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Applying a Direct Approach in Linguistic Assessment and Aggregation on Supply Performance

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Abstract**—**The supply performance has the dynamic continuity behaviors which cover the past, present and future of time horizons. The assessment of supply performance possesses properties of uncertainty and inaccuracy, and is associated with multiple dimensions of supply behavior. Given the difficulty of executing the assessment with quantification, this study uses linguistic variable to assess supply behavior. Linguistic variables then are aggregated using a linguistic ordered weighted averaging operator with maximal entropy to enhance the tolerance and maximize information gathering from the individual behaviors in the aggregation process. In addition, the assessment embeds the product strategy by fuzzy linguistic quantifier for emulating mental decision making in humans, and to ensure the assessment results meet the enterprise strategy. The viewpoint of this paper is to offer a method different from numeric environment (Chang et al. (2006), Wang et al. (2006)) for decision maker to deal with pure linguistic information on the aggregation of decision making.

Keywords**—**Supply performance, Fuzzy linguistic quantifier, Linguistic ordered weighted averaging operator, Product life cycle

1. INTRODUCTION

The current trend for enterprises is to integrate companies with unique core competences so as to create competition advantages. To achieve this goal, enterprises are constructing horizontal-integration structure type supply chains by employing virtual e-business technologies. Undoubtedly, supplier management is to become the core mission of supply chain, and supply performance assessment is the major task. Since the assessment of supply performance being related to an extensive range of measures, it cannot be represented by only a few supply behaviors, thus, making the assessment process more complicated.

Clearly, supply performance is a type of dynamic continuity behavior which comprises the past, present and future. Therefore, supply performance involves not only future uncertainty (i.e. ability on R&D) but also past and present inaccuracy (i.e. defect and delivery). Formerly, crisp values were used to represent supply behavior, however, the overall supply performance was difficult to represent objectively.

Considering the difficulty of assessing all involved attributes, this study uses linguistic variable (Zadeh (1975)) rather than numerical variable for assessing each supply behavior. Then the maximal entropy (Filev and Yager (1995)) linguistic ordered weighted averaging operator (ME-LOWA) (Herrera et al. (1996)) aggregates linguistic variables using the direct approach, which ensures that the assessment process and aggregation result will objectively reflect the actual supply performance. Additionally, the weighted operation, which endues with weights by subjectivity, represents not only the importance of the assessed behavior, but also relate to the aggregation result. To assign the weight with a crisp value is more difficult than the direct linguistic assessment. Therefore, fuzzy linguistic quantifier (Herrera et al. (2000)) is introduced into ME-LOWA to guide the improvement of the weighted operation. Furthermore, the importance of the assessment behavior is adjusted to adapt to the supply chain strategy (Carbonara et al. (2002)) associated with the product life cycle (Aitken et al. (2003)) even incorporating demand uncertainty (Lee (2003)). Hence, this study uses a fuzzy linguistic quantifier to represent the fuzzy majority concept (Kacprzyk (1986)) of importance under different strategies.

Section 2 reviews literatures focused on relevant to supply performance. Section 3 describes linguistic decision

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analysis including linguistic assessment and linguistic aggregation. Section 4 presents a linguistic decision model for supply performance and the algorithm. Section 5 gives a numerical example detailing how to apply this approach. Finally, section 6 discusses conclusions obtained using the proposed approach.

2. SUPPLY PERFORMANCE

Choi and Hartley (1996) evaluated supplier-performance based on consistency, reliability, relationship, flexibility, price, service, technological capability and finances, and also addressed 26 supplier-selection criteria. Verma and Pullman (1998) ranked the importance of the supplier attributes of quality, on-time delivery, cost, lead-time and flexibility. Vonderembse and Tracey (1999) discussed the supplier and manufacturing performances could be determined by supplier selection criteria and supplier involvement. Furthermore, they concluded that the supplier selection criteria could be evaluated by quality, availability, reliability and performance, while supplier involvement could be evaluated by product R&D and improvement, and supplier performance could be evaluated by stoppage, delivery, damage and quality. Additionally, manufacturing performance could be evaluated by cost, quality, inventory and delivery.

Krause et al. (2001) devised a purchasing strategy based on competitiveness in cost, quality, delivery, flexibility and innovation. Tracey and Tan (2001) developed supplier selection criteria, including quality, delivery, reliability, performance and price, and assessed customer satisfaction based on price, quality, variety and delivery. Moreover, Kannan and Tan (2002) determined supplier selection based on commitment, needs, capability, fit and honesty, and developed a system for supplier evaluation based on delivery, quality, responsiveness and information sharing. Kannan and Tan also evaluated supplier selection and performance based on the weights of evaluation attributes or criteria with crisp values that depend on subjective individual judgments.

Muralidharan et al. (2002) compared the advantages and limitations of nine previously developed methods of supplier rating, and combined multiple criteria decision making and analytic hierarchy processes to construct multi-criteria group decision making model for supplier rating. The attributes of quality, delivery, price, technique capability, finance, attitude, facility, flexibility and service were used for supplier evaluation, and the attributes of knowledge, skill, attitude and experience were used for individual assessments. Sarkis and Talluri (2002) suggested that purchasing function has been attracting growing interest as a critical component of supply chain management, and multiple factors have been considered in supplier selection and evaluation, including strategic, operational, tangible and intangible measures within planning horizon, culture, technology, relationship, cost, quality, time and flexibility.

