A Geometric Mean-based DEMATEL Model for Evaluating the Critical Challenges of Spare Parts Planning

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Abstract

We present a method for evaluating the critical challenges of spare parts planning (SPP) to help planners develop appropriate SPP strategies. The purpose of this study is to propose a framework that clarifies key factors shaping the understanding of critical challenges of SPP. Through a literature review, 16 critical challenges of the SPP criteria of planning are identified. Field study data are acquired through questionnaires given to logistics managers at a well-known computer company. After the data are analyzed through principal component analysis (PCA), the geometric mean is calculated, and we then evaluate these critical challenges of the SPP criteria using the decision making trial and evaluation laboratory (DEMATEL) approach by visualizing the structure of complex causal relationships among these criteria and obtaining the criteria influence level. The most critical criteria found in this study were "Planning for new product introduction", "Lack of system integration", "High cost" and "High number of parts". Our contribution is to effectively integrate logistics managers' experience to identify critical challenges of SPP under limited resources for adoption in real business. In addition, this study is to evaluate the critical challenges of SPP using a systematic and logical approach method.

Keywords: DEMATEL, Spare parts planning, Inventory Service parts planning

1 Introduction

Interest in the critical challenges of spare parts planning (SPP) has been increasing. While consensus is that availability of the right parts at the right place with a "just-in-time" inventory level has become one of the main challenges of SPP, opinions differ as to the most critical challenges of inventory management in the process of spare parts supply, including the lack of a system to provide a holistic perspective [1]. Some scholars have argued against the consensus view; for example, Cohen et al. [2] suggested that moving spare parts to the right places of an entire supply chain to meet service-level requirements is the main challenge of SPP. Other researchers, including the present authors, contend that both factors are challenges in SPP. The distributed nature of the spare parts, relatively large number of stock keeping units, varying demand patterns, and lead time variation are various factors that increase the complexity of SPP optimization [3].

The present study investigates the probable existence of a geometric mean-based decision making trial and evaluation laboratory (DEMATEL) model for evaluating the critical challenges of SPP. Our structured method can provide valuable information to evaluate the relationships among the critical challenges of SPP, which is why we explore this topic using an objective and systematic analysis. Our study data are acquired through questionnaires given to logistics managers who have been working at a well-known computer company in Taiwan. Having professional managers evaluating these critical criteria without a structured approach becomes a challenging task, and the existing literature is unclear regarding which criteria play the most significant role in SPP improvement. Thus, a structured tool such as the DEMATEL method can help elucidate complex causal relationships through digraphs with cause-and-effect diagramming. The advantage of this method is that the prioritizing criteria are of the same type of relationship as other criteria but that challenges arise when attempting to describe an uncertain relationship [4]; however, the geometric mean algorithm is an approach that can integrate uncertainty and ambiguity into the evaluation process [5]. This method is an effective approach for theoretical analysis of systems with imprecise information and incomplete samples. Based on these advantages, a geometric mean algorithm is used to calculate the score before the data are inputted into the DEMATEL model.

DEMATEL is used by teams of people who are processing complex issues, especially those involving judgment and perception [6]. DEMATEL converts these evaluations into numerical values, thereby allowing diverse and incommensurable criteria to be

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compared with one another in a rational and consistent manner, which distinguishes DEMATEL from other multi-criteria decision-making (MCDM) methods or personal experience [7]. In addition, Ghorabaee et al. [8] reviewed a total of 339 publications related to MCDM approaches, including book chapters and papers from peer-reviewed journals and reputable conferences from 2001 to 2016; this review indicated single and several major combinations of hybrid approaches, and the results showed that the analytic hierarchy process (AHP) method was the most popular single approach model, whereas DEMATEL was also a valuable cause-and-effect method in both single and hybrid approach that is suitable for this study. According to the previous introduction of the advantages of the DEMATEL method, the prioritizing criteria and elucidating complex causal relationships through digraphs with cause-and-effect diagramming, this indicates for that DEMATEL is an extended method for building and analyzing a structural model for analyzing the influence relation among complex criteria, which is why this study integrates the advantages of a geometric mean-based DEMATEL to present evaluating the critical challenges of SPP as a service guide for managers in the context of limited resources.

The purpose of this study is to propose a framework that clarifies key factors shaping the understanding of critical challenges of SPP. We present 16 challenges for service in SPP as a specific type of service guide for managers to easily understand and improve the most critical challenges in the context of limited resources in SPP. This study makes two contributions. First, we address the fact that the majority of the literature has lacked evaluations and explanations of each critical challenge of SPP in detail. Second, we present implications for existing methods of understanding design for research practice and teaching this subject in business. In this study, we prepared, distributed, and analyzed questionnaires that address the critical challenges of SPP that have appeared in the literature in the context of planning criteria in section 2. In Section 3, we describe the general design of the research model. The evaluation procedure for an empirical example is introduced in Section 4. We outline major findings, discussion and results at the end of Section 5. Conclusions and future research plans are presented in Section 6.

2 Literature Review

The list shown in Table 1 summarizes the 16 criteria and supporting references identified as SPP challenge criteria in questionnaires. Those 16 criteria are the most frequently appearing attributes in the SPP literature.

Table 1. Critical challenges of SPP in the literature

Section	Challenge of SPP
2.1	Inaccuracy of spare parts forecasts (C_1)
2.2	Planning for the service requirements of aging products (C_2)
2.3	Planning for new product introduction (NPI) (C_3)
2.4	Irregular variation of demand (C_4)
2.5	Repair versus buy decision (C_5)
2.6	Defective parts return of reverse logistics (C_6)
2.7	Multi-echelon network management (C_7)
2.8	Last time buy (LTB) decision (C_8)
2.9	High number of storage locations (C_9)
2.10	Lead time variability (C_{10})
2.11	Lack of a system (C_{11})
2.12	Lack of system integration (C_{12})
2.13	Interchangeable (C_{13})
2.14	High cost (C_{14})
2.15	High number of parts (C_{15})
2.16	Complex product lifecycle (C_{16})

2.1 Inaccuracy of Spare Parts Forecasts

Planners are accustomed to using past-usage quantities obtained from several different statistical methods to predict future demand quantities [9]. One can state only that the method selected was the best-fitting one in the past; that method will not necessarily be the best-fitting one in terms of future demand [10].

