International Journal of Computational Intelligence Systems, Vol. 10 (2017) 815–823

Supply chain downstream strategic cost evaluation using L-COPRAS method in cross-border E-commerce

Lipeng Feng [1,2,3], Jun Ma [3], Yong Wang [1]*, Jie Yang [3]

[1] *School of Economics and Business Administration, Chongqing University, Shapingba, Chongqing, 400044, China*

[2] *School of Economics and Management, Chongqing University of Arts and Sciences, Yongchuan, Chongqing, 402160, China*

[3] *SMART Infrastructure Facility, Faculty of Engineering and Information Sciences, University of Wollongong, Northfields Ave, Wollongong, NSW 2522, Australia*

E-mail: lpfeng@uow.edu.au, jma@uow.edu.au, wangyongcq@126.com, jiey@uow.edu.au

Received 16 November 2016

Accepted 8 December 2016

Abstract

Cross-border E-commerce has grown exponentially in the past decade in global market. To gain global competition in product-convergent markets, China's over 200 thousands cross-border E-commerce businesses have focused more on the service and cost control of supply chain downstream. In this study, we analyse three strategic cost control measures, summarise ten evaluation criteria for cost and develop an evaluation method for cost control using an extended COmplex PRoportion ASsessment (COPRAS) method, named L-COPRAS. This method is proposed to deal with uncertain or linguistic expression on strategic cost measures with varied weights to different alternatives. A case study of helping a Chinese E-commerce business to select strategic cost control measure on supply chain downstream is conducted. This study indicates that the proposed method is able to deal flexibly with uncertain information in supply chain downstream strategic cost evaluation.

Keywords: Supply chain downstream, Strategic cost evaluation, COPRAS, Cross-border E-commerce

1. Introduction

In recent years, cross-border E-commerce arose and has become a burgeoning model. According to Accenture's predictive report, the global market of cross-border E-commerce will balloon in size to $1 trillion in 2020 and more than 900 million people around the world will be online consumers. China is becoming the largest cross-border market in the world and its transaction volume of imported goods purchased online will reach $245 billion by 2020. One of the most important reasons for the dramatic development on E-commerce is that E-commerce business along the supply chain can lead to big cost savings [6].

Because of the impact of cost on cross-border E-commerce business, the importance of measuring the cost control cannot be overemphasised. Many cost control studies have been performed by using different criteria, such as quality , time and flexibility. As the pace of market globalization quickens, the number of criteria to be considered will in-

* Corresponding author.

crease [1]. With criteria increasing, the chance of qualitative and quantitative criteria appearing simultaneously will be certainly greater.Therefore,using a method which can evaluate simultaneously qualitative and quantitative criteria is a must. The COPRAS [14] is a well-known approach for multi-criteria decision-making (MCDM) problem. In this study, we improved the standard COPRAS method to meet the demand of qualitative and quantitative criteria in supply chain downstream strategic cost control on cross-border E-commerce. This new method, called L-COPRAS, offers a more flexible way to solve evaluating problems in the real-world. Furthermore this study focuses on strategic cost control measures regarding to separately assigned weights. This application has few attempts before.

The reminder of the paper is organised as follows. Section 2 presents the L-COPRAS method in detail. Section 3 overviews strategic cost control measures in supply chain downstream and discusses the selection of criteria in strategic cost control. Section 4 focuses on the application of the L-COPRAS method on a cross-border E-commerce and compared it with the TOPSIS method. Finally, Section 5 presents the conclusion and directions for further steps of this study.

2. The L-COPRAS method

In this section, we firstly overview the standard COPRAS method and preliminary definitions of fuzzy numbers. Then we present an extended COPRAS method, the L-COPRAS method.

2.1. The COPRAS method

The COPRAS method is a widely-used multi-criteria decision making technique, which contains three main steps [14]: (1) normalises initial assessments regarding to each individual evaluation criterion; (2) calculates two optimisation indexes for each alternative based on criteria' optimisation directions (decision directions); and (3) ranks alternatives based on an overall ranking index calculated from optimisation indexes. These steps are briefly described below.

