PRINT: ISSN 0972-0073 ONLINE: ISSN 2456-6802
Anthropologist, 17(3): 865-872 (2014)
DOI: 10.31901/24566802.2014/17.03.19

Construction Cost and Service Quality for the Supply Chain by Using Weighted RST Decision Rules

Cheng-Che Chiang[1] and Mei-Li Chou[2]

[1]Department of Business Administration, Far East University, No. 49, Chung Hua Rd., Hsin-Shih, Tainan County 744, Taiwan, ROC
[2]Department of Leisure and Sports Management, Far East University,No.49, Chung Hua Rd., Hsin-Shih. Tainan County 744, Tainan, ROC
E-mail: [1]< ba123@cc.feu.edu.tw>, [2]< meili@cc.feu.edu.tw>

KEYWORDS Equivalent Classification. Weighting Factor. Cost. SERVQUL. Technology

ABSTRACT As well known, the rough set theory (RST) has better identification ability for processing similar or conflict information. When applying the RST to the supply chain management, it is possible that the cost would not be the only consideration for the decision maker and customers. There were many other attribute elements that need to be involved. Different groups of attributes would represent the degree of importance that the supply chain could provide to variety customer needs. But the information model of RST was limited by the universe and attribute sets, the decision maker could only select the well-defined decisions. This would cause the final decision driven by the system coding process. In this paper, weighted decision rules of the rough set theory would be developed, and the method of balancing construction cost and service quality for the supply chain combination would be deduced. By using weighting factors on different groups of attributes would help the designated company to select the optimal combination of supply chain members. The selected criteria could be useful to enhance business decision-making ability.

INTRODUCTION

Due to the globalization, the business environment has no longer required lower construction price, overall service quality is equally emphasized as well. In this paper, the local supply chain combinations would be designed as the universe set, and these elements were possible selecting items for every individual customer requirements. Furthermore, the construction cost and service quality would be combined to form the attribute set. Elements of the construction cost set includes the labor cost (a_1), shipment cost (a_2), raw material cost (a_3), and other costs (a_4) that is simplified from the payment delay, cost control, technical ability, infrastructure and equipment, marketing capability, deliveries/shipments, and other quality (Zou et al. 2011), and the manufacturing, administration, warehouse, distribution, capital, and installation costs (Pettersson and Segerstedt 2013). The service quality attributes were based on the well-defined 5 dimensions: tangibles (a_5), reliability (a_6), responsiveness (a_7), assurance(a_8), and empathy(a_9) (Parasuraman et al. 1998). The designated company would be able to combine different considering properties in the same attribute set because the weighting factor would adjust the degree of importance for every element in the set. Each collected elements would be evaluated, and the indiscernibility relation table would be established. By using the Boolean algebra, the discernibility function could be found for each local supply chain combinations, and the overall information system was well established.

However, the customer requirement would be the decision rules, and two weighted factors (w_1 w_2) would be designed to represent whether the customer requirement was in favor of the construction cost or the service quality? The norm between the customer decision vector and the indiscernibility relation table would show the favorable condition that every element in the universe set could provide. The actual data and the feasibility would be supported by the corporative company, and the overall manipulating process and the related performance test would be checked.

Address for correspondence:
Dr. Mei-Li Chou
Department of Leisure and Sports Management,
Far East University,No.49, Chung Hua Rd.,
Hsin-Shih.
Tainan County 744, Tainan, ROC
E-mail: meili@cc.feu.edu.tw

Literature Review

The Rough Set Theory

In 1982, Pawlak developed the rough set theory and summarized in 1991, but did not obtain too much attention. In Walczak's paper, 1999, he addressed that every element in the universe set was equally evaluated by each attributes, and called the indiscernibility relation. It was assumed that the evaluation of the element had the equivalent classification as the other element. This assumption resulted in the lower bound and upper bound of RST, and the rough classification process would be built (Pawlak 1999, 2002, 2005). The ratio between the two bounds is known as the accuracy of approximation, and using upper and lower bounds can establish data classification rules (Yang and John 2006, 2008; Quian et al. 2008).

