

Fuzzy-scorecard based logistics management in robust SCM

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ABSTRACT

Due to the IT advances, the logistics management faces a change to the new era. This article proposes a novel method to evaluate the real-time overall performance of a logistics network for a supply chain. The corresponding strategies to manage the underperformed channels can be subsequently obtained in the method. Thus, the logistics network can be managed timely under the stochastic environment, and it makes the SCM robust. The overall performance of the logistics network is integrated by the individual logistics channel real-time performance which can be easily obtained by the new IT technologies such as RFID, etc. The fuzzy-scorecard is introduced to indicate the measured key performance indicators (KPI) for the network. Some numerical examples are presented to illustrate the various scenarios of management for the proposed method.

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1. Introduction

The term Supply Chain Management (SCM) has been used to explain the planning and control of materials and information flows along with the logistic activities not only internally in a company but also externally between companies (Supply Chain Council, 2008). SCM is now an important strategy for companies to gain competitiveness chain-widely. However, the cost is still the key factor to face (Lambert & Cooper, 2000). Since the globalized economy changes very fast, the logistic dynamics for each firm's supply chain is also versatile (Bogataj & Bogataj, 2007). To realize such changes, measurement and metrics were developed by many researchers (Chen & Paulraj, 2004; Cooper & Ellram, 1993), but such information were available only after a long period of investigation. The short-term evaluation and measurement methods are important for success in such a versatile environment. Lin (2009) proposed an integrated framework to use the radio frequency identification (RFID) technology in SCM for the quick measurement of logistic activities. Bhagwat and Sharma (2007) presented the balanced scorecard approach for SCM that measures and evaluates day-to-day business operations. Hou and Huang (2006) gave the case study in SCM of the printing industry by using the RFID technology. Lee and Chan (2009) presented another case study in SCM of the reverse logistics management by using the RFID technology. Baars, Kemper, Lasi, and Siegel (2008) even combined the RFID technology with the business intelligence functions to optimize the SCM. Hsiao, Lin, and Huang (2010) proposed a method to solve the lot size problem

between firms in a serial supply chain by integer programming technique. Hwang (2002) solved the routing problem for supply chain logistics with genetic algorithm. A detailed review about the soft computing techniques dealing with SCM problems was given by Ko, Tiwari, and Mehnen (2010). However, all of them only dealt with the deterministic supply chain issues.

Although these efforts have enhanced the capability of short-term evaluation and measurement in SCM, the real-time evaluation of overall performance for the logistics networks in a stochastic environment still remains very limited. In practice, the capacity of logistics between firms is stochastic in nature (Lin, 2010). They may also fail sometimes. For example, the container or cargo through each transportation channel may be in maintenance, reserved by other agents or in other conditions. This gives great difficulty in making a precise management.

This article proposes a novel method to evaluate the real-time overall performance of a logistics network in a stochastic environment. The overall performance of the logistics network is integrated by the individual logistics channel real-time performance which can be easily obtained by the new IT technologies such as RFID, etc. Then, the fuzzy-scorecard is introduced to indicate the calculated key performance indicators (KPI) for the network. Now, the KPI management is an important activity in the modern corporation. Parmenter (2007) presented various KPI constructions in the real applications. Because scorecarding (IBM, 2011) which was derived from the concept of balanced scorecard (Kaplan & Norton, 1996) is mature and popular in the modern (KPI) management tools, the fuzzy-scorecard approach is proposed as a variant of the balanced scorecard approach. However, most of the tools only used the management experience to set the target of the individual performance (or scorecard). It may cause the aggregated scorecard inconsistent or distortion.

