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A new fuzzy network slacks-based DEA model for evaluating performance of supply chains with reverse logistics

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Abstract. Supply chain performance evaluation problems are complex problems with multiple criteria and multi-layered internal linking activities. Data Envelopment Analysis (DEA) has been used to evaluate the relative performance of organizational units called Decision Making Units (DMUs). However, the conventional DEA models cannot take into account the complex nature of supply chains with internal linking activities. Although network DEA models are used to address this drawback, most of them use Farrell radial measures of efficiency and ignore input slacks and/or output slacks and are not suitable for measuring efficiencies when inputs and outputs may change non-proportionally. In response, network DEA models using Slacks-Based Measures (SBMs) of efficiency are used when inputs and outputs are non-radial. Furthermore, crisp input and output data are fundamentally indispensable in a conventional DEA evaluation process. However, the input and output data in real-world problems are often imprecise or ambiguous. Fuzzy DEA models are used to address the impreciseness and ambiguity associated with the input and output data. Finally, conventional supply chain performance evaluation models primarily consider forward logistics dealing with the flow of products from manufacturing to customers. We propose a new Network SBM (NSBM) model in the fuzzy environment. The proposed fuzzy NSBM model considers non-radial measures of efficiency in a unified framework for evaluating performance of supply chain networks with forward and reverse logistics. A case study is presented to demonstrate the applicability of the proposed fuzzy NSBM model and exhibit the efficacy of the procedures in evaluating the performance of a supply chain in the semiconductor industry.

Keywords: Data envelopment analysis, network slacks-based measure, supply chain, reverse logistics

1. Introduction

Competition in the manufacturing environment has shifted from individual firms to supply chains and only a firm with an agile and versatile supply chain can sustain an effective competitive edge [4, 20, 22, 25, 33]. Recently, Data Envelopment Analysis (DEA) has been extended to examine the efficiency of supply chain operations. DEA, originated from the work of Charnes et al. [5], is a linear programming, nonparametric method used to measure the relative efficiency of peer Decision Making Units (DMUs) with multiple inputs and outputs. Supply chain performance evaluation covers

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a wide range of problems from evaluating the performance of independent organizations among supply chains to evaluating the performance of a whole supply chain system [36]. Several researchers have studied the performance of the independent organizations in supply chains in the past such as purchasing performance evaluation [11], distribution centers performance evaluation [27] and vendor performance evaluation [31]. However, these independent organizations among supply chains have their own objectives and these objectives are often conflicting. Consequently, there is a need for a comprehensive performance evaluation framework to integrate and evaluate the performance of these independent organizations simultaneously.

In conventional DEA, the production process is treated as a black box and what goes on inside the box is typically ignored because the inputs and outputs are the focus of inquiry. However, some production systems such as supply chains have a network structure where the production by one member of the supply chain results in an intermediate output that is an input to another member in the supply chain. In these cases, managers are likely to glean more information from individual organizations (supply chain members) efficiency measures than from the efficiency measures in the whole supply chain. Kleinsorge [17], Weber and Desai [34], Azoulay-Schwartz et al. [2] and Kumar et al. [18] have applied DEA to evaluate the performance of different organizations among the supply chain.

In addition, uncertainty is common in real-world problems such as fuzziness, randomness and roughness. In spite of that, a great deal of the supply chain performance evaluation models have assumed deterministic input and output parameters in the supply chain [1, 3, 14, 15, 24, 26]. However, real-world problems are subject to uncertainty, and some factors such as supplies, demands, expenses and revenues are often not deterministic. Therefore, we must consider the supply chain performance evaluation problem under uncertainty.

Measuring supply chain performance has become a difficult and challenging task because of the need to deal with the multiple performance measures related to the supply chain members and to effectively integrate and coordinate their performance. Several authors have abandoned the "black box" perspective and taken into account an internal structure in the DEA models to measure the efficiency of supply chain networks [6–10, 12, 13, 16, 19, 21, 28, 29, 32, 38].

Although these studies have made great strides in evaluating network structures, most of them: (1) do not consider impreciseness and ambiguity in the input and output data; (2) use Farrell radial measures of efficiency and ignore input slacks and/or output slacks that can arise when measuring efficiency in piecewise linear technologies; and (3) do not consider reverse logistics in more sophisticated supply chain networks. In this study we propose a fuzzy Network Slacks-Based Measures (NSBM) model for evaluating supply chain networks with imprecise data and reverse logistics.

The remainder of this paper is organized as follows. In Section 2, we present a review of the relevant literature in DEA and supply chain management. In Section 3, we present the mathematical details of the proposed fuzzy NSBM model. In Section 4, we present a case study for performance evaluation in the semiconductor industry. In Section 5, we present our conclusions and future research directions.

2. Literature review

The traditional supply chains were driven by manufacturers who managed and controlled the pace at which products were manufactured and delivered to customers [30]. Generally, the efficiency in traditional supply chains was measured by taking the ratio of revenue over the total supply chain operational costs [23]. However, in recent years, the rise of multiple performance measures has rendered the efficiency measurement task difficult and challenging [37]. DEA has been widely used for performance measurement in supply chains. Wong and Wong [35] have discussed the motivation of using DEA as a supply chain performance measurement tool by giving ample evidences, literature supports and reasons on the suitability of DEA as a performance measurement tool in supply chain management.

Färe and Grosskopf [12] developed a network activity analysis model that explicitly recognized that some inputs are produced and consumed within the production technology. Their model consisted of two production units that were interconnected in a network to form a production technology. Lewis and Sexton [19] argued that DEA models treat the DMU as a "black box" and it is difficult, if not impossible, to provide individual DMU managers with specific information regarding the sources of inefficiency within a DMU. They showed how to use DEA to look inside the DMU and reveal greater insight as to the sources of organizational inefficiency. Their model applied to DMUs that consisted of a network of individual organizations, some of which consume resources produced by other individual organizations and some of which produce resources consumed by other individual organizations. Golany et al. [13] developed an efficiency measurement framework for systems composed of two subsystems arranged in series that simultaneously computed the efficiency of the aggregate system and each subsystem. Their approach expanded the technology sets of each subsystem by allowing each to acquire resources from the other in exchange for delivery of the appropriate (intermediate or final) product, and to form composites from both subsystems.

