Network-Oriented Uncertainty Evaluation of Industrial Product-Service Collaborative Readiness

Christopher Durugbo*, Xiaojun Wang

Department of Management, University of Bristol, United Kingdom

* Corresponding author. Tel.: +44 (0) 117 331 0520. E-mail address: christopher.durugbo@bristol.ac.uk

Abstract

Industrial practitioners and scholars have argued that collaboration for the delivery of an industrial product-service system (IPSS) has become an increasingly important strategy for industrial firms. Further, the requirements for IPSS implementation are different from traditional sales of manufactured products. Consequently, an understanding of uncertainty sources is therefore crucial to managing network complexity and allocating resource for uncertainty mitigation. Along these lines, a fuzzy analytical framework for evaluating supply chain uncertainty is proposed in this paper for prioritising sources of network uncertainty. A stainless steel manufacturing case company illustrates how the proposed framework of uncertainty measures and fuzzy-based techniques can be applied and can help researchers and practitioners to prioritise uncertainties from a practical point of view.

1. Introduction

Studies of industrial trends suggest increasing shifts in traditional manufacturing paradigms to more services-oriented strategies for future production and economies (e.g. [1]). Furthermore, scholars and practitioners now widely acknowledge that the blending of goods and equipment with industrial services, a transformative process termed servitization [2], increasingly offers an important avenue for firms and supply chains to lock out competitors, lock in customers, and enhance differentiation levels [1,3]. How industrial firms approach this shift towards service-oriented strategies tends to vary. This is due to a variety of existing and emerging sources of uncertainty that make it difficult for supply chains to extrapolate from past service operations – to make forecasts for future service projects.

Traditionally, uncertainty poses decision making challenges for product development by supply chains and is expressed by questions “such as: what will my customers order, how many products should we have in stock, and will the supplier deliver the requested goods on time and according to the demanded specifications” [4]? However, requirements for partnerships within supply chains pose different questions such as: who can we best work with, how many geographical dispersed companies or multinational corporations should we have, and will partners coordinate and share information on time and according to agreed operating policies and contracts? In view of the product-service arrangements needed to facilitate service encounters and processes, these uncertainties tend to plague supply chains for service operations particularly with regards to determining collaborating partners. With firms increasingly no longer competing as individual businesses but now as parts of supply chains, there is a need for a common and recognised methodology to evaluate readiness of partnering firms to enter into collaborations.

Collaborative readiness (CR) is used in this paper to mean the preparedness and willingness to collaborate [5]. With this perspective in mind, studies have tended to use network based approaches that examine how partners join, leave, or remain in collaborations [6,7]. These works focus on aspects such as
accreditation reports, competencies, relationships and past performances. However, there is a need for multi-criteria decision support that leverages the knowledge of domain experts. This is because the knowledge of experts such as designers and manufacturers is crucial for clarifying service operations and network uncertainties [5].

Along these lines, this research concentrates on CR and proposes an uncertainty evaluation framework for prioritising sources of network uncertainty. Informed by the literature, the framework identifies measures for demand, supply, manufacturing (and process) and control uncertainty sources with a far-reaching perspective of how network uncertainty could be evaluated. The proposed framework also applies a tool set of fuzzy-based techniques (fuzzy extent analysis and fuzzy TOPSIS) to evaluate levels of fuzziness for industrial product-service CR. An industrial product-service systems (IPS) shifts traditional business-to-business ‘product thinking’ focus towards more ‘systems thinking’ attitudes in which value propositions are developed based on product-orientation (product related services and advice/consultancy), use-orientation (product lease, product renting/sharing and product pooling) and result-orientation (activity management, pay per service unit and functional result) [9]. A stainless steel manufacturing case company illustrates how the proposed framework of uncertainty measures and fuzzy-based techniques can be applied and can help researchers and practitioners to prioritise uncertainties from a practical point of view.

