group discussion, and built fuzzy positive reciprocal matrices for primary and secondary functions. Taking the weight calculation of primary functions for example, pairwise comparison linguistic values given by the team were converted into corresponding fuzzy numbers. The fuzzy positive reciprocal matrix is shown below:

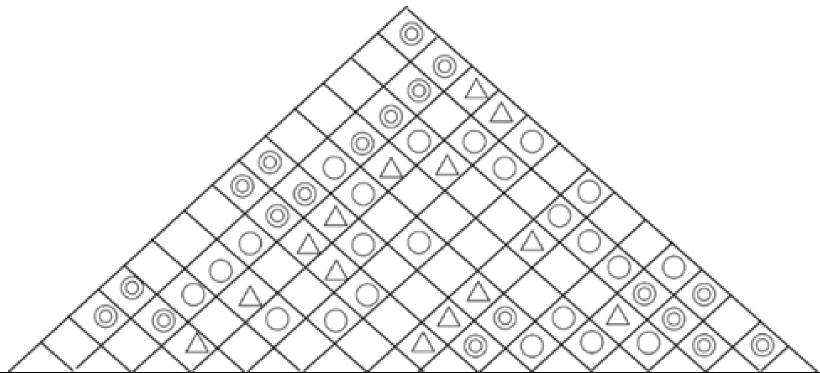
$$\begin{bmatrix} (1,1,1) & (4,5,6) & (\frac{1}{4},\frac{1}{3},\frac{1}{2}) & (4,5,6) \\ (\frac{1}{6},\frac{1}{5},\frac{1}{4}) & (1,1,1) & (\frac{1}{6},\frac{1}{5},\frac{1}{4}) & (2,3,4) \\ (2,3,4) & (4,5,6) & (1,1,1) & (9,9,9) \\ (\frac{1}{6},\frac{1}{5},\frac{1}{4}) & (\frac{1}{4},\frac{1}{3},\frac{1}{2}) & (\frac{1}{9},\frac{1}{9},\frac{1}{9}) & (1,1,1) \end{bmatrix}$$

According to Eq. (2), the primary function weight was computed. To evaluate the rationality of the matrix, the CI and CR of the matrix were calculated to examine its consistency using Eq. (3). The calculated CI＝0.089 and CR=0.099 were both less than 0.1, indicating that this fuzzy positive reciprocal matrix had consistency. Similarly, the team calculated weights of secondary functions and examined the consistency of the matrices. The obtained weights of primary and secondary functions are shown in Table 1.

Table 1. Fuzzy weights of primary and secondary functions.

Primary function	Secondary function
PF_1: (0.227,0.32,0.442)	SF_1: (0.025,0.057,0.126)
	SF_2: (0.011,0.021,0.042)
	SF_3: (0.057,0.121,0.252)
	SF_4: (0.057,0.121,0.252)
PF_2: (0.08,0.124,0.182)	SF_5: (0.016,0.031,0.064)
	SF_6: (0.038,0.093,0.215)
PF_3: (0.393,0.509,0.664)	SF_7: (0.070,0.148,0.313)
	SF_8: (0.151,0.308,0.626)
	SF_9: (0.031,0.052,0.100)
PF_4: (0.038,0.046,0.061)	SF_{10}: (0.010,0.017,0.032)
	SF_{11}: (0.014,0.024,0.043)
	SF_{12}: (0.003,0.005,0.009)

Since it was difficult for the team to evaluate the supplier performance in various secondary functions directly, the secondary function was converted into more easily assessed evaluation factor. After reviewing related literature and analyzing the secondary functions, the team generated 14 evaluation criteria related to secondary VMI functions through team discussion. Further, the team selected proper symbols (◎: strong relation, ○: medium relation, or △: weak relation) to evaluate the relationship degree between the secondary function and evaluation factor, and among evaluation factors so as to build a QFD table, as shown in Figure 2.



		EF_1	EF_2	EF_3	EF_4	EF_5	EF_6	EF_7	EF_8	EF_9	EF_{10}	EF_{11}	EF_{12}	EF_{13}	EF_{14}
PF_1	SF_1	△	◎	△	○	△		○				○	○	○	◎
	SF_2	○	◎			◎		○	○	○		○	○	○	△
	SF_3	○		◎				△							△
	SF_4	△		△				△							◎
PF_2	SF_5		◎	△		○		△				△	○		△
	SF_6	△	◎	○				△				○	◎		△
PF_3	SF_7		△			◎							○		
	SF_8		△			◎									
	SF_9		◎			△							◎		
PF_4	SF_{10}		◎						△	◎	△		○		
	SF_{11}	○	◎				○		△	◎	△		○		
	SF_{12}		◎			△			△	○	△				

Figure 2. QFD table for the company.

The symbols in Figure 2 were then converted into corresponding triangular fuzzy numbers, and Eqs. (4) and (5) were used to calculate adjusted weights of evaluation factors, as shown in Table 2.