Chan (2003) discriminated between quantitative (cost, resource utilization) and qualitative (quality, flexibility, visibility, trust, innovativeness) performance measurements from the supply chain, and defined the belonging dimension and scale. Sharland et al. (2003) described supplier selection based on cycle time, proximity, manufacturing quality, comparative price and ease of qualifying to construct the supplier performance and relationship. Moreover, Otto and Kotzab (2003) derived the goals of supply chain management from six perspectives, and described standard problems, solutions and performance metrics. Additionally, Gunasekaran et al. (2004) proposed a framework for supply chain performance measurement based on order planning, supplier, production and delivery performance, and defined the related activities into three layers (strategic, tactical and operational). Furthermore, Talluri and Narasimhan (2004) believed strategic sourcing to be critical for firms implementing supply chain management, and grouped supplier capability and performance assessment into six and five categories, respectively. Talluri and Narasimhan also demonstrated 15 proposed vendor evaluation techniques.

3. LINGUISTIC DECISION ANALYSIS

This section is aimed at the demonstration on linguistic assessment and linguistic aggregation. The definition of linguistic variable and the purpose of direction adjustment will be illustrated in subsection of linguistic assessment. The procedure of aggregation will be showed in subsection of linguistic aggregation.

3.1 Linguistic assessment

To achieve uniformity of aggregation, all linguistic assessed results must transform respectively into positive direction before aggregating. This section discusses how to compute the linguistic variable and direction adjustment.

3.1.1 Linguistic variable

This study uses the linguistic variable $S = \{s_0, s_2, ..., s_8\}$, which is defined by the linguistic term set (LTS) (Herrera et al. (2000)) with nine semantic elements, to assess the behaviors. The semantic element (SE) is defined in the unit interval [0, 1] of the linear triangular membership function using fuzzy set (x_L, x_m, x_R), as shown in Fig. 1, where x_L and x_R represent the left and right limits of the corresponding SE by the membership function, and x_m indicates the value at which the membership grade equals 1. Applications can also use the trapezoid membership function for defining the SEs within LTS.

3.1.2 Direction adjustment

The linguistic variables considered in this study are finite and totally ordered LTS, which requires the following properties (Herrera et al. (1995)):

- The set is ordered: $s_i \geq s_j$ if $i \geq j$

Code	SE	(x_L, x_m, x_R)
s_0	None	(0,0,0.12)
s_1	Very Low	(0,0.12,0.25)
s_2	Low	(0.12,0.25,0.37)
s_3	Almost Low	(0.25,0.37,0.5)
s_4	Medium	(0.37,0.5,0.62)
s_5	Almost High	(0.5,0.62,0.75)
s_6	High	(0.62,0.75,0.87)
s_7	Very High	(0.75,0.87,1)
s_8	Perfect	(0.87,1,1)

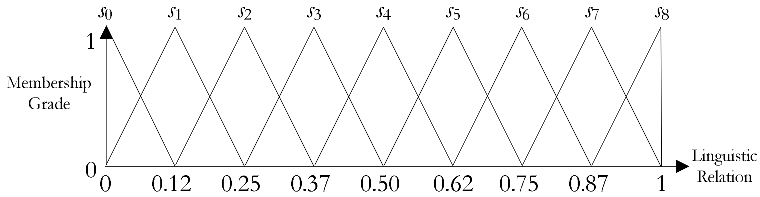


Figure 1. Definition of linguistic variable *S*.

- The negative operator is defined: $Neg(s_i) = s_j$ such that $j = 8 - i$
- Maximization operator: $\max(s_i, s_j) = s_i$ if $s_i \geq s_j$
- Minimization operator: $\min(s_i, s_j) = s_i$ if $s_i \leq s_j$

Consequently, the results of negatively directed behaviors shall apply a negative operator to transform into a positive direction.

3.2 Linguistic aggregation

This section explains the complete process of linguistic aggregation; meeting the selected supply chain strategy, maximizing the entropy aggregation weighted vector, and proceeding linguistic aggregation using the ME-LOWA operator. The philosophy of product strategy based decision criteria and entropy maximization has also been demonstrated in Chang et al. (2006 and 2007), Wang et al. (2006), and Wang (2007).

3.2.1 Using the fuzzy linguistic quantifier for guidance to meet the selected supply chain strategy

The aggregation weighted vector *W* is a mapping to membership function *Q*(*r*) guided by a monotonically non-decreasing fuzzy linguistic quantifier, *Q*, repersented as Eqs. (1) to (2). The membership function *Q*(*r*) represents the membership grade on *r* that belongs to *Q*. The membership function also differs from *Q* (Herrera et al. (2000)). This study uses three quantifiers to fit the supply chain strategy depending on the importance of attribute, as illustrated in Fig. 2.

$$w_k = Q\left(\frac{k}{n}\right) - Q\left(\frac{k-1}{n}\right)\frac{1}{2} \qquad k = 1,\ldots,n \tag{1}$$

$$Q(r) = \begin{cases} 0 & if \quad r < a \\ \dfrac{r-a}{b-a} & if \quad a \leq r \leq b \quad a,b,r \in [0,1] \\ 1 & if \quad r > b \end{cases} \tag{2}$$

As listed in Table 1, the focal company will adopt different supply chain strategies, to meet the market demand, in gaining the competitive advantages during different phases of product life cycle (Aitken et al. (2003)). Thus, the focal company needs to apply different selection criteria for different product development strategies to enable the use of different fuzzy linguistic quantifiers to aggregate behavior among attributes to produce the fuzzy majority rule. This study adopted three perspectives on meeting supply chain strategy for attributes. "Critical" factor is used for fuzzy linguistic quantifier "At least half" to emphasize the stronginfluence of aggregating on results. "Major" factor is used for fuzzy linguistic quantifier "Most" to emphasize the medium influence of aggregation on the results. Finally, "Fundamental" factor is used for fuzzy linguistic quantifier "As many as possible" to represent the degree to which essential requests are satisfied.