Let $A = \{a_1, a_2, \ldots, a_n\}$ be a set of alternatives for a decision problem, $C = \{c_1, c_2, \ldots, c_m\}$ be a set of evaluation criteria and $W = \{w_1, w_2, \ldots, w_m\}$ be the associated weights with C. Suppose X is the initial assessment (score) matrix

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{pmatrix} \tag{1}$$

where x_{ij} is the assessment on alternative a_i with respect to criterion c_j. Given X, C and W, we can use the COPRAS method to rank alternatives $a_1, \cdots, a_n$.

2.1.1. Normalisation

The normalisation step converts each score x_{ij} in X to a normalised score $\bar{x}_{ij}$ by

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{k=1}^{n} x_{kj}}, \tag{2}$$

for each individual criterion c_j, $j = 1, 2, \ldots, m$. The normalised score matrix is denoted by $\overline{X} = (\bar{x}_{ij})_{n\times m}$. Then the weight of each criterion c_j is imported into $\overline{X}$ to get a weighted score matrix $\widehat{X} = (\widehat{x}_{ij})_{n\times m}$, where

$$\widehat{x}_{ij} = \bar{x}_{ij} \cdot w_j, \quad i = 1, \ldots, n; j = 1, \ldots, m. \tag{3}$$

2.1.2. Optimisation indexes

The calculation of optimisation indexes is determined by the preferable optimisation direction of each criterion. A c_j is associated with one of two preferable optimisation directions, i.e., positive (the bigger the better) or negative (the smaller the better). Without loss of generality, let C^+ be the set of criteria with positive optimisation direction and C^- be the set of criteria with negative optimisation direction, then for each alternative $a_i \in A$ two optimisation indexes corresponding to C^+ and C^- respectively can be calculated as

$$S_i^+ = \sum_{c_j \in C^+} \widehat{x}_{ij}, \quad S_i^- = \sum_{c_j \in C^-} \widehat{x}_{ij}, \quad i = 1, 2, \ldots, n \tag{4}$$

2.1.3. Ranking index

Using these two optimisation indexes, an overall ranking index Q_i is therefore calculated for each alternative a_i:

$$Q_i = S_i^+ + \frac{\sum_{k=1}^{n} S_k^-}{S_i^- \sum_{k=1}^{n} \frac{1}{S_k^-}}, \quad i = 1,2,\ldots,n \tag{5}$$

Finally, Q_i, $(i = 1,2,\ldots,n)$ is used to rank alternatives. A higher Q_i means a better assessment on a_i.

2.2. Fuzzy numbers and their operations

Strategic cost evaluation is an MCDM problem. Particularly because of the introduction of qualitative evaluation, using linguistic methods to process qualitative evaluation becomes more and more popular [11, 15]. In these methods, fuzzy set is a widely used representation of qualitative information.

A fuzzy set $\widetilde{A}$ of a universe of discourse U is defined by a membership function $\mu_{\widetilde{A}}$ such that for any $u \in U$, $\mu_{\widetilde{A}}(u) \in [0,1]$.

A fuzzy number $\widetilde{u}$ is a convex and normal fuzzy set, such that $\mu_{\widetilde{u}}(\alpha u_1 + (1-\alpha)u_2) \geqslant \min\{\mu_{\widetilde{u}}(u_1), \mu_{\widetilde{A}}(u_2)\}$ for any u_1, $u_2 \in U$ and $\alpha \in [0,1]$ and exists $u \in U$ such that $\mu_{\widetilde{u}}(u) = 1$.