2. Proposed Methodology

2.1. Measures of uncertainty

Supply chains as ‘complex networks’ [4] are plagued by and this study applies measures of demand, supply, manufacturing (and process) and control uncertainty, as shown in Table 1. These sources have been widely researched and applied by scholars for use in clarifying uncertainties for partnering firms in supply chains (see for instance [10-14]). Demand uncertainty represents unpredictable variations in the quality, quantity and timing of demand that is experienced across this supply chain [10,11]. This comes down to the amount of forecast error i.e. the difference between actual demand and forecast demand [12]. Supply uncertainty triggered by supplier performance variability and inconsistency that result in delayed, deficient or defective deliveries [10,11]. It is brought about by machine breakdowns, downtimes during manufacturing, quality and yield problems, order-entry errors, forecast inaccuracies or logistical malfunctions [12]. Manufacturing uncertainty refers to volatility in process performances caused by unreliable manufacturing and production processes [10,13]. This form of unpredictability results in poor production yields, scraps and write-offs [4]. Control uncertainty stands for unpredictable and unknown variations of system controls [12-14] due to wrong decision rules and stale, noisy or incomplete information. The different measurement items captured for each uncertainty source, as shown in Table 1, are derived from survey instruments tested by management researchers [11].

### Table 1. Measurement items of network uncertainty.

| Source                  | Tag | Item                                      | Ref          |
|-------------------------|-----|-------------------------------------------|--------------|
| **C1, Demand**          |     | **and distribution (uncertainty)**       |              |
|                         | C11 | Rate of new product introduction          | [4, 10-13]   |
|                         | C12 | Predictability of product demand          |              |
|                         | C13 | Number of sales channels                  |              |
|                         | C14 | Sharing demand forecast with customer     |              |
|                         | C15 | Heterogeneity of channel                  |              |
|                         | C16 | Frequency of channel replacement          |              |
|                         | C17 | Product life-cycle                        |              |
|                         | C18 | Product variety                           |              |
|                         | C19 | Frequency of change in order content      |              |
|                         | C20 | Stability of quality of critical material |              |
|                         | C21 | Frequency of replacement of critical      | [4, 10-13]   |
|                         |     | material suppliers                        |              |
|                         | C22 | Number of critical material suppliers     |              |
|                         | C23 | Variance of material supply lead-time     |              |
|                         | C24 | Complexity of critical material           |              |
|                         | C25 | Complexity of procurement                 |              |
|                         | C26 | technology for critical material          |              |
|                         | C27 | Time specificity of material procurement  |              |
|                         | C28 | Delivery frequency of critical material   |              |
|                         | C29 | Degree of impact imposed by on-time       |              |
|                         |     | delivery                                 |              |
|                         | C30 | Delay of critical material delivery       |              |
|                         | C31 | Impact of change in pre-process on        | [4, 10-13]   |
|                         |     | post-process                              |              |
|                         | C32 | Impact of pre-process output on           |              |
|                         |     | post-process performance                  |              |
|                         | C33 | Degree of a product decomposable to       |              |
|                         |     | simpler components                        |              |
|                         | C34 | Degree of modularization of product       |              |
|                         | C35 | Frequency of redesigns                    |              |
|                         | C36 | Number of items changed per redesign      |              |
|                         | C37 | Information accuracy                      |              |
|                         | C38 | Information through-put times             | [14-16]      |
|                         | C39 | Information availability and transparency |              |
| **C2, Supply**          |     | **uncertainty**                           |              |
|                         | C41 | Information availability and transparency |              |
|                         | C42 | Information through-put times             |              |
| **C3, Manufacturing**   |     | **and process (uncertainty)**             |              |
|                         | C51 | Information about product                 |              |
|                         | C52 | Information about channels                |              |
|                         | C53 | Information about information            |              |
|                         | C54 | Information about quality                 |              |
|                         | C55 | Information about logistics               |              |
| **C4, Control**         |     | **and planning (uncertainty)**            |              |
|                         | C61 | Information about product                 |              |
|                         | C62 | Information about channels                |              |
|                         | C63 | Information about information            |              |
|                         | C64 | Information about quality                 |              |
|                         | C65 | Information about logistics               |              |

#### 2.2. Fuzzy extent Analysis

Here, fuzzy synthetic extent analysis method [17] is utilised to calculate the synthetic extent value of the pairwise comparison. The triangular fuzzy scale of preferences is given in Table 1, in which triangular fuzzy numbers (TFNs) are used to represent the pair-wise comparison of decision variables from “Equal” to “Absolutely Better”. It is defined based on standard Analytic Hierarchical Process (AHP) pairwise comparison. However, these definitions can be modified based on expert panel recommendations or conducting surveys through the Delphi method.