Tone and Tsutsui [32] argued that one of the drawbacks of the conventional DEA models is the neglect of intermediate products or linking activities. After pointing out the needs for including the intermediate products in DEA models, they proposed a Slacks-Based Measure (SBM) model that could deal with intermediate products. Using this model they evaluated divisional efficiencies along with the overall efficiency of the DMUs. Cook et al. [10] argued that in spite of the fact that many real-world problems are characterized by multiple individual organizations (e.g., supply chains and many manufacturing processes), the traditional DEA literature on serial processes has tended to concentrate on closed systems. They examined the more general problem of a network structure with multiple individual organizations where some outputs from a given individual organization may leave the system while others become inputs to another individual organization in the system. They represented the overall efficiency of such a structure as an additive weighted average of the efficiencies of the individual organizations that make up the network structure.

Kao [16] argued that traditional studies in DEA view systems as a whole when measuring the efficiency and ignore the operation of individual organizations within a system. He built a relational network DEA model and took into account the interrelationship of the individual organizations within the system, to measure the efficiency of the system and those of the individual organizations at the same time. Cook et al. [9] considered the DMUs in two-stage or network processes. They studied those processes in which all the outputs from the first stage are the only inputs to the second stage and categorized them as using either Stackelberg (leader-follower), or cooperative game concepts.

Liang et al. [21] identified the existence of multiple measures that characterized the performance of supply chain members and the existence of conflicts between the members of the supply chain with respect to specific measures as two hurdles in measuring the performance of a supply chain and its members. They argued that conventional DEA cannot directly measure the performance of supply chain and its members because of the existence of the intermediate measures connecting the supply chain members. They developed several DEA-based approaches for characterizing and measuring supply chain efficiency when intermediate measures are incorporated into the performance evaluation. Chen et al. [7] investigated the efficiency game between two supply chain members (i.e., supplier and manufacturer). They showed that numerous Nash equilibriums efficiency plans exists for the supplier and the manufacturer with respect to their efficiency functions. The proposed a bargaining model to analyze the supplier and manufacturer's decision process and to determine the best efficiency plan strategy. They also studied DEA efficiency for supply chain operations for the central control and the decentralized control cases.

Yang et al. [38] defined two types of supply chain production possibility sets, which were proved to be equivalent to each other. Based upon the production possibility set, a supply chain performance measurement model is proposed to appraise the overall technical efficiency of supply chains. The major advantage of their model lies in the fact that it could help to find out the most efficient production possibilities in supply chains, by replacing or improving inefficient individual organizations (supply chain members). The proposed model also directly identified the benchmarking units for inefficient supply chains to improve their performance. Chen and Yan [6] developed an alternative network DEA model that embodied the internal structure for supply chain performance evaluation. They introduced three different network DEA models under the concept of centralized, decentralized and mixed organization mechanisms. Efficiency analysis including the relationship between supply chain and divisions, and the relationship among the three different organization mechanisms were discussed. In the next section we propose a fuzzy NSBM that considers non-radial measures of efficiency in a unified framework for evaluating the performance of supply chain networks with forward and reverse logistics.

3. Preliminary definitions

3.1. Fuzzy network SBM (NSBM)

In this section, the following NSBM model proposed by Tone and Tsutsui [32] is revised in the presence of fuzzy data and reverse logistics within a supply chain:

$$\min \rho_o = \sum_{h=1}^{k} w_h \left(1 - \frac{1}{m_h} \sum_{i=1}^{m_h} \frac{s_i^{h-}}{x_{io}^h}\right)$$

s.t.

$$\sum_{j=1}^{n} x_{ij}^h \lambda_j^h + s_i^{h-} = x_{io}^h, i = 1, \ldots, m_h, h = 1, \ldots, k, \tag{1-1}$$

$$\sum_{j=1}^{n} y_{rj}^h \lambda_j^h \geq y_{ro}^h, \ r=1, \ldots, s_h, \ h = 1, \ldots, k, \tag{1-2}$$

$$\sum_{j=1}^{n} z_j^{(h,h')} \lambda_j^h = \sum_{j=1}^{n} z_j^{(h,h')} \lambda_j^{h'}, \forall (h, h'). \tag{1-3}$$

$$\lambda_j^h \geq 0, \ s_i^{h-} \geq 0 \tag{1-4}$$

where x_{ij}^h and y_{rj}^h are the ith ($i=1, \ldots m_h$) input and the rth ($r=1, \ldots, s_h$) output, respectively; which correspond to the hth ($h=1, \ldots, k$) division from the jth ($j=1, \ldots, n$) DMU. s_i^{h-} is the amount of slacks slack related to the ith input of the hth division. The subscript "o" refers to the DMU under evaluation. $z_j^{(h,h')}$ is an intermediate measure from the hth division to $h' \left(\neq h, h' = 1, \ldots, k\right)$. λ_j^h is the intensity vector for division h.

Let us consider the overall supply chain structure depicted in Fig. 1 to develop the fuzzy version of Model (1).

As shown in Fig. 1, the inputs and outputs related to each division are fuzzy. Furthermore, a reverse logistics is considered in addition to the forward logistics. The forward logistics is shown by a continuous line while the reverse logistics is shown by a dotted line. Considering the fuzzy input and output data and the forward and reverse logistics in Fig. 1, Model (1) can be further developed as follows:

$$\min \tilde{\rho}_o = \sum_{h=1}^{k} w_h \left(1 - \frac{1}{m_h} \sum_{i=1}^{m_h} \frac{\tilde{s}_i^{h-}}{\tilde{x}_{io}^h}\right)$$

s.t.