2.2 Planning for the Service Requirements of Aging Products

Spare parts requirements become less predictable as the products for sale and the spare parts increase in age from the stage of mass production (MP) to the end-of-life (EOL) stage [11]. Preparing spare parts for those EOL aging products is risky for service planners because such parts often become excess stock.

2.3 Planning for New Product Introduction (NPI)

NPI programs present a considerable challenge for effective planning control because the frequent introduction of new products is common in the computer industry, which results in insufficient return merchandise authorization (RMA) cases and insufficient historical spare parts usage to predict future demand [12].

2.4 Irregular Variation of Demand

The spare parts demand curve is typically erratic, and requirements occur in irregular variation, making it challenging to predict future demand [13]. Occasionally, the requirement is large and then occasionally drops sharply to a lower level.

2.5 Repair Versus Buy Decision

It is challenging to analyze the cost of buying new spare parts and the cost of repairing defective parts because the expense cost, overhead cost, sunk cost and quality of repaired parts should be incorporated [14]. The repair of a faulty part may cost more than buying a new one.

2.6 Defective Parts Return of Reverse Logistics

The purpose of defective parts returns is ensuring that faulty parts are returned to stock in a serviceable condition. It is challenging to control the return of faulty parts from the authority service party (ASP) because some parts are valuable to return but some parts are disposed of directly [15].

2.7 Multi-echelon Network Management

Multi-echelon network management fulfills different requirement in different regions and moves spare parts to the appropriate places of the entire supply chain to meet service-level requirements [16]. One of the recurrent challenges is where to place spare parts in a multi-echelon network. The remaining challenge of the multi-echelon network management is the minimization of the total cost of the supply network. Moreover, each site has different supplies in terms of the price, quality, cost, delivery time, quantity, response time, and service conditions, which result in quite a few conflicts among supply partners, and negotiation is the main conflict [17].

2.8 Last Time Buy (LTB) Decision

The challenge of LTB planning is to determine the right time and right quantity to minimize obsolescence [18]. Considering the joint optimization of the LTB quantity for products sold under warranty is challenging in capability planning for EOL parts due to unavailability of long-term forecasting to supply phased-out model parts. The response may include other unit products in MP stages running those spare parts or the introduction of other substitution parts, in which case, it is unnecessary to perform LTB planning for those spare parts.

2.9 High Number of Storage Locations

Current trends in planning for high numbers of storage locations affect the efficiency of the consumer response. It is challenging to predict where requirements will arise and where the most recent requirement arises in which physical place [19].

2.10 Lead Time Variability

Variability in supplier and customer requirement lead time can have a significant impact on inventory levels and order quantity. For example, customers call for a short-order lead time, yet for manufacturers, the lead times are long, as shown in Figure 1 [20]. This situation forces higher stock levels to be maintained at the front-side repair center in electronic and computer industry.

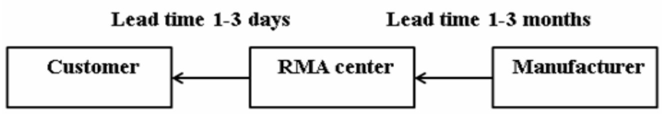

Figure 1. Lead time of spare parts in the supply chain

2.11 Lack of a System

The application software providers in the current market scope of SPP have been dominated by a select group of small specialist vendors because SPP is a specialized subset of the supply chain planning market. Costantino et al. [21] confirmed the need of a systemic perspective to deal with irregular demand for SPP management.

2.12 Lack of System Integration

The lack of information system integration and information sharing among suppliers, repairers and customers results in a bullwhip effect [22].

2.13 Interchangeable

Research and development (R&D) managers may change the production bill-of-materials (BOM) even when the product is being sold to the market, while the service department planners are unaware of configuration changes or revisions until a technician is on site. Such inaccurate configuration and revision data complicates service efforts and creates the need to keep additional spare parts in stock [23].

2.14 High Cost

The ability to deliver spare parts quickly is a main success factor of after-sales services. Ikhwan and Burney [24] stated that the most severe problem in Saudi Arabia was the delays in obtaining spare parts; it was necessary to keep a substantial amount of spare parts in stock despite the associated high inventory costs.

2.15 High Number of Parts

Finished goods are assembled from many spare parts, and each spare part is provided by several vendors to reduce costs and manufacturing risk [25].

2.16 Complex Product Lifecycle

Spare parts are assembled into different model computers, but each computer has different product lifecycles such that the life cycle of spare parts requires cross checking of all product units [26]. Spare parts in each lifecycle are given different conditions by suppliers, such as the supply lead time and price. Thus, it becomes necessary to calculate the expected shortages for each time point within the entire spare parts lifecycle to ensure a correct strategic order by investigating optimization of spare parts performance with big data. [27].

3 Methods

The proposed model of evaluating the critical challenges of SPP consists of four main phases:

- Data collection by questionnaires.
- Data analysis using the principal component analysis (PCA) method.
- Processing the score of each question using the geometric mean algorithm before the data are inputted into the DEMATEL analysis.
- System analysis using the DEMATEL method and creation of a causal relationship diagram of the criteria.

3.1 Questionnaires

16 different criteria are recognized and classified through PCA to extract 13 criteria remaining in four common factors according to the data obtained from the first questionnaire. We evaluated the critical challenges of SPP based on the data obtained from the second questionnaire.

3.2 Principal Component Analysis

PCA, invented in 1901 by Karl Pearson, is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of value factors called principal components.