The triangular fuzzy numbers are most used and can be expressed as below. A triangular fuzzy number $\widetilde{u}$ is denoted by a triple (u_1,u_2,u_3) and the membership function $\mu_{\widetilde{u}}$ is

$$\mu_{\widetilde{u}}(u) = \begin{cases} 0.0, & u < u_1 \\ \dfrac{u-u_1}{u_2-u_1}, & u_1 \leqslant u < u_2 \\ \dfrac{u_3-u}{u_3-u_2}, & u_2 \leqslant u < u_3 \\ 0.0, & u_3 < u \end{cases} \tag{6}$$

The principle of extension on fuzzy sets can be used to induce operations on fuzzy numbers. In general form, the principle of extension is expressed as: Suppose U and V are two universes of discourse and f is a mapping from U to V. Let $\widetilde{A}$ be a fuzzy set of U, then under the mapping f, a fuzzy set $\widetilde{B}$ of V is obtained with membership function

$$\mu_{\widetilde{B}}(v) = \bigvee_{v=f(u)} \mu_{\widetilde{A}}(u) \tag{7}$$

where $\bigvee$ is the superior of $\mu_{\widetilde{A}}(u)$s. Similarly, we can apply the principle of extension to extend the binary operators "$+$, $-$, $\times$" on $\mathbb{R}$ to the set of all fuzzy numbers. Take two triangular fuzzy numbers $\widetilde{u} = (u_1,u_2,u_3)$ and $\widetilde{v} = (v_1,v_2,v_3)$ for example

$$\widetilde{u}\widehat{+}\widetilde{v} = (u_1+v_1, u_2+v_2, u_3+v_3) \tag{8}$$

$$\widetilde{u}\widehat{-}\widetilde{v} = (u_1-v_3, u_2-v_2, u_3-v_1) \tag{9}$$

$$\widetilde{u}\widehat{\times}\alpha = (u_1\times\alpha, u_2\times\alpha, u_3\times\alpha) \tag{10}$$

$$\widetilde{u}\widehat{\times}\widetilde{v} \approx (u_1\times v_1, u_2\times v_2, u_3\times v_3) \tag{11}$$

where α is a (crisp) real number. Note that in Eq. (11), the result is just a trapezoidal approximation [4, 5] which may lead to errors in complex calculation involving many multiplications.

Table 1. Commonly used linguistic variables expressed in triangular fuzzy numbers.

Linguistic variable	Triangular Fuzzy Number
Very Low (VL)	(1.0, 1.0, 3.0)
Low (L)	(1.0, 3.0, 5.0)
Medium (M)	(3.0, 5.0, 7.0)
High (H)	(5.0, 7.0, 9.0)
Very High (VH)	(7.0, 9.0, 9.0)

In real applications, fuzzy numbers are often used to represent linguistic variables which convey uncertainty in opinions, assessments or evaluations. Several typical sets of linguistic variables and corresponding triangular fuzzy numbers are shown in Table 1. From these preliminary linguistic variables, complex linguistic variables can be induced through operations on fuzzy numbers.

2.3. The L-COPRAS method

The motivation of the L-COPRAS method comes from three aspects: adapting advanced defuzzification techniques, providing a general form of ranking index and assigning different weights for each alternative.

Step 1: Defuzzify linguistic variables to numeric form in the initial assessment matrix X if required

Defuzzifying the linguistic expression is the first step when handling uncertainty using fuzzy logic and fuzzy numbers. Many defuzzification techniques (such as mean of maxima, centre of gravity, centre of mean, and midpoint of area) have been presented and developed in engineering applications to achieve a common target of converting a fuzzy sets into a numeric value [12]. For example, the centre of gravity method calculates the x-coordinator of the centre of a fuzzy set as

$$G = \frac{\int \mu_{\widetilde{A}}(u) \cdot u du}{\int \mu_{\widetilde{A}}(u) du}. \tag{12}$$

In this study, we claim that using advanced defuzzification techniques can provide more options to solve real-world problems. For its popularity in applications and simplicity in calculation, the centre of gravity method will be used as the default defuzzification technique below.

Step 2: Normalise defuzzified assessment matrix to normalised assessment matrix $\overline{X}$ following standard COPRAS method

There are many different normalisation methods. Some of them are (ref: `https://cran.r-project.org/web/packages/clusterSim/clusterSim.pdf`):

Table 2. Compared normalisation methods.

