OPERATIONS AND SUPPLY CHAIN MANAGEMENT
Vol. 19, No. 2, 2026, pp. 322 – 338
ISSN 1979-3561| EISSN 2759-9363

Network DEA-Based Evaluation of Cost and Revenue Efficiency in Global Supply Chains

Xu Wang
Faculty of Informatics, Gunma University, Japan
Email: xu.wang@gunma-u.ac.jp (*Corresponding Author*)

Qian Huang
Department of Business Design and Management
Waseda University, Tokyo, Japan
Email: huang@aoni.waseda.jp

Shunichi Ohmori
Department of Industrial and Management Systems Engineering
Waseda University, Tokyo, Japan
Email: ohmori@waseda.jp

Takashi Hasuike
Department of Industrial and Management Systems Engineering
Waseda University, Tokyo, Japan
Email: thasuike@waseda.jp

ABSTRACT

This study proposes a novel network Data Envelopment Analysis (DEA) model to evaluate supply chain performance from both cost and revenue perspectives. Although DEA is a widely used method for evaluating the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs, traditional DEA models encounter difficulties when applied to multi-stage systems involving intermediate products, such as supply chains. To overcome these challenges, we extend the well-established Range Adjusted Measure (RAM) to develop a customized network DEA model that effectively captures the internal structure of supply chains. Our model enables accurate efficiency evaluation across different production stages and offers valuable insights into inefficiency sources. A case example of global supply chain network is conducted, incorporating data from suppliers, factories, sales distributors, and customers across multiple regions. We conducted five distinct evaluation scenarios that reflect various strategic objectives and supply configurations. Through these scenarios, we analyze the performance of diverse supply chain structures, identify inefficiency factors, and explore decision-making strategies such as suggested sourcing of parts factories and selection of parts and assy factories. Furthermore, we compare the consistency and difference between the overall and the stage-level scores in each scenario, thereby demonstrating the necessity and effectiveness of our proposed model for evaluating supply chain efficiency. Consequently, the results indicate that the model not only evaluates performance but also supports strategic supply chain design and improvement.

Keywords: *data envelopment analysis, network structure, range adjusted measure, cost and revenue efficiency, supply chain performance*

1. INTRODUCTION

In recent years, evaluating the cost and revenue efficiency of supply chains has become increasingly important due to growing global competition, economic uncertainty, and rising stakeholder expectations. Firms face constant pressure to optimize operations, reduce inefficiencies, and improve overall profitability while maintaining service levels and adaptability. A comprehensive understanding of both cost efficiency (how effectively a supply chain minimizes its costs) and revenue efficiency (how well it generates income from its operations) is therefore crucial for informed strategic decision-making and long-term sustainability.

Various analytical tools and modeling approaches have been proposed to evaluate supply chain performance, including simulation-based approach (Oliveira *et al.*, 2016), risk modeling approach for the evaluation and design of network supply chain (Klibi & Martel, 2012), fuzzy multi-criteria approach (Awasthi *et al.*, 2010), hybrid multi-criteria decision-making approach (Govindan *et al.*, 2015), and risk analytics in digital supply chains (Ivanov *et al.*, 2019). These approaches often aim to optimize specific objectives such as minimizing total logistics costs or maximizing service levels. However, they typically rely on detailed functional forms and parameter estimations, which may be difficult to obtain or unreliable in complex and data-limited environments. Furthermore, many traditional models face challenges when simultaneously evaluating multiple inputs and outputs, particularly when analyzing trade-offs between cost and revenue across different supply chain entities. These limitations underscore the need for flexible, data-driven methods capable of handling multiple performance dimensions without requiring restrictive assumptions, thus motivating the application of Data Envelopment Analysis (DEA) in supply chain efficiency evaluation studies. A review by Soheilirad *et al.* (2018) of 75 published articles from 35 international scholarly journals and conferences between 1996 and 2016 has been conducted to provide a comprehensive overview of DEA models used in evaluating supply chain.