3.3 The Geometric Mean Algorithm

The geometric mean was calculated based on Gauss' definition from 1796: the nth score of one question that planner managers answered as x_1, x_2, ..., x_n, i.e., if the planner managers chose x_1, x_2, ..., x_n, as a set of answers for a certain question, the geometric mean is defined as shown in equation (1).

$$(\prod_{i=1}^{n} X_i)^{\frac{1}{n}} \sqrt[n]{x_1 x_2 \cdots x_n} \quad \textbf{(1)}$$

3.4 The DEMATEL Method

The DEMATEL method was introduced by the Geneva Research Centre of the Battelle Memorial Institute in 1973. Fontela and Gabus developed the following steps.

- Generating the direct-relation matrix
- Normalizing the direct-relation matrix
- Attaining the total-relation matrix
- Producing a cause-and-effect diagram

3.5 The Evaluation Procedure

To accomplish the comprehensive model, certain step-by-step procedures are implemented. First, 16 criteria in section 2 are listed through using the 1st questionnaire forms to survey the importance of the criteria in section 4.1. Second, 16 different criteria are recognized and classified through PCA to extract 13 criteria remaining in four common factors in section 4.2. Third, we investigated the influence between each criterion using a 2nd questionnaire, and the casual model identifies the main causes and effects using a geometric-mean-based DEMATEL analysis method that specifies the priorities of each factor in section 4.3 and section 4.4. Finally, the influenced-influencing matrix and key criteria are determined. The research method and evaluation procedures are illustrated in Figure 2.

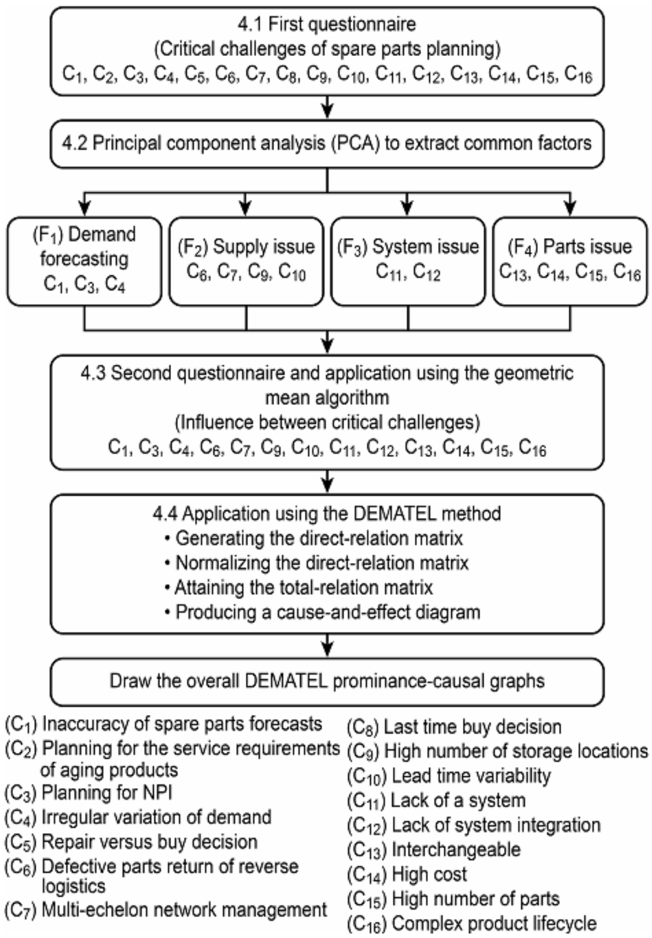

Figure 2. Research method and evaluation procedures

4 Material and Result of the Evaluation Procedure for an Empirical Example

Surveys using these two questionnaires were conducted through e-mails sent to nine logistics managers who had been working for more than 10 years at a well-known computer company in Taiwan. These managers worked at the headquarters in Taiwan and a branch company in the United States, Singapore, Australia, the Netherlands and the Czech Republic. They encountered planning problems each day and were knowledgeable of the critical challenges of SPP.

MCDM method was adapted to effectively study dynamic engagement behaviour analysis in a cloud-based environment [28], analysis of factors affecting customer satisfaction in e-commerce [29], dense small cells heterogeneous networks [30], and analysis of traffic offload in heterogeneous shared networks [31] which demonstrated the suitability of MCDM for addressing decision-making tasks under uncertainty. Most of these articles were adapted to using questionnaires in their research so we operationalized a systematic approach utilizing questionnaires for suvery of our topic as operational definitions of constructs in section 4.1.

4.1 First Questionnaire

The purpose of the first questionnaire is to filter out principal components of the critical challenges of SPP criteria from the literature and to group them by criteria into several common factors. This questionnaire ranks the various attributes on a 10-point scale ranging from 10 (extremely high) to 1 (extremely low). Based on a review of the literature in section 2, 16 critical challenges of SPP criteria of planning were included in the questionnaire as Table 2, which rates the following critical challenges of SPP according to the impact of on the prediction of future parts usage and that of inventory optimization. If you feel that “Inaccuracy of spare parts forecasts” has an extremely high impact on the prediction of future parts usage, you can fill in 9, as Table 2 illustrates. The data were filtered into 13 key criteria out of 16 and then extracted into four common factors using PCA in section 4.2. The software used was Statistica (TIBCO Software, Palo Alto, CA, USA).