### Table 2. Linguistic classification of triangular fuzzy numbers.

|Rating level| Linguistic values| Triangular fuzzy numbers |
|------------|------------------|-------------------------|
|1           | Equal            | (1, 1, 1)               |
|3           | Moderately more important | (2, 3, 4)   |
|5           | Fairly more important | (4, 5, 6) |
|7           | Much more important | (6, 7, 8)   |
|9           | Absolute more important | (9, 9, 9) |
|2,4,6,8    | Mid-point preference values lying between above values | (1,2,3), (3,4,5), (5,6,7), (7,8,9) |

Let $P=\{p_1, p_2, ..., p_n\}$ be an object set, and $Q=\{q_1, q_2, ..., q_m\}$ be a goal set. According to the method of extent analysis [14],
each object is taken and extent analysis is performed for each goal respectively. Therefore, the $m$ extent analysis values for each object are obtained as: $M_1^f, M_2^f, \ldots, M_n^f, i=1, 2, \ldots, n$, where all the $M_i^f (j=1, 2, \ldots, m)$ are TFNs. The value of fuzzy synthetic extent with respect to the $i^{th}$ object is defined as:

$$S = \sum M_i^f \otimes \left( \sum \sum M_i^f \right)$$  \hspace{1cm} (1)

and $\left( \sum \sum M_i^f \right)$ can be calculated as

$$\sum \sum M_i^f = \left( \frac{1}{m_1} \sum m_1, \frac{1}{m_2} \sum m_2, \ldots, \frac{1}{m_n} \sum m_n \right)$$  \hspace{1cm} (2)

The degree of possibility of $M_i \geq M_j$ is defined as

$$V(M_i \geq M_j) = \sup \{ \min u_+(x), u_-(y) \}$$  \hspace{1cm} (3)

When a pair $(x, y)$ exists such that $x \geq y$ and $u_+(x) = u_-(y) = 1$, then we have $V(M_i \geq M_j) = 1$. Since $M_i$ and $M_j$ are convex fuzzy numbers we have that $V(M_i \geq M_j) = 1$ if $m_1 \geq m_2$,

$$V(M_i \geq M_j) = \operatorname{lgt}(M_i \cap M_j) = \mu_i(d),$$  \hspace{1cm} (4)

where $d$ is the ordinate of the highest intersection point between $\mu_i$ and $\mu_j$. When $M_i = (m_{1i}, m_{2i}, m_{3i})$ and $M_j = (m_{1j}, m_{2j}, m_{3j})$ then ordinate of $D$ is computed by

$$V(M_i \geq M_j) = \operatorname{lgt}(M_i \cap M_j) = \frac{m_i - m_j}{m_m - m_m}$$  \hspace{1cm} (5)

To compare $M_i$ and $M_j$, both the values of $V(M_i \geq M_j)$ and $V(M_j \geq M_i)$ are required. The degree possibility for a convex fuzzy number to be greater than $k$ convex fuzzy numbers $M_i (i = 1, 2, \ldots, k)$ can be defined by

$$V(M_i \geq M_j \cap \cdots \cap M_k) = \min \left( V(M_i \geq M_j \cap \cdots \cap M_k) \right)$$  \hspace{1cm} (6)

$$d(X) = \min \{ d(X) \}$$  \hspace{1cm} (7)

For $k=1, 2, \ldots, n, i \neq i$, then the rating vector is given by

$$W^r = (d(X_1), d(X_2), \ldots, d(X_n))$$  \hspace{1cm} (8)

where $X_i (i = 1, 2, \ldots, n)$ are $n$ design alternatives. Via normalization, the normalized rating vectors are:

$$W = (\bar{R}(X_1), \bar{R}(X_2), \ldots, \bar{R}(X_n))$$  \hspace{1cm} (9)

where $W$ is a non-fuzzy number that provides priority weights of an uncertainty criterion or sub-criterion over others.