DEA is a non-parametric methodology for evaluating the efficiency of decision-making units (DMUs) in operations research, as originally proposed by Charnes *et al.* (1978). DEA utilizes mathematical programming techniques to evaluate the relative efficiency of various DMUs, such as educational institutions, financial organizations, healthcare facilities, and other operational entities. This evaluation is based on input-output data: inputs may include resources such as costs or number of employees, while outputs can represent performance indicators like profits or sales. One of its key strengths lies in its ability to identify inefficiencies without requiring predefined functional forms, making it well-suited for complex, data-rich environments. DEA offers a quantitative approach to identifying inefficiencies and provides specific benchmarks and improvement targets for underperforming units. Thus, in supply chain, DEA provides a powerful tool for benchmarking, enabling the identification of best-performing DMUs and offering concrete improvement targets for underperforming DMUs. This capability is critical for guiding strategic decisions and driving operational enhancements across the supply chain network.

Conventional DEA models calculate efficiency scores, rank DMUs, and provide improvement targets for inefficient DMUs based on input-output data. In DEA, improvement targets are set to indicate the direction in which inefficient DMUs can improve their efficiency. The original DEA model, known as the Charnes-Cooper-Rhodes (CCR) model, was proposed by Charnes *et al.* (1978). Later, a variation of the CCR model, the Banker-Charnes-Cooper (BCC) model, was proposed by Banker *et al.* (1984). Both the CCR and BCC models are oriented and radial. For instance, the input-oriented CCR model evaluates efficiency by proportionally reducing all inputs to set improvement targets, while the output-oriented CCR model does so by proportionally increasing all outputs. Thus, both models rely on radial improvements to make an inefficient DMU efficient, either by proportionally reducing all inputs or increasing all outputs. In contrast, the additive model, proposed by Charnes *et al.* (1985), is a non-oriented DEA model that maximizes simultaneous improvements in both inputs and outputs (decreases and increases). Unlike the CCR and BCC models, the additive model is non-radial and does not provide an efficiency score for each DMU.

To address this limitation, the range-adjusted measure (RAM) model was proposed by Cooper *et al.* (1999). The RAM model is a well-defined DEA model that provides an efficiency score ranging from 0 to 1. It also satisfies several important properties:

- Unit invariance: The efficiency score is unaffected by the units of inputs and outputs.
- Translation invariance: A shift in inputs and outputs in the same direction does not alter the efficiency score, enabling the model to handle negative data.
- Monotonicity: An increase in any input, while holding other inputs and all outputs constant, either reduces or maintains the same efficiency score, and similarly on the output side.

Due to these advantageous properties, the RAM model is chosen as the foundational model for this study.

In many real-world decision-making scenarios, it is essential to measure the performance of DMUs with multiple components, where the output from one component serves as the input for another. Conventional DEA models, whether oriented or non-oriented, radial or non-radial, evaluate a DMU based solely on the inputs and outputs of individual stages. Under such models, system efficiency reflects the end-to-end transformation from overall inputs to final outputs, whereas the efficiency of each stage captures only the performance of its corresponding local process. As a result, even if all stages are locally efficient, the overall system may still be inefficient, illustrating the well-known phenomenon that local optimality does not necessarily lead to global optimality. Conversely, a multi-stage process may be evaluated as efficient even when some of its internal components are inefficient. Therefore, when the focus of evaluation is the overall system, conventional DEA models are not appropriate.

To address this issue, DEA models incorporating multi-stage network structures to evaluate overall performance have garnered considerable attention from DEA researchers. The comparison between DMUs in DEA and a two-stage network DEA is illustrated in Figure 1. Cook *et al.* (2010) reviewed two-stage network DEA models and established connections among various approaches. Among these approaches, the two-stage approach based on the CCR model has been widely applied, including studies on performance evaluation of non-life insurance companies in Taiwan (Kao & Hwang, 2008) and major Brazilian banks (Wanke & Barros, 2014). Beyond the CCR model, the well-defined RAM model is also highly regarded and frequently chosen as the foundation for developing two-stage network DEA models. For example, Fu (2018) developed a two-stage network DEA model with undesirable intermediate products based on the RAM model and applied it to air quality evaluation and improvement in China. Similarly, Wang *et al.* (2021) evaluated the environmental efficiency of China's industrial system using a two-stage network RAM model.