In general, if the accuracy of approximation was greater than 0.7~0.75 or above, the representative system would be specifically identified, and the decision selecting options would be limited. Otherwise, if the accuracy of approximation was small, it means that the representative information system was not fully recognized, and the new decision could not be easily selected (Hu 2012). Based on the Bayesian decision procedure, three thresholds and decision rules would be calculated by using the concept of the precise value of loss function to triangular fuzzy decision-theoretic rough sets (Liang et al. 2013). It seems that rough set modeling could be transformed to different forms, and more information would be abstracted (Ali et al. 2013).

How to discover knowledge from hybrid data using rough sets, researchers have developed several fuzzy rough set models and a neighborhood rough set model (Liang and Qian 2012). The dual-universes model of RST was introduced by using the character function, relation matrix, and proposed algorithms for obtaining lower and upper approximation (Liu 2010; Yan et al. 2010; Liu et al. 2012). The entropy and its variants have been applied to measure uncertainty in RST that will enable attribute selection in incomplete decision systems based on information-theoretical measurement of attribute importance (Dai et al. 2013). On the other hand, some researchers applied the Bayes' theorem to analyze and design the decision algorithm and decision table, and it was called the stochastic-coding information system (Pawlak 2003; Slezak and Ziarko 2005; Ziarko 2008, Zhang et al. 2012).

Many techniques of the RST were developed to analyze the dual universe sets problem, and even the stochastic approach had been applied to evaluate the modeling performance of the rough set system (Yan et al. 2010; Liu 2010; Yao 2010; Yang et al. 2012; Zhang and Miao 2013). Various applications by using RST were gradually increased such as: financial time-sequence analysis (Yao 2009), mining the R&D innovation performance processes for high-tech firms (Wang et al. 2010), supply chain management and retailers selection (Chang and Hung 2010; Zou et al. 2011), high risk management for the power enterprise (Li et al. 2012), forecasting tourist services demand (Celotto et al. 2012), predicting bankruptcy by using a hybrid random forest and rough set theory approach (Yeh et al. 2014), extended applications to medicine, medical diagnosis researches, and tumor classification (Pattaraintakorn 2008; Zhang 2009; Yang and Wu 2009; Dai and Xu 2013; Kaya and Uyar 2013).

There were a few researchers combining neural network and fuzzy logics with RST (Ahn et al. 2000) to engineering applications such as: designing fuzzy logic controller with RST (Cheng et al. 2010), the hybrid recognizer to identify industrial boiler fault alarms (Geng and Zhu 2009), and the fuzzy rough set model of emergency material demand prediction over two universes (Sun et al. 2013). These results showed that the rough set theory was capable of solving problems in many different fields.

The Service Quality Theory

The service model could be classified as the customer model and the service provider model, and both model shared the service quality model (Rust and Matters 1996). When the service quality model had been applied to a certain categories such as the grocery retailer, the scale items for the quality dimensions could be identified (Magi and Julander 1996). Based on Parasuraman et al. (1985, 1998) research, the service quality was different from the quality of the products because of having intangible nature, indivisible, cannot be stored, heterogeneity, perishable, and etc. The application of the SERVQUAL scale could be used in the context of public health care services (Purcarea et al. 2013). More details about the internal service quality and service quality scale had been discussed by Chen (2013) and Vera (2013). On the other hand, the consumer always had difficult to describe the service quality specifically. However, the service quality does have the following characteristics:

"Invisible": Service is not, and cannot be measured. It cannot be tested, not in stock, and no quality check before the sale.

"Indivisibility": The production and consumption of many services is treated as a whole part. By means of information technology and databases to collect, help solve the needs of different customers, custom purpose could be fulfilled.

"Must not store": The customers have joined the process, when they came to accept the service, and services are not stored.

"Heterogeneity": The service quality was not easy to control, maintain, and did not provide different services for different service providers and customers.

"Transience": When a customer accepts the completion service, service is gone, and can't be stored.

Therefore, the well-applied service quality system was measured by the SERVQUL scale: tangibles, reliability, responsiveness, assurance, and empathy (Parasuraman et al. 1998). Facilities, equipment and appearance of personnel would perform the tangibles dimension of the quality system. Reliability reflects the ability of the provider to perform the accurate service level. Responsiveness implies the service provider's willingness to serve customers. Assurance consisted in the knowledge of the organization employee and courtesy as well as the ability to inspire trust and confidence. Empathy includes the ability of the organization employee to provide caring and individualized attention to every customer.