Type	Formula
n1	$\bar{x}_{ij} = \frac{x_{ij} - \bar{\boldsymbol{x}}_j}{s_j}$
n3	$\bar{x}_{ij} = \frac{x_{ij} - \bar{\boldsymbol{x}}_j}{r_j}$
n4	$\bar{x}_{ij} = \frac{x_{ij} - \min_i\{x_{ij}\}}{r_j}$
n5	$\bar{x}_{ij} = \frac{x_{ij} - \bar{\boldsymbol{x}}_j}{\max_i \lvert x_{ij} - \bar{\boldsymbol{x}}_j \rvert}$
n6	$\bar{x}_{ij} = \frac{x_{ij}}{s_j}$
n7	$\bar{x}_{ij} = \frac{x_{ij}}{r_j}$
n8	$\bar{x}_{ij} = \frac{x_{ij}}{\max_i\{x_{ij}\}}$
n9	$\bar{x}_{ij} = \frac{x_{ij}}{\bar{\boldsymbol{x}}_j}$
n10	$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}$
n11	$\bar{x}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}$
n12	$\bar{x}_{ij} = \frac{x_{ij} - \bar{\boldsymbol{x}}_j}{\sqrt{\sum_{i=1}^{n} (x_{ij} - \bar{\boldsymbol{x}}_j)^2}}$
n13	$\bar{x}_{ij} = \frac{x_{ij} - m_j}{r_j/2}$

where

- $\bar{\boldsymbol{x}}_j$ – mean for the j-th criterion
- s_j – standard deviation for the j-th criterion
- r_j – range for j-th criterion
- m_j – mid-range for the j-th criterion, i.e. $m_j = \frac{\max_i\{x_{ij}\} + \min_j\{x_{ij}\}}{2}$

We can see that the standard COPRAS method uses the type "n10".

Step 3: Generate weighted assessment matrix $\widehat{X}$ by $\widehat{x}_{ij} = \bar{x}_{ij} \cdot w_{ij}$

Compared with the standard COPRAS method, the L-COPRAS method uses a weight matrix; while the standard COPRAS method uses a vector, which can be seen as a special case of the L-COPRAS method.

Step 4: Calculate optimisation indexes for each alternative by $S^+ = \sum_{c_j \in C^+} \bar{x}_{ij} \cdot w_{ij}$ and $S^- = \sum_{c_j \in C^-} \bar{x}_{ij} \cdot w_{ij}$

The sum of S_i^+ and S_i^- by Eq. (3) and Eq. (4) is

$$S_i^+ + S_i^- = \sum_{c_j \in C} \bar{x}_{ij} \cdot w_j \tag{13}$$

It is the weighted sum of normalised scores on a_i with respect to all criteria. Because the weighted sum is one of typical aggregation operators, we can replace it by other popular aggregation operators such as the geometric mean. Moreover, the weight associated to a criterion is the same for all alternatives by the standard COPRAS method, which is unusual to the practical problems. Commonly, different alternatives have different emphases on different criteria and associate the criteria with different weights. Hence, it is rational to replace w_j by w_{ij} in Eq. (13), i.e. the extended S_i^+ and S_i^- are calculated by

$$\begin{aligned} S_i^+ &= \sum_{c_j \in C^+} \widehat{x}_{ij} = \sum_{c_j \in C^+} \bar{x}_{ij} \cdot w_{ij}, \\ S_i^- &= \sum_{c_j \in C^-} \widehat{x}_{ij} = \sum_{c_j \in C^-} \bar{x}_{ij} \cdot w_{ij}, \quad i = 1, \ldots, n \end{aligned} \tag{14}$$

Step 5: Select ranking function f to calculate ranking index Q_i

Recall Eq. (5), the ranking index Q_i is completely determined by optimisation indexes S_i^+ and