Beyond the above studies, a wide range of applications of network DEA has been reported in recent years. Chen *et al.* (2021) adopted an extended two-stage network DEA approach to evaluate the operating efficiency of 52 universities in China, addressing limitations of traditional models by explicitly capturing both teaching and research processes. Wu *et al.* (2024) applied a three-stage network DEA model to evaluate the performance of 26 international airlines from 2019 to 2022, providing managerial insights into the global airline industry under the impact of the COVID-19 pandemic. In the healthcare sector, Afonso *et al.* (2024) employed a network DEA framework to examine potential trade-offs between efficiency, quality, and access in hospitals, contributing to ongoing debates regarding performance management in healthcare systems. In addition, two recent literature reviews—Ratner *et al.* (2023) and Alves and Meza (2023)—provide comprehensive overviews of network DEA

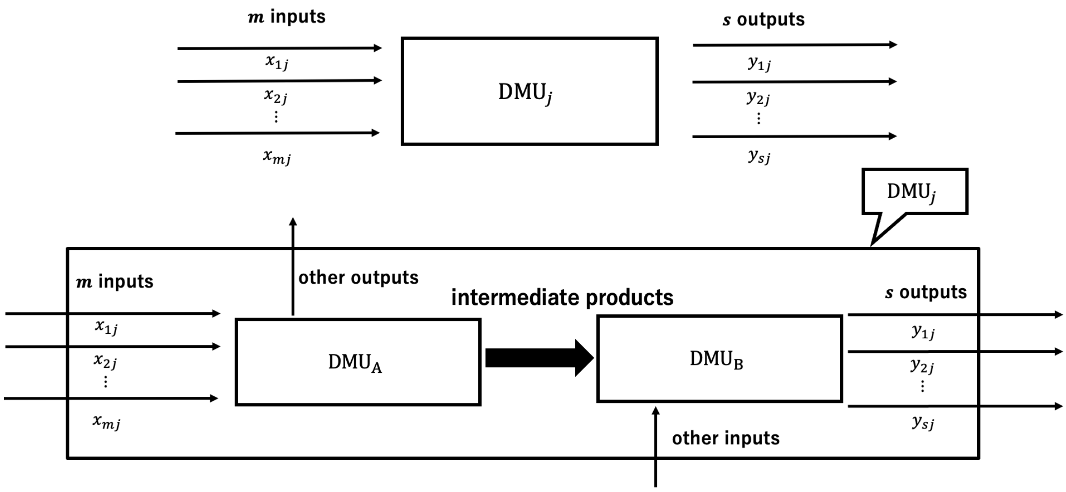

Figure 1 DMUs in DEA and a two-stage network DEA

models, their diverse applications, and emerging research directions. These studies collectively demonstrate the versatility of network DEA for analyzing complex, multi-stage or chain-like systems across various domains.

In supply chains, which function as DMUs composed of multiple interdependent components, evaluating the overall system efficiency—rather than the efficiency of individual stages in isolation—is essential. Because supply chains inherently operate as multi-stage processes, a proper assessment must consider both the end-to-end transformation and the interactions among internal stages. However, conventional single-stage DEA models treat the supply chain as a black box, ignoring intermediate products and the internal structure. This approach often yields biased efficiency evaluation and fails to reveal internal bottlenecks, thereby overemphasizing local performance at the expense of understanding the true system-level efficiency. In contrast, multi-stage network DEA models explicitly incorporate intermediate flows and capture the performance of each sub-process, enabling stage-level inefficiency diagnostics while still focusing on the evaluation of overall process efficiency. Therefore, adopting a multi-stage network DEA framework is crucial for accurately evaluating supply chain performance and understanding how individual stages contribute to system-wide efficiency.