OBSERVATION AND DISCUSSION

The information system would be coded discretely, and the RST could be applied as the following:

(1) Discrete-coding the information system: The attribute set would be the construction cost A_1(Zou et al. 2011; Pettersson and Segerstedt 2013) and the service quality A_2 of the SERVQUL scale. The overall attribute set would be shown in equation (1).

$$A_1=\{a_1 \quad a_2 \quad a_3 \quad a_4\} \text{ and, } A_2=\{a_5 \quad a_6 \quad a_7 \quad a_8 \quad a_9\}$$

$$A=\{A_1 \quad A_2\}=\{a_1 \quad a_2 \quad a_3 \quad a_4 \quad a_5 \quad a_6 \quad a_7 \quad a_8 \quad a_9\} \quad (1)$$

where a_1 represents the average labor cost, a_2 as the average shipment cost, a_3 as the average raw material cost, and a_4 as the other costs. The service quality includes: represents "tangibles", as "reliability", as "responsiveness", as "assurance", and as "empathy".

The actual data would be provided by the corporative company, and every element in the universe set would represent a certain combination of supply chain members, as shown in equation (2).

$$U=\{\chi_1, \chi_2, ..., \chi_9\} \quad (2)$$

where represents the core company and supply chain member one, as the core company with

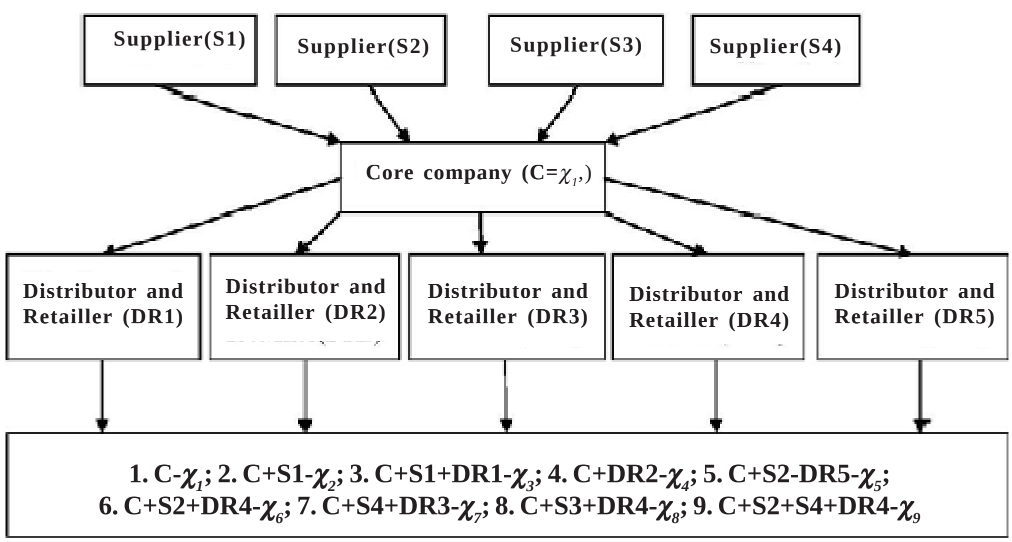

Fig. 1. The combination of local supply chain members for the designated company

supply chain member two, …, etc., as shown in Figure1.

Based on the collected data provided by the designated company on the year of 2012 and 2013, the indiscernibility relation matrix could be formulated as shown in Table 1.

(2) According to the indiscernibility relation, the simplification process would result in the discernibility relation functions and the discernibility matrix by using Boolean algebra, as shown in equation (3)~(11), and Table 2. It should note that was the controllable variable, and could be arbitrarily assigned to declare the importance of the construction cost and the service quality.

$$f(x_1)=\omega_1[(a_3)(a_2+a_4)]+\omega_2[(a_7+a_9)(a_5+a_6+a_8)(a_5+a_7+a_8)(a_6+a_8+a_9)] \tag{3}$$

$$f(x_2)=\omega_1[(a_2)(a_3)]+\omega_2[(a_6+a_7)(a_6+a_9)(a_5+a_6+a_8)(a_5+a_6+a_9)(a_5+a_7+a_8)] \tag{4}$$

$$f(x_3)=\omega_1[(a_1+a_3)(a_2+a_3)(a_2+a_4)(a_3+a_4)]+\omega_2[(a_5)(a_6+a_9)] \tag{5}$$