Table 2. First questionnaire

1. Rate the following critical challenges of spare parts planning according to the impact of *the prediction of future parts usage* on a scale from 1 (extremely low) to 10 (extremely high)			
9	Inaccuracy of spare parts forecasts	______	High number of storage locations
______	Planning for the service requirements of aging products	______	Lead time variability
______	Planning for new product introduction (NPI)	______	Lack of a system
______	Irregular variation of demand	______	Lack of system integration
______	Repair versus buy decision	______	Interchangeable
______	Defective parts return of reverse logistics	______	High cost
______	Multi-echelon network management	______	High number of parts
______	Last time buy (LTB) decision	______	Complex product lifecycle
2. Rate the following critical challenges of spare parts planning according to the impact of *inventory optimization* on a scale from 1 (extremely low) to 10 (extremely high)			
______	Inaccuracy of spare parts forecasts	______	High number of storage locations
______	Planning for the service requirements of aging products	______	Lead time variability
______	Planning for new product introduction (NPI)	______	Lack of a system
______	Irregular variation of demand	______	Lack of system integration
______	Repair versus buy decision	______	Interchangeable
______	Defective parts return of reverse logistics	______	High cost
______	Multi-echelon network management	______	High number of parts
______	Last time buy (LTB) decision	______	Complex product lifecycle

4.2 PCA to Extract Common Factors

PCA was used to isolate four common factors based on factor loading greater than 0.65, as shown in Figure 3 and the variance explained is as high as 83.48%. After the axis is rotated using the “Varimax raw” method, the four criteria C_{13}, C_{14}, C_{15} and C_{16} have a higher loading factor in common-factor 1 that we rename as “Parts issue”, and criteria C_1, C_3 and C_4 are formed as a new common-factor termed “Demand forecasting”. C_6, C_7, C_9 and C_{10} are then combined as “Supply issue”, and C_{11} and C_{12} are grouped as “System issue”. Finally, the remaining 13 criteria of a pairwise influence questionnaire are used in the second questionnaire. The second questionnaire is described in Section 4.3.

Variable	Factor Loadings (Varimax raw) Extraction: Principal components (Marked loadings are > .650000)			
	Factor 1	Factor 2	Factor 3	Factor 4
Inaccuracy of spare parts forecasts (C_1)	0.0106	**0.8914**	0.3485	-0.1334
Planning for the service requirements of ageing products (C_2)	0.6303	-0.0418	0.4729	0.2462
Planning for new product introduction (C_3)	0.1352	**0.8791**	-0.3320	0.0712
Irregular variation of demand (C_4)	-0.1549	**0.8794**	-0.0922	-0.2543
Repair versus buy decision (C_5)	0.5832	0.5821	-0.1444	0.125
Defective parts return of reverse logistics (C_6)	0.2977	0.0432	**0.8813**	-0.1070
Multi-echelon network management (C_7)	-0.1616	0.4341	**0.7468**	0.2002
Last time buy decision (C_8)	0.5483	-0.2748	0.4821	0.5718
High number of storage locations (C_9)	0.6126	-0.2124	**0.6685**	0.1607
Lead time variability (C_{10})	0.0885	0.2985	**-0.8272**	-0.1822
Lack of a system (C_{11})	0.0946	0.1945	-0.0115	**-0.8961**
Lack of system integration (C_{12})	-0.0303	0.0334	0.1024	**0.9468**
Interchangeable (C_{13})	**0.9466**	0.1642	-0.1766	0.0064
High cost (C_{14})	**0.7945**	-0.0602	0.1686	0.0541
High number of parts (C_{15})	**0.7242**	0.0590	0.3415	-0.3152
Complex product life cycle (C_{16})	**0.8548**	-0.0772	0.1481	-0.1803
Expl.Var	**4.3705**	**3.1603**	**3.3915**	**2.4347**
Prp.Totl	**0.2732**	**0.1975**	**0.2120**	**0.1522**
Cumulative	**27.32%**	**47.06%**	**68.26%**	**83.48%**

Figure 3. Principal component analysis

4.3 Second Questionnaire and Application Using the Geometric Mean Algorithm

The purpose of the second questionnaire, a pairwise influence questionnaire, is to analyze the degree of influence between each criterion to determine the important criteria for the critical challenges of SPP. Based on the 13 criteria remain in section 4.2, the second questionnaire was designed to rank the influence among each criterion using a specific pair-wise influence question; we illustrate this second questionnaire in Figure 4. An example specific pairwise influence question would be "How much influence does criterion 1 (C_1) have on criterion 3 (C_3)" and vice versa. Defining the linguistic scale in this questionnaire is a five-level scale with the following descriptions: 0. No effect: 1. Little effect: 2. Strong effect: 3. Very strong effect: 4. Extremely strong effect. When the managers complete questionnaires, they can select multiple answers from 0, 1, 2, 3, and 4 or choose a single answer from this group. For example, if the managers consider that criterion 1 (C_1) sometimes has a high influence on criterion 3 (C_3) but that criterion 1 (C_1) occasionally has a very low influence on criterion 3 (C_3), they can choose "1 Little effect" and "3 Very strong effect". The geometric mean algorithm in equation (2) is used to calculate the score, which in this case is 1.73, which becomes the component of x in equation (3).

$$(\prod_{i=1}^{n} X_i)^{\frac{1}{n}} \sqrt[2]{1*3} = 1.73 \quad \textbf{(2)}$$

Thus, using the geometric mean algorithm, we implement a fuzzy base to solve uncertainty problems. The data are then analyzed using the DEMATEL model in Excel as described in Section 4.4.

4.4 Application Using the DEMATEL Method

The DEMATEL method is composed of the following major steps.

Step 1: Generating the direct-relation matrix.

First, the direct-relation matrix is developed. To measure the relationship between the criteria $c=\{c_i|_{i=1,2,3,\ldots\ldots,j}\}$, a decision group of n specialists are asked to develop sets of pairwise comparisons in linguistic terms. Accordingly, matrices [Xn] is such as [X^1], [X^2],... [X^n]. From the response of each specialist and using the geometric mean as the elements x, we obtain equation (3).