$$\sum_{j=1}^{n} \tilde{x}_{ij}^h \lambda_j^h + \tilde{s}_i^{h-} = \tilde{x}_{io}^h, i = 1, \ldots, m_h, h = 1, \ldots, k, \tag{2-1}$$

$$\sum_{j=1}^{n} \tilde{y}_{rj}^h \lambda_j^h \geq \tilde{y}_{ro}^h, r = 1, \ldots, s_h, h = 1, \ldots, k, \tag{2-2}$$

$$\sum_{j=1}^{n} \sum_{f_{(1,2)}=1}^{F_{(1,2)}} z_{f_{(1,2)}j}^{(1,2)} \lambda_j^1 = \sum_{j=1}^{n} \sum_{f_{(1,2)}=1}^{F_{(1,2)}} z_{f_{(1,2)}j}^{(1,2)} \lambda_j^2, \tag{2-3}$$

$$\sum_{j=1}^{n} \sum_{f_{(2,1)}=1}^{F_{(2,1)}} z_{f_{(2,1)}j}^{(2,1)} \lambda_j^1 = \sum_{j=1}^{n} \sum_{f_{(1,2)}=1}^{F_{(1,2)}} z_{f_{(2,1)}j}^{(2,1)} \lambda_j^2, \tag{2-4}$$

$$\sum_{j=1}^{n} \sum_{f_{(k,k-1)}=1}^{F_{(k,k-1)}} z_{f_{(k,k-1)}j}^{(k,k-1)} \lambda_j^k = \sum_{j=1}^{n} \sum_{f_{(k,k-1)}=1}^{F_{(k,k-1)}} z_{f_{(k,k-1)}j}^{(k,k-1)} \lambda_j^{k-1} \tag{2-5}$$

$$\sum_{j=1}^{n} \sum_{f_{(k-1,k)}=1}^{F_{(k-1,k)}} z_{f_{(k-1,k)}j}^{(k-1,k)} \lambda_j^k = \sum_{j=1}^{n} \sum_{f_{(k-1,k)}=1}^{F_{(k-1,k)}} z_{f_{(k-1,k)}j}^{(k-1,k)} \lambda_j^{k-1}, \tag{2-6}$$

$$\sum_{j=1}^{n} \sum_{f_{(h,h-1)}=1}^{F_{(h,h-1)}} z_{f_{(h,h-1)}j}^{(h,h-1)} \lambda_j^h + \sum_{j=1}^{n} \sum_{f_{(h,h+1)}=1}^{F_{(h,h+1)}} z_{f_{(h,h+1)}j}^{(h,h+1)} \lambda_j^h$$
$$= \sum_{j=1}^{n} \sum_{f_{(h,h-1)}=1}^{F_{(h,h-1)}} z_{f_{(h,h-1)}j}^{(h,h-1)} \lambda_j^{h-1}$$
$$+ \sum_{j=1}^{n} \sum_{f_{(h,h+1)}=1}^{F_{(h,h+1)}} z_{f_{(h,h+1)}j}^{(h,h+1)} \lambda_j^{h+1}, h=2, \ldots, k-1 \tag{2-7}$$

$$\sum_{j=1}^{n} \sum_{f_{(h-1,h)}=1}^{F_{(h-1,h)}} z_{f_{(h-1,h)}j}^{(h-1,h)} \lambda_j^h + \sum_{j=1}^{n} \sum_{f_{(h+1,h)}=1}^{F_{(h+1,h)}} z_{f_{(h+1,h)}j}^{(h+1,h)} \lambda_j^h$$
$$= \sum_{j=1}^{n} \sum_{f_{(h-1,h)}=1}^{F_{(h-1,h)}} z_{f_{(h-1,h)}j}^{(h-1,h)} \lambda_j^{h-1}$$
$$+ \sum_{j=1}^{n} \sum_{f_{(h+1,h)}=1}^{F_{(h+1,h)}} z_{f_{(h+1,h)}j}^{(h+1,h)} \lambda_j^{h+1}, h=2, \ldots, k-1 \tag{2-8}$$

$$\lambda_j^h \geq 0, \tilde{s}_i^{h-} \geq 0.$$

where $\tilde{x}_{ij}^h$ is the ith fuzzy input related to the hth division ($h=1, \ldots, k$) which is represented by the triangular fuzzy number $\left(x_{ij}^{h^L}, x_{ij}^{h^M}, x_{ij}^{h^U}\right)$. $\tilde{y}_{rj}^h$ is the rth fuzzy output related to the hth division and is represented by the triangular fuzzy number $\left(y_{rj}^{h^L}, y_{rj}^{h^M}, y_{rj}^{h^U}\right)$. $z_{f_{(h,h+1)}j}^{(h,h+1)}$ represents the intermediate measure from the hth division to the $h+1$st division. $f_{(h,h+1)}$ is also the counter indice of the intermediate measure $\left(f_{(h,h+1)} = 1, \ldots, F_{(h,h+1)}\right)$. $\tilde{s}_i^{h-}$ is the slack which

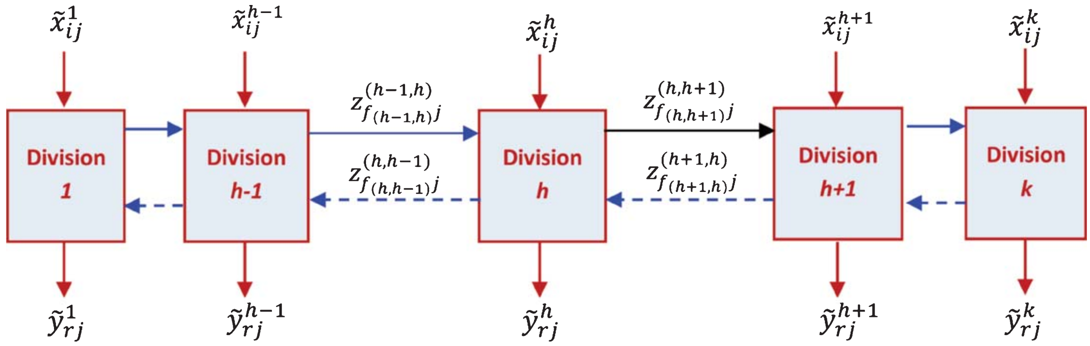

Fig. 1. The supply chain's overall structure including fuzzy data and the reverse logistics.

corresponds to the ith input and is represented by the triangular fuzzy number $\left(s_i^{h-L}, s_i^{h-M}, s_i^{h-U}\right)$. The constraints (2-3) and (2-4) show the intermediate measures exiting Division 1 and entering Division 2, respectively. The constraints (2-5) and (2-6) represent the intermediate measures exiting Division k and entering Division k, respectively. The constraints (2-7) and (2-8) depict the intermediate measures exiting the hth division and entering the other divisions and then the hth division ($h = 1, \ldots, k$). It is obvious that constraints (2-7) and (2-8) show the state of $k > 2$. In the case of $k = 2$, constraints (2-3) and (2-4) are equivalent to constraints (2-5) and (2-6).