$$f(x_4)=\omega_1[(a_3)(a_4)]+\omega_2[(a_7+a_9)(a_6+a_7+a_8)] \tag{6}$$

$$f(x_5)=\omega_1[(a_1+a_2)(a_1+a_4)(a_2+a_3)]+\omega_2[(a_5+a_6+a_8)(a_5+a_8+a_9)(a_7+a_8+a_9)] \tag{7}$$

$$f(x_6)=\omega_1[(a_1)(a_2+a_4)]+\omega_2[(a_5+a_6)(a_5+a_7+a_9)(a_7+a_8+a_9)] \tag{8}$$

$$f(x_7)=\omega_1[(a_1)(a_2)]+\omega_2[(a_5+a_6)(a_5+a_9)(a_6+a_7+a_8)(a_6+a_7+a_9)(a_6+a_8+a_9)] \tag{9}$$

$$f(x_8)=\omega_1[(a_4)(a_1+a_2)(a_1+a_3)]+\omega_2[(a_5)(a_6+a_7+a_9)] \tag{10}$$

$$f(x_9)=\omega_1[(a_3)(a_1+a_4)(a_2+a_4)]+\omega_2[(a_5+a_9)(a_6+a_7)(a_5+a_6+a_8)] \tag{11}$$

Eventually, the overall discernibility relation function can be simplified as:

$$f(x)=f(x_1)f(x_2)\ldots f(x_9)=\omega_1[a_1a_2a_3a_4]+\omega_2[a_5\ldots] \tag{12}$$

Therefore, and would be the core attribute, but it only implied the attribute characteristic of the universe set (based on the present combination of supply chain members).

(3) By inspecting Table 1, to check the upper bound, lower bound, and accuracy of approximation implies the modeling precision of the rough set. The decision rule would be deduced, as shown in equation (13). The accuracy of approximation would be checked in Table 3, and it could show that the information system was explicitly coded.

$$c_{\text{Favorable}}=\omega_1\{x_1,\ x_2\}\cup\omega_2\{x_1,\ x_4,\ x_8\}\rightarrow d=\textit{Favorable}$$
$$c_{\text{Avaerage}}=\omega_1\{x_3,\ x_4,\ x_5,\ x_6,\ x_7,\ x_9\}\cup\omega_2\{x_2,\ x_3,\ x_6,\ x_7\}\rightarrow d=\textit{Average}$$
$$c_{\text{Unfavorable}}=\omega_1\{x_8\}\cup\omega_2\{x_5,\ x_9\}\rightarrow d=\textit{Unfavorable} \tag{13}$$

where represents the favorable decision, as the average decision, and as the unfavorable decision.

(3) Applying the requirement of the customer one (D_1), as shown in equation (14):

$$D_1=\{M,\ *,\ L,\ H,\ G,\ *,\ G,\ *,\ *\} \tag{14}$$

Which means that a_3 needs to be Low, a_1 be Medium, a_4 be High, a_6 and a_8 be Good. This customer prefers the higher construction cost than the service quality, that is ω_1 = Favourable and ω_2 = Average. The weighting vector would be formulated as shown in equation (15):

$$w=\{F,\ F,\ F,\ F,\ A,\ A,\ A,\ A,\ A\} \tag{15}$$

The norm condition of the customer one would be shown in Table 4, and the minimum sum of norms appeared at the supply chain member x_3.

In another words, according to the record of supply chain (the indiscernibility relation table), the RST model chooses member x_3 to be the optimal selection for the customer one that specifies the requirement. Repeating the iteration process would enable the decision maker to have two designing freedoms: first, any customers

Table 1: The indiscernibility relation (Data provided by the core company)