Numerous theoretical and empirical studies have applied network DEA to assess supply chain performance or other chain-type DMU systems. A comprehensive review of prior research on supply chain benchmarking and enhanced DEA modeling approaches is provided in Peng Wong and Yew Wong (2008). In addition, Liang *et al.* (2006) developed several DEA-based methods to evaluate supply chain performance, employing a two-stage network model that includes both buyer and seller components, thereby capturing the interrelationships between them. Similarly, Tavana *et al.* (2013) proposed a novel network DEA model based on Epsilon-Based Measures to assess the performance of ten supply chains in the semiconductor industry. Ebrahimi *et al.*, 2021 proposed a three-stage network DEA model capable of handling interval data and applied it to assess the sustainability of supply chains in the printing industry. Wanke *et al.* (2022) proposed stochastic network DEA models incorporating random ratio data for the two-stage systems and applied their proposed approach to 11 airlines in Iran. More recently, Hong (2023) applied a general two-stage network DEA model to the design of humanitarian supply chain systems, evaluating configurations under disruption risk by transforming decision units into two-stage DMUs. Tavassoli *et al.* (2023) applied a network RAM-DEA model to evaluate the performance of sixteen Iranian electricity supply chains from both internal and external perspectives. Previous studies have widely employed two-stage or three-stage network DEA models to assess the performance of supply chains and other chain-type DMU systems with intermediate products. This paper advances the well-defined RAM model by extending it into a n-stage network RAM model, which can incorporate intermediate products and enable a more comprehensive measurement of supply chain performance.

The main contributions of this study are summarized as follows:

- Proposal of a multi-stage network RAM DEA model;
- Demonstration of its practicality and advantages through application to the evaluation of supply chain efficiency from the perspectives of cost and revenue;
- Illustration of its potential applicability to other supply chains and general multi-stage DMU structures.

The developed multi-stage network RAM model—introduced in the next section—can be used to evaluate the overall performance of supply chains consisting of several interconnected stages. Following the model's introduction, we apply it in a case example to evaluate the performance of a four-stage supply chain network, as shown in Figures 3, 4 and 5. Through this case example, we conduct an efficiency analysis and comparison across various scenarios, identifying the sources of inefficiency in certain cases. Besides, we also conduct an efficiency comparison between the overall score and the stage-level scores in each scenario. The numerical results demonstrate that the proposed model is a valid DEA framework for performance evaluation when DMUs consist of complex, multi-stage network structures with intermediate products.

The remainder of this paper is organized as follows. Section 2 introduces key DEA concepts and presents the formulations of the RAM model and the proposed multi-stage network RAM model. Section 3 presents a case example in which the four-stage network RAM model is applied to evaluate the cost and revenue efficiency of global supply chains. Finally, Section 4 concludes the paper and outlines directions for future research.

2. METHODOLOGY: DEA MODELS

2.1. Notations

The notations used in this paper and their corresponding definitions are summarized in Table 1.

2.2. Concepts

In DEA, DMU_j comprises a set of m inputs x_{ij} and s outputs y_{rj}. This configuration is called an activity and represents a distinct combination of inputs and outputs, illustrating a production or operational process. It can be expressed by the notation (x_{ij}, y_{rj}). The set of feasible activities is referred to as the production possibility set and is denoted by T. T needs to satisfy the following properties accepted in DEA (Cooper *et al.*, 2007):

- (**P1**) All observed DMUs are in T;
- (**P2**) $\forall\ (x_{ij}, y_{rj}) \in T$, if $(x_{ij}, -y_{rj}) \leq (\bar{x}_{ij}, -\bar{y}_{rj}) \Rightarrow (\bar{x}_{ij}, \bar{y}_{rj}) \in T$;
  Any activity with input no less than or equal to x_{ij} in any component and with output no greater than or equal to y_{rj} in any component is feasible.
- (**P3-1**) $\forall\ (x_{ij}, y_{rj}) \in T$, $\forall k > 0 \Rightarrow k(x_{ij}, y_{rj}) \in T$.
  This property is called the constant returns to scale (CRS) assumption, which corresponds to the CCR model.
  (**P3-2**) $\forall\ (x_{ij}, y_{rj}) \in T$, $\forall\ (x'_{ij}, y'_{rj}) \in T$, $\forall \alpha \in [0,1] \Rightarrow \alpha(x_{ij}, y_{rj}) + (1-\alpha)(x'_{ij}, y'_{rj}) \in T$.
  This property is called the variable returns to scale (VRS) assumption, which corresponds to the BCC model.
- (**P-4**) Any semi-positive linear combination of DMUs in T belongs to T. In this sense, semi-positive means all values are non-negative, but at least one should be positive. In fact, (P3-1) and (P3-2) are included in (P4) but are separated out for special emphasis.