In the above model, constraints (2-1) and (2-2) are in fuzzy form. To solve the model, all fuzzy constraints should be changed into crisp form. To defuzzify Model (2), the fuzzy arithmetic operations are used on the fuzzy data. Consider the following fuzzy arithmatic operations for the two fuzzy triangular numbers $\tilde{a} = \left(a^L, a^M, a^U\right)$ and $\tilde{b} = \left(b^L, b^M, b^U\right)$:

$$Addition: \tilde{a} + \tilde{b} = \left(a^L + b^L, a^M + b^M, a^U + b^U\right)$$

$$Subtraction: \tilde{a} - \tilde{b} = \left(a^L - b^U, a^M - b^M, a^U - b^L\right)$$

$$Multiplication: \tilde{a}.\tilde{b} = \left(a^L.b^L, a^M.b^M, a^U.b^U\right)$$

$$Division: \tilde{a}/\tilde{b} = \left(a^L/b^U, a^M + b^M, a^U/b^L\right)$$

$$Equality: \tilde{a} = \tilde{b} \text{ if } a^L = b^L \text{ and } a^M = b^M \text{ and } a^U = b^U$$

$$Inequality: a^M > b^M \rightarrow \tilde{a} \geq \tilde{b}$$

The objective function of Model (2) can be written as follows:

$$\tilde{\rho}_o = \sum_{h=1}^{k} w_h \left(1 - \frac{1}{m_h} \sum_{i=1}^{m_h} \frac{\left(s_i^{h-L}, s_i^{h-M}, s_i^{h-U}\right)}{\left(x_{io}^{hL}, x_{io}^{hM}, x_{io}^{hU}\right)}\right), \tag{3}$$

Using the fuzzy division and addition arithmetic, Objective Function (3) can be expressed as follows:

$$\tilde{\rho}_o = \sum_{h=1}^{k} w_h \left(1 - \frac{1}{m_h}\left(\sum_{i=1}^{m_h} \frac{s_i^{h-L}}{x_{io}^{hU}}, \sum_{i=1}^{m_h} \frac{s_i^{h-M}}{x_{io}^{hM}}, \sum_{i=1}^{m_h} \frac{s_i^{h-U}}{x_{io}^{hL}}\right)\right), \tag{4}$$

Using the fuzzy subtraction and multiplication arithmetic, Objective Function (4) can be expressed as follows:

$$\tilde{\rho}_o = \begin{pmatrix} \sum_{h=1}^{k} w_h \left(1 - \frac{1}{m_h} \sum_{i=1}^{m_h} \frac{s_i^{h-U}}{x_{io}^{hL}}\right), \\ \sum_{h=1}^{k} w_h \left(1 - \frac{1}{m_h} \sum_{i=1}^{m_h} \frac{s_i^{h-M}}{x_{io}^{hM}}\right), \\ \sum_{h=1}^{k} w_h \left(1 - \frac{1}{m_h} \sum_{i=1}^{m_h} \frac{s_i^{h-L}}{x_{io}^{hU}}\right) \end{pmatrix}, \tag{5}$$

The Objective Function (5) can be stated as $\tilde{\rho}_o = \left(\rho_o^L, \rho_o^M, \rho_o^U\right)$, in which

$$\rho_o^L = \sum_{h=1}^{k} w_h \left(1 - \frac{1}{m_h} \sum_{i=1}^{m_h} \frac{s_i^{h-U}}{x_{io}^{hL}}\right), \tag{6}$$

$$\rho_o^M = \sum_{h=1}^{k} w_h \left(1 - \frac{1}{m_h} \sum_{i=1}^{m_h} \frac{s_i^{h-M}}{x_{io}^{hM}}\right), \tag{7}$$

$$\rho_o^U = \sum_{h=1}^{k} w_h \left(1 - \frac{1}{m_h} \sum_{i=1}^{m_h} \frac{s_i^{h-L}}{x_{io}^{h^U}} \right), \qquad (8)$$

Constraint (2-1) can be rewritten as follows:

$$\sum_{j=1}^{n} \left(x_{ij}^{h^L}, x_{ij}^{h^M}, x_{ij}^{h^U} \right) \lambda_j^h + \left(s_i^{h-L}, s_i^{h-M}, s_i^{h-U} \right) = \left(x_{io}^{h^L}, x_{io}^{h^M}, x_{io}^{h^U} \right), \qquad (9)$$

Using the fuzzy addition and multiplication arithmetic, the above constraint can be expressed as follows:

$$\begin{pmatrix} \sum_{j=1}^{n} x_{ij}^{h^L} \lambda_j^h + s_i^{h-L}, \\ \sum_{j=1}^{n} x_{ij}^{h^M} \lambda_j^h + s_i^{h-M}, \\ \sum_{j=1}^{n} x_{ij}^{h^U} \lambda_j^h + s_i^{h-U} \end{pmatrix} = \left(x_{io}^{h^L}, x_{io}^{h^M}, x_{io}^{h^U} \right) \qquad (10)$$

Considering the fuzzy equation arithmetic, we have:

$$\sum_{j=1}^{n} x_{ij}^{h^L} \lambda_j^h + s_i^{h-L} = x_{io}^{h^L}, \qquad (11)$$

$$\sum_{j=1}^{n} x_{ij}^{h^M} \lambda_j^h + s_i^{h-M} = x_{io}^{h^M}, \qquad (12)$$

$$\sum_{j=1}^{n} x_{ij}^{h^U} \lambda_j^h + s_i^{h-U} = x_{io}^{h^U}, \qquad (13)$$

Constraint (2-2) can be written as follows:

$$\sum_{j=1}^{n} \left(y_{rj}^{h^L}, y_{rj}^{h^M}, y_{rj}^{h^U} \right) \lambda_j^h \geq \left(y_{ro}^{h^L}, y_{ro}^{h^M}, y_{ro}^{h^U} \right), \qquad (14)$$

Using the fuzzy addition and multiplication arithmetic, Constraint (14) can be expressed as follows:

$$\left(\sum_{j=1}^{n} y_{rj}^{h^L} \lambda_j^h, \sum_{j=1}^{n} y_{rj}^{h^M} \lambda_j^h, \sum_{j=1}^{n} y_{rj}^{h^U} \lambda_j^h \right) \geq \left(y_{ro}^{h^L}, y_{ro}^{h^M}, y_{ro}^{h^U} \right), \qquad (15)$$