Att.	*Weighting factors of construction cost ω_1 ε {F, A, U}*				*Decision*	*Weighting factors of service quality ω_2 ε {F, A, U}*					
Uni.	*Labour cost a_1*	*Shipment cpst a_2*	*Raw material cost a_3*	*Other cost a_4*		*tangibles a_5*	*reliability a_6*	*responsive a_7*	*assurance a_8*	*empathy a_9*	*Decision*
X_1	High	Medium	Medium	Low	F	Good	Good	Fair	Good	Poor	F
X_2	High	Low	Medium	Medium	F	Fair	Good	Good	Fair	Poor	A
X_3	Medium	Medium	Medium	High	A	Fair	Fair	Good	Fair	Fair	A
X_4	High	Medium	High	Low	A	Good	Good	Poor	Good	Good	F
X_5	Medium	Low	High	High	A	Poor	Fair	Good	Poor	Poor	U
X_6	Medium	High	Medium	Medium	A	Poor	Fair	Fair	Fair	Good	A
X_7	Low	High	Medium	Medium	A	Good	Poor	Fair	Fair	Good	A
X_8	Low	Medium	High	High	U	Good	Fair	Good	Fair	Fair	F
X_9	Low	Low	High	Medium	A	Fair	Poor	Fair	Fair	Poor	U

Where the decision 「F」 represents the favorable decision「A」 represents the average decision, and ?U? represents the unfavorable decision.

Table 2: The discernibility matrix

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9
x_1	※	$\omega_1(a_2,a_4)$ $\omega_2(a_5,a_7,a_8)$	$\omega_1(a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8,a_9)$	$\omega_1(a_3)$ $\omega_2(a_7,a_9)$	$\omega_1(a_1,a_2,a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8)$	$\omega_1(a_1,a_2,a_4)$ $\omega_2(a_5,a_6,a_8,a_9)$	$\omega_1(a_2,a_4)$ $\omega_2(a_6,a_8,a_9)$	$\omega_1(a_3,a_4)$ $\omega_2(a_6,a_7,a_8,a_9)$	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_5,a_6,a_8)$
x_2	$\omega_1(a_2,a_4)$ $\omega_2(a_5,a_7,a_8)$	※	$\omega_1(a_1,a_2,a_4)$ $\omega_2(a_6,a_9)$	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_5,a_7,a_8,a_9)$	$\omega_1(a_1,a_3,a_4)$ $\omega_2(a_5,a_6,a_8)$	$\omega_1(a_1,a_2)$ $\omega_2(a_5,a_6,a_7,a_9)$	$\omega_1(a_2)$ $\omega_2(a_5,a_6,a_7,a_9)$	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_5,a_6,a_9)$	$\omega_1(a_3)$ $\omega_2(a_6,a_7)$
x_3	$\omega_1(a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8,a_9)$	$\omega_1(a_1,a_2,a_4)$ $\omega_2(a_6,a_9)$	※	$\omega_1(a_1,a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8,a_9)$	$\omega_1(a_2,a_3)$ $\omega_2(a_5,a_8,a_9)$	$\omega_1(a_2,a_4)$ $\omega_2(a_5,a_7,a_9)$	$\omega_1(a_1,a_2,a_4)$ $\omega_2(a_5,a_6,a_7,a_9)$	$\omega_1(a_1,a_3)$ $\omega_2(a_5)$	$\omega_1(a_1,a_2,a_3,a_4)$ $\omega_2(a_6,a_7,a_9)$
x_4	$\omega_1(a_3)$ $\omega_2(a_7,a_9)$	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_5,a_7,a_8,a_9)$	$\omega_1(a_1,a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8,a_9)$	※	$\omega_1(a_1,a_2,a_4)$ $\omega_2(a_5,a_6,a_7,a_8,a_9)$	$\omega_1(a_1,a_2,a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8)$	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_6,a_7,a_8)$	$\omega_1(a_4)$ $\omega_2(a_6,a_7,a_8,a_9)$	$\omega_1(a_2,a_4)$ $\omega_2(a_5,a_6,a_7,a_8,a_9)$
x_5	$\omega_1(a_1,a_2,a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8)$	$\omega_1(a_1,a_3,a_4)$ $\omega_2(a_5,a_6,a_8)$	$\omega_1(a_2,a_3)$ $\omega_2(a_5,a_8,a_9)$	$\omega_1(a_1,a_2,a_4)$ $\omega_2(a_5,a_6,a_7,a_8,a_9)$	※	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_7,a_8,a_9)$	$\omega_1(a_1,a_2,a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8,a_9)$	$\omega_1(a_1,a_2)$ $\omega_2(a_5,a_8,a_9)$	$\omega_1(a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8)$
x_6	$\omega_1(a_1,a_2,a_4)$ $\omega_2(a_5,a_6,a_8,a_9)$	$\omega_1(a_1,a_2)$ $\omega_2(a_5,a_6,a_7,a_9)$	$\omega_1(a_2,a_4)$ $\omega_2(a_5,a_7,a_9)$	$\omega_1(a_1,a_2,a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8)$	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_7,a_8,a_9)$	※	$\omega_1(a_1)$ $\omega_2(a_5,a_6)$	$\omega_1(a_1,a_2,a_3,a_4)$ $\omega_2(a_5,a_7,a_9)$	$\omega_1(a_1,a_2,a_3)$ $\omega_2(a_5,a_8,a_9)$
x_7	$\omega_1(a_2,a_4)$ $\omega_2(a_6,a_8,a_9)$	$\omega_1(a_2)$ $\omega_2(a_5,a_6,a_7,a_9)$	$\omega_1(a_1,a_2,a_4)$ $\omega_2(a_5,a_6,a_7,a_9)$	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_6,a_7,a_8)$	$\omega_1(a_1,a_2,a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8,a_9)$	$\omega_1(a_1)$ $\omega_2(a_5,a_6)$	※	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_6,a_7,a_9)$	$\omega_1(a_2,a_3)$ $\omega_2(a_5,a_9)$
x_8	$\omega_1(a_3,a_4)$ $\omega_2(a_6,a_7,a_8,a_9)$	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_5,a_6,a_9)$	$\omega_1(a_1,a_3)$ $\omega_2(a_5)$	$\omega_1(a_4)$ $\omega_2(a_6,a_7,a_8,a_9)$	$\omega_1(a_1,a_2)$ $\omega_2(a_5,a_8,a_9)$	$\omega_1(a_1,a_2,a_3,a_4)$ $\omega_2(a_5,a_7,a_9)$	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_6,a_7,a_9)$	※	$\omega_1(a_2,a_4)$ $\omega_2(a_5,a_6,a_7,a_9)$
x_9	$\omega_1(a_2,a_3,a_4)$ $\omega_2(a_5,a_6,a_8)$	$\omega_1(a_3)$ $\omega_2(a_6,a_7)$	$\omega_1(a_1,a_2,a_3,a_4)$ $\omega_2(a_6,a_7,a_9)$	$\omega_1(a_2,a_4)$ $\omega_2(a_5,a_6,a_7,a_8,a_9)$	$\omega_1(a_3,a_4)$ $\omega_2(a_5,a_6,a_7,a_8)$	$\omega_1(a_1,a_2,a_3)$ $\omega_2(a_5,a_8,a_9)$	$\omega_1(a_2,a_3)$ $\omega_2(a_5,a_9)$	$\omega_1(a_2,a_4)$ $\omega_2(a_5,a_6,a_7,a_9)$	※