Cause and effect (Criteria)	(C_1) Inaccuracy of spare parts forecasts	(C_3) Planning for new product introduction	(C_4) Irregular variation of demand	(C_6) Defective parts return of reverse logistics	(C_7) Multi-echelon network management	(C_9) High number of storage locations	(C_{10}) Lead time variability	(C_{11}) Lack of a system	(C_{12}) Lack of system integration	(C_{13}) Interchangeable	(C_{14}) High cost	(C_{15}) High number of parts	(C_{16}) Complex product lifecycle
(C_1) Inaccuracy of spare parts forecasts	X	(1,3)											
(C_3) Planning for new product introduction		X											
(C_4) Irregular variation of demand			X										
(C_6) Defective parts return of reverse logistics				X									
(C_7) Multi-echelon network management					X								
(C_9) High number of storage locations						X							
(C_{10}) Lead time variability							X						
(C_{11}) Lack of a system								X					
(C_{12}) Lack of system integration									X				
(C_{13}) Interchangeable										X			
(C_{14}) High cost											X		
(C_{15}) High number of parts												X	
(C_{16}) Complex product lifecycle													X

Figure 4. Second questionnaire

$$Matrix\,[X^{n}] = \begin{matrix} c_1 \\ \vdots \\ c_j \end{matrix} \begin{bmatrix} x_{11}^{n} & \cdots & x_{j1}^{n} \\ \vdots & \ddots & \vdots \\ x_{1j}^{n} & \cdots & x_{jj}^{n} \end{bmatrix} \quad (3)$$

Second, we combine all direct-relation matrices X^{n} into an aggregate matrix X using an averaging process, as shown in equation (4).

$$X = \left(\frac{\Sigma_{i=1}^{n} x^{n}}{n} \right) \quad (4)$$

The process must be completed for each of the specialists' direct-relation matrices. The aggregated direct-relationship matrix of the critical challenges of SPP is shown in Table 3.

Step 2: Normalizing the direct-relation matrix.

On the basis of the overall geometric mean matrix direct-relation matrix X, the normalized geometric mean matrix direct-relation matrix Y can be obtained through equations (5) and (6). The Y matrix for these case study evaluations is shown in Table 4.

$$S = \max(\max_{0 \le a \le 1} \Sigma_{b=1}^{j} x_{ab},\ \max_{0 \le b \le 1} \Sigma_{a=1}^{j} x_{ab}) \quad (5)$$

$$\mathrm{Y} = \frac{x}{\mathrm{s}} \quad (6)$$

Step 3: Attaining the total-relation matrix.

The total-relation matrix Z is determined by equation (7), where "I" stands for the identity matrix. The empirical case total relation matrix is illustrated in Table 5.

$$\mathrm{Z} = \Sigma_{n=1}^{\infty} \mathrm{Y}^{n} = \mathrm{Y}(\mathrm{I} - \mathrm{Y})^{-1} \quad (7)$$

Step 4: Producing a cause-and-effect diagram.

First, we determine row D_a and column R_b for summation of each row a and column b, respectively, from the total relation matrix Z as in equations (8), (9) and (10).

$$\text{Matrix } Z = [z_{ab}],\ _{a,b \in \{1,2,\ldots\ldots j\}} \quad (8)$$

$$\text{Row } D_a = \Sigma_{b=1}^{j} z_{ab\,[a,\,b \in (1,\,2,\,\ldots\ldots j)]} \quad (9)$$

$$\text{Column } R_b = \Sigma_{a=1}^{j} z_{ab\,[a,\,b \in (1,\,2,\,\ldots\ldots j)]} \quad (10)$$

Table 3. Generation of the direct-relation matrix

Criterion	C_1	C_3	C_4	C_6	C_7	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}
C_1	0.00	2.67	1.56	1.41	1.44	2.56	1.78	1.78	2.22	2.78	2.89	2.33	2.00
C_3	2.44	0.00	2.78	1.78	2.44	2.22	1.89	1.44	1.78	3.44	3.33	3.00	3.22
C_4	2.78	2.67	0.00	1.78	2.56	1.89	1.78	1.22	1.67	2.33	1.78	2.00	2.00
C_6	1.33	2.00	2.22	0.00	2.41	2.44	2.78	1.78	1.33	1.56	1.67	1.67	1.78
C_7	1.74	2.11	2.44	2.33	0.00	3.00	2.89	1.56	1.56	2.44	2.33	2.11	1.89
C_9	0.89	2.33	2.33	2.44	2.56	0.00	2.89	1.67	1.78	2.00	2.44	2.44	2.22
C_{10}	2.00	2.00	1.89	1.56	2.48	2.22	0.00	1.56	1.67	2.56	2.33	2.44	2.33
C_{11}	2.11	1.78	2.11	2.22	2.22	2.22	1.78	0.00	3.48	2.11	2.78	2.15	2.67
C_{12}	1.37	2.00	2.00	2.00	1.89	2.11	2.44	3.30	0.00	2.44	2.89	2.56	2.89
C_{13}	1.11	1.85	1.89	1.67	2.00	2.44	1.78	1.56	2.00	0.00	2.11	2.67	3.22
C_{14}	1.56	2.11	2.33	1.89	2.00	2.44	1.89	1.67	2.11	2.44	0.00	2.41	3.22
C_{15}	1.67	2.00	1.89	1.78	2.44	2.22	1.89	1.67	2.11	2.33	2.56	0.00	3.11
C_{16}	1.56	2.67	2.44	1.67	2.11	2.11	1.89	1.63	1.74	3.00	2.56	2.78	0.00

Note. (C_1) Inaccuracy of spare parts forecasts; (C_3) Planning for NPI; (C_4) Irregular variation of demand; (C_6) Defective parts return of reverse logistics; (C_7) Multi-echelon network management; (C_9) High number of storage locations; (C_{10}) Lead time variability; (C_{11}) Lack of a system; (C_{12})Lack of system integration; (C_{13}) Interchangeable; (C_{14}) High cost; (C_{15}) High number of parts; (C_{16}) Complex product lifecycle.