For the accuracy of the method, the consistency measure is performed to screen out inconsistency of responses. Since $M_i$ is a triangular number, it has to be defuzzified into a crisp number to compute the consistency ratio (CR). The graded mean integration approach is used here for defuzzifying $M_i$. According to the graded mean integration approach, a TFN $M = (m_1, m_2, m_3)$ can be defuzzified into a crisp value by:

$$P(M) = \frac{m_1 + 4m_2 + m_3}{6}$$  \hspace{1cm} (10)

Therefore, the CR of each judgment can be calculated and checked to ensure that it is lower than or equal to 0.1.

2.3. Fuzzy TOPSIS

TOPSIS is a technique to evaluate the performance of alternatives through the similarity with the ideal solution proposed by Hwang & Yoon [18]. The main concept of TOPSIS is to define the positive ideal solution and negative ideal solution. The most preferred alternative should have the shortest distance from the positive ideal solution and the longest distance from the negative ideal solution. Despite its popularity and simplicity in concept, TOPSIS is often criticized because of its inability to deal adequately with uncertainty and imprecision inherent in the process of mapping the perceptions of decision-makers [19]. To address the limitation of TOPSIS, some scholars have made use of fuzzy logic to solve various MCDM problems such as plant location selection [20], supplier selection and evaluation [21], and risk assessment [22, 23].

To evaluate a set of alternative solutions, a fuzzy decision matrix, $\bar{D}$, is constructed based on a given set of categories and criteria. Referring to the hierarchy framework in Table 1, there are $n$ alternatives $A_i (k=1, 2, \ldots, n)$ and four main categories. Each category has $c_j$ criteria where the total number of criteria is equal to $\sum c_j$. $\bar{x}_i$ represents the value of the $j^{th}$ sub-criterion within $i^{th}$ main criterion of the $k^{th}$ alternative, which can be crisp data or appropriate linguistic variables which can be further represented by fuzzy numbers e.g. $\bar{x}_i = (a_i, b_i, c_i)$. In general, the criteria can be classified into two categories: benefit and cost. The benefit criterion means that a higher value is better while for the cost criterion it is lower than or equal to 0. The data of the decision matrix $D$ come from different sources. Therefore it is necessary to normalize it in order to transform it into a dimensionless matrix, which allows the comparison of the various criteria. In this research, the normalized fuzzy decision matrix is denoted by $\bar{R}$ shown as following:

$$\bar{R} = \begin{bmatrix} \bar{r}_{11} & \bar{r}_{12} & \cdots & \bar{r}_{1k} \\ \bar{r}_{21} & \bar{r}_{22} & \cdots & \bar{r}_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{r}_{n1} & \bar{r}_{n2} & \cdots & \bar{r}_{nk} \end{bmatrix},$$  \hspace{1cm} (11)

where $k = 1, 2, \ldots, n; i = 1, 2, 3, 4; j = 1, 2, \ldots, c_i; m = \sum c_i$. The normalization process can then be performed by the following fuzzy operations:
According to the weighted normalized fuzzy decision matrix, we defined as:

\[
\bar{r}_i = \begin{cases} 
\frac{a_i}{u} \frac{m}{u} \frac{b_i}{u} \quad & \forall, \bar{x}_i \text{ is a benefit criterion} \\
\frac{u}{a} \frac{m}{u} \frac{b_i}{u} \quad & \forall, \bar{x}_i \text{ is a cost criterion} 
\end{cases}
\] (12)

where \(\bar{u}^j\) and \(\bar{u}^c\) present the largest and the lowest value of each criterion respectively. The weighted fuzzy normalized decision matrix is shown as:

\[
\bar{F} = [\bar{v}_{ik} \mid \bar{r}_i, k = 1, 2, \ldots, n; i = 1, 2, 3, 4; \\
j = 1, 2, \ldots, c; m = \sum_c^j c;
\]

where \(\bar{v}_{ik} = \bar{r}_i \otimes \bar{w}_k\).