Table 3: Check the accuracy of approximation

Decision set	Element #		Upper Bound		Lower Bound		Accuracy of approximation	
	ω_1	ω_2	ω_1	ω_2	ω_1	ω_2	ω_1	ω_2
$C_{\text{Favorable}}$	2	3	2	3	2	3	1.0	1.0
C_{Average}	6	4	6	4	6	4	1.0	1.0
$C_{\text{Unfavorable}}$	1	2	1	1	1	1	1.0	1.0

Table 4: Norm condition of customer one with decision

Decision Universe	Norm of construction cost n_1	Norm of service quality n_2	Sum of two norms $\omega_1 n_1+\omega_2 n_2$
X_1	2.45	1.0	9.35
X_2	1.73	1.0	7.19
X_3	1.0 (Minimum)	1.0	5.0 (Minimum)
X_4	3.0	2.0	13.0
X_5	2.0	2.0	10.0
X_6	1.41	2.24	8.71
X_7	1.73	1.0	7.19
X_8	2.24	0 (Minimum)	6.72
X_9	2.45	1.41	10.17

could specify its own requirements as the decision criterion, and secondly the core company could continuously update the indiscernibility relation table of the supply chain member that would change the interior of the information system.

CONCLUSION

Coding the information system is crucial to the RST application, because it is assumed that most of the original data was well-defined and only few obscure data hidden in the system. Once the RST could be applied to select the final decision, the flexibility of decision making process would be limited. The overall RST application would result in the known system coding leading to the known decisions.