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The fuzzy-scorecard approach is a scorecarding technique which uses fuzzy mathematics and flow network theory to aggregate the individual performance consistently. To simplify the explanation of the proposed approach without loss of generality, we use but not limit to the fuzzy sets, $\Gamma = \{\text{underperformed, normal, overperformed}\}$, to indicate the performance status of each individual channel, and $\Theta = \{\text{underperformed, normal}\}$, to indicate the performance of the overall logistic network since no one will be blamed for the over performance of a department in a corporation. Similarly, we use but not limit to the triangular membership function to explain the fuzzy calculation in this approach. More complicated membership functions are applicable in this approach for more specific applications. This article also uses the colored symbols (called scorecards) to indicate the fuzzy words. For example, the red triangular “▲” denotes “underperformed”; the green circle “●” denotes “normal”; the orange diamond “◆” denotes “overperformed.” The optimal planning of the capacity for each individual transportation channel can be derived by the method proposed by Chen (2010), which can derive the lowest cost plan for the capacity allocation of each individual channel. Chen presented a very efficient algorithm to solve the non-linear integer programming problem for the optimal capacity planning in robust SCM. Then, the planned capacity is taken as the standard target for the “normal” status of that channel. After the calculation of fuzzy-scorecards, the corresponding strategies to manage the underperformed channels can be subsequently obtained. Thus, the logistics network can be managed timely under the stochastic environment. The calculation is based on the popular Minimum Path (MP) technique (Ford & Fulkerson, 1962). Please also refer to the works of Chen and Lin (2008), Lin (2001), Lin, Jane, and Yuan (1995), Xue (1985), Yeh (2008) to learn more details of the MP technique. A robust supply chain means that the supply chain is functioning even in the partial failure of some channels. Such status can be aware of by the respective individual scorecard. The remainder of the work is described as follows: The assumptions for the approach are presented in Section 2. Section 3 describes the logistics network model in robust SCM. A solution procedure to evaluate the performance is proposed subsequently in Section 4. Then, the calculation of fuzzy-scorecard is illustrated by some numerical examples and scenarios in Section 5. Section 6 draws the conclusion and discussions of this article.

2. Assumptions

Let $G = (A, B, M)$ be a logistics network where $A = \{a_i | 1 \leq i \leq n\}$ is the set of arcs representing the logistics channels between places, $B = \{b_j | 1 \leq j \leq s\}$ is the set of nodes representing the warehouses or firms in different places, and $M = (m_1, m_2, \dots, m_n)$ is a vector with m_i (an integer) being the maximal capacity of arc a_i . Note that m_i can be derived from the upper bound of the corresponding empirical distribution of each channel. Such a G is assumed to satisfy the following assumptions:

- i. The capacity of arc a_i is an integer-valued random variable which takes values from the set $\{0, 1, 2, \dots, m_i\}$ according to an empirical distribution function μ_i , which can be collected from any feasible performance indicator (PI) for the channel. For example, the “throughput” of the corresponding channel to successfully complete the transportation is a feasible PI. Note that 0 in capacity often denotes a failure or being unavailable.
- ii. The nodes are perfect, which means the warehouses (nodes) will not fail and are excluded from the calculation of network reliability.

- iii. Flow in G must satisfy the flow-conservation law (Ford & Fulkerson, 1962), which means no flow will be created or destroyed at any channel while the network is functioning.
- iv. The arcs are statistically independent from each other.

The feasible PI for the arc means an indicator satisfying both Assumptions iii and iv. Since a different arc represents a different channel in the network, the respective probability distribution is also different from each other. The corresponding distribution is governed by μ_i for each arc a_i . In certain conditions, one can adopt the same distribution function for all arcs when applying the proposed method for simplification.

3. The logistics network model

Suppose mp_1, mp_2, \dots, mp_z are totally the MPs from the source (the shipper) to the sink (the consignee). Thus, the network model can be described in terms of two vectors: the capacity vector $X = (x_1, x_2, \dots, x_n)$ and the flow vector $F = (f_1, f_2, \dots, f_z)$, where x_i denotes the current capacity on a_i and f_j denotes the current flow on mp_j . Then, such a vector F is feasible if and only if

$$\sum_{j=1}^z \{f_j | a_i \in mp_j\} \leq m_i, \quad \text{for } i = 1, 2, \dots, n. \tag{1}$$

Eq. (1) describes that the total flow through a_i cannot exceed the maximal capacity on a_i . We denote such set of F as $U_M \equiv \{F | F \text{ is feasible under } M\}$. Similarly, F is feasible under $X = (x_1, x_2, \dots, x_n)$ if and only if

$$\sum_{j=1}^z \{f_j | a_i \in mp_j\} \leq x_i, \quad \text{for } i = 1, 2, \dots, n. \tag{2}$$

For clarity, let $U_X = \{F | F \text{ is feasible under } X\}$. The maximal flow under X is defined as $V(X) \equiv \max\{\sum_{j=1}^z f_j | F \in U_X\}$.