3.2.2 Optimizing the aggregation weighted vector

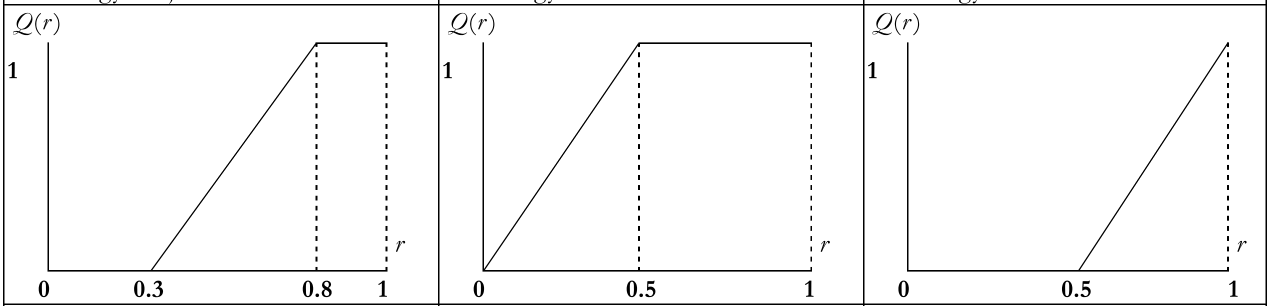
Optimizing the aggregation weighted vector requires calculating the degree of "Orness" and "Entropy" (Dispersion). The calculation is based on the aggregation weighted vector *W*, displayed in Eqs. (3) to (4). Orness, which lies in the unit interval, is a good measurement for characterizing the degree to which the aggregation is an Or-like (Max-like) or And-like (Min-like) operation. When Orness equals 1, the aggregation equals the maximum operation; when Orness equals 0, the aggregation equals the minimum operation; and when Orness equals 0.5, the aggregation equals the arithmetic mean operation. Simultaneously, Entropy represents the measurement for characterizing the degree to which information on the individual behaviors in the aggregation process is used (Yager (1988)).

$$Orness(W) = \frac{1}{n-1}\sum_{k=1}^{n}(n-k)w_k \tag{3}$$

$$Entropy(W) = -\sum_{k=1}^{n} w_k \ln w_k \tag{4}$$

The concept and purpose of optimization is based on the premise that the current Orness should be kept constant to implement an amendment process for maximizing the Entropy. Eq. (5) illustrates the approach to proceed (Filev and Yager (1995)).

Quantifier: Most Fit strategy: Major factor	Quantifier: At least half Fit strategy: Critical factor	Quantifier: As many as possible Fit strategy: Fundamental factor



$Q(r)=\begin{cases} 0 & if \quad r<.3 \\ \dfrac{r-.3}{.8-.3} & if \quad .3\le r\le .8 \\ 1 & if \quad r>.8 \end{cases}$ $a,b,r\in[0,1]$	$Q(r)=\begin{cases} 0 & if \quad r<0 \\ \dfrac{r-0}{.5-0} & if \quad 0\le r\le .5 \\ 1 & if \quad r>.5 \end{cases}$ $a,b,r\in[0,1]$	$Q(r)=\begin{cases} 0 & if \quad r<.5 \\ \dfrac{r-.5}{1-.5} & if \quad .5\le r\le 1 \\ 1 & if \quad r>1 \end{cases}$ $a,b,r\in[0,1]$

Figure 2. Monotonically non-decreasing fuzzy linguistic quantifier.

Table 1. Product factor on product life cycle

Phase	Introduction	Growth	Maturity	Saturation	Decline
Character	Short life cycle Infant stage	Low volume	High volume Low variety	High volume High variety	Low volume
Critical factor	R&D	Service	Cost	Cost	Service
Major factor	Quality Cost Response	Cost Quality Response	Quality Service Response	Quality Response R&D	Cost Quality Response
Fundamental factor	Service	R&D	R&D	Service	R&D

$$Max \quad -\sum_{k=1}^{n} w_k \ln w_k \tag{5}$$

Subject to $Orness(W)=\dfrac{1}{n-1}\sum_{k=1}^{n}(n-k)w_k$ (5a)

$$\sum_{k=1}^{n} w_k = 1 \quad w_k\in[0,1] \quad k=1,\ldots,n \tag{5b}$$

Furthermore, the Lagrange multiplier method can be used to obtain the maximal Entropy aggregation weighted vector W^*, which can aggregate the maximum information from behaviors. Filev and Yager (1995) presented the detailed information. Eqs. (5) can be further simplified as Eqs. (6) and (7). Moreover, the numerical analysis approach can be used to obtain h from Eq. (6), and h can be substituted into Eq. (7) to obtain W^*. The initial vector of W thus is replaced by the new W^*, thus optimizing the aggregation weighted vector.