RECOMMENDATIONS

In this paper, we develop the weighting factor for the dual attribute sets, and introduce the concept of multiple property collection. Therefore, the size of the universe and attribute sets could be expanded to include all possible combination of supply chain members and customer considerations. It provides the extra-freedom for the decision-making process that enables each customer have its own requirements and special designed services. RST methodology can abstract the hidden information from the system by fixing the dimension of the universe and attribute sets, but the practical system is dynamically changing rather than statically stalling. That is why this study would not limit elements of the universe set, and would put weighting factor on the attribute set. Unbalanced the evaluation of the attribute set without eliminating a certain parts of it would cause the variety selection of the decision-making. Based on the result of this paper, the rough set could adjust itself to the expanding indiscernibility relation table, and the decision maker would have more choices in the decision space. This would describe the real information system than the original RST, and it would be the main contribution of this paper.

REFERENCES

Ahn B, Cho S, Kim C 2000. The integrated methodology of rough set theory and artificial neural network for business failure prediction. *Expert Systems with Applications*, 18(2): 65-74.

Ali M I, Davvaz B, Shabir M 2013. Some properties of generalized rough sets. *Information Sciences*, 22(4): 170-179.

Celotto E, Ellero A, Ferretti P 2012. Short-medium term tourist services demand forecasting with Rough Set Theory. *Procedia Economics and Finance*, 3: 62 – 67.

Chang B, Hung H 2010. A study of using RST to create the supplier selection model and decision-making rules. *Expert Systems with Applications*, 37(12): 8284-8295.

Chen W 2013. Factors influencing internal service quality at international tourist hotels. *International Journal of Hospitality Management,* (35): 152-160.

Cheng C, Chen T, Wei L 2010. A hybrid model based on rough sets theory and genetic algorithms for stock price forecasting. *Information Sciences*, 180(9): 1610-1629.

Dai J, Wang W, Tian H, Liu L 2013. Attribute selection based on a new conditional entropy for incomplete decision systems. *Knowledge-Based Systems*, 39: 207-213.

Dai J, Xu Q 2013. Attribute selection based on information gain ratio in fuzzy rough set theory with application to tumor classification. *Applied Soft Computing,* 13(1): 211-221.

Geng Z, Zhu Q 2009. Rough set-based heuristic hybrid recognizer and its application in fault diagnosis. *Expert Systems with Applications*, 36(2): 2711-2718.

Hu W 2012. Developing perturbation rate of the rough set theory to evaluate the electronic transaction quality of on-line shopping. *Pakistan Journal of Statistics*, 28(5): 581-596.

Kaya Y, Uyar M 2013. A hybrid decision support system based on rough set and extreme learning machine for diagnosis of hepatitis disease. *Applied Soft Computing*, 13(8): 3429-3438.

Li Z, Wang M, Ma X, Shen X 2012. High risk management model for the power enterprise based on rough set theory. *System Engineering Procedia*, (3): 63-68.

Liang LW, Qian Y 2012. A comparative study of rough sets for hybrid data. *Information Sciences*, 190: 1-16.

Liang D, Liu D, Pedrycz W, Huaand P 2013. Triangular fuzzy decision-theoretic rough sets. *International Journal of Approximate Reasoning*, 54(8): 1087-1106.

Liu C, Miao D, Zhang N 2012. Graded rough set model based on two universes and its properties, *Knowledge-Based Systems*, 33: 65-72.

Liu G 2010. Rough set theory based on two universal sets and its applications, *Knowledge-Based Systems*, (23): 110-115.

Magi A, Julander C 1996. Perceived service quality and customer satisfaction in a store performance framework. *Journal of Retailing and Customer Services*, 3(1): 33-41.

Parasuraman A, Zeithaml VA, Berry L L 1985. A conceptual model of service quality and its implications for future research. *Journal of Marketing*, 49: 41-50.

Parasuraman A, Zeithaml VA, Berry LL 1988. SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing*, 64(1): 12-40.

Parasuraman A, Zeithaml VA, Malhotra A 2005. e-S-Qual: A multiple-item scale for assessing electronic service quality. *Journal of Service Research*, 7(3): 213-233.

Pattaraintakorn P, Cercone N 2008. Integrating rough set theory and medical applications. *Applied Mathematics Letters*, 21(4): 400-403.

Pawlak Z 1982. Rough sets. *International Journal of Computer and Information Scienc*es, 11: 341-356.