S_i^-, $i = 1, 2, \cdots, n$. Furthermore, Q_i can be any function $f(S_i^+, S_i^-)$ of S_i^+ and S_i^- such that f is increasing with S_i^+ and decreasing with S_i^-. Some typical forms of such f are

1. difference between S_i^+ and S_i^-: $f_1(S_i^+, S_i^-) = S_i^+ - S_i^-$
2. ratio between S_i^+ and S_i^-: $f_2(S_i^+, S_i^-) = \frac{S_i^+}{S_i^-}$
3. positive proportion of S_i^+: $f_3(S_i^+, S_i^-) = \frac{S_i^+}{S_i^+ + S_i^-}$

Similarly, we can build more complex form of f as the ranking index provided that the f is increased with S_i^+ and decreased with S_i^-.

Step 6: Make final decision based on Q_i

3. Criteria choice on Supply chain downstream strategic cost control measures

Cost is an important element that has direct impact on efficiency in business [10]. Now, business need to implement strategies to manage and reduce costs not only on a short-term basis, but also in a long run for intense competitive pressures [8]. Cost control problem on E-commerce business is more prominent than the other business, because most products in E-commerce business need to achieve through logistics and distribution. In the study, we focus on the evaluation of supply chain downstream strategic cost on E-commerce business and provide three strategic cost control measures from different perspectives.

Measure 1: to choose the right logistics operation modes

Measure 2: to achieve value chain by entire process of supply chain management (SCM)

Measures 3: to improve facility development and information & communication technology (ICT)

With the above three strategic cost control measures, we can evaluate supply chain strategic cost performance from different perspectives. In this study, we summarise these costs in ten categories as criteria to evaluate the three potential strategic cost control measures. They are:

Rental cost (c_1) is the dominant cost on cross-border E-commerce business. It includes the cost of business operation platform, bond, annual fee for technical service, and capital cost, etc.

Operating cost (c_2) includes packaging cost, maintenance costs, order handling cost, shipping cost, administration cost, warehouse cost, distribution cost and labour cost, etc.

Safety cost (c_3) is the cost caused by the business's reputation, brand, scale, and organisational impact, etc. Though it is intangible, it will have a marked impact on the future of E-commerce business.

Risk cost (c_4) is the legal and economic cost caused by different international economy and politics, international policy, customs risk and exchange rate, etc. All these can dramatically bring cost fluctuations.

Added service capacity (c_5) is the ability to provide additional services for individual customers. It can generate additional revenue by offering increased benefits. So the more service the business can provide, the less average cost it has. It is extremely important to E-commerce business, because E-commerce business does not create value itself and it just realises value by its service. The service is one of the most important factors to win competition.

Timely distribution rate (c_6) is the cost caused by delayed or not on-time delivery. Distribution is the process that business is most close to customer. So this process can best reflect the real reaction of customers.

No return rate (c_7) is the cost caused by low performance-price ratio. Return is the process from supply chain downstream to upstream.To E-commerce business, the product is provided by supply chain upstream. But it is the customers in supply chain downstream who measure the quality. If the product has low performance-price ratio, customers usually return it. No doubt, the return will increase the cost of the whole supply chain.

Customer complaint rate (c_8) is the cost caused by customer dissatisfaction with poor service level. Customer satisfaction is the ultimate purpose for E-commerce business, but it is not easy to quantify an exact figure. So in the study, we quantify service satisfaction with exact customer compliant rate.

Information and communication technology (c_9) is the cost caused by systems quality, information quality, environmental and technical characteristics, technical support, support functions cost and information technology, etc.

Facility management (c_{10}) is the cost caused by geographical location, environmental compliance and capacity, etc.

The selection of the ten criteria is based on the research of many scholars and third-party consultancies [2, 3, 7, 9, 13]. The criteria are dramatically different which can be quantitative or qualitative. Though that costs are often used by decision-makers to appraise the efficiency, it is difficult to differentiate these costs in an E-commerce business. Furthermore the costs are rarely constant and predictable. So we developed the L-COPRAS method to evaluate the costs.