Then, the team searched for possible VMI supplier candidates via the Internet, industry recommendation and contact with well-known suppliers. Four qualified candidates (A_1 – A_4) were found. Further, the team conducted an analysis and evaluation on these four suppliers, and gave proper linguistic ratings to their performance under each evaluation factor. The linguistic ratings were converted into corresponding fuzzy numbers in order to build a fuzzy decision-making matrix, which can be converted into the final rating matrix. Both matrices are shown as follows:

$$\begin{bmatrix} (0.8,1,1) & (0.8,1,1) & (0.7,0.85,1) & (0.7,0.85,1) & (0.8,1,1) & (0.8,1,1) & (0.7,0.85,1) & (0.7,0.85,1) & (0,0.15,0.3) & (0.7,0.85,1) & (0.7,0.85,1) & (0.3,0.5,0.7) & (0.3,0.5,0.7) & (0.8,1,1) \\ (0.7,0.85,1) & (0.7,0.85,1) & (0.5,0.65,0.8) & (0,0.15,0.3) & (0.7,0.85,1) & (0.7,0,85,1) & (0.8,1,1) & (0.5,0.65,0.8) & (0.5,0.65,0.8) & (0.8,1,1) & (0.5,0.65,0.8) & (0.7,0.85,1) & (0.7,0.85,1) & (0.7,0.85,1) \\ (0.3,0.5,0.7) & (0.5,0.65,0.8) & (0.3,0.5,0.7) & (0.8,1,1) & (0.5,0.65,0.8) & (0.5,0.65,0.8) & (0.3,0.5,0.7) & (0.8,1,1) & (0.2,0.35,0.5) & (0.5,0.65,0.8) & (0.3,0.5,0.7) & (0.2,0.35,0.5) & (0.2,0.35,0.5) & (0.5,0.65,0.8) \\ (0.5,0.65,0.8) & (0.3,0.5,0.7) & (0.8,1,1) & (0.3,0.5,0.7) & (0.3,0.5,0.7) & (0.3,0.5,0.7) & (0.2,0.35,0.5) & (0.3,0.5,0.7) & (0.3,0.5,0.7) & (0.3,0.5,0.7) & (0.8,1,1) & (0.8,1,1) & (0.5,0.65,0.8) & (0.2,0.35,0.5) \end{bmatrix}$$

$$\begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccc} 1st & 2nd & 3rd & 4th \end{array} \\ \begin{bmatrix} (0.027,0.111,0.413) & (0.044,0.450,1.051) & (0.000,0.167,1.040) & (0.000,0.000,0.877) \\ (0.017,0.098,0.357) & (0.030,0.213,0.942) & (0.012,0.416,1.909) & (0.000,0.026,0.391) \\ (0.130,0.953,2.765) & (0.125,0.740,2.936) & (0.000,0.000,0.000) & (0.000,0.000,0.149) \\ (0.189,1.028,3.848) & (0.019,0.142,0.618) & (0.008,0.061,0.244) & (0.008,0.046,0.915) \end{bmatrix} \end{array}$$

Table 2. Adjusted weights of evaluation factors.

Evaluation factor	Adjusted fuzzy weight	Evaluation factor	Adjusted fuzzy weight
C_1	(0.062,0.241,0.737)	C_8	(0.027,0.112,0.386)
C_2	(0.141,0.461,1.314)	C_9	(0.039,0.131,0.413)
C_3	(0.076,0.294,0.889)	C_{10}	(0.024,0.121,0.384)
C_4	(0.024,0.115,0.357)	C_{11}	(0.048,0.202,0.609)
C_5	(0.166,0.491,1.332)	C_{12}	(0.11,0.426,1.003)
C_6	(0.013,0.055,0.193)	C_{13}	(0.038,0.173,0.489)
C_7	(0.061,0.2680.841)	C_{14}	(0.094,0.36,0.811)

The final rating matrix was transformed into the fuzzy linear assignment model using Eq. (8), as follows:

$$Min \ (0.027,0.111,0.413)t_{11} + (0.044,0.450,1.051)t_{12} + \cdots + (0.008,0.061,0.244)t_{43} + (0.008,0.046,0.915)t_{44}$$

$$\begin{aligned} s.t. \quad & t_{11} + t_{12} + t_{13} + t_{14} = 1 \\ & t_{21} + t_{22} + t_{23} + t_{24} = 1 \\ & t_{31} + t_{32} + t_{33} + t_{34} = 1 \\ & t_{41} + t_{42} + t_{43} + t_{44} = 1 \\ & t_{11} + t_{21} + t_{31} + t_{41} = 1 \\ & t_{12} + t_{22} + t_{32} + t_{42} = 1 \\ & t_{13} + t_{23} + t_{33} + t_{43} = 1 \\ & t_{14} + t_{24} + t_{34} + t_{44} = 1 \\ & \forall t_{ij} = 0 \ or \ 1 \end{aligned}$$

By using Eq. (9), the fuzzy linear assignment model was converted into a crisp mathematical programming model, which can be solved by the software LINGO, as shown as follows:

$$\begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ A_4 \end{array} \begin{array}{c} \begin{array}{cccc} 1st & 2nd & 3rd & 4th \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \end{array}$$

According to the above matrix, the selection priority sequence was $A_1 > A_2 > A_4 > A_3$. Hence, supplier A_1 is the best VMI supplier selected for the case company.