$$\sum_{k=1}^{n}\left(\frac{n-k}{n-1}-Orness(W)\right)h^{n-k}=0 \tag{6}$$

$$w_k{}^* = \frac{h^{n-k}}{\sum_{k=1}^{n} h^{n-k}} \tag{7}$$

3.2.3 Linguistic aggregation by the ME-LOWA operator

The linguistic aggregation is performed using the ME-LOWA operator based on the maximal Entropy aggregation weighted vector. Let $E = \{e_1, e_2, \ldots, e_m\}$ denote a set of semantic elements to be aggregated, then the ME-LOWA operator F_Q is defined as follows (Herrera et al. (1996)):

$$\begin{aligned} F_Q(e_1,e_2,\ldots,e_m) &= W^*\cdot B^T = C^m\{w_k^*, b_k, k=1,2,\ldots,m\} \\ &= w_1^*\otimes b_1 \oplus (1-w_1^*)\otimes C^{m-1}\{\beta_h, b_h, h=2,3,\ldots,m\} \end{aligned} \tag{8}$$

where $W^* = [w_1^*, w_2^*, \ldots, w_m^*]$, is a maximal Entropy aggregation weighted vector, such that, $w_1^* \in [0, 1]$ and $\sum_i w_i^* = 1$; $\beta_h = \dfrac{w_h^*}{\sum_{k=2}^{m} w_k^*}$, h = 2, 3, ..., m, and B is the associated ordered semantic element (SE) vector. Each SE $b_i \in B$ is the ith largest SE in the collection $e_1, e_2, \ldots, e_m$. C^m is the convex combination operator of m SEs, ⊗ is the general product of a SE by a positive real number and ⊕ is the general additional of SEs (Delgado et al. (1992)). If m = 2, then F_Q is defined as below:

$$\begin{aligned} F_Q(e_1,e_2) &= W^*\cdot B^T = C^2\{w_i^*, b_i, i=1,2\} \\ &= w_1^*\otimes s_j \oplus (1-w_1^*)\otimes s_i = s_k, \quad s_j, s_i\in S, \; j\ge i \end{aligned}$$

such that $k = \min\{8, i + \mathrm{round}(w_1^* \cdot (j - i))\}$, where *round* is the usual round operation, and $b_1 = s_j$, $b_2 = s_i$. If $w_j = 1$ and $w_i = 0$ with $i \neq j\ \forall i$, then the convex combination is defined as $C^m = \{ w_i^*, b_i, i = 1, 2, \ldots, m\} = b_j$.

4. A LINGUISTIC DECISION MODEL FOR SUPPLY PERFORMANCE

This section will lead to construct the multiple attribute matrix for supply performance with pure linguistic environment, and offer a clear algorithm.

4.1 Constructing the multiple attribute matrix for supply performance

Generally, supply performance is related to contract content and realization. Contract attributes and supplier behavior are defined by separating the performance criteria mentioned in previous investigations, and the multiple attribute matrix for supply performance $A = [a_{ijk}]$ constructs on these perspectives. Table 2, modified slightly from Chang et al. (2006), lists the integral description and direction, where suppliers $i = 1, 2, \ldots, m$, attributes $j = 1, 2, \ldots, 5$ and behaviors $k = 1, 2, \ldots, n$ belong to attribute j. The positive (+) direction indicates that a behavior attribute is the more the better, and the negative direction (−) the less the prefer.

4.2 Algorithm

The algorithm for the proposed approach is organized sequentially into five steps, illustrated in Fig. 3 and explained as follows:

Step 1. Constructing the multiple attribute matrix for supply performance. For each supplier, a linguistic variable (see Fig. 1) assesses all of the behaviors listed in Table 1. Then using the negative operator makes the assessment results positive.

Step 2. Using the fuzzy linguistic quantifier for guidance to meet the selected supply chain strategy. From Fig 2, each attribute is fitted with a fuzzy linguistic quantifier according to the supply chain strategy of the focal company. The number of behaviors comprising each attribute then is considered to determine the aggregation weighted vector W using Eqs. (1) and (2).

Step 3. Optimizing the aggregation weighted vector. The degree of Orness is calculated with initial aggregation weighted vector W using Eq. (3), and optimization then is performed on the premise that the current Orness is kept constant to obtain the maximal Entropy aggregation weighted vector W^* using Eqs. (6) and (7).

Table 2. Influencing factors on supply performance (attributes and behaviors)

Attribute	Behavior		Integral description	Direction
R&D (supplier) a_{i1k}	Design	a_{i11}	Upgrading ability on existing design	+
	Technique	a_{i12}	Upgrading ability on existing manufacturing	+
	Odds	a_{i13}	Surpassing in trade on existing character	+
	Customization	a_{i14}	Breadth and depth variety on supply	+
	Innovation	a_{i15}	Innovating ability on the future	+
Cost (contract) a_{i2k}	Price	a_{i21}	Normal unit price	−
	Quantity	a_{i22}	Normal order quantity	−
	Discount	a_{i23}	Average discount ratio on increasing quantity	+
	Decrement	a_{i24}	Average premium ratio on decreasing quantity	−
	Rush	a_{i25}	Average premium ratio on shortening delivery	−
Quality (supplies) a_{i3k}	Import	a_{i31}	Defect ratio on incoming inspection	−
	On-line	a_{i32}	Defect ratio on in-process inspection	−
	Reliability	a_{i33}	Maintenance ratio on after-sales warrant	−
	Stability	a_{i34}	Standard deviation on incoming inspection	−
Service (supplier) a_{i4k}	Delivery	a_{i41}	Match ratio on arrangement delivery	+
	Accuracy	a_{i42}	Match ratio on arrangement quantity	+
	Assurance	a_{i43}	Duration on assurance	+
	Stockout	a_{i414}	Annual stockout ratio	−
Response (contract) a_{i5k}	Regular	a_{i51}	Normal delivery lead-time	−
	Emergency	a_{i52}	Minimum delivery lead-time	−
	Volume	a_{i53}	Requiring lead-time on changing volume	−
	Specification	a_{i54}	Requiring lead-time on changing specification	−
	Modification	a_{i55}	Requiring lead-time on changing design	−