4. Case study

In this section, we use the presented L-COPRAS method to evaluate three potential strategic cost control measures for a cross-boarder E-commerce business in China.

4.1. Background

A Chinese cross-boarder E-commerce business wants to select one of three strategic cost control measures given in Section 3 to increase the whole performance in its supply chain. The company consulted a third-party consultancy to evaluate the three potential strategic cost control measures in terms of the 10 cost-related criteria given in Section 3. Regarding each individual criterion, the consultancy defined its optimisation direction and weights for each alternative measure which are listed in Table 3.

Table 3. Criteria for strategic cost control measures with decision directions and predefined weights.

Criterion	a_1	a_2	a_3	Direction
c_1	0.10	0.10	0.10	negative
c_2	0.15	0.09	0.08	negative
c_3	0.15	0.09	0.08	negative
c_4	0.10	0.10	0.10	negative
c_5	0.12	0.15	0.08	positive
c_6	0.12	0.15	0.08	positive
c_7	0.12	0.15	0.08	positive
c_8	0.12	0.15	0.08	negative
c_9	0.01	0.01	0.16	positive
c_{10}	0.01	0.01	0.16	positive

With respect to the 10 criteria, evaluations on the three strategic cost control measures are given (see Table 4) and expressed using linguistic terms listed in Table 1.

We apply the L-COPRAS method to rank alternatives as follows:

Step 1: Defuzzify the linguistic expression

Let $X = (x_{ji})_{3\times 10}$ be the raw score matrix, we use the centre of gravity of the corresponding triangular fuzzy number to replace the initial assessment in X. Given a triangular fuzzy number $\widetilde{a} = (a_1, a_2, a_3)$, the centre of gravity of $\widetilde{a}$ is simply $(a_1 + a_2 + a_3)/3$. Hence a defuzzified score matrix X' is obtained:

Step 2: Normalise the defuzzified score matrix

Based on the standard COPRAS method, a normalised score matrix $\overline{X}$ is obtained from X'.

Step 3: Generate weighted assessment matrix $\widehat{X}$

Noted that $\widehat{x}_{ij} = \overline{x}_{ij} \cdot w_{ij}$, we get $\widehat{X}$.

Step 4: Calculate optimisation indexes S_i^+ and S_i^-

In this example, $C^- = \{c_1, c_2, c_3, c_4, c_8\}$ and $C^+ = \{c_5, c_6, c_7, c_9, c_{10}\}$, hence S_i^+, S_i^- and Q_i ($i = 1, 2, 3$) are calculated and listed in Table 6.

Table 6. Ranking indexes of optional strategic cost control measures based on default ranking index Q_i and alternative ranking indexes given in Section 2.3.

	S^-	S^+	Q	f_1	f_2	f_3
a_1	0.281	0.110	0.215	-0.171	0.390	0.281
a_2	0.164	0.211	0.391	0.047	1.285	0.562
a_3	0.112	0.246	0.508	0.133	2.184	0.686

Table 4. Initial assessment matrix in linguistic expression ("+" = positive, "-" = negative).

Criteria	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
Direction	-	-	-	-	+	+	+	-	+	+
a_1	VH	VH	H	H	M	M	M	M	L	L
a_2	M	M	L	L	H	VH	VH	VH	L	L
a_3	M	M	L	L	L	M	M	M	VH	VH

Table 5. Case study steps 1–3.

Defuzzified score matrix X'									
8.33	8.33	7.00	7.00	5.00	5.00	5.00	5.00	3.00	3.00
5.00	5.00	3.00	3.00	7.00	8.33	8.33	8.33	3.00	3.00
5.00	5.00	3.00	3.00	3.00	5.00	5.00	5.00	8.33	8.33
Normalised defuzzified score matrix $\overline{X}$									
0.454	0.454	0.538	0.538	0.333	0.273	0.273	0.273	0.209	0.209
0.273	0.273	0.231	0.231	0.467	0.454	0.454	0.454	0.209	0.209
0.273	0.273	0.231	0.231	0.200	0.273	0.273	0.273	0.581	0.581
Weighted assessment matrix $\widehat{X}$									
0.045	0.068	0.081	0.054	0.040	0.033	0.033	0.033	0.002	0.002
0.027	0.025	0.021	0.023	0.070	0.068	0.068	0.068	0.002	0.002
0.027	0.022	0.018	0.023	0.016	0.022	0.022	0.022	0.093	0.093