Here \(\bar{v}_{ik}\) is the final weight core for each criterion which is the product of the criterion weight score and the associated main evaluation category weight score as follows:

\[
\begin{align*}
\bar{w}_i &= w_i \otimes w_c \\
&= w_i \otimes \begin{bmatrix} w_{i1} \\ w_{i2} \\ \vdots \\ w_{ic} \end{bmatrix}, \\
&= \begin{cases} 
w_{i1} & (i = 1) \\
w_{i2} & (i = 2) \\
\vdots & (i = 3) \\
w_{ic} & (i = 4)
\end{cases}
\end{align*}
\] (14)

where \(w_{ik}\) and \(w_{ic}\) denote the \(i\)th main category weight score and the criterion weight score with respect this main category respectively. Both \(w_{ik}\) and \(w_{ic}\) are obtained through pairwise comparison.

Subsequently, the fuzzy additon principle is used to aggregate the values within each main category as follows:

\[
\bar{v}_{ik} = \sum_k \bar{v}_k, \\
k = 1, 2, \ldots, n; i = 1, 2, 3, 4
\] (15)

The matrix \(\bar{F}\) is thus converted into the final weighted normalized fuzzy decision matrix \(\bar{V}'\)

\[
\bar{V}' = \begin{bmatrix} C_1 & C_2 & C_3 & C_4 \\
A_1 \bar{v}_1' & \bar{v}_2' & \bar{v}_3' & \bar{v}_4' \\
\vdots & \vdots & \vdots & \vdots \\
A_4 \bar{v}_1' & \bar{v}_2' & \bar{v}_3' & \bar{v}_4'
\end{bmatrix}
\] (16)

This addition operation is important as the hierarchical structure can be reflected only when aggregation of the weighted values within each main criterion is conducted.

Now, let \(A'\) and \(A'\) denote the fuzzy positive idea solution (FPIS) and fuzzy negative ideal solution (FNIS) respectively. According to the weighted normalized fuzzy-decision matrix, we have:

\[
A' = (\bar{v}, \bar{v}, \bar{v}, \bar{v})
\]

where \(\bar{v}\) and \(\bar{v}\) are the fuzzy numbers with the largest and the smallest generalized mean respectively. The generalized mean for the fuzzy number \(\bar{v} = (a, m, b)\), \(\forall i\), is defined as:

\[
M(\bar{v}) = \frac{-a_i + b_i - a_m + m_i + b_i}{3(a_m)}
\] (18)

For each column \(i\), the greatest generalized mean of \(\bar{v}\) and the lowest generalized mean of \(\bar{v}\) can be obtained respectively. Consequently, the FPIS \((A')\) and FNIS \((A'\) are derived. Then, the distances \((d'\) and \(d'\) of each alternative from \(A'\) and \(A'\) can be calculated by the area compensation method as:

\[
\begin{align*}
d' &= \sum_{i=1}^{n} d(\bar{v}_i, \bar{v}) \quad k = 1, 2, \ldots, n; \quad i = 1, 2, 3, 4 \\
d' &= \sum_{i=1}^{n} d(\bar{v}_i, \bar{v}) \quad k = 1, 2, \ldots, n; \quad i = 1, 2, 3, 4
\end{align*}
\] (20)

\[
d'(A, B) = \frac{1}{3} \left[ (a_m - b_m) + (a_m - b_m) + (a_m - b_m) \right]
\] (22)

By combining the difference distances \(d'\) and \(d'\), the relative closeness index is calculated as follows:

\[
C_i = \frac{d'}{d' + d'}
\] (23)

3. Application of Evaluation Framework

Here the proposed framework is used to evaluate the network uncertainty of a manufacturing case company. The company was set up at the southeast region of China in 2001 and produces customized stainless steel band. Demand for stainless steel products has increased significantly in recent years with major changes in global sourcing and high levels of price competition. High volatility of raw material price, low predictability and a level of impulse purchase add further uncertainty for firms. Thus, the management team was keen to implement new strategies to create new revenue streams. For this case, the focus was on evaluating network uncertainty for implementing IPS2 value propositions of product related services \((A_1)\), advice and consultancy \((A_2)\), product lease \((A_3)\), product renting/sharing \((A_4)\), product pooling \((A_5)\), activity management/outsourcing \((A_6)\), pay per service unit \((A_7)\), and functional result \((A_8)\). Since the focus is on CR in relation to network uncertainty, service oriented parameters and collaboration issues were beyond the scope of the application.