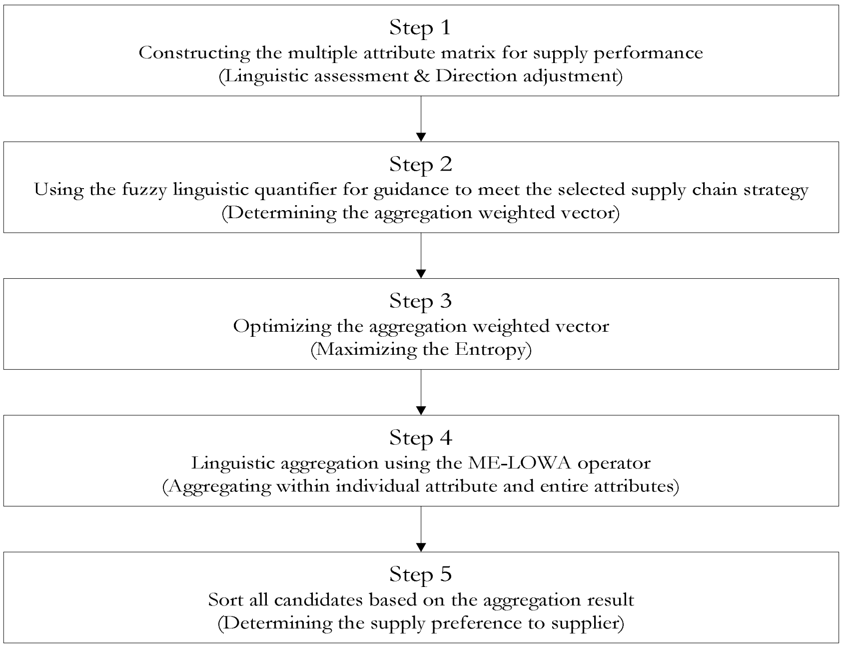


Figure 3. The algorithm procedure.

Step 4. Linguistic aggregation using the ME-LOWA operator. Depending on the number of behaviors in each attribute, the results of uniformed assessment and the maximal Entropy aggregation weighted vector W^* are substituted into Eq. (8) to yield the linguistic aggregation result. Furthermore, the linguistic aggregation of all of the attributes of each supplier are computed respectively.

Step 5. Sort all candidates based on the aggregation result. High aggregation result from Step 4 indicates that the supplier can achieve higher supply performance under the current supply chain strategy, and vice versa.

5. NUMERICAL EXAMPLE

For illustrating the proposed approach, the hypothetical example has given as follows. Considering the case of a focal company specialized in manufacturing notebook computers, it has to select a supplier from three possible candidates to create a local supply chain. Supplier A possesses an advantage in R&D, Supplier B in manufacturing, and Supplier C in distribution. However, the product life cycle of notebook computers is considered in the "Maturity" phase. All behaviors are assessed using the linguistic variable. Table 3 lists the multiple attribute matrix for supply performance and the uniformity results from negative behaviors. An example of the uniformity process of a_{121}, a_{221}, a_{321} by negative operator is displayed below:

Adjusting the result S_7 assessed from negative behavior $a_{121} = S_{8-7} = S_1$
Adjusting the result S_2 assessed from negative behavior $a_{221} = S_{8-2} = S_6$
Adjusting the result S_1 assessed from negative behavior $a_{321} = S_{8-1} = S_7$

The aggregation weighted vector W and maximal Entropy aggregation weighted vector W^* are calculated according to the number of behaviors within an attribute, and an appropriate supply chain strategy is determined, as listed in Tables 4 and 5. The computing process dealing with the fuzzy linguistic quantifier "Most" and involving four items, $k = 1, 2, \ldots, 4$, is displayed below:

$$w_1 = Q\left(\frac{1}{4}\right) - Q\left(\frac{0}{4}\right) = 0 - 0 = 0 \qquad w_2 = Q\left(\frac{2}{4}\right) - Q\left(\frac{1}{4}\right) = \frac{0.5-0.3}{0.8-0.3} - 0 = 0.4$$

$$w_3 = Q\left(\frac{3}{4}\right) - Q\left(\frac{2}{4}\right) = \frac{0.75-0.3}{0.8-0.3} - \frac{0.5-0.3}{0.8-0.3} = 0.5 \qquad w_4 = Q\left(\frac{4}{4}\right) - Q\left(\frac{3}{4}\right) = 1 - \frac{0.75-0.3}{0.8-0.3} = 0.1$$

$$Orness(W) = \frac{1}{4-1}\sum_{j=1}^{4}(4-j)w_j = \frac{1}{3}(3w_1 + 2w_2 + w_3) = 0.4333333$$

$$\sum_{j=1}^{4}\left(\frac{4-j}{4-1}-0.4333\right)h^{4-j}=(1-0.4333)h^3+(\frac{2}{3}-0.4333)h^2+(\frac{1}{3}-0.4333)h-0.4333=0 \qquad h=0.8511435$$

$$w_1^*=\frac{h^3}{\sum_{j=1}^{4}h^{4-j}}=\frac{h^3}{h^3+h^2+h+1}=0.1931607 \qquad w_2^*=\frac{h^2}{\sum_{j=1}^{4}h^{4-j}}=\frac{h^2}{h^3+h^2+h+1}=0.2269426$$

$$w_3^*=\frac{h}{\sum_{j=1}^{4}h^{4-j}}=\frac{h}{h^3+h^2+h+1}=0.2666326 \qquad w_4^*=\frac{1}{\sum_{j=1}^{4}h^{4-j}}=\frac{1}{h^3+h^2+h+1}=0.3132640$$