Considering the fuzzy inequality arithmetic, we have:

$$\sum_{j=1}^{n} y_{rj}^{h^M} \lambda_j^h \geq y_{ro}^{h^M}, \qquad (16)$$

Now, using the crisp constraints (11), (12), (13), and (16), and also the constraints related to the intermediate measures, Model (2) can be written as follows:

$$\min\ \rho_o^L = \sum_{h=1}^{k} w_h \left(1 - \frac{1}{m_h} \sum_{i=1}^{m_h} \frac{s_i^{h-U}}{x_{io}^{h^L}} \right),$$

s.t.

$$\sum_{j=1}^{n} x_{ij}^{h^L} \lambda_j^h + s_i^{h-L} = x_{io}^{h^L}, \qquad (17\text{-}1)$$

$$\sum_{j=1}^{n} x_{ij}^{h^M} \lambda_j^h + s_i^{h-M} = x_{io}^{h^M}, \qquad (17\text{-}2)$$

$$\sum_{j=1}^{n} x_{ij}^{h^U} \lambda_j^h + s_i^{h-U} = x_{io}^{h^U}, \qquad (17\text{-}3)$$

$$\sum_{j=1}^{n} y_{rj}^{h^M} \lambda_j^h \geq y_{ro}^{h^M}, \qquad (17\text{-}4)$$

$$\sum_{j=1}^{n} \sum_{f_{(1,2)}=1}^{F_{(1,2)}} z_{f_{(1,2)}j}^{(1,2)} \lambda_j^1 = \sum_{j=1}^{n} \sum_{f_{(1,2)}=1}^{F_{(1,2)}} z_{f_{(1,2)}j}^{(1,2)} \lambda_j^2 \qquad (17\text{-}5)$$

$$\sum_{j=1}^{n} \sum_{f_{(2,1)}=1}^{F_{(2,1)}} z_{f_{(2,1)}j}^{(2,1)} \lambda_j^1 = \sum_{j=1}^{n} \sum_{f_{(1,2)}=1}^{F_{(1,2)}} z_{f_{(2,1)}j}^{(2,1)} \lambda_j^2 \qquad (17\text{-}6)$$

$$\sum_{j=1}^{n} \sum_{f_{(k,k-1)}=1}^{F_{(k,k-1)}} z_{f_{(k,k-1)}j}^{(k,k-1)} \lambda_j^k = \sum_{j=1}^{n} \sum_{f_{(k,k-1)}=1}^{F_{(k,k-1)}} z_{f_{(k,k-1)}j}^{(k,k-1)} \lambda_j^{k-1}, \qquad (17\text{-}7)$$

$$\sum_{j=1}^{n} \sum_{f_{(k-1,k)}=1}^{F_{(k-1,k)}} z_{f_{(k-1,k)}j}^{(k-1,k)} \lambda_j^k = \sum_{j=1}^{n} \sum_{f_{(k-1,k)}=1}^{F_{(k-1,k)}} z_{f_{(k-1,k)}j}^{(k-1,k)} \lambda_j^{k-1}, \qquad (17\text{-}8)$$

$$\sum_{j=1}^{n} \sum_{f_{(h,h-1)}=1}^{F_{(h,h-1)}} z_{f_{(h,h-1)}j}^{(h,h-1)} \lambda_j^h + \sum_{j=1}^{n} \sum_{f_{(h,h+1)}=1}^{F_{(h,h+1)}} z_{f_{(h,h+1)}j}^{(h,h+1)} \lambda_j^h = \sum_{j=1}^{n} \sum_{f_{(h,h-1)}=1}^{F_{(h,h-1)}} z_{f_{(h,h-1)}j}^{(h,h-1)} \lambda_j^{h-1} + \sum_{j=1}^{n} \sum_{f_{(h,h+1)}=1}^{F_{(h,h+1)}} z_{f_{(h,h+1)}j}^{(h,h+1)} \lambda_j^{h+1}, h = 2, \ldots, k-1 \qquad (17\text{-}9)$$

$$\sum_{j=1}^{n}\sum_{f_{(h-1,h)}=1}^{F_{(h-1,h)}} z_{f_{(h-1,h)}j}^{(h-1,h)}\lambda_j^h+\sum_{j=1}^{n}\sum_{f_{(h+1,h)}=1}^{F_{(h+1,h)}} z_{f_{(h+1,h)}j}^{(h+1,h)}\lambda_j^h$$
$$=\sum_{j=1}^{n}\sum_{f_{(h-1,h)}=1}^{F_{(h-1,h)}} z_{f_{(h-1,h)}j}^{(h-1,h)}\lambda_j^{h-1}$$
$$+\sum_{j=1}^{n}\sum_{f_{(h+1,h)}=1}^{F_{(h+1,h)}} z_{f_{(h+1,h)}j}^{(h+1,h)}\lambda_j^{h+1},\ h=2,\ldots,k-1 \tag{17-10}$$

$\lambda_j^h \geq 0, s_i^{h-U} \geq 0.$

Model (17) is a fuzzy NSBM and the value of $\rho_o^{L^*}$ can be acquired by solving the fuzzy NSBM model. To obtain $\rho_o^{M^*}$ and $\rho_o^{U^*}$, Equations (7) and (8) are substituted in the objective function of Model (17) which is then solved with the same constraints.

A DMU is fuzzy NSBM efficient, if its efficiency score equals to 1:

$$\tilde{\rho}_o^* = \left(\rho_o^{L^*},\ \rho_o^{M^*},\ \rho_o^{U^*}\right) = 1, \tag{18}$$

The divisions' efficiency score is $\tilde{\rho}_o^h = \left(\rho_o^{h^{L^*}}, \rho_o^{h^{M^*}}, \rho_o^{h^{U^*}}\right)$, which can be obtained from the following relations:

$$\rho_o^{h^{L^*}} = 1-\frac{1}{m_h}\sum_{i=1}^{m_h}\frac{s_i^{h-U^*}}{x_{io}^{h^{L^*}}}, \tag{19}$$

$$\rho_o^{h^{M^*}} = 1-\frac{1}{m_h}\sum_{i=1}^{m_h}\frac{s_i^{h-M^*}}{x_{io}^{h^{M^*}}}, \tag{20}$$

$$\rho_o^{h^{U^*}} = 1-\frac{1}{m_h}\sum_{i=1}^{m_h}\frac{s_i^{h-L^*}}{x_{io}^{h^{U^*}}}, \tag{21}$$

A division is efficient if its efficiency score equals to 1:

$$\tilde{\rho}_o^{h^*} = \left(\rho_o^{h^{L^*}}, \rho_o^{h^{M^*}}, \rho_o^{h^{U^*}}\right) = 1 \tag{22}$$

A DMU becomes efficient if all the divisions for that DMU are efficient. A suitable method is needed next to rank all the DMUs $\left(i.\text{e.}, \tilde{\rho}_j^* = \left(\rho_j^{L^*}, \rho_j^{M^*} \rho_j^{U^*}\right)\right)$.