3.1. The fuzzy-scorecard for the individual channel

Through the advanced IT technologies such as RFID technology, the feasible PI for each individual channel can be obtained from sampling a fixed moving time frame for a proper long period. The corresponding empirical distribution μ_i is then derived from the collected statistics. A moving average \bar{x}_i for the fixed time frame is also obtained to represent the current status of the channel. Let λ_i be the membership function mapping from Γ to $[0, 1]$ for the fuzzy-scorecard of a_i and o_i be the optimal allocated capacity for that channel (i.e., the contract capacity). In practice, an allowance $\Delta\delta$ is used by the channel owner to manage the transportation operations. Fig. 1 denotes the scorecards and the conventional shape of λ_i (Kosko, 1997). The current fuzzy-scorecard \bar{x}_i of each channel is then defuzzified by the following equation:

$$\bar{x}_i = \lambda_i^{-1}(\bar{x}_i), \tag{3}$$

where λ_i^{-1} is a reverse function of λ_i .

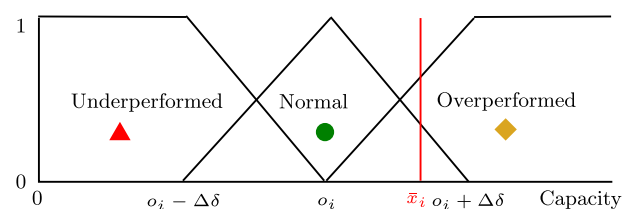


Fig. 1. The scorecards and the shape of the membership function λ_i .

3.2. The fuzzy-scorecard for the overall network

Given a level d , the network performance R_d is the probability that the maximal flow is no less than d , i.e., $R_d \equiv \Pr\{X|V(X) \geq d\}$. To calculate R_d , it is advantageously to find the minimal vector in the set $\{X|V(X) \geq d\}$. A minimal vector X is said to be a lower boundary point (LBP) for d if and only if (i) $V(X) \geq d$ and (ii) $V(Y) < d$ for any other vector Y such that $Y < X$, in which $Y \leq X$ if and only if $y_j \leq x_j$ for each $j = 1, 2, \dots, n$ and $Y < X$ if and only if $Y \leq X$ and $y_j < x_j$ for at least one j . Suppose there are totally t lower boundary points for d : X_1, X_2, \dots, X_t , and $E_i = \{X|X \geq X_i\}$, the probability R_d can be equivalently calculated via the inclusion–exclusion principle (or, the Poincaré theory) as

$$R_d = \Pr\left\{\bigcup_{i=1}^t E_i\right\} = \sum_{k=1}^t (-1)^{k-1} \sum_{I \subset \{1,2,\dots,t\}, |I|=k} \Pr\left\{\bigcap_{i \in I} E_i\right\}, \tag{4}$$

where

$$\Pr\left\{\bigcap_{i \in I} E_i\right\} = \prod_{j=1}^n \sum_{l=\max\{x_{ij}|\forall i \in I\}}^{m_j} \mu_j(l).$$

Let λ_R be the membership function mapping from fuzzy set Θ to $[0, 1]$. Then, the fuzzy-scorecard \tilde{R}_d is defuzzified by the following equation:

$$\tilde{R}_d = \lambda_R^{-1}(R_d), \tag{5}$$

where λ_R^{-1} is a reverse function of λ_R . Fig. 2 denotes the scorecards and the conventional shape of λ_R .