Step 5 and Step 6: Calculate the ranking index Q_i and rank available measures

The index Q_i and other three alternative indexes f_1, f_2, and f_3 indicate a_3 is the best option which is followed by a_2 and a_1.

4.2. Discussion

4.2.1. Alternative calculation for optimisation index

In Section 2.3, we mentioned that we can use other aggregation methods to calculate the two optimisation indexes S_i^+ and S_i^-. For example, considering that the geometric mean is a kind of information fusion which can better handle normalised values and cope with varied ranges of values, we use it to calculate the two optimisation indexes, i.e.,

$$S_i^+ = \sqrt[|C^+|]{\prod_{c_j \in C^+} \widehat{x}_{ij}}, \quad S_i^- = \sqrt[|C^-|]{\prod_{c_j \in C^-} \widehat{x}_{ij}}. \tag{15}$$

Using geometric mean for optimisation indexes in the L-COPRAS method, the ranking indexes are calculated accordingly and listed in Table 7. The comparison indicates that similar rankings of alternative, $a_3 > a_2 > a_1$, is obtained.

Table 7. Comparison of ranking indexes based on alternative calculation of optimisation indexes.

	S^-	S^+	Q	f_1	f_2	f_3
	by weighted-sum					
a_1	0.281	0.110	0.215	-0.171	0.390	0.281
a_2	0.164	0.211	0.391	0.047	1.285	0.562
a_3	0.112	0.246	0.508	0.133	2.184	0.686
	by geometric mean					
a_1	0.054	0.011	0.563	-0.042	0.212	0.175
a_2	0.029	0.017	1.022	-0.012	0.579	0.367
a_3	0.022	0.037	1.360	0.014	1.641	0.621

4.2.2. Comparison with TOPSIS

TOPSIS is one of the most popular methods for strategy selection and evaluation problems. The L-COPRAS method presented is similar to it in two points: 1) both methods need to identify the optimisation direction of criteria, and 2) both methods need to normalise the initial decision matrix. The main differences between them are: 1) the L-COPRAS method uses a weight matrix in processing, while the TOPSIS method uses a weight vector; and 2) the L-COPRAS method uses the two optimisation indexes to build the ranking index, while the TOPSIS uses the distances to two ideal (optimal and worst) solutions to build the ranking index. We compared both methods using the above data and using different normalisation methods (see Table 8). An interesting outcome of using the TOPSIS method is that it gives the same ranking, i.e., $a_3 > a_2 > a_1$, using the normalisation methods in Table 2. Although this outcome shows the stability of the TOPSIS method in terms of ranking, this fact may not be a good sign in applications because it means the difference between different criteria is not significant any more after normalisation when considering their impacts on the decision problem.

Table 8. Comparison between the L-COPRAS and the TOPSIS methods.

normalisation type	L-COPRAS			TOPSIS		
	a_1	a_2	a_3	a_1	a_2	a_3
n1	3	1	2	3	2	1
n3	3	1	2	3	2	1
n4	2	1	3	3	2	1
n5	3	1	2	3	2	1
n6	3	2	1	3	2	1
n7	3	2	1	3	2	1
n8	3	2	1	3	2	1
n9	3	2	1	3	2	1
n10	3	2	1	3	2	1
n11	3	2	1	3	2	1
n12	3	1	2	3	2	1
n13	2	1	3	3	2	1