Pawlak Z 1991. *Rough Sets – Theoretical Aspects of Reasoning about Data*. Norwell, MA: Kluwer Academic Publishers..

Pawlak Z 1997. Rough set approach to knowledge-based decision support. *European Journal of Operational Research*, 99: 48-57.

Pawlak Z 1999. Rough sets and intelligent data analysis. *International Journal of Human-Computer Studies*, 51: 369-383.

Pawlak Z 2002. Rough classification. *Information Sciences*, 147: 1-12.

Pawlak Z 2003. Rough set, Bayes' theorem and flow graphs. *Intelligent Systems for Information Processing: From Representation to Applications*, 243-252.

Pawlak Z 2005. Some remark on conflict analysis. *European Journal of Operational Research*, 166(3): 649-654.

Pettersson A I, Segerstedt A 2013. Measuring supply chain cost. *International Journal Production Economics*, 143(2): 257-363.

Purcarea V L, Gheorghe I R, Petrescu C M 2013. The assessment of perceived service quality of public health care. *Procedia Economics and Finance*, 6: 573-585.

Qian Y, Liang J, Li D, Zhang H, Dang C 2008. Measures for evaluating the decision performance of a decision table in rough set theory. *Information Sciences*, 178(1): 181-202.

Rust RT, Matters R 1996. Mathematical models of service. *European Journal of Operational Research*, 91(3): 427-439.

Slezak D, Ziarko W 2005. The investigation of the Bayesian Rough Set Model. *International Journal of Approximate Reasoning,* 40(1-2): 81-91.

Vera J, Trujillo A 2013. Service quality dimensions and superior customer perceived value in retail banks: An empirical study on Mexican consumers. *Journal of Retailing and Consumer Services*, 20(6): 579-586.

Sun B, Ma W, Zhao W 2013. A fuzzy rough set approach to emergency material demand prediction over two universes. *Applied Mathematical Modeling*, 37(10-11): 7062-7070.

Wang C, Chin Y, Tzeng G 2010. Mining the R&D innovation performance processes for high-tech firms based on rough set theory. *Technovation,* 30: 447-458.

Yan R, Zheng J, Liu J, Zhai Y 2010. Research on the model of rough set over dual-universes. *Knowledge-Based Systems*, 23(8): 817-822.

Yang H, Li S, Wang S, Wang J 2012. Bipolar fuzzy rough set model on two different universes and its application. *Knowledge-Based Systems*, 35: 94-101.

Yang H, Wu C 2009. Rough sets to help medical diagnosis–Evidence from a Taiwan's clinic, *Expert Systems with Applications*, 36(5): 9293-9298.

Yang Y, John R 2006. Roughness bounds in rough set operations. *International Journal of Information Sciences*, 176: 3256-3267.

Yang Y, John R 2008. Generalization of roughness bounds in rough set operations. *International Journal of Approximate Reasoning*, 48(3): 868-878.

Yao Y 2010. Three-way decisions with probabilistic rough sets. *Information Sciences*, (180): 341-353.

Yao J, Herbert J 2009. Financial time-series analysis with Rough Sets. *Applied Soft Computing*, 9(3): 1000-1007.

Yeh C, Chi D, Lin Y 2014. Going-concern prediction using hybrid random forests and rough set approach. *Information Science*, 254: 98-110.

Zhai L, Khoo L , Zhong Z 2009. A rough set based QFD approach to the management of imprecise design information in product development. *Advanced Engineering Informatics*, 23: 222-228.

Zhang X , Miao D 2013. Two basic double-quantitative rough set models of precision and grade and their investigation using granular computing. *International Journal of Approximate Reasoning*, 54: 1130-1148.

Zhang Z, Shi Y, Gao G 2009. A Rough Set-based Multiple Criteria Linear Programming Approach for The Medical Diagnosis and Prognosis. *Expert Systems with Applications*, 36: 8932-8937.

Zhang H, Zhou J, Miao D, Gao C 2012. Bayesian rough set model: A further investigation. *International Journal of Approximate Reasoning*, 53: 541-557.

Ziarko W 2008. Probabilistic approach to rough sets. *International Journal of Approximate Reasoning,* (49): 272-284.

Zou Z, Tseng T, Sohn H, Song G ,Gutierrez R 2011. A rough set based approach to distributor selection in supply chain management. *Expert Systems with Applications,* 38: 106-115.