3.1. Case application

To build the pairwise comparison matrixes for the main criteria and their associated sub-criteria, a questionnaire was provided to three senior managers in the case company. The consistency of the pairwise judgement of comparison matrixes obtained through the questionnaire was first checked. Then the geometric mean of individual evaluations was calculated to form the fuzzy pairwise comparison matrix. Using the fuzzy extent analysis, the priority weights with respect to the supply chain uncertainty and their associated criterion were determined. By integrating the local weights of sub-criteria and their corresponding main criteria, the final weights for all the uncertainty factors can be estimated and ranked. The full results are displayed in Table 3.
Table 3. Summary of priority ratings with respect to criteria in all life cycle phases.

| Rating level                      | Linguistic values | Triangular fuzzy numbers |
|-----------------------------------|-------------------|-------------------------|
| C1 Demand (and distribution)      | 0.326             | C11 0.068 0.022         |
| uncertainty                       |                   | C12 0.352 0.115         |
|                                  |                   | C13 0.058 0.019         |
|                                  |                   | C14 0.271 0.088         |
|                                  |                   | C15 0.054 0.017         |
|                                  |                   | C16 0.012 0.004         |
|                                  |                   | C17 0.014 0.005         |
|                                  |                   | C18 0.015 0.005         |
|                                  |                   | C19 0.157 0.051         |
|                                  | C2 Supply         | 0.301                   |
| uncertainty                       |                   | C21 0.356 0.107         |
|                                  |                   | C22 0.054 0.016         |
|                                  |                   | C23 0.108 0.033         |
|                                  |                   | C24 0.129 0.039         |
|                                  |                   | C25 0.053 0.016         |
|                                  |                   | C26 0.062 0.019         |
|                                  |                   | C27 0.007 0.002         |
|                                  |                   | C28 0.081 0.024         |
|                                  |                   | C29 0.080 0.024         |
|                                  |                   | C30 0.069 0.021         |
| C1 Manufacturing (and process)    | 0.241             | C31 0.353 0.085         |
| uncertainty                       |                   | C32 0.221 0.053         |
|                                  |                   | C33 0.164 0.040         |
|                                  |                   | C34 0.168 0.040         |
|                                  |                   | C35 0.051 0.012         |
|                                  |                   | C36 0.044 0.011         |
|                                  |                   | C37 0.222 0.029         |
| C2 Control (and planning)        | 0.133             | C41 0.160 0.021         |
| uncertainty                       |                   | C42 0.222 0.029         |
|                                  |                   | C43 0.618 0.082         |

Next, questionnaires were given to three key decision makers (the general management, the deputy general manager and the factory manager) for the evaluation of the eight alternative IPS² value propositions. Participants were asked to give ratings to the propositions with respect to all the evaluation criteria. The qualitative explanation of rating levels their corresponding triangular fuzzy numbers are described in Table 4. Values from the responses were averaged to integrate the fuzzy judgement values of the different decision makers regarding the same evaluation criteria. The results were then used to construct a hierarchical decision making matrix $\mathbf{\tilde{D}}$. The hierarchical decision making matrix was then normalized using Eqn. 16.

Table 4. Linguistic classification of triangular fuzzy numbers.

| Rating level          | Linguistic values | Triangular fuzzy numbers |
|-----------------------|-------------------|-------------------------|
| 1                     | Extremely high    | (0, 0, 1/3)             |
| 2                     | Very high         | (0, 1/6, 2/6)           |
| 3                     | High uncertainty  | (1/6, 2/6, 3/6)         |
| 4                     | Medium            | (2/6, 3/6, 4/6)         |
| 5                     | Low uncertainty   | (3/6, 4/6, 5/6)         |
| 6                     | Very low          | (4/6, 5/6, 1)           |
| 7                     | Excellent         | (5/6, 1, 1)             |