3.3. Generation of all LBPs for d

At first, we find the flow vector $F \in U_M$ such that the total flow of F equals d . It is defined in the following demand constraint:

$$\sum_{j=1}^z f_j = d. \tag{6}$$

Then, let $T = \{F|F \in U_M \text{ and satisfy Eq. (6)}\}$. We show that if an LBP X for d exists, then there is an $F \in T$ by the following lemmas:

Lemma 3.1. *If X is an LBP for d , then there is an $F \in T$ such that*

$$x_i = \sum_{j=1}^z \{f_j|a_i \in mp_j\} \quad \text{for each } i = 1, 2, \dots, n. \tag{7}$$

Proof. If X is a lower boundary point for d , then there is an F such that $F \in U_X$ and $F \in T$. It is known that $\sum_{j=1}^z \{f_j|a_i \in mp_j\} \leq x_i, \forall i$. Suppose there is a k such that $x_k > \sum_{j=1}^z \{f_j|a_k \in mp_j\}$. Set $Y = (y_1, y_2, y_{k-1}, y_k, y_{k+1}, \dots, y_n) = (x_1, x_2, \dots, x_{k-1}, x_k - 1, x_{k+1}, \dots, x_n)$. Hence, $Y < X$ and $F \in U_Y$ (since $\sum_{j=1}^z \{f_j|a_i \in mp_j\} \leq y_i, \forall i$), which indicates that $V(Y) \geq d$ and contradicts to that X is a lower boundary point for d . Thus, $x_i = \sum_{j=1}^z \{f_j|a_i \in mp_j\}, \forall i$. \square

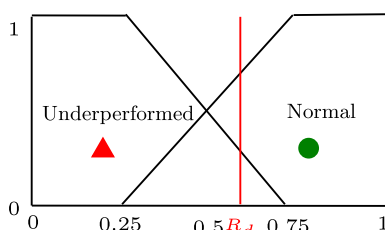


Fig. 2. The scorecards and the shape of the membership function λ_R .

Given $F \in T$, we generate a capacity vector $X_F = (x_1, x_2, \dots, x_n)$ via Eq. (7). Then the set $\Omega = \{X_F|F \in T\}$ is built. Let $\Omega_{min} = \{X|X \text{ is a minimal vector in } \Omega\}$. Lemma 3.1 implies that the set Ω includes all LBPs for d . The following lemma further proves that Ω_{min} is the set of LBPs for d .

Lemma 3.2. *Ω_{min} is the set of LBPs for d .*

Proof. Firstly, suppose $X \in \Omega_{min}$ (note that $V(X) \geq d$) but it is not a lower boundary point for d . Then, there is a lower boundary point Y for d such that $Y < X$, which implies $Y \in \Omega$ and thus, contradicts to that $X \in \Omega_{min}$. Hence, X is a lower boundary point for d . Conversely, suppose X is a lower boundary point for d (note that $X \in \Omega$) but $X \notin \Omega_{min}$, i.e., there is a $Y \in \Omega$ such that $Y < X$. Then, $V(Y) \geq d$ which contradicts to that X is a lower boundary point for d . Hence $X \in \Omega_{min}$. \square

4. Solution procedure

Fig. 3 denotes the proposed procedure for the applications. Firstly, the logistics network for the supply chain is created. The lower boundary points for the network are generated by the algorithm stated in Section 4.1. Meanwhile, the fuzzy-scorecard for the individual channel is obtained from sampling a fixed moving time frame for a proper long period. Then, the performance R_d is calculated as the overall logistics performance at this moment. By defuzzifying R_d , the fuzzy-scorecard \tilde{R}_d is obtained from the calculation discussed in Section 3.2.

4.1. Algorithm

Searching for all MPs from a 2-state network is NP-complete (Ball, 1986). Therefore, we take the same manner as the work of Chen and Lin (2009), and suppose that all MPs have been pre-computed. For a recent discussion about how to efficiently search for all MPs in a general directed flow network, Chen proposed an efficient way to do this search (Chen, Guo, & Zhou, 2010). All lower boundary points for d can be generated by Algorithm 1.

Algorithm 1. Search for all lower boundary points for d .