Table 3. Linguistic assessment and direction adjustment of supply performance

Attribute	Behavior	Direction	Supplier A a_{1jk}		Supplier B a_{2jk}		Supplier C a_{3jk}	
			Assessed	Adjusted	Assessed	Adjusted	Assessed	Adjusted
R&D (supplier) a_{i1k}	a_{i11}	+	s_7	s_7	s_5	s_5	s_3	s_3
	a_{i12}	+	s_5	s_5	s_7	s_7	s_4	s_4
	a_{i13}	+	s_8	s_8	s_7	s_7	s_4	s_4
	a_{i14}	+	s_7	s_7	s_5	s_5	s_3	s_3
	a_{i15}	+	s_8	s_8	s_5	s_5	s_3	s_3
Cost (contract) a_{i2k}	a_{i21}	−	s_7	s_1	s_2	s_6	s_1	s_7
	a_{i22}	−	s_7	s_1	s_7	s_1	s_2	s_6
	a_{i23}	+	s_1	s_1	s_5	s_5	s_7	s_7
	a_{i24}	−	s_6	s_2	s_5	s_3	s_3	s_5
	a_{i25}	−	s_5	s_3	s_7	s_1	s_4	s_4
Quality (supplies) a_{i3k}	a_{i31}	−	s_3	s_5	s_1	s_7	s_7	s_1
	a_{i32}	−	s_3	s_5	s_1	s_7	s_6	s_2
	a_{i33}	−	s_3	s_5	s_1	s_7	s_4	s_4
	a_{i34}	−	s_4	s_4	s_1	s_7	s_4	s_4
Service (supplier) a_{i4k}	a_{i41}	+	s_7	s_7	s_7	s_7	s_2	s_2
	a_{i42}	+	s_7	s_7	s_7	s_7	s_3	s_3
	a_{i43}	+	s_6	s_6	s_4	s_4	s_2	s_2
	a_{i44}	−	s_6	s_2	s_4	s_4	s_2	s_6
Response (contract) a_{i5k}	a_{i51}	−	s_4	s_4	s_4	s_4	s_3	s_5
	a_{i52}	−	s_3	s_5	s_3	s_5	s_2	s_6
	a_{i53}	−	s_2	s_6	s_2	s_6	s_1	s_7
	a_{i54}	−	s_2	s_6	s_2	s_6	s_4	s_4
	a_{i55}	−	s_3	s_5	s_5	s_3	s_7	s_1

Table 4. Vector W and W^* on fitting supply chain strategy with four items

Strategy	Fuzzy linguistic quantifier	w_1	w_2	w_3	w_4	$Orness(W)$
		w_1^*	w_2^*	w_3^*	w_4^*	$Orness(W^*)$
Major	Most	0	0.4	0.5	0.1	0.4333
		0.1932	0.2269	0.2666	0.3133	0.4333
Critical	At least half	0.5	0.5	0	0	0.8333
		0.6478	0.2355	0.0856	0.0311	0.8333
Fundamental	As many as possible	0	0	0.5	0.5	0.1667
		0.0311	0.0856	0.2355	0.6478	0.1667

Table 5. Vector *W* and *W** on fitting supply chain strategy with five items

Strategy	Fuzzy linguistic quantifier	w_1 / w_1^*	w_2 / w_2^*	w_3 / w_3^*	w_4 / w_4^*	w_5 / w_5^*	*Orness*(*W*) / *Orness*(*W**)
Major	Most	0	0.2	0.4	0.4	0	0.4500
		0.1620	0.1791	0.1980	0.2189	0.2420	0.4500
Critical	At least half	0.4	0.4	0.2	0	0	0.8000
		0.5307	0.2565	0.1240	0.0599	0.0290	0.8000
Fundamental	As many as possible	0	0	0.2	0.4	0.4	0.2000
		0.0290	0.0599	0.1240	0.2565	0.5307	0.2000

Table 6. Linguistic aggregating behaviors within individual attribute and entire attributes (Maturity)

Attribute	R&D	Cost	Quality	Service	Response	Performance
Strategy	Fundamental factor	Critical factor	Major factor	Major factor	Major factor	Major factor
Supplier A	s_6	s_3	s_4	s_5	s_4	s_3
Supplier B	s_5	s_5	s_7	s_5	s_4	s_4
Supplier C	s_3	s_7	s_2	s_3	s_4	s_3

Then the ME-LOWA operator is introduced to proceed with intra-attribute (behaviors within individual attribute) and inter-attribute (entire attribute) linguistic aggregation. Since the industry of notebook computer has reached the "Maturity" phase of its product life cycle, the "Cost" of the attribute is assignd to the "Critical" factor and "Quality", "Service" and "Response" of attributes are considered the "Major" factor. Because the mass production system is generally adopted for a mature industry, R&D advantage is no longer the focus of attention, and thus the "R&D" of the attribute is considered a "Fundamental" factor. Table 6 lists the results of aggregating behaviors within individual attribute on the ME-LOWA operator using the fuzzy linguistic quantifier considering the strategy at the "Maturity" phase of product life cycle. To deserve to be mentioned, the aggregation may cause higher result due to round up and lower aggregation threshold generated from the linguistic quantifier. An example of linguistic aggregating behaviors within individual attribute "Cost" of Supplier B is listed below:

$$\begin{aligned} F_Q(s_6,s_1,s_5,s_3,s_1) &= W^* \cdot B^T = [0.5307, 0.2565, 0.1240, 0.0599, 0.0290]\cdot[s_6,s_5,s_3,s_1,s_1]^T \\ &= C^5\{(0.5307,s_6),(0.2565,s_5),(0.1240,s_3),(0.0599,s_1),(0.0290,s_1)\} \\ &= 0.5307 \otimes s_6 \oplus (1-0.5307)\otimes C^4\{(0.5465,s_5),(0.2641,s_3),(0.1277,s_1),(0.0617,s_1)\} \end{aligned}$$

$$C^4\{(0.5465,s_5),(0.2641,s_3),(0.1277,s_1),(0.0617,s_1)\} = 0.5465\otimes s_5 \oplus (1-0.5465)\otimes C^3\{(0.5824,s_3),(0.2815,s_1),(0.1361,s_1)\}$$
$$C^3\{(0.5824,s_3),(0.2815,s_1),(0.1361,s_1)\} = 0.5824\otimes s_3 \oplus (1-0.5824)\otimes C^2\{(0.6742,s_1),(0.3258,s_1)\}$$
$$C^2\{(0.6742,s_1),(0.3258,s_1)\} = 0.6742\otimes s_1 \oplus (1-0.6742)\otimes s_1 = s_k$$

where $k = \min\{8, 1+round[0.6742\times(1-1)]\} = \min\{8,1\} = 1$
such that $C^2\{(0.6742,s_1),(0.3258,s_1)\} = s_1$

$$C^3\{(0.5824,s_3),(0.2815,s_1),(0.1361,s_1)\} = 0.5824\otimes s_3 \oplus (1-0.5824)\otimes s_1 = s_k$$

where $k = \min\{8, 1+round[0.5824\times(3-1)]\} = \min\{8,2\} = 2$
such that $C^3\{(0.5824,s_3),(0.2815,s_1),(0.1361,s_1)\} = s_2$

$$C^4\{(0.5465,s_5),(0.2641,s_3),(0.1277,s_1),(0.0617,s_1)\} = 0.5465\otimes s_5 \oplus (1-0.5465)\otimes s_2 = s_k$$

where $k = \min\{8, 2+round[0.5465\times(5-2)]\} = \min\{8,4\} = 4$
such that $C^4\{(0.5465,s_5),(0.2641,s_3),(0.1277,s_1),(0.0617,s_1)\} = s_4$

$$C^5\{(0.5307, s_6), (0.2565, s_5), (0.1240, s_3), (0.0599, s_1), (0.0290, s_1)\} = 0.5307 \otimes s_6 \oplus (1-0.5307) \otimes s_4 = s_k$$

where $k = \min\{8, 4 + round[0.5307 \times (6-4)]\} = \min\{8, 5\} = 5$

such that $C^5\{(0.5307, s_6), (0.2565, s_5), (0.1240, s_3), (0.0599, s_1), (0.0290, s_1)\} = s_5$

Table 7. Linguistic aggregating behaviors within individual attribute and entire attributes (Introduction)

Attribute	R&D	Cost	Quality	Service	Response	Performance
Strategy	Critical factor	Major factor	Major factor	Fundamental factor	Major factor	Major factor
Supplier A	s_8	s_1	s_4	s_3	s_4	s_4
Supplier B	s_7	s_3	s_7	s_4	s_4	s_4
Supplier C	s_4	s_5	s_2	s_2	s_4	s_3

Finally, Table 6 also lists the aggregation of all attributes on the ME-LOWA operator, which is considered the fuzzy majority rule "Most". The aggregation results indicate that Supplier B has the highest performance, while Suppliers A and C have equal performance based on the current strategy. Besides, Table 7 is offered to be a comparison with "Maturity" and "Introduction" phases. The ability of "R&D" on Supplier A is outstood at "Introduction" phase.As mentioned in the section of Introduction, supplier behaviors are dynamic and continuous in the target period such that they can not be assessed precisely. The linguistic approach is developed exactly for the assessment of vague information. The decrease of sensitivity caused by linguistic approach can be improved with usage of a narrow LTS.

6. CONCLUSION

This study employs a direct approach to linguistic assessment and aggregation on supply performance to reflect uncertainty regarding actual supply behavior and quantification inaccuracy. Simultaneously, the business strategy is considered in a trade-off mechanism of aggregation operation to emulate the mental processes involved in human decision-making. Although the linguistic results will provide the less sensitivity than numeric results, the proposed approach will suit to deal with the information under vague environment and to be consultations for decision makers. This study does not discuss whether decision-makers influence mental cognition and experiential characteristics but Chang et al. (2007) considered the usage of multiple linguistic scales. Therefore, how to deal with assessment inconsistency with different LTSs (Wang et al. (2006)) and how to improve the sensitivity of aggregation result by 2-tuple linguistic variable (Herrera and Martinez (2000a, 2000b, and 2001), Wang, (2007)) will be the topics for future research.