5. Conclusion

The rapid development of E-commerce owes to the saving of transaction cost. Nevertheless, there is surprisingly little empirical evidence as to the impact of E-commerce on the cost of business. Based on the analysis of characteristics of cross-border E-commerce, we explored the issue of strategic cost control in supply chain downstream. We have argued that researchers in E-commerce need to take advantage of strategic cost, because traditional cost models usually focus on estimating cost and they do not have mechanism for alternative selection to make decision. Consequently, we have summarised three strategic cost control measures and evaluated them with an extended COPRAS method. Furthermore we have developed and assigned different weight set to each strategic cost measure. Then, we facilitated the experts to evaluate alternatives with ten different criteria. At last this in-depth case study indicates that the facility improvement and its related ICT proved to be most valuable. This is the basis for cross-border E-commerce supply chain wide application. It will enable a new level of transparency and thus a more sophisticated supply chain.

Acknowledgment

The authors would like to acknowledge financial supports of Social Science Planning Project of Chongqing (2014BS105), Chongqing University of Arts and Science, and National Natural Science Foundation of China(71672015).

References

1. Feyzan Arikan. An interactive solution approach for multiple objective supplier selection problem with fuzzy parameters. *Journal of Intelligent Manufacturing*, 26(5):989–998, 2015.
2. Arunas Burinskas, Galina Merkuryeva, and Aurelija Burinskienė. Evaluation and comparison of selling terms in inter national e-commerce. *European Integration Studies*, 4:30–39, 2010.
3. William H. Delone and Ephraim R. McLean. Measuring e-commerce success: applying the delone & mclean information systems success model. *International Journal of Electronic Commerce*, 9(1):31–47,

2004.
4. János Fodor and Barnabás Bede. Arithmetics with fuzzy numbers: a comparative overview. In *Proceedings of the 4th Slovakian-Hungarian Joint Symposium on Applied Machine Intelligence*, pages 54–68, Herlany, Slovakia, 2006.
5. Robert Fullér. On product-sum of triangular fuzzy numbers. *Fuzzy Sets and Systems*, 41(1):83–87, 1991.
6. P. Jain, K. Jain, and P.K. Jain. E-commerce and its global impact. *Innovare Journal of Engineering & Technology*, 2:1–5, 2016.
7. Arturas Kaklauskas, Edmundas Kazimieras Zavadskas, Saulius Raslanas, Romualdas Ginevicius, Arunas Komka, and Pranas Malinauskas. Selection of low-e windows in retrofit of public buildings by applying multiple criteria method COPRAS: A Lithuanian case. *Energy and Buildings*, 38(5):454–462, 2006.
8. S. P. Nimocks, R. L. Rosiello, and O. Wright. Managing overhead costs. *The McKinsey Quarterly*, 2:106–117, 2005.
9. Annelie I. Pettersson and Anders Segerstedt. Measuring supply chain cost. *International Journal of Production Economics*, 143(2):357–363, 2013.
10. Farhad Rezaei, Farima Alilou, and Nima Naraghi. Determining effective elements on participation in a b2b e-commerce system by considering time and cost. *Journal of Automation and Control Engineering*, 1(4):332–335, 2013.
11. Rosa M. Rodríguez, Álvaro Labella, and Luis Martínez. An overview on fuzzy modelling of complex linguistic preferences in decision making. *International Journal of Computational Intelligence Systems*, 9(supp 1):81–94, 2016.
12. Shounak Roychowdhury and Witold Pedrycz. A survey of defuzzification strategies. *International Journal of Intelligent Systems*, 16(6):679–695, 2001.
13. Liang-Chuan Wu. Supplier selection under uncertainty: a switching options perspective. *Industrial Management & Data Systems*, 109(2):191–205, 2009.
14. Edmundas Kazimieras Zavadskas, Arturas Kaklauskas, and V. Sarka. The new method of multicriteria complex proportional assessment of projects. *Technological and Economic Development of Economy*, 1(3):131–139, 1994.
15. Zhen Zhang, C. Guo, and Luis Martínez. Managing multi-granular linguistic distribution assessments in large-scale multi-attribute group decision making. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, PP(99):1–14, 2016.