Efficiency score's ranking via truth function

In this subsection, the truth function (Zimmermann, 1996) is used to rank the obtained efficiency scores $\left(\tilde{\rho}_j^*\right)$. Suppose:

$$\tilde{\rho}_i^* = \left(\rho_i^{L^*}, \rho_i^{M^*}, \rho_i^{U^*}\right) \text{ and } \tilde{\rho}_j^* = \left(\rho_j^{L^*}, \rho_j^{M^*}, \rho_j^{U^*}\right)$$

are the efficiency scores for the ith and the jth DMU, respectively. In this case, the truth function value of $\tilde{\rho}_i^* \geq \tilde{\rho}_j^*$ can be expressed as follows:

$$T\left(\tilde{\rho}_i^* \geq \tilde{\rho}_j^*\right) = \sup\left\{\min\left(\mu^*_{\tilde{\rho}_i^*}(x), \mu^*_{\tilde{\rho}_j^*}(y)\right), (x \geq y)\right\} \tag{23}$$

This can be stated as follows:

$$t_{ij} = T\left(\tilde{\rho}_i^* \geq \tilde{\rho}_j^*\right) = \begin{cases} 1 & if\ \rho_i^{M^*} \geq \rho_j^{M^*} \\ 0 & if\ \rho_i^{U^*} \leq \rho_j^{L^*} \\ \frac{\rho_j^{L^*}-\rho_i^{U^*}}{(\rho_i^{M^*}-\rho_i^{U^*})-(\rho_j^{M^*}-\rho_j^{L^*})} & otherwise \end{cases} \tag{24}$$

Using t_{ij}, the truth matrix can be represented as follows:

$$T_{n\times n} = \left[t_{ij}\right]_{n\times n} = \begin{array}{c} \\ \tilde{\rho}_1^* \\ \vdots \\ \tilde{\rho}_i^* \\ \vdots \\ \tilde{\rho}_n^* \end{array} \begin{array}{c} \tilde{\rho}_1^* \cdots \tilde{\rho}_j^* \cdots \tilde{\rho}_n^* \\ \begin{bmatrix} 1 & \cdots & t_{j1} & \cdots & t_{1n} \\ \vdots & \ddots & \vdots & & \vdots \\ t_{i1} & \cdots & 1 & & \\ \vdots & & & \ddots & \\ t_{n1} & & \cdots & & 1 \end{bmatrix} \end{array}$$

The following equation is then used to rank the DMUs:

$$\bar{t}_{\text{i}} = \frac{\sum_{\text{j}=1}^{\text{n}} t_{ij}}{n},$$

According to Equation (25), the DMU with a larger $\bar{t}_{\text{i}}$ has a higher ranking.

4. Case study

In this section, we present a case study to demonstrate the applicability of the proposed method in the semicon-

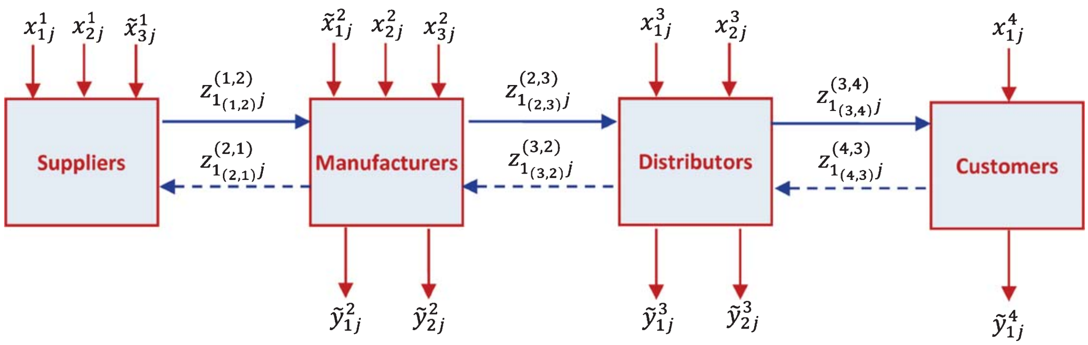

Fig. 2. The semiconductor industry supply chain.

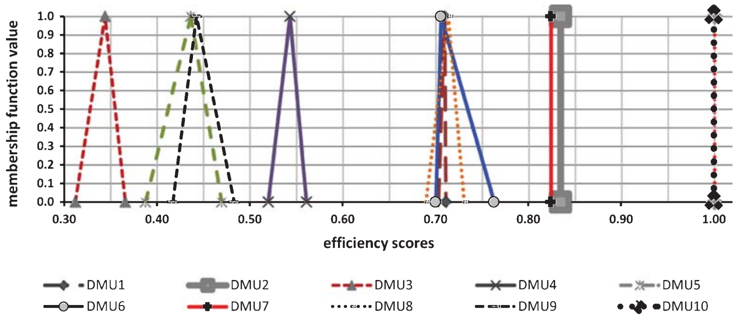

Fig. 3. Fuzzy efficiency scores obtained from the fuzzy NSBM model.

ductor industry. The semiconductor industry is a rapidly growing cornerstone industry. However, it is also a very harsh business due to complicated production and distribution processes with multi-layered internal linking activities among suppliers, manufacturers, distributors, and customers. The model presented in section 3 was used to help Semicon Technologies[1], a large manufacturer of semiconductor equipment, memory chips, microprocessors and microcontrollers located in Jersey City. With the increased complexity of the production and distribution processes, there is a compelling trend to streamline the production and distribution processes at Semicon Technologies with 10 supply chains (DMUs) with forward and reverse logistics. Semicon's supply chain is depicted in Fig. 2.

