Resilient Supplier Selection under Uncertainty Using the Extended TOPSIS Method: The Case of Electronic Components Procurement

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***Abstract*—Due to globalization, supply chains are interrupted by unpredictable natural or man-made disasters, as well as other kinds of disruptive events. The selection of suppliers based on resilience strategies, therefore, has been considered a necessary factor for mitigating such uncertainties. However, the studies that provide practical methods using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to support resilient supplier selection in the electronic industry is still limited. Most of electronic products are made up of a variety of components. Logical supplier selection process is therefore necessary in this industry. This study aims to identify critical criteria for the resilient supplier selection that is applicable to electronic manufacturers. The extended TOPSIS method is then adopted to facilitate the selection process. Uncertain and unavailable data, which tends to exist in actual resilient supplier selection problems, can be managed logically. The effective use of the supplier resilience strategies helps electronic firms be prepared for unpredictable disasters. The proposed method can be applied not only for resilient supplier selection but also any cases of multi-criteria decision making.**

***Index Terms*—Disaster, Disruption, Electronic Industry, Resilience, Supplier selection**

I. INTRODUCTION

In the current business environment, supply chain management (SCM) has received increasing attention and has become an important factor for enterprises to achieve competitiveness [1]. The success or failure of SCM depends on a suitable SCM system and on appropriate suppliers. A review of the relevant literature shows that supplier selection is a critical element in the procurement process, as it enables a firm to have high quality products, enhance its customer satisfaction, and increase its competitive advantage [2]. Therefore, effective supplier selection is considered to be a key strategy in the industrial purchasing process [3].

Recently, supply chains (SC) have been disrupted by unpredictable disasters or events that can be natural (e.g., earthquakes, hurricanes, tsunamis, floods), man-made (e.g., labor strikes, fires, traffic accidents, terrorist attacks) or technological; these disasters have tended to occur more frequently and to be more severe. Due to this, the term ‘resilience’ has gained in importance in business management, as it is a necessary factor in supplier selection. Relatedly, supply chain resilience is the ability of the system to recover its performance to its original state after being disrupted.

Supplier resilience capability is multidimensional, and it is highly likely that it needs to be assessed using uncertain information. This is because some disasters or disruptive events might never have happened in the past, and suppliers may have no experience to deal with them. Therefore, the ability of suppliers to handle these situations may be difficult to assess with definite information.

Thus, the purpose of this study is to identify critical criteria for the assessment of supplier resilience capability and to apply the extended TOPSIS method to the case of resilient supplier selection. This method is developed by Sureeyatanapas et al. [3] as a method to solve multiple criteria decision making (MCDM) problems when uncertain or unavailable data exists. This study focuses on the case of components procurement for electronic manufacturers, due to a wide range of sub-components required for electronic products and because the electronic industry is one of the significant sectors influencing the global economy.

This paper is organized as follows. Section II describes the research methodologies. Section III presents a review of criteria for resilient supplier selection and typical criteria generally used in the electronic industry. Section IV then present a numerical example to demonstrate the application of the extended TOPSIS for the resilient supplier selection in the electronic industry. The last section concludes and provides suggestions for future research.

II. Research Methodology

The research methodology starts from a review of the literature, with the aim of gathering critical criteria that are suitable for resilient supplier selection in the face of disruptive events in the electronic industry. To this end, two groups of studies have been reviewed, which are articles addressing cases of supplier selection under catastrophic, disaster or crisis situations and articles that mention problems of supplier selection within the electronic industry. The gathered criteria were grouped according to their meanings or definitions, and they were then classified into two categories: (i) resilience capabilities and (ii) general criteria for the electronic industry. The extended TOPSIS method is then applied to solve the selection problem. This method can deal with uncertain or unavailable information in MCDM problems [3]. A numerical example was created to demonstrate the application of the extended TOPSIS to a case of resilient supplier selection. The calculation process is described step by step to show that the proposed method can logically solve the problem.