-
- Step 1. Find all feasible flow vector $F = (f_1, f_2, \dots, f_z)$ satisfying both capacity and demand constraints.
 - i. **enumerate** f_j for $1 \leq j \leq z$ and $0 \leq f_j \leq \min\{m_i|a_i \in mp_j\}$ **do**
 - ii. **if** f_j satisfies the following equations

$$\sum_{j=1}^z \{f_j|a_i \in mp_j\} \leq m_i \quad \text{and} \quad \sum_{j=1}^z f_j = d, \quad \text{for } 1 \leq i \leq n,$$
 - then** $T = T \cup \{F\}$ **endif**
 - end enumerate**
 - Step 2. Generate the set $\Omega = \{X_F|F \in T\}$.
 - i. **for** F in T **do**
 - ii. $x_i = \sum_{j=1}^z \{f_j|a_i \in mp_j\}$, for $i = 1, 2, \dots, n$.
 - iii. $U_X = U_X \cup \{X_F\}$. //where $X_F = (x_1, x_2, \dots, x_n)$ may have duplicates.
 - endfor**
 - iv. **for** X in U_X **do** //Remove the redundant vectors.
 - v. **if** $X \notin \Omega$, **then** $\Omega = \Omega \cup \{X\}$ **endif**

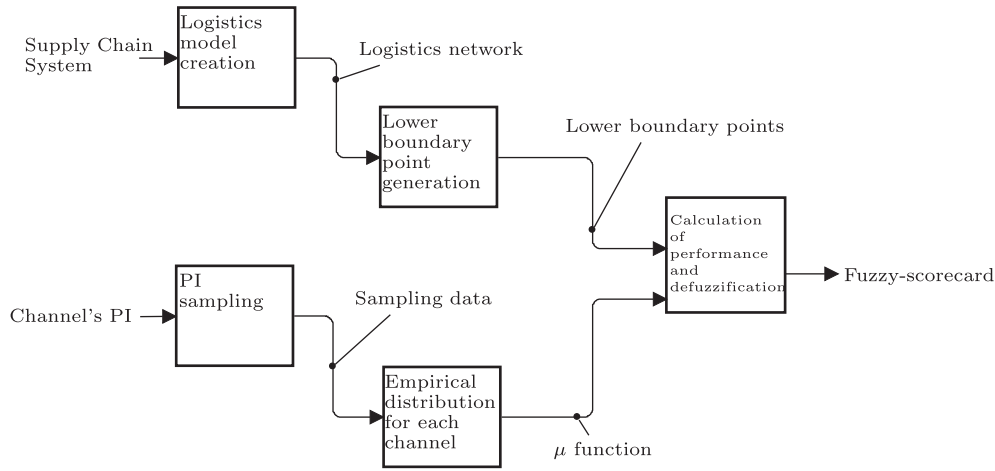


Fig. 3. The generation procedure of the fuzzy-scorecard \tilde{R}_d .

endfor

- Step 3. Find the set $\Omega_{min} = \{X|X \text{ is a minimal vector in } \Omega\}$.
 Let $J = \{j|X_j \notin \Omega_{min}\}$.
- i. for $i \notin J$ and $1 \leq i \leq |\Omega|$ do //where $|\Omega|$ denotes the number of elements in Ω .
 - ii. for $j \notin J$ and $i < j \leq |\Omega|$ do
 - iii. if $X_j \leq X_i$, then $J = J \cup \{i\}$ and goto Step 3v.
 else if $X_j > X_i$, then $J = J \cup \{j\}$ endif
 endfor
 - iv. $\Omega_{min} = \Omega_{min} \cup \{X_i\}$.
 - v. endfor

Step 1 indicates that according to the MPs, the feasible F under Eqs. (1) and (6) was enumerated into set T . Then, the candidate vector set Ω for lower boundary points can be derived from T under Eq. (7) in Step 2. Finally, the set Ω_{min} of lower boundary points was filtered out by pairwise comparison from Step 3.

4.2. Storage and computational complexity analyses

The number of solutions for T was bounded by $\binom{z-1}{z+d-1}$. The number of X_F generated was then bounded by $\binom{z-1}{z+d-1}$. The storage space needed for Ω_{min} was bounded by $O\left(\binom{z-1}{z+d-1}\right)$ in the worst case. In sum, the total storage space needed was $O\left(\binom{z-1}{z+d-1}\right)$ in the worst case. The pairwise comparisons were required for generating Ω_{min} from $\binom{z-1}{z+d-1}$ solutions. This took $O\left(n^2 \binom{z-1}{z+d-1}\right)$ time to generate Ω_{min} . In short, the total computation time required was $O\left(n^2 \binom{z-1}{z+d-1}\right)$ in the worst case.