Through computing the product of the normalized hierarchical decision matrix $\mathbf{\tilde{B}}$ and the final weight scores for each evaluation criterion, the weighted normalized fuzzy decision matrix $\mathbf{\tilde{P}}$ was obtained. By aggregating the values that belong to each main evaluation category using the fuzzy addition principle, the final weighted normalized fuzzy decision matrix $\mathbf{\tilde{P}}$ was obtained. Since each element in $\mathbf{\tilde{P}}$ is a fuzzy number, its generalized mean $M(\mathbf{\tilde{P}})$ was then calculated. The largest generalized mean and the smallest generalized mean of each main criterion were then selected constituting the FPIS ($A^+$) and the FNIS ($A^-$). Next, the difference distances of the alternatives ($d^i_1$ and $d^i_2$) were calculated. Finally, combining the difference distances, the relative closeness index for each alternative solution can be obtained. The results are presented in Table 5, together with the corresponding rankings based on the index values. Among the eight alternatives, IPS² solution management/outsourcing ($A_9$) has the highest relative closeness index and was therefore recommended as the preferred IPS² value proposition.

Table 5. The relative closeness index of alternative Industrial product-service solutions along with the final ranking.

| Value proposition | $d^i_1$ | $d^i_2$ | $C_i$ | Ranking |
|-------------------|--------|--------|------|---------|
| A₁                | 0.111  | 0.446  | 0.881| 2       |
| A₂                | 0.187  | 0.370  | 0.664| 3       |
| A₃                | 0.469  | 0.093  | 0.165| 6       |
| A₄                | 0.485  | 0.078  | 0.139| 7       |
| A₅                | 0.556  | 0.000  | 0.000| 8       |
| A₆                | 0.013  | 0.543  | 0.977| 1       |
| A₇                | 0.400  | 0.159  | 0.284| 5       |
| A₈                | 0.296  | 0.262  | 0.469| 4       |

3.2. Industrial product-service readiness

In contrast to those IPS² solutions at the top end of the ranking list, three use-oriented IPS² solutions ($A_3$, $A_4$ and $A_5$) all exhibit a low relative closeness index and should not be recommended. This is due to the nature of products the case company produces. The cool rolled stainless steel bands are often used as a raw material by its downstream supply chain customers. This is also highlighted by the questionnaire response from the general manager, who gave the lowest grade to all three use oriented IPS² solutions. Although activity management/outsourcing ($A_9$) tops the ranking list among the eight alternative solutions, other IPS² solutions particular product related service ($A_5$) has a high relative closeness index. In order to provide further insight of the selection decision, analysis was conducted to look at the weighted performance ratings of the top three IPS² solutions with respect to the main uncertainty categories. Fig. 1 shows that activity management/outsourcing performed better than the other two alternatives in the demand uncertainty category. In fact, the demand uncertainty has the highest weighting in the pairwise comparison as illustrated in Table 3. Activity management for its clients will help the case company to address some demand aspects of the uncertainty such as predictability of product demand. Similarly, product related service will also help to deal with certain aspects of the uncertainty such as product variety, rate of new product induction, and predictability of product demand. In view of the support for multiple domain expert opinions, the evaluation framework could be leveraged for effective
4. Conclusions

In this paper, a comprehensive fuzzy approach has been developed to evaluate network uncertainty for industrial product-service systems. Network uncertainty evaluation criteria were selected through a systematic literature review. The importance levels of evaluation criteria were calculated using fuzzy extent analysis. Finally, fuzzy TOPSIS was applied to evaluate the alternative IPS2 solutions and determine the final rank. The proposed approach was tested using data from a stainless steel product manufacturer which demonstrates the effectiveness of the proposed approach.

In spite of the benefits outlined, there are some limitations. The main challenge of this research is to provide a single ranking index to represent those important factors that firms should pay attention to for collaboration as part of a network. All criteria and its associated sub-criteria have to be weighted and accounted in the evaluation. Users have to make subjective decisions when conducting pair-wise comparisons to obtain weights. In fact, the functionality of the model is highly dependent on the knowledge, expertise and communication skills of users. Therefore, one future research is to consider a more objective weighting technique such as entropy method. In addition, we assumed independencies among criteria and sub-criteria. The dynamic characteristics and interconnection among the decision criteria and sub-criteria would require intensive and robust analysis in the decision making process. One possible future research direction is to use the decision-making trial and evaluation laboratory (DEMATEL) method to identify the interdependence among the evaluation criteria and sub-criteria through a causal diagram using digraphs to portray the basic concept of contextual relationships and the strengths of influence among the criteria and sub-criteria.