Table 4. Normalization of the direct-relation matrix

Criterion	C_1	C_3	C_4	C_6	C_7	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}
C_1	0.00	0.09	0.05	0.05	0.05	0.08	0.06	0.06	0.07	0.09	0.09	0.08	0.07
C_3	0.08	0.00	0.09	0.06	0.08	0.07	0.06	0.05	0.06	0.11	0.11	0.10	0.11
C_4	0.09	0.09	0.00	0.06	0.08	0.06	0.06	0.04	0.05	0.08	0.06	0.07	0.07
C_6	0.04	0.07	0.07	0.00	0.08	0.08	0.09	0.06	0.04	0.05	0.05	0.05	0.06
C_7	0.06	0.07	0.08	0.08	0.00	0.10	0.09	0.05	0.05	0.08	0.08	0.07	0.06
C_9	0.03	0.08	0.08	0.08	0.08	0.00	0.09	0.05	0.06	0.07	0.08	0.08	0.07
C_{10}	0.07	0.07	0.06	0.05	0.08	0.07	0.00	0.05	0.05	0.08	0.08	0.08	0.08
C_{11}	0.07	0.06	0.07	0.07	0.07	0.07	0.06	0.00	0.11	0.07	0.09	0.07	0.09
C_{12}	0.04	0.07	0.07	0.07	0.06	0.07	0.08	0.11	0.00	0.08	0.09	0.08	0.09
C_{13}	0.04	0.06	0.06	0.05	0.07	0.08	0.06	0.05	0.07	0.00	0.07	0.09	0.11
C_{14}	0.05	0.07	0.08	0.06	0.07	0.08	0.06	0.05	0.07	0.08	0.00	0.08	0.11
C_{15}	0.05	0.07	0.06	0.06	0.08	0.07	0.06	0.05	0.07	0.08	0.08	0.00	0.10
C_{16}	0.05	0.09	0.08	0.05	0.07	0.07	0.06	0.05	0.06	0.10	0.08	0.09	0.00

Note. (C_1) Inaccuracy of spare parts forecasts; (C_3) Planning for NPI; (C_4) Irregular variation of demand; (C_6) Defective parts return of reverse logistics; (C_7) Multi-echelon network management; (C_9) High number of storage locations; (C_{10}) Lead time variability; (C_{11}) Lack of a system; (C_{12})Lack of system integration; (C_{13}) Interchangeable; (C_{14}) High cost; (C_{15}) High number of parts; (C_{16}) Complex product lifecycle.

Table 5. Total-relation matrix

Criterion	C_1	C_3	C_4	C_6	C_7	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}
C_1	0.29	0.45	0.42	0.37	0.42	0.47	0.42	0.35	0.40	0.50	0.50	0.48	0.50
C_3	0.41	0.43	0.51	0.43	0.51	0.52	0.48	0.39	0.44	0.58	0.58	0.56	0.60
C_4	0.37	0.44	0.36	0.36	0.44	0.44	0.40	0.32	0.37	0.47	0.46	0.45	0.48
C_6	0.31	0.40	0.40	0.29	0.42	0.43	0.41	0.32	0.34	0.42	0.43	0.42	0.44
C_7	0.36	0.45	0.45	0.40	0.39	0.49	0.46	0.35	0.39	0.50	0.50	0.48	0.50
C_9	0.33	0.45	0.45	0.40	0.46	0.40	0.46	0.35	0.39	0.48	0.50	0.49	0.51
C_{10}	0.35	0.43	0.42	0.36	0.45	0.45	0.36	0.34	0.38	0.49	0.48	0.47	0.50
C_{11}	0.38	0.46	0.46	0.42	0.47	0.49	0.45	0.32	0.46	0.51	0.53	0.50	0.55
C_{12}	0.36	0.47	0.46	0.41	0.47	0.49	0.47	0.42	0.36	0.53	0.54	0.52	0.56
C_{13}	0.32	0.41	0.41	0.36	0.42	0.45	0.40	0.33	0.38	0.40	0.46	0.47	0.51
C_{14}	0.35	0.44	0.45	0.39	0.45	0.47	0.43	0.35	0.40	0.50	0.42	0.49	0.54
C_{15}	0.35	0.44	0.43	0.38	0.45	0.46	0.42	0.35	0.40	0.49	0.50	0.41	0.53
C_{16}	0.35	0.46	0.45	0.38	0.45	0.47	0.43	0.35	0.39	0.52	0.50	0.50	0.44

Note. (C_1) Inaccuracy of spare parts forecasts; (C_3) Planning for NPI; (C_4) Irregular variation of demand; (C_6) Defective parts return of reverse logistics; (C_7) Multi-echelon network management; (C_9) High number of storage locations; (C_{10}) Lead time variability; (C_{11}) Lack of a system; (C_{12})Lack of system integration; (C_{13}) Interchangeable; (C_{14}) High cost; (C_{15}) High number of parts; (C_{16}) Complex product lifecycle.

The row values D_a stands for the direct and indirect effect by criterion a on the other criteria for the challenges of SPP. The column value R_b demonstrates that the criterion b receives the summation of direct and indirect effects from the other criterion for the challenges of SPP. Second, we establish the overall prominence and net effect of criterion for the challenges of SPP using the expressions in equations (11) and (12).

$$\text{Prominence P} = \{D_a + R_b \mid a = b\} \quad \textbf{(11)}$$

$$\text{Net effect E} = \{D_a - R_b \mid a = b\} \quad \textbf{(12)}$$

The prominence P indicates the degree of importance that the critical challenges of criterion a play in the entirety of SPP. In contrast, the net effect E denotes the criterion contribution to improving the critical challenges of SPP. Furthermore, if the net effect E is positive, then the criterion is a net cause of improving the challenges of SPP; otherwise, the net effect E is the net receiver when E is negative. The results of this empirical study are shown in Table 6. The overall DEMATEL prominence causal graphs are based on the data in Table 6. The final two columns of Table 6 are plotted on a two-dimensional axis for the critical challenges of SPP, with Figure 5 showing the overall prominence and net effect results of the 13 criteria. The four common factors are plotted onto Figure 6. The two-way significant relationships are represented by two-way arrow solid lines, whereas the one-way relationships are represented by one-way arrow solid lines.