5. Numerical examples

Suppose a shipper was at Shanghai and a consignee was at Taipei (Chen, 2010). Assume that the load should pass the third place such as Hong Kong or Tokyo before arriving Taipei. Fig. 4 denotes such logistics network, where a_1, a_2, a_5 and a_6 are the cheaper channels by sea, and a_3 and a_4 are the more expensive backup

channels via air. The optimal capacity plan obtained was: $\{a_1 = 5, a_2 = 5, a_3 = 1, a_4 = 1, a_5 = 5, a_6 = 5\}$ (unit in 10 tons) from the work of Chen (2010). The allowance ($\Delta\delta$) for the transportation operation was 1 unit (or 10 tons). There were totally 4 MPs found: $mp_1 = \{a_1, a_2\}$, $mp_2 = \{a_1, a_3, a_6\}$, $mp_3 = \{a_5, a_6\}$, $mp_4 = \{a_5, a_4, a_2\}$. To facility the illustration of the proposed method, the throughput of the channel was taken as the individual performance indicator in the integration. The standard throughput level for the entire network was 5 units (or 50 tons) per week. The fixed time frame was seven days moving every day and the observation period was 1 month. Two scenarios with the corresponding improving strategies of performance are demonstrated in the following subsections.

5.1. Scenario one – the port service failure

In this scenario, assume an accident in the Tokyo's port stopped the transportation service from Shanghai to Tokyo and from Tokyo to Taipei. The throughputs were sampled. Before the accident, Table 1 gives the results of sampling from those channels at the normal condition. The corresponding empirical distributions are shown in Table 2. After the accident, Table 3 gives the results of sampling from those channels at the abnormal condition.

From Table 2, the calculated network performance R_5 was 0.991783 at the normal condition, and the overall fuzzy-scorecard \tilde{R}_5 is "normal". To explain the calculation, the data in Table 3 at the abnormal condition was used for the step-by-step explanation as follows:

- Step 1. Find all feasible vector $F = (f_1, f_2, f_3, f_4)$ satisfying both capacity and demand constraints.

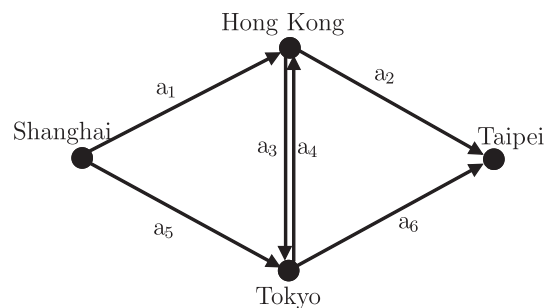


Fig. 4. A logistics network from Shanghai to Taipei.

Table 1
The throughputs and scorecards of the six channels at the normal condition.

The channels	The number of units per week							\bar{x}_i/\bar{x}_i
	0 ^a	1	2	3	4	5	6	
a_1	0 ^b	2	3	5	11	90	24	●/5
a_2	0	2	3	6	12	93	19	●/5
a_3	95	24	6	0	0	0	0	●/1
a_4	93	20	7	0	0	0	0	▲/0
a_5	0	2	3	4	10	94	22	●/5
a_6	0	2	3	6	12	95	17	●/5

▲: Underperformed; ●: Normal; ◆: Overperformed.
^a Unit in 10 tons.
^b The counts of occurrence.

Table 2
The empirical distributions for Table 1.

Distr. functions	The number of units per week						
	0	1	2	3	4	5	6
μ_1	0.000	0.015	0.022	0.037	0.081	0.667	0.178
μ_2	0.000	0.015	0.022	0.044	0.089	0.689	0.141
μ_3	0.760	0.192	0.048	0.000	0.000	0.000	0.000
μ_4	0.775	0.167	0.058	0.000	0.000	0.000	0.000
μ_5	0.000	0.015	0.022	0.030	0.074	0.696	0.163
μ_6	0.000	0.015	0.022	0.044	0.089	0.704	0.126
\bar{R}_5/R_5	●/0.991783						

▲: Underperformed; ●: Normal; ◆: Overperformed.