The input factors for the supplier component of the suply chain are: on-time delivery, location, and price (x^1_{1j}, x^1_{2j}, and$\tilde{x}^1_{3j}$), respectively. The input factors for the manufacturer component of the supply chain are the number of stoppages, the number of laborors and setup time of the lines ($\tilde{x}^2_{1j}$, $\tilde{x}^2_{2j}$, and $\tilde{x}^2_{3j}$), respectively. The output factors of the manufacturer component are the flexibility and equipment technology level ($\tilde{y}^2_{1j}$ and $\tilde{y}^2_{2j}$). The cost per dollar revenue and on-time delivery (x^3_{1j} and x^3_{2j}) are the inputs and the sales average and service level ($\tilde{y}^3_{1j}$ and $\tilde{y}^3_{2j}$) are the ouput variables for the distributor component in the supply chain. The number of order cancellations (x^4_{1j}) is the input and the performance history ($\tilde{y}^4_{1j}$) is the output for the customer component in the system. In addition to these input and output factors, there are several intermediate measures between different components in the supply chain. In this study, the product flow is considered a forward logistics while the information on demand forecast is considered as a reverse logistics. The product flow represents the actual amount of products delivered between different components and the demand forecast reflects the amount of product needed by each component in the supply chain. The following definitions are provided for the variables used in the proposed model:

Supplier factors:

x^1_{1j} On-time delivery: The standard deviation of the delivery times (days).

[1]Some of the names and data presented in this study are changed to protect the anonymity of the company.

x^1_{2j} Location: The geographical distance to the manufacturers (kilometers).

$\tilde{x}^1_{3j}$ Price: The price compared with the other suppliers (a fuzzy variable between 0–5).

Manufacturer factors

$\tilde{x}^2_{1j}$ Number of stoppages: The number of interruption in production (fuzzy value).

x^2_{2j} Number of laborers.

x^2_{3j} Setup time: The setup time of the production facility (hours).

$\tilde{y}^2_{1j}$ Flexibility: The flexibility to change production plan (a fuzzy variable between 0–5).

$\tilde{y}^2_{2j}$ Equipment technology level: The production capabilities (a fuzzy variable between 0–5).

Table 1
The input and output data for the components

Division 1: Suppliers (Importance Weight = 0.3)

DMU	x^1_{1j}	x^1_{2j}	$\tilde{x}^1_{1j}$
1	2	250	(4.1, 4.3, 4.6)
2	0.7	180	(2.8, 3.9, 4.9)
3	4.5	390	(4, 5, 5)
4	1.1	330	(2.4, 2.7, 3.1)
5	1.1	100	(3.3, 5.4)
6	2.5	200	(1, 1.7, 2.4)
7	3.9	14	(2.2, 2.8, 3.5)
8	4.8	300	(2.8, 3, 3.2)
9	1	250	(2.7, 3.7, 4.7)
10	2.8	150	(2.8, 3.8, 4.8)

Division 2: Manufacturers (Importance Weights = 0.2)

DMU	$\tilde{x}^2_{1j}$	$\tilde{x}^2_{2j}$	$\tilde{x}^2_{3j}$	$\tilde{y}^2_{1j}$	$\tilde{y}^2_{2j}$
1	(14, 17, 20)	23	23	(2.3, 3, 3.7)	(0.9, 1.1, 1.3)
2	(8, 11, 14)	35	14.5	(3.5, 4.1, 4.8)	(4.3, 5, 5)
3	(10, 14, 18)	39	25.6	(2.4, 3, 3 6)	(4, 5, 5)
4	(23, 25, 27)	29	15.2	(3, 4, 5)	(1.8, 2.8, 3.8)
5	(15, 20, 25)	44	28	(2.3, 3.3, 4.3)	(2.9, 3.9, 4.9)
6	(4, 7, 10)	99	8	(3.1, 4, 5)	(1.4, 2.4, 3.4)
7	(13, 17, 21)	16	14.2	(3.1, 4, 5)	(0.9, 1.9, 2.9)
8	(35, 42, 49)	36	16.8	(4, 4.3, 4.7)	(2.9, 3.5, 4.2)
9	(8, 12, 16)	29	.3	(0.2, 0.4, 0.6)	(2.3, 3.3, 7)
10	(7, 12, 17)	67	5.3	(1.1, 2, 3)	(2.3, 3.2, 4.1)

Division 3: Distributors (Importance Weight = 0.3)

DMU	x^3_{1j}	x^3_{2j}	$\tilde{y}^3_{1j}$	$\tilde{y}^3_{2j}$
1	0.3	5.2	(200, 210, 220)	(97, 98, 99)
2	0.18	4.3	(341, 371, 391)	(97.3, 98.3, 99.3)
3	0.35	5.5	(433, 450, 467)	(99.5, 99.6, 99.7)
4	0.28	0.9	(127, 145, 163)	(98, 98.3, 98.6)
5	0.29	6.2	(4200, 4300, 4500)	(99.1, 99.3, 99.5)
6	0.27	0.5	(800, 850, 900)	(96.5, 97, 97.5)
7	0.34	2.3	(6500, 7200, 7900)	(98.5, 99, 99.5)
8	0.37	4.2	(143, 151, 159)	(98, 98.5, 99)
9	0.41	6.7	(650, 740, 830)	(99.1, 99.2, 99.3)
10	0.19	2.1	(580, 630, 680)	(98.8, 99, 99.2)

Division 4: Customers (Importance Welght = 0.2)

DMU	x^4_{1j}	$\tilde{y}^4_{1j}$
1	0.1	(97.5, 98, 98.5)
2	0.6	(95, 96, 97)
3	1.1	(99, 99, 100)
4	0.5	(97, 97.4, 97.8)
5	1.3	(94, 95, 96)
6	0.1	(91.3, 92, 92.7)
7	0.8	(93.3, 94, 94 7)
8	0.1	(99, 99.5, 100)
9	0.4	(96.4, 97.7, 98.8)
10	0.1	(97, 98, 99)

Table 2
The intermediate measures of the supply chain components

DMU	Product flow (Forward logistics)			Demand forecast (Reverse logistics)		
	$z_{1_{(1,2)}j}^{(1,2)}$	$z_{1_{(2,3)}j}^{(2,3)}$	$z_{1_{(3,4)}j}^{(3,4)}$	$z_{1_{(4,3)}j}^{(4,3)}$	$z_{1_{(3,2)}j}^{(3,2)}$	$z_{1_{(2,1)}j}^{(2,1)}$
1	450	83	18	39	89	570
2	70	15	11	18	9.5	92
3	50	32	4	9	38	62
4	74	6	0.4	2.3	7.1	89
5	310	340	340	210	80	278
6	8.4	0.6	0.9	4	0.2	9.2
7	610	55	72	75	46	550
8	135	24	55	70	21	152
9	32	18	35	5	20	38
10	1450	350	155	130	320	1300