III. A Review of Criteria for Resilient Supplier Selection in the Electronic Industry

A number of relevant literature sources were reviewed. They include studies on resilient supplier selection in several sectors, such as the automotive industry [4][5][6], plastic manufacturing [7], logistics [8], construction supply chain [9] and resilient supplier selection in general [1][10][11][12][13]. Studies relating specifically to supplier selection in the electronic industry were also reviewed to identify specific characteristics or concerns of electronic components procurement [14][15][16][17][18]. Many criteria were collected, and they were eventually synthesized and classified into 17 criteria, as shown in Table I.

TABLE I
SYNTHESIZED CRITERIA FOR RESILIENT SUPPLIER SELECTION FOR THE ELECTRONIC INDUSTRY

Category	Criteria	Definition
Resilience capabilities	1. Responsiveness	The ability to quickly react or respond to customer requirements.
	2. Safety stock inventory	The supplier's capacity to hold adequate amounts of essential materials and goods to support a customer during disruptive events.
	3. Invulnerable location	The supplier's location, which should be in a place with no risk of natural disasters to minimize impacts on the supply chain processes, or be in a safe or low-risk area.
	4. Backup supplier contracts	The presence of a supplier's outsourcing contracts, which enables a customer to overcome a shortage of supply capacity in the case of disruption.
	5. Robustness	Physical protection infrastructure and safety system of a supplier's building and facilities, to minimize negative impacts of disruption, especially in the case of natural disasters.
	6. Delivery rerouting	Rerouting options (based on the supplier's location) or the supplier's capability to adjust transportation routes during disruptive events.
	7. Restoration	The supplier's capability to restore damaged facilities and equipment or to resume production to a normal state of operations.
	8. Risk of production shutdown	The possibility of production shutdown, which might be caused by failure of the facilities, machine breakdown, labor strikes, natural disaster, and technological problems.
	9. Risk of transportation failure	The possibility of transportation failure, which might be caused by vehicles failure, route insecurity, terrorist attacks, and natural disasters.
	10. Risk of communication breakdown and losing information	The possibility of the communication and transactions breakdown which might be caused by system errors and instability, as well as the insecurity of the information system.

TABLE I
SYNTHESIZED CRITERIA FOR RESILIENT SUPPLIER SELECTION FOR THE ELECTRONIC INDUSTRY(CONT.)

Category	Criteria	Definition
General criteria for the electronic industry	1. Production capacity	The volume of products that can be produced and delivered by the supplier using their current resources.
	2. Delivery performance	2.1 The supplier's order cycle time. 2.2 The supplier's on-time delivery performance. 2.3 The supplier's shipping accuracy.
	3. Service and support	3.1 The supplier's ability and willingness to assist with the design process. 3.2 The supplier's ability to provide technical assistance and support for post-sales services.
	4. Innovation and technology	The supplier's innovation and technological advances.
	5. Firm's image and reputation	The supplier's profile, image, market share, and brand recognition.
	6. Product quality	6.1 Defect rate found at the customer's plant. 6.2 The supplier's process capability.
	7. Product price	The unit price of the product.

IV. A NUMERICAL EXAMPLE

This section presents a numerical example to demonstrate the application of the extended TOPSIS to the case of resilient supplier selection in the electronic industry. The numerical example is employed, instead of the report of actual data, due to the confidential information concerned by most electronic manufacturers. In practice, when companies select suppliers, it is highly likely that most companies do not consider all the above-mentioned criteria. They generally select only the criteria that are critical or significant for their business strategy. In this research, five criteria were selected based on an interview of a purchasing engineer of a company producing various components of a computer system. Three criteria were selected to represent the resilience capability: 'responsiveness', 'safety stock inventory', and 'restoration'; two criteria were selected as the general criteria for the electronic industry, which were 'innovation and technology' and 'product quality'. Examples of their indicators and measurement units are shown in Table II. In fact, each criterion can be measured in either qualitative or quantitative ways, or both, depending on the assessor's perception and preference. However, for this study, 'responsiveness', 'restoration', and 'innovation and technology' were set as qualitative criteria, while the other two were quantitative criteria. For qualitative criteria, a rating scale was used and definitions were attached to each point on the scale. For quantitative criteria, an indicator and measurement unit were defined for each criterion.