Table 6. The degree of prominence and net effect

Criterion	D_a	R_b	Prominence $D_a + R_b$	Net effect $D_a - R_b$
C_1	5.57	4.51	10.08	1.06
C_3	6.41	5.71	12.13	0.70
C_4	5.35	5.68	11.03	-0.32
C_6	5.04	4.95	9.99	0.08
C_7	5.72	5.80	11.53	-0.08
C_9	5.66	6.05	11.70	-0.39
C_{10}	5.47	5.59	11.06	-0.13
C_{11}	6.01	4.56	10.57	1.45
C_{12}	6.06	5.09	11.16	0.97
C_{13}	5.32	6.39	11.72	-1.07
C_{14}	5.68	6.39	12.07	-0.71
C_{15}	5.60	6.23	11.83	-0.62
C_{16}	5.70	6.64	12.34	-0.94

Note. (C_1) Inaccuracy of spare parts forecasts; (C_3) Planning for NPI; (C_4) Irregular variation of demand; (C_6) Defective parts return of reverse logistics; (C_7) Multi-echelon network management; (C_9) High number of storage locations; (C_{10}) Lead time variability; (C_{11}) Lack of a system; (C_{12})Lack of system integration; (C_{13}) Interchangeable; (C_{14}) High cost; (C_{15}) High number of parts; (C_{16}) Complex product lifecycle.