References

[1] Neely, A. 2008. Exploring the financial consequences of the servitization of manufacturing. Operations Management Research, 1, 103-118.
[2] Vandermerwe, S., Rada, J., 1988. Servitization of business: adding value by adding services. European Management Journal, 6, 314-324.
[3] Baines, T.S., Lightfoot, H.W., Benedettini, O., Kay, J.M., 2009. The servitization of manufacturing: A review of literature and reflection on future challenges. Journal of Manufacturing Technology Management, 20, 547-567.
[4] Van der Vorst, J., Beulens, A., 2002. Identifying sources of uncertainty to generate supply chain redesign strategies. International Journal of Physical Distribution & Logistics Management, 32, 409-30.
[5] Durugbo, C., Riedel, J., 2013. Readiness assessment of collaborative networked organisations for integrated product and service delivery. International Journal of Production Research, 51, 598-613.
[6] Rosas, J., Camarinha-Matos, L.M., 2009. An approach to assess collaboration readiness. International Journal of Production Research, 47, 471-4735.
[7] Chitac, C.-M., Nof, S.Y., 2007. The Join/Leave/Remain (JLR) decision in collaborative networked organizations. Computers and Industrial Engineering, 53, 173-195.
[8] Ermlírová, E., Afšármanesh, H. 2007. Modeling and management of profiles and competencies in VBEs. Journal of Intelligent Manufacturing, 18, 561-586.
[9] Takker, A., 2004. Eight types of product-service system: Eight ways to sustainability? Experiences from suspronet. Business Strategy and the Environment, 13, 246-260.
[10] Davis, T., 1993. Effective supply chain management. Sloan Management Review, 34, 35-46.
[11] Ho, C.-F., Chi, Y.-P., Tai, Y.-M., 2005. A structural approach to measuring uncertainty in supply chains. International Journal of Electronic Commerce, 9, 91-114.
[12] Fynes, B., de Búrca, S., Marshall, D., 2004. Environmental uncertainty, supply chain relationship quality and performance. Journal of Purchasing and Supply Management, 10, 179-190.
[13] Chen, I.J., Paulraj, A., 2004. Towards a theory of supply chain management: the constructs and measurements. Journal of Operations Management, 22, 119-150.
[14] Mason-Jones, R., Towill, D.R., 1998. Shrinking the supply chain uncertainty circle. Control, 24, 17-22.
[15] Childerhouse, P., Towill, D.R., 2004. Reducing uncertainty in European supply chains. Journal of Manufacturing Technology, 15, 585-598.
[16] Rodrigues, V.S., Stantchev, D., Potter, A., Naim, M., Whiteing, A. 2008. Establishing a transport operation focused uncertainty model for the supply chain. International Journal of Physical Distribution and Logistics Management, 38, 388-411.
[17] Chang, D.Y., 1996. Applications of the extent analysis method on fuzzy AHP. European Journal of Operational Research, 95, 649-655.
[18] Hwang, C.L., Yoon, K., 1981. Multiple attributes decision making methods and applications. Berlin: Springer.
[19] Kroling, R.A., Canpahanro, V.C., 2011. Fuzzy TOPSIS for group decision making: A case study for accidents with oil spill in the sea. Expert Systems with Applications, 38, 4190-4197.
[20] Ergüçgil, I., Karakaşoğlu, N., 2008. Comparison of fuzzy AHP and fuzzy TOPSIS methods for facility location selection. International Journal of Advanced Manufacturing Technology, 39, 783-795.
[21] Ďubíček, G., Zlateckí, G., 2012. A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers. Expert Systems with Applications, 39, 3000-3011.
[22] Samvedi, A., Jain, V., Chan, T.S., 2013. Ranking fuzzy data in a supply chain through integration of fuzzy AHP and fuzzy TOPSIS. International Journal of Production Research, 51, 2433-2442.
[23] Wang, X., Chan, H.K., 2013. A hierarchical fuzzy TOPSIS approach to assess improvement area when implementing green supply chain initiatives. International Journal of Production Research, 51, 3117-3130.