Table 3
The empirical distributions and scorecards at the abnormal condition.

Distr. functions	The number of units per week							\bar{x}_i/\bar{x}_i
	0	1	2	3	4	5	6	
μ_1	0.000	0.013	0.020	0.026	0.079	0.632	0.230	◆/6
μ_2	0.000	0.012	0.018	0.036	0.078	0.584	0.271	◆/6
μ_3	0.923	0.077	0.000	0.000	0.000	0.000	0.000	▲/0
μ_4	1.000	0.000	0.000	0.000	0.000	0.000	0.000	▲/0
μ_5	0.933	0.048	0.019	0.000	0.000	0.000	0.000	▲/0
μ_6	0.891	0.064	0.045	0.000	0.000	0.000	0.000	▲/0
\bar{R}_5/R_5	●/0.738622							

▲: Underperformed; ●: Normal; ◆: Overperformed.

- i. **enumerate** f_j for $0 \leq f_1 \leq 6, 0 \leq f_2 \leq 1, 0 \leq f_3 \leq 0, 0 \leq f_4 \leq 2$ **do**
- ii. **if** f_j satisfies the following equations:
 $f_1 + f_2 \leq 6, f_1 + f_4 \leq 6, f_2 \leq 1, f_4 \leq 0, f_3 + f_4 \leq 2, f_2 + f_3 \leq 2$
 and
 $f_1 + f_2 + f_3 + f_4 = 5,$
then $T = T \cup \{F = (3, 0, 2, 0)\}$ **endif**
 ...
end enumerate
 The result of T is

$$\{(3, 0, 2, 0), (3, 1, 1, 0), (4, 0, 1, 0), (4, 1, 0, 0), (5, 0, 0, 0)\}.$$

- Step 2. Generate the set $\Omega = \{X_F | F \in T\}$.
 - i. **for** $F = (3, 0, 2, 0)$ in T **do**
 - ii. $x_1 = 3 = f_1 + f_2, x_2 = 3 = f_1 + f_4, x_3 = 0 = f_2, x_4 = 0 = f_4,$
 $x_5 = 2 = f_3 + f_4, x_6 = 2 = f_2 + f_3,$
 - iii. $U_X = U_X \cup \{X_F = (3, 3, 0, 0, 2, 2)\}$.
 ...
endifor
 - iv. **for** $X = (3, 3, 0, 0, 2, 2)$ in U_X **do**
 - v. **if** $X \notin \Omega,$ **then** $\Omega = \Omega \cup \{X = (3, 3, 0, 0, 2, 2)\}$ **endif**
 ...

endifor

The result of Ω is

$$\{X_1 = (3, 3, 0, 0, 2, 2), X_2 = (4, 3, 1, 0, 1, 2), X_3 = (4, 4, 0, 0, 1, 1), X_4 = (5, 4, 1, 0, 0, 1), X_5 = (5, 5, 0, 0, 0, 0)\}.$$

- Step 3. Find the set $\Omega_{min} = \{X | X \text{ is a minimal vector in } \Omega\}$.
 - i. **for** $i = 1 \leq 5$ **do**
 - ii. **for** $j = 2 \leq 5$ **do**
 - iii. Because $X_2 = (4, 3, 1, 0, 1, 2) \leq X_1 = (3, 3, 0, 0, 2, 2)$ is false and $X_2 = (4, 3, 1, 0, 1, 2) > X_1 = (3, 3, 0, 0, 2, 2)$ is false, **then** do nothing.
 - ii. $j = 3,$ repeat the loop again.
 ...
endifor
 - iv. $\Omega_{min} = \phi \cup \{X_1 = (3, 3, 0, 0, 2, 2)\}$.
 ...
endifor
 The result of Ω_{min} is

$$\{X_1 = (3, 3, 0, 0, 2, 2), X_2 = (4, 3, 1, 0, 1, 2), X_3 = (4, 4, 0, 0, 1, 1), X_4 = (5, 4, 1, 0, 0, 1), X_5 = (5, 5, 0, 0, 0, 0)\}.$$