TABLE II
EXAMPLE OF INDICATORS AND MEASUREMENT UNITS FOR EACH CRITERION

Criteria	Indicator and measurement unit
Responsiveness	Rating scale 1-4 (1) Excellent: Very fast response (within an hour). (2) Good: Fast response (within three hours). (3) Fair: Response within one day. (4) Poor: Slow response (longer than one day).
Safety stock inventory	The length of time that the supplier can supply raw material (days).
Restoration	Rating scale 1-4 (1) Excellent: Evidence shows that the risks and impacts of disruptive events that affect business operations have been identified and managed according to their business continuity plan (BCP) for each scenario. The procedures and tools are specified for responding to the damage and restoring the operations, including the recovery time objective (RTO) for each scenario. (2) Good: Evidence shows that the risks and impacts of disruptive events that affect business operations have been identified. The BCP is provided for each scenario. However, there is no clear evidence of procedure and tools for responding to the damage and restoring the operations for each scenario. (3) Fair: Evidence shows that the risks and impacts of disruptive events that affect business operations have been identified. The supplier is in the process of developing the BCP for each scenario. There is no evidence of procedure and tools for responding to the damage and restoring the operations for each scenario. (4) Poor: There is no evidence of identifying any disruptive events that tend to impact on business operations.
Innovation and Technology	Rating scale 1-4 (1) Excellent: Supplier uses state-of-the-art technologies for manufacturing new products and new process developments. (2) Good: Supplier uses new technologies in their new product and new process development. (3) Fair: Supplier applies commonly used technologies to their products but there is no new process development. (4) Poor: Supplier uses the obsolete or out-of-date technologies in their product and there is no new process development.
Product Quality	Average rate of defects per lot.

Three candidate suppliers were then taken into consideration, and they were assessed using the five criteria. The assessment data were generated to include all feasible forms, including precise information, a range of possible information, and unknown information, as shown in Table III. For instance, for supplier 3, the restoration performance was completely unknown, since this supplier had no experience dealing with a disruptive event. Next, to normalize the assessment data, the data of each criterion is transformed into the utility scores using the equivalent rules shown in Table IV. For this example, the equivalent rules are given by the authors in order to only demonstrate the calculation method. In reality, practitioners or decision makers can determine the equivalent rules by themselves in order to reflect their preferences. The data of quantitative criteria is transformed using (1) and (2) [3], while the data of qualitative criteria can be transformed directly using the equivalent rules. The transformed utility scores are then displayed in Table V.

TABLE III
THE ASSESSMENT MATRIX OF 3 ALTERNATIVES WITH 5 SELECTED CRITERIA (BEFORE TRANSFORMATION)

Criteria	**Weight**	**Supplier**		
		1	2	3
1.Responsiveness (rating scale 1-4)	0.20	2	2-3	3-4
2.Safety stock inventory (days)	0.20	7	5	10
3.Restoration (rating scale 1-4)	0.35	2-3	3	Unknown
4.Innovation and Technology (rating scale 1-4)	0.15	1	2	2
5.Product quality (average rate of defects per lot)	0.10	0.50%	1.05%	0.85%

TABLE IV
EQUIVALENCE OF ASSESSMENT DATA AND UTILITY SCORES

Criteria	Rating scale or numerical data	Utility scores
1. Responsiveness	1	100
	2	80
	3	50
	4	0
2.Safety stock inventory	10 days (or above)	100
	3 days (or lower)	0
3.Restoration	1	100
	2	70
	3	40
	4	0

TABLE IV
EQUIVALENCE OF ASSESSMENT DATA AND UTILITY SCORES (Cont.)