Thereafter, based on the properties mentioned above, the VRS production possibility set, which satisfies (P1), (P2), (P3-2), and (P4), is defined as follows and is used in this study:

$$T = \left\{ (x_{io}, y_{ro}) \;\middle|\; \begin{array}{l} \sum_{j=1}^{n} x_{ij}\lambda_j \leq x_{io}, \\ \sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{ro}, \\ \sum_{j=1}^{n} \lambda_j = 1, \quad \lambda_j \geq 0. \end{array} \right\}. \tag{1}$$

In this study, we use this VRS production possibility set that satisfies the properties of free disposal, minimum extrapolation, and convexity.

2.3. Models

As introduced in the Introduction, we select the RAM model due to its many desirable properties in DEA. This non-radial DEA model is an extension of the additive model and is formulated as a linear programming problem as follows (referred to as **Model 1** in this study).

$$\delta = \underset{s_{io}^-, s_{ro}^+, \lambda_j}{\text{minimize}}\ 1 - \frac{1}{m+s}\left(\sum_{i=1}^{m}\frac{s_{io}^-}{R_i^-} + \sum_{r=1}^{s}\frac{s_{ro}^+}{R_r^+}\right) \tag{2}$$

$$\text{s.t.}\ \sum_{j=1}^{n} x_{ij}\lambda_j = x_{io} - s_{io}^-\ (i = 1, 2, \cdots, m), \tag{3}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j = y_{ro} + s_{ro}^+\ (r = 1, 2, \cdots, s), \tag{4}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{5}$$

$$\lambda_j \geq 0, s_{io}^- \geq 0, s_{ro}^+ \geq 0. \tag{6}$$

The RAM model is translation invariant only when the condition $\sum_{j=1}^{n} \lambda_j = 1$ is included in Model 1. Because the numerators and denominators in the objective function of Model 1 are stated in the same units, the efficiency score δ of RAM model is unit invariant. Moreover, because of the specific ranges of the input and output, R_i^- and R_r^+, in the objective function of Model 1, the efficiency score δ is between 0 and 1. The definition of RAM-efficiency is provided as follows:

RAM-efficiency

Suppose that δ^* is the optimal solution of Model 1. DMU_o is efficient if and only if $\delta^* = 1$. DMU_o is inefficient when $\delta^* < 1$.

We proceed to develop the multi-stage network RAM model, with its formulation shown in Model 2 and the definition of its efficiency provided as follows (referred to as **Model 2**):

$$\hat{\delta} = \underset{s_{i'}^{t-}, s_{r'}^{t+}, s_{k'o}^{t+}, \lambda_j^t}{\text{minimize}}\ 1 - \frac{\sum_{t=1}^{n}\left(\sum_{i'=1}^{m^t}\frac{s_{i'o}^{t-}}{R_{i'}^{t-}} + \sum_{r'=1}^{s^t}\frac{s_{r'o}^{t+}}{R_{r'}^{t+}} + \sum_{k'=1}^{k^t}\frac{s_{k'o}^{t+}}{R_{k'}^{t+}}\right)}{\sum_{t=1}^{n}(m^t + s^t + k^t)} \tag{7}$$

$$\text{s.t.}\quad \sum_{j=1}^{n} x_{i'j}^t\lambda_j^t = x_{i'o}^t - s_{i'o}^{t-}\ (i' = 1, 2, \cdots, m^t), \tag{8}$$