Finally, R_5 can be calculated in terms of five lower boundary points. At first, let $E_1 = \{X | X \geq X_1\}, E_2 = \{X | X \geq X_2\}, E_3 = \{X | X \geq X_3\}, E_4 = \{X | X \geq X_4\}$ and $E_5 = \{X | X \geq X_5\}$. From Eq. (4), we got $R_5 = \Pr\{\bigcup_{i=1}^5 E_i\} = 0.738622$. Fig. 5 denotes the membership function for R_5 . We get $\bar{R}_5 = \lambda_R^{-1}(0.738622) = \text{“Normal”}$. Although the channels from Shanghai to Tokyo and from Tokyo to Taipei were failed, the logistics network still keeps alive. This is because the flow from Shanghai to Hong Kong and from Hong Kong to Taipei can fulfill the partial demand. However, the performance has slightly decreased in comparison with that of the normal condition. A new route may be recommended to cover the lost flow if the failure will be continued for a long time.

5.2. Scenario two – the ship maintenance

In Scenario two, assume the ship from Hong Kong to Taipei stopped for maintenance. The throughputs were sampled. Table 4 gives the results of sampling from those channels. R_5 is calculated as 0.772561. We get $\bar{R}_5 = \lambda_R^{-1}(0.772561) = \text{“Normal”}$. Although the ship from Hong Kong to Taipei stopped for maintenance, the optimal capacity plan made the logistics network survived. Nonetheless, the performance was still higher than that of Scenario one. A new transportation company may be suggested to replace with if the maintenance will be continued for a long time.

6. Conclusion and discussion

This article proposed a novel approach to evaluate the real-time overall performance of a logistics network in a stochastic environment. The overall performance of the logistics network was integrated by the individual logistics channel real-time performance which could be easily obtained by the new IT technologies such as RFID, etc. The fuzzy-scorecard approach was a scorecarding technique which uses fuzzy mathematics and flow network theory to aggregate the individual performance consistently. Accompanying the optimal capacity plan, a robust supply chain management can be fulfilled by the observation of those derived fuzzy-scorecards. The corresponding strategies to manage the underperformed channels can be subsequently obtained in the derivation.

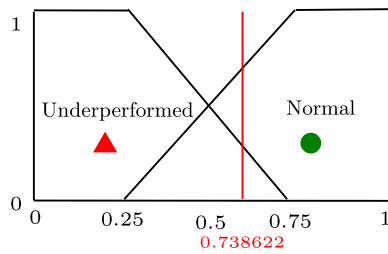


Fig. 5. The derived fuzzy-scorecard for Scenario one.

Table 4

The empirical distributions and scorecards for Scenario two.

Distr. functions	The number of units per week							\bar{x}_i/\bar{x}_i
	0	1	2	3	4	5	6	
μ_1	0.000	0.227	0.455	0.227	0.091	0.000	0.000	▲/2
μ_2	1.000	0.000	0.000	0.000	0.000	0.000	0.000	▲/0
μ_3	0.255	0.426	0.319	0.000	0.000	0.000	0.000	◆/2
μ_4	1.000	0.000	0.000	0.000	0.000	0.000	0.000	▲/0
μ_5	0.000	0.006	0.012	0.024	0.091	0.591	0.274	●/5
μ_6	0.000	0.000	0.027	0.043	0.108	0.527	0.296	◆/6
\bar{R}_5/R_5	●/0.772561							

▲: Underperformed; ●: Normal; ◆: Overperformed.

Although the management of key performance indicators (KPI) has been now popular in the modern management practice or the business intelligence activities, the consistent approaches for calculating those performance indicators are still very limited. Then, the fuzzy-scorecard approach provided a novel and consistent way to calculate the efficient and effective performance indicator for a logistics network in a stochastic environment. By the illustration of numerical examples and various scenarios, the proposed approach is easy to implement and can be used as a business intelligence function to help people making decision in management activities.

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