Criteria	Rating scale or numerical data	Utility scores
4.Innovation and Technology	1	100
	2	80
	3	50
	4	0
5.Product quality	0.3% (or lower)	100
	1.5% (or above)	0

TABLE V
THE ASSESSMENT MATRIX OF 3 ALTERNATIVES WITH 5 SELECTED CRITERIA (AFTER TRANSFORMATION)

Criteria	Utility	Supplier		
		1	2	3
1.Responsiveness	Min	80	50	0
	Max	80	80	50
2.Safety stock inventory	Min	57.14	28.57	100
	Max	57.14	28.57	100
3.Restoration	Min	40	40	0
	Max	70	40	100
4.Innovation and Technology	Min	100	80	80
	Max	100	80	80
5.Product quality	Min	83.33	37.50	54.17
	Max	83.33	37.50	54.17

For quantitative criteria, the utility of the benefit criteria can be calculated by (1), where $u(h_{i,j})$ denotes the utility score of alternative i on criterion j, $h_{max,j}$ is the best value of criterion j when comparing all alternatives, and $h_{min,j}$ is the worst value.

$$u(h_{i,j}) = \left(\frac{h_{i,j}-h_{min,j}}{h_{max,j}-h_{min,j}}\right).100 \quad (1)$$

To exemplify the transformation, the safety stock inventory data could be transformed as follow:

Supplier 1: $u(h_{1,2}) = \left(\frac{7-3}{10-3}\right).100 = 57.14$

Supplier 2: $u(h_{2,2}) = \left(\frac{5-3}{10-3}\right).100 = 28.57$

Supplier 3: $u(h_{3,2}) = \left(\frac{10-3}{10-3}\right).100 = 100$

The utility of cost criteria can be calculated using (2), where $h_{min,j}$ is the best value of criterion j when comparing all alternatives, and $h_{max,j}$ becomes the worst value.

$$u(h_{i,j}) = \left(\frac{h_{max,j}-h_{i,j}}{h_{max,j}-h_{min,j}}\right).100 \quad (2)$$

For example, the average rate of defect per lot could be transformed as follows:

Supplier 1: $u(h_{1,5}) = \left(\frac{1.5-0.5}{1.5-0.3}\right).100 = 83.33$

Supplier 2: $u(h_{2,5}) = \left(\frac{1.5-1.05}{1.5-0.3}\right) .100 = 37.50$

Supplier 3: $u(h_{3,5}) = \left(\frac{1.5-0.85}{1.5-0.3}\right) .100 = 54.17$

After the transformation of the data, the extended TOPSIS was applied as an MCDM technique for selecting the best alternative. The underlying concept of TOPSIS is to choose alternatives with the shortest distance from the positive ideal solution (PIS) and the longest distance from the negative ideal solution (NIS) of each criterion. The closeness coefficient to the ideal solutions *(CC_i)* can then be calculated for each alternative *i*, and it can be used as an indicator to compare and rank alternatives. The extended TOPSIS has been developed by Sureeyatanapas et al. [3] to enhance the ability of the TOPSIS method to deal with uncertainties and unavailability of information. In resilience supplier selection, suppliers' performances may not be precisely assessed for some criteria since the assessor may have only limited information or a complete lack of information. For these cases, their performance could be of any value, as it falls within a range of possible information. Thus, the traditional TOPSIS has been modified to allow for the input of a possible range of values (minimum and maximum values) for each criterion, as shown in Table V, where each element Z_{ij} in the table (the transformed assessment data of alternative *i* on criterion *j*) is now in the form of a utility score. When the assessment is precise and certain, $Z_{ijMin} = Z_{ijMax}$.

Because the input information can be of any value in the specified range, the minimum CC_i (Min CC_i) and maximum CC_i (Max CC_i) for alternative *i* can also be determined. The extended TOPSIS clarifies that the alternative *i* will reach the minimum value (Min CC_i) only when all Z_i $(Z_{i1}, Z_{i2}, ..., Z_{ij})$ are at the lowest level and all Z_k $(k \neq i)$ are at the highest level. Meanwhile, the alternative *i* will reach the maximum score (Max CC_i) only when all Z_i $(Z_{i1}, Z_{i2}, ..., Z_{ij})$ are at the highest level and all Z_k $(k \neq i)$ are at the lowest level, as described by (3) and (4). For example, Table VI shows the modified decision matrix when Min CC_1 is considered. Overall, the extended TOPSIS method can be described using (3) – (10) [3].