$$\sum_{j=1}^{n} y_{r'j}^t\lambda_j^t = y_{r'o}^t + s_{r'o}^{t+}\ (r' = 1, 2, \cdots, s^t), \tag{9}$$

$$\sum_{j=1}^{n} y_{k'o}^t\lambda_j^t = y_{k'o}^t + s_{k'o}^{t+}\ (k' = 1, 2, \cdots, k^t), \tag{10}$$

$$\sum_{j=1}^{n} \lambda_j^t = 1, \tag{11}$$

$$\sum_{j=1}^{n} y_{k'o}^t\lambda_j^t \geq \sum_{j=1}^{n} y_{k'o}^t\lambda_j^{t+1}, \tag{12}$$

$$\lambda_j^t \geq 0,\ s_{i'o}^{t-} \geq 0,\ s_{r'o}^{t+} \geq 0,\ s_{k'o}^{t+} \geq 0. \tag{13}$$

Table 1 Summary of Notations

Notation	Description
n	Number of DMUs
DMU$_j$	The jth decision-making unit ($j = 1, \ldots, n$)
DMU$_o$	The DMU under evaluation
x_{ij}	The ith input of DMU$_j$ ($i = 1, \ldots, m$)
$x^t_{i'j}$	The i'th input of DMU$_j$ in stage t ($i' = 1, \ldots, m^t$)
y_{rj}	The rth output of DMU$_j$ ($r = 1, \ldots, s$)
$y^t_{r'j}$	The r'th output of DMU$_j$ in stage t ($r' = 1, \ldots, s^t$)
$y^t_{k'j}$	The k'th intermediate product of DMU$_j$ between stages t and $t+1$ ($k' = 1, \ldots, k^t$)
R^-_i	Range of input i: $\max\limits_j x_{ij} - \min\limits_j x_{ij}$
$R^{t-}_{i'}$	Range of input i' in stage t: $\max\limits_j x^t_{i'j} - \min\limits_j x^t_{i'j}$
R^+_r	Range of output r: $\max\limits_j y_{rj} - \min\limits_j y_{rj}$
$R^{t+}_{r'}$	Range of output r' in stage t: $\max\limits_j y^t_{r'j} - \min\limits_j y^t_{r'j}$
$R^{t+}_{k'}$	Range of intermediate product k' in stage t: $\max\limits_j Y^t_{k'j} - \min\limits_j Y^t_{k'j}$
s^-_{ij}	Input slack of input i for DMU$_j$
$s^{t-}_{i'j}$	Input slack of input i' for DMU$_j$ in stage t
s^+_{rj}	Output slack of output r for DMU$_j$
$s^{t+}_{r'j}$	Output slack of output r' for DMU$_j$ in stage t
$s^{t+}_{k'j}$	Slack of intermediate product k' for DMU$_j$ between stages t and $t+1$
λ_j	Weight of DMU$_j$
λ^t_j	Weight of DMU$_j$ in stage t

Multi-stage network RAM-efficiency

Suppose that $\hat{\delta}^*$ is the optimal solution of Model 2. The supply chain o (all of the stages) is efficient if and only if $\hat{\delta}^* = 1$. The supply chain o is inefficient when $\hat{\delta}^* < 1$.

The developed multi-stage network RAM model is a linear programming problem, making it easy to solve. In Model 2, the superscripts t on each variable represent the stage. For example, $y^1_{k'o}$ and $y^2_{k'o}$ denote intermediate products between each stages, namely those between the first and second stages, and between the second and third stages. The variables $s^{1+}_{k'o}$ and $s^{2+}_{k'o}$ represent the corresponding slacks. If we want to keep a particular intermediate product $y^t_{k'o}$ constant—similar to the case example in this paper, where product volume in each supply chain remain fixed—we can adjust the model by setting $s^{t+}_{k'o} = 0$. Additionally, the inequality constraints, $\sum\limits_{j=1}^{n} y^t_{k'o}\lambda^t_j \geq \sum\limits_{j=1}^{n} y^t_{k'o}\lambda^{t+1}_j$, link the stages t and $t+1$. These constraints ensure that specific conditions are met: the optimal production of the preceding stage should exceed the consumption of the subsequent stage. It can also be adapted or expanded with additional constraints depending on the analysis scenarios and requirements. For example, evaluations could be performed under conditions where certain inputs or outputs remain unchanged, or by introducing some undesirable outputs. In this study, the numerical experiments are conducted using the actual four-stage network RAM model to analyze the corresponding supply chains. A fully specified formulation of the four-stage RAM model is provided in the Appendix.