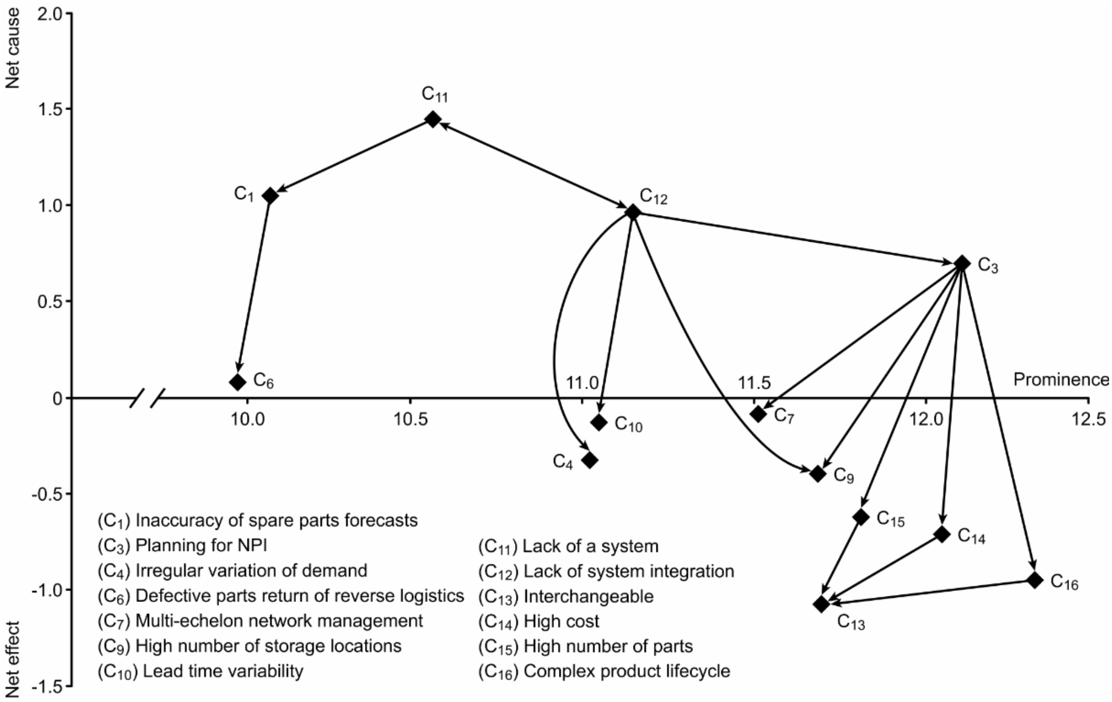

Figure 5. Prominence causal relationship diagram of criteria

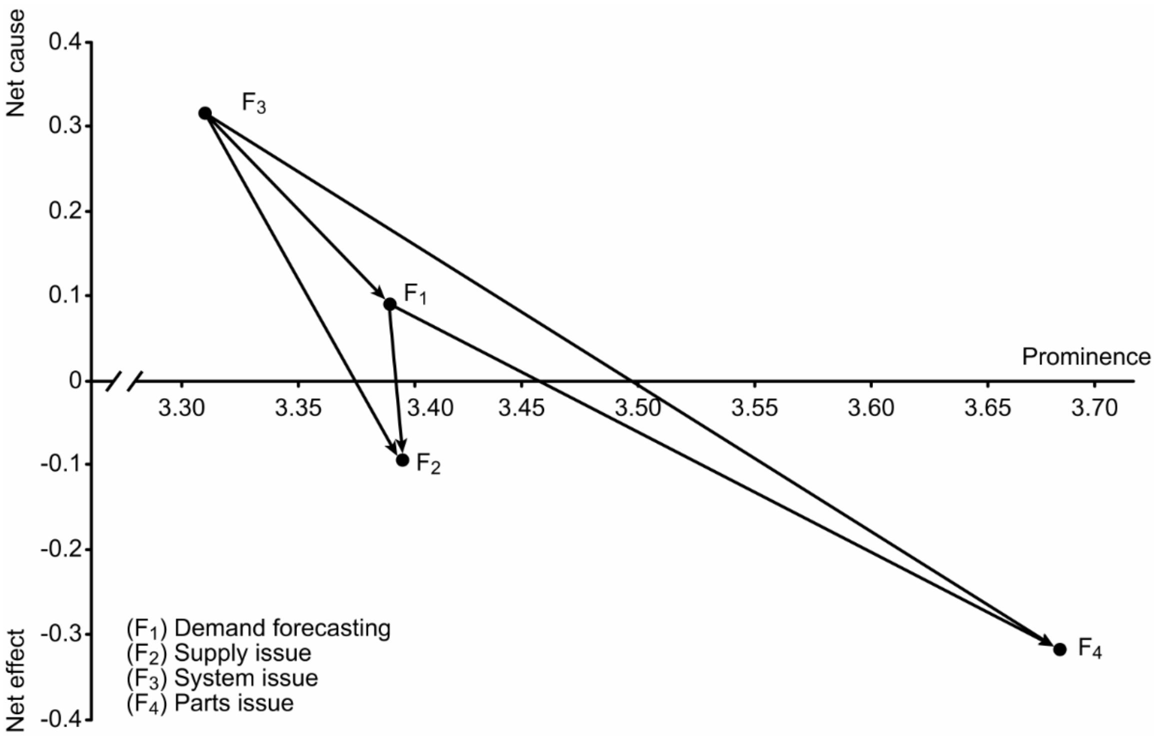

Figure 6. Prominence causal relationship diagram of factors

5 Discussions

The top four important criteria are “Complex product lifecycle (C_{16})”, “Planning for NPI (C_3)”, “High cost (C_{14})” and “High number of parts (C_{15})”. C_{14}, C_{15} and C_{16} are parts issues, and C_3 is a factor of demand forecasting. The appearance of C_{16}, C_{14} and C_{15} as the most prominent critical challenges of SPP is not surprising, as shown in Figure 5. Many studies have shown that designing for service, designing for disassembly and modularizing spare parts can reduce an excess of spare parts and make planning easier [32]. C_3 is challenging for demand forecasting because of a lack of historic data and intermittent demand. Additionally, the direction of significant influences among C_{16}, C_{14}, C_{15} and C_3 is unidirectional. This result fits within the design for service planning of NPI and will reduce the complex product lifecycles, parts interchangeability, high cost and high number of parts [33]. Insights into the direct and indirect relationships among those criteria and planning for NPI results from both relationship types are designed for service, and system integration perspectives are presented.

Figure 6 illustrates that the system issue is not the most important critical challenges of SPP, but this issue could improve not only demand and supply management but also the forecasting accuracy and parts lifecycle management. According to Figure 5, the two system criteria “Lack of a system (C_{11})” and “Lack of system integration (C_{12})” have a significant influence on the net cause of prominence. Parts management by these two system criteria, C_{11} and C_{12}, also influences C_{14}, C_{15} and C_{16}. These are more tool-based, operational criteria that are in place to record parts information, product and parts lifecycle alignment. An important observation regarding this finding is that these buyer–seller alliances are often designed to enhance collaborative relationships, enhance information sharing, and lead to a synchronized supply chain due to system integration among all supply chain vendors [34].

Interestingly, our results show that parts issues are more critical than system issues and that staff can overcome SPP issues by management so that the system acts only as an assistance tool. In contrast, our impression has been that it is common for most staff members to view the system as the most critical criterion. Surprisingly, “Lack of a system (C_{11})” and “Lack of system integration (C_{12})” are not the top critical challenges of SPP in our study. In general, planners typically responded that they lack a powerful system to control planning, which is why the planning is beyond their control. Our findings are not in contradiction with those of the empirical studies discussed above. With regard to inaccuracy of demand forecasting being one of the important challenges of inventory management, our findings are consistent with those of Boone et al. [1], although important differences exist regarding other aspects of the studies.

The most important influencing criteria that have an effect on improving critical challenges of SPP, with the highest score of D_a - R_b in Table 6, are related primarily to internal capability. From Figure 5, we can identify two key net causes influencing criteria with net effect scores greater than 0. Two criteria feature highly valued cause valuations: “Planning for NPI (C_3)” and “Lack of system integration (C_{12})”. The improving critical challenge of SPP will begin with these two criteria. The first involves planning for NPI to ensure that each new product is designed for service with structures of parts lists to reduce parts volumes, cost and parts interchangeability, making it straightforward for planners to prepare spare parts. Second, Figure 5 illustrates that "High number of storage locations (C_9)", "Irregular variation of demand (C_4)" and "Planning for NPI (C_3)" can be managed more efficiently through system integration. The remaining similar net cause criteria for improving the critical challenges of SPP are "Inaccuracy of spare parts forecasts (C_1)" and "Defective parts return of reverse logistics (C_6)", which belong to demand and supply issues and occur day by day but are not as prevalent in terms of their relationships with other criteria. C_{11} and C_{12} point to C_1 and C_6, which represent those demand and supply issues that can be addressed using effective systems.

The resulting criteria are the factors that may be the last ones that planners must address. These criteria are not necessarily less important since many of the important influencing net causal criteria can point to one result of the criteria. Figure 5 illustrates eight key net effect critical challenges of SPP criteria with net effect scores below 0. Five out of those eight criteria are net effects of the critical challenges of SPP, although they are not significant causes for any other criteria. These criteria are C_4, C_7, C_9, C_{10} and C_{13}. The significant causes of these 5 criteria are similar, including C_{12} and C_3. Such results indicate that these five criteria are generally severe issues at later stages and can be addressed after the 2 net cause criteria are improved.

6 Conclusions

The ultimate purpose of this study, rather, is to illustrate that the systematic approach of DEMATEL enables reasonable decision making and that this approach focuses on introducing those critical challenges of SPP so that managers can more easily and thoroughly understand which critical challenge criteria under limited resources contribute the most value and should be adopted in real businesses. The following insights to the practice of a geometric-mean-based DEMATEL model for evaluating critical challenges of SPP are gained: first, the process helps ensure that SPP is currently receiving significant practical and research attention in contexts closer to meeting real business requirements and situations. Second, the criteria demonstrated above are well documented in the literature, but their relationships, conceptual mapping and cause have been explored to a lesser extent in SPP. Third, we also present a bridge between practitioners and researchers. The results of this effort are expected to help future researchers to explore topics relevant to spare parts.

Future research can strive to expand one of the 16 criteria functioning in deep discussion of topics and issues directly impacting SPP. For instance, Figure 5 indicates that "Defective parts return of reverse logistics (C_6)" is not a significant net causal or effect factor. The managers in this study view the defective parts return of reverse logistics as less contributory for meeting the critical challenges of SPP. However, this factor can reduce the purchase of new parts to saving purchase costs by repairing defective parts to stock in a serviceable condition. Consequently, defective parts return of reverse logistics is indicated as a future research direction in the final section because this topic is challenging to address in the context of reverse logistics.

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