If objective function = *Min CC_i*,

$$\hat{Z}_{kj} = \begin{cases} Z_{kj(min)}, & k = i \\ Z_{kj(max)}, & k \neq i \end{cases} \quad (3)$$

If objective function = *Max CC_i*,

$$\hat{Z}_{kj} = \begin{cases} Z_{kj(max)}, & k = i \\ Z_{kj(min)}, & k \neq i \end{cases} \quad (4)$$

$$V_{ij} = W_j Z_{ij} \quad (5)$$

$$PIS_j = Max\ (V_{ij}) \quad (6)$$

$$NIS_j = Min\ (V_{ij}) \quad (7)$$

$$S_{PIS_i} = \sqrt{\sum_{j=1}^{n} (V_{ij} - PIS_j)^2} \quad (8)$$

$$S_{NIS_i} = \sqrt{\sum_{j=1}^{n} (V_{ij} - NIS_j)^2} \quad (9)$$

$$CC_i = S_{NISi}/(S_{PISi} + S_{NISi}) \quad (10)$$

TABLE VI
EXAMPLE OF MATRIX $\hat{Z}$ OF MIN CC_1 WITH 3 ALTERNATIVES

Criteria	Weight	Supplier		
		1	2	3
1.Responsiveness	0.20	80	80	50
2.Safety stock inventory	0.20	57.14	28.57	100
3.Restoration	0.35	40	40	100
4.Innovation and technology	0.15	100	80	80
5.Product quality	0.10	83.33	37.50	54.17

For the numerical example, the Min CC_i and Max CC_i were calculated for each alternative *i*, as shown in Table VII. To consider the best alternative, the decision maker (DM) may refer to the average of Min CC_i and Max CC_i (hereafter Avg CC_i). Since it appears that supplier 1 has the greatest Avg CC_i, it would be selected. However, this decision approach may overlook the uncertainty of the information. For example, at the date of purchasing, it is possible that supplier 1's performance will drop to its worst level (Min CC_1 = 0.3045), which is lower than the worst level of supplier 3. Therefore, it is suggested that Min CC_i and Max CC_i should be considered in the decision-making process along with the DM's risk attitudes. For example, if the DM has a 'risk-seeking' attitude, they may select the alternative with the highest Max CC_i, which is still supplier 1 (Max CC_1 = 0.7796). On the other hand, if the DM has a 'risk-averse' attitude, they may select supplier 3, as it has the highest level of Min CC_i (Min CC_3 = 0.3660).

TABLE VII
THE CLOSENESS COEFFICIENT TO THE IDEAL SOLUTIONS *(CC_I)* OF THE THREE CANDIDATE SUPPLIERS

Supplier	Min and Max CC_i		Avg CC_i
Supplier 1	Min	0.3045	0.5421
	Max	0.7796	
Supplier 2	Min	0.0000	0.2929
	Max	0.5857	
Supplier 3	Min	0.3660	0.4013
	Max	0.4366	

V. CONCLUSION

This study has identified criteria from the literature review that can be applied to resilient supplier selections in the case of a disruptive event in the electronic industry. The criteria are then synthesized and classified into two groups. Ten criteria are identified for the first group that reflect supplier resilience capabilities, while another seven criteria are identified for the second group that present general criteria for electronic components procurement. These criteria can be also generalized to every industry for the consideration of supplier selection under the supplier resilience strategy. The application of the extended TOPSIS method is proposed for cases of supplier selection with uncertain information, which will likely occur in resilient supplier selection processes. This method allows DMs to make a decision by considering the range of CC_i together with their risk attitudes, as described in Section IV. Since the input information is uncertain, the output should be also uncertain. Therefore, this solution can preserve uncertain characteristics and avoid a potential loss of important information.

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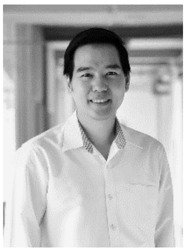

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