The proposed n-stage network RAM model offers several methodological advantages that justify its use for evaluating the global efficiency of multi-stage supply chains. First, as a network DEA framework, the model is capable of evaluating the overall system efficiency while fully accounting for the interconnections among stages via intermediate products. In this regard, it achieves the same analytical purpose as other network DEA models, ensuring a comprehensive and system-wide evaluation rather than a fragmented stage-by-stage analysis. Second, because the model is constructed on the RAM foundation, it inherits several desirable properties of the RAM model. These include a linear programming structure, which makes computation straightforward and scalable; unit invariance, meaning that efficiency scores remain unaffected by differences in measurement units; and an interpretable efficiency scale ranging from 0 to 1, which facilitates clear managerial interpretation. Additionally, the translation invariance property ensures that the model can appropriately handle data containing negative values—a feature particularly relevant for our dataset, which includes both negative and zero observations. Most importantly, the RAM model—and by extension, the proposed n-stage network RAM model—is well-suited for datasets with large variability or wide value ranges. Through the use of range-adjusted slack normalization in the objective function, the model produces more stable and robust efficiency scores, avoiding distortions that may arise under alternative DEA formulations. Taken together, these advantages highlight the necessity and suitability of the proposed n-stage network RAM model for evaluating supply chain efficiency in complex, multi-stage and heterogeneous environments.

3. CASE EXAMPLE

3.1. Description of the Supply Chain Network

The numerical experiments in this study are based on a representative case of a Japanese heavy machinery manufacturer with a global production and sales network. The focus is on a four-stage supply chain involving suppliers, parts factories, assy factories, and sales distributors. The supply chain network consists of multiple nodes and arcs, representing the flow of materials and transactions across multiple regions including the United States, Germany, Japan, China, Thailand, and ASEAN countries. The product under consideration is a large-scale industrial machine with a modular structure composed of key and general components. The dataset used in the model covers a variety of cost and operational indicators, including fixed and variable production costs, transportation unit prices, tariff rates, corporate tax rates, regional demand, and intra-company transfer prices (low, medium, and high scenarios). For generalization purposes, this study adopts medium scenarios. Input/output definitions at each stage follow the structure of the bill of materials and transaction flows along the supply chain. The data sources include annual financial reports, product information from official websites (Komatsu Ltd., 2025), and technical references such as lean manufacturing BOM examples (Kenki-parts, 2024). In addition, certain parameters are estimated based on publicly available industrial cost benchmarks and internal modeling assumptions, such as Organisation for Economic Co-operation and Development (OECD) (2025) and World Trade Organization (WTO) (2025). This data framework enables a comprehensive and realistic evaluation of supply chain performance from both cost and revenue perspectives under different sourcing and configuration scenarios.

3.2. Structure of the Supply Chain Network

The structure of the supply chain to be evaluated is shown in Figure 2. This diagram confirms the existence of both key parts factories and general parts factories. So, this study considers the following two production conditions:

(1) The assy factory uses parts from either key parts factories or general parts factories, but not both. (Figures 3 and 4)
(2) The assy factory uses parts from both key parts factories and general parts factories. (Figure 5)

Examples of supply chain structures corresponding to each case are shown in Figures 3, 4 and 5. Figure 3 also illustrates the four stages and the input/output indicators used at each stage. Note that the quantity of products at each stage is treated as an intermediate product (y^t_M, Here, the subscript M in y^t_M is used to indicate that this variable represents an intermediate product, corresponding to k' in Table 1, where intermediate outputs are defined.