To evaluate the accuracy and reliability of the proposed method, we requested each team member to prioritize the four VMI supplier candidates based on their own analysis method. The ranking result of each team member is shown in Table 3.

Table 3. Ranking result of each team member.

Team member	Ranking sequence
1	$A_1 > A_4 > A_2 > A_3$
2	$A_2 > A_1 > A_3 > A_4$
3	$A_1 > A_3 > A_2 > A_4$
4	$A_1 > A_2 > A_4 > A_3$
5	$A_2 > A_1 > A_3 > A_4$

In Table 3, supplier A_1 is ranked first by three team members and second by two team members. Compared to the other suppliers, supplier A_1 can be considered as the best supplier candidate, apparently consistent with our evaluation result. This finding shows that the proposed model had demonstrated a high degree of accuracy and reliability for analyzing VMI supplier selection problems.

Discussion

The previous section describes the application of the proposed model on the selection of VMI suppliers for an electronic OEM company. The following points are worth discussing: (1) The fuzzy ranking result of primary function weights in Table 1 is inventory management (PF_3) > supply management (PF_1) > customer response (PF_2) > warehouse management (PF_4), indicating that the team prefers inventory management and supply management functions in terms of VMI function requirement. (2) As to secondary function weight ranking in Table 1, the top four important secondary functions are commodity barcode (SF_8), electronic ordering system (SF_7), demand data sharing (SF_3), and sales data sharing (SF_4), respectively. These four secondary functions are the subfunctions of two primary functions, i.e., inventory management and supply management, indicating that the team has significant consistency in evaluating the weights of primary functions and secondary functions. (3) In regard to evaluation factor weight ranking in Table 2, the top five important evaluation factors are EDI capability (C_5), delivery time (C_2), geographic location (C_{12}), communication (C_{14}), and price (C_3), respectively; but previous literature on general supplier selection has emphasizes more on service quality (C_{10}), JIT shipping (C_{11}), and rapid response (C_{13}), which are not among the top five factors. It is probably because the operation and demands of the case company differ from the cases in the previous literature. (4) This study makes a valuable contribution to managerial and practical implication in two folds. First, this study provides a thorough VMI function analysis result. Thus, managers in the case company can easily identify what VMI primary (or secondary) functions perform well, and what VMI primary (or secondary) functions should be enhanced. This information can help managers understand the advantages and disadvantages in the outsourcing plastic material problem. Second, this study provides a framework for a comprehensive evaluation of VMI suppliers. Further, the proposed method is applicable for various companies in Taiwan's electronics OEM enterprises with few modifications since they may face similar outsourcing problems.

Conclusions and Suggestions

As there are scanty studies on VMI supplier selection, we develop a comprehensive and systematic VMI supplier selection approach to address the following two issues: the unique characteristics and nature of the VMI mechanism and the uncertainty inherent in the supplier selection process. In this paper, we propose strategies and methods on the complete VMI supplier selection process, from VMI function analysis, supplier evaluation factor construction, to selection of the best VMI supplier. Moreover, VMI supplier selection approach developed in this study can offer abundant useful information to decision analysts, such as construction of primary and secondary functions in VMI mechanism, VMI function hierarchical structure, construction of supplier selection factors, selection of the optimal VMI supplier, VMI primary and secondary function weight ranking, and evaluation factor weight ranking. Besides the VMI supplier selection model, the proposed fuzzy MCDM model can also be applied in various decision-making fields, including general decision-making issues such as factory site selection, investment project selection, etc. Furthermore, the VMI selection approach can be applied in related supplier selection field (e.g., selection of the third-party logistics provider) upon slight modification.

Although this study aims to make a comprehensive analysis on VMI supplier selection, there are still some improvements that can be made to enhance the practicability. This study assumes that candidate suppliers have sufficient capacities to meet various demands on products, and does not consider the possibility of capacity shortage, which can be further studied. In addition, this study adopts triangular fuzzy numbers, which are more commonly used and convenient to calculate, to build the fuzzy set, other different kinds of fuzzy sets can be used in future studies (e.g., trapezoidal fuzzy number, bell shaped fuzzy number) so as to better meet decision-maker linguistic rating. Finally, the proposed approach can be further developed into a decision support system to expedite the selection process and enhance the practicability and accuracy.

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