REFERENCE

1. Aitken, J., Childerhouse, P., and Towill, D. (2003). The impact of product life cycle on supply chain strategy. *International Journal of Production Economics*, 85(2): 127-140.
2. Carbonara, N., Giannoccaro, I., and Pontrandolfo, P. (2002). Supply chains within industrial districts: A theoretical framework. *International Journal of Production Economics*, 76(2): 159-176.
3. Chan, F.T.S. (2003). Performance measurement in a supply chain. *International Journal of Advanced Manufacturing Technology*, 21(7): 534-548.
4. Chang, S.L., Wang, R.C., and Wang, S.Y. (2006). Applying fuzzy linguistic quantifier to select supply chain partners at different phases of product life cycle. *International Journal of Production Economics*, 100(2): 348-359.
5. Chang, S.L., Wang, R.C., and Wang, S.Y. (2007). Applying a direct multi-granularity linguistic and strategy-oriented aggregation approach on the assessment of supply performance. *European Journal of Operational Research*, 177(2): 1013-1025.
6. Choi, T.Y., and Hartley, J.L. (1996). An exploration of supplier selection practices across the supply chain. *Journal of Operations Management*, 14(4): 333-343.
7. Delgado, M., Verdegay, J.L., and Vila, M.A. (1992). Linguistic decision making models. *International Journal of Intelligent Systems*, 7(5): 479-492.
8. Filev, D. and Yager, R.R. (1995). Analytic properties of maximum entropy OWA operators. *Information Sciences*, 85(1-3): 11-27.
9. Gunasekaran, A., Patel, C., and McGaughey, R.E. (2004). A framework for supply chain performance measurement. *International Journal of Production Economics*, 87(3): 333-347.
10. Herrera, F., Herrera-Viedma, E., and Martinez, L. (2000). A fusion approach for managing multi-granularity linguistic term sets in decision making. *Fuzzy Sets and Systems*, 114(1): 43-58.
11. Herrera, F., Herrera-Viedma, E., and Verdegay, J.L. (1995). A sequential selection process in group decision making with a linguistic assessment approach. *Information Sciences*, 85(4): 223-239.
12. Herrera, F., Herrera-Viedma, E., and Verdegay, J.L. (1996). Direct approach processes in group decision making using linguistic OWA operators. *Fuzzy Sets and Systems*, 79(2): 175-190.
13. Herrera, F. and Martinez, L. (2000a). A 2-tuple fuzzy linguistic representation model for computing with

words. *IEEE Transactions on Fuzzy Systems*, 8(6): 746-752.

14. Herrera, F. and Martinez, L. (2000b). An approach for combining numerical and linguistic information based on the 2-tuple fuzzy linguistic representation model in decision making. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 8(5): 539-562.
15. Herrera, F. and Martinez, L. (2001). A model based on linguistic 2-tuples for dealing with multigranularity hierarchical linguistic contexts in multiexpert decision-making. *IEEE Transactions on Systems, Man, and Cybernetics. Part B: Cybernetics*, 31(2): 227-234.
16. Kacprzyk, J. (1986). Group decision making with a fuzzy liguistic majority. *Fuzzy Sets and Systems*, 18(2): 105-118.
17. Kannan, V.R. and Tan, K.C. (2002). Supplier selection and assessment: Their impact on business performance. *Journal of Supply Chain Management*, 38(4): 11-21.
18. Krause, D.R., Pagell, M., and Curkovic, S. (2001). Toward a measure of competitive priorities for purchasing. *Journal of Operations Management*, 19(4): 497-512.
19. Lee, H.L. (2003). Aligning supply chain strategies with product uncertainties. *IEEE Engineering Management Review*, 31(2): 26-34.
20. Muralidharan, C., Anantharaman, N., and Deshmukh, S.G. (2002). A multi-criteria group decisionmaking model for supplier rating. *Journal of Supply Chain Management*, 38(4): 22-33.
21. Otto, A. and Kotzab, H. (2003). Does supply chain management really pay? Six perspectives to measure the performance of managing a supply chain. *European Journal of Operational Research*, 144(2): 306-320.
22. Sarkis, J. and Talluri, S. (2002). A model for strategic supplier selection. *Journal of Supply Chain Management*, 38(1): 18-28.
23. Sharland, A., Eltantawy, R.A., and Giunipero, L.C. (2003). The impact of cycle time on supplier selection and subsequent performance outcomes. *Journal of Supply Chain Management*, 39(3): 4-12.
24. Talluri, S. and Narasimhan, R. (2004). A methodology for strategic sourcing. *European Journal of Operational Research*, 154(1): 236-250.
25. Tracey, M. and Tan, C.L. (2001). Empirical analysis of supplier selection and involvement, customer satisfaction, and firm performance. *Supply Chain Management*, 6(3-4): 174-188.
26. Verma, R. and Pullman, M.E. (1998). An analysis of the supplier selection process. *Omega*, 26(6): 739-750.
27. Vonderembse, M.A. and Tracey, M. (1999). The impact of supplier selection criteria and supplier involvement on manufacturing performance. *Journal of Supply Chain Management*, 35(3): 33-39.
28. Wang, S.Y., Chang, S.L., and Wang, R.C. (2006). Assessment of supplier performance based on product-development strategy by applying multi-granularity linguistic term sets. *Omega – The International Journal of Management Science*, (accepted).
29. Wang, S.Y. (2007). Applying 2-tuple multi-granularity linguistic variables to determine the supply performance in dynamic environment based on product-oriented strategy. *IEEE Transactions on Fuzzy Systems*, (accepted).
30. Yager, R.R. (1988). On ordered weighted averaging aggregation operators in multicriteria decisionmaking. *IEEE Transactions on Systems, Man, and Cybernetics*, 18(1): 183-190.
31. Zadeh, L.A. (1975). The concept of a linguistic variable and its application to approximate reasoning. Part I. *Information Sciences*, 8(3): 199-249; Part II. *Information Sciences*, 8(4): 301-357; Part III. *Information Sciences*, 9(1): 43-80.