Table 3
The efficiency scores of the supply chains using the fuzzy NSBM model

DMU	Product flow (Forward logistics)			Demand forecast (Reverse logistics)		
	$z_{1_{(1,2)}j}^{(1,2)}$	$z_{1_{(2,3)}j}^{(2,3)}$	$z_{1_{(3,4)}j}^{(3,4)}$	$z_{1_{(4,3)}j}^{(4,3)}$	$z_{1_{(3,2)}j}^{(3,2)}$	$z_{1_{(2,1)}j}^{(2,1)}$
1	450	83	18	39	89	570
2	70	15	11	18	9.5	92
3	50	32	4	9	38	62
4	74	6	0.4	2.3	7.1	89
5	310	340	340	210	80	278
6	8.4	0.6	0.9	4	0.2	9.2
7	610	55	72	75	46	550
8	135	24	55	70	21	152
9	32	18	35	5	20	38
10	1450	350	155	130	320	1300

Distributer factors

- x_{1j}^3 Cost per dollar revenue: The distribution cost per dollar of revenue.
- x_{2j}^3 On-time delivery: The standard deviation of the delivery time (days).
- $\tilde{y}_{1j}^3$ Sales average: The distributer's sales amount (fuzzy value).
- $\tilde{y}_{2j}^3$ Service level: The level of service provided to customers (fuzzy value).

Customer factors:

- x_{1j}^4 Order cancellations: the percentage of customers cancelling their orders.
- $\tilde{y}_{1j}^4$ Performance history: The percentage of fulfilled orders (a fuzzy value).

Intermediate measures:

- $z_{1_{(h,h+1)}j}^{(h,h+1)}$ Product flow: The forward logistics transferred from the hth division to $h+1st$ division ($h = 1, 2, 3$)
- $z_{1_{(h+1,h)}j}^{(h+1,h)}$ Demand forecast: The reverse logistics transferred from the $h+1$st to the hth component ($h = 1, 2, 3$).

The data related to the ten supply chains considered in this study are shown in Tables 1 and 2.

Table 1 shows the input and output data for the four divisions along with the importance weight of each division judged by the decision makers. Table 2 presents the intermediate product flow and the demand forecast measures for each supply chain considered as a DEMU. We then ran Model (17) and found the efficiency scores for each division and DMU presented in Fig. 3 and Table 3.

As shown in Fig. 3, DMU 10 with the efficiency score of 1 is the best supply chain in the system. As mentioned earlier, if a DMU is efficient in a division, all the DMUs in that division are also efficient. According to Table 3, the efficiency score of DMU 10 is equal to 1 in all divisions. In other words, the four divisions (i.e., suppliers, manufacturers, distributers, and customers) in DMU 1 perform better than the remaining nine DMUs

Table 4
The truth matrix for the achieved fuzzy efficiency scores

DMU	1	2	3	4	5	6	7	8	9	10	$\bar{t}_j$	Rank
1	1.000	0.000	1.000	1.000	1.000	0.039	0.000	0.327	1.000	0.000	0.537	5
2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000	0.900	2
3	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.100	10
4	0.000	0.000	1.000	1.000	1.000	0.000	0.000	0.000	1.000	0.000	0.400	7
5	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.040	0.000	0.204	9
6	0.007	0.000	1.000	1.000	1.000	1.000	0.000	0.031	1.00	0.000	0.504	6
7	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000	0.800	3
8	1.000	0.000	1 000	1.000	1.000	1.000	0.000	1.000	1.000	0.000	0.700	4
9	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	1.000	0.000	0.300	8
10	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1

in the system. Figure 3 shows that Supply Chains 2 and 7 are ranked second and third, respectively in the system. However, the overall performance of the remaining seven supply chains is not very clear. For example, the efficiency scores of Supply Chains 1, 6, and 8 are so close that it becomes extremey difficult to compare them. Therefore, we use Equation (24) and calculate the $\bar{t}_j$ values for all supply chains and construct the truth matrix shown in Table 4.

As shown in this table, Supply Chains 10, 2, and 7 are ranked first, second, and third, respectively. The inefficient supply chains are the remaining Supply Chains 8, 1, and 6 which are ranked 4th, 5th, and 6th, respectively. Finally, Supply Chain 3 is the most inefficient supply chain in the system.

5. Conclusions and future research directions

The process of transforming raw materials into final products and delivering those products to customers, known as supply chain management, is becoming increasingly complex. Supply chain performance evaluation problems cover a wide range from evaluating the performance of independent organizations in supply chains to evaluating the performance of a whole supply chain system. It has become increasingly obvious that improvements in the individual supply chain organizations does not lead to improvement of the supply chain as a whole.

Several researchers have studied the performance of the independent organizations in supply chains in the past such as purchasing performance evaluation, distribution centers performance evaluation and vendor performance evaluation, among others. However, these independent organizations among supply chains have their own objectives and these objectives are often conflicting. Therefore, there is a need for a comprehensive performance evaluation framework to integrate and evaluate the performance of these independent organizations simultaneously.

Several authors have abandoned the "black box" perspective and taken into account the internal structure in the DEA models to measure the efficiency of supply chain networks. Although these studies have made great strides in evaluating network structures, most of them: (1) do not consider impreciseness and ambiguity in the input and output data; (2) use Farrell radial measures of efficiency and ignore input slacks and/or output slacks that can arise when measuring efficiency in piecewise linear technologies; and (3) do not consider reverse logistics in more sophisticated supply chain networks. In this study we proposed a fuzzy NSBM model for evaluating supply chain networks with imprecise data and reverse logistics. A case study was presented to demonstrate the applicability of the proposed fuzzy NSBM model and exhibit the efficacy of the procedures in evaluating the performance of a supply chain in the semiconductor industry.

The supply chain performance evaluation problem is subject to many sources of uncertainty besides fuzzy uncertainty studied in this paper. In a practical decision-making process, we could face random uncertainty and rough uncertain environment. The problem considered in this study is at the initial stage of investigation. Further research can be done by applying the proposed model in random and rough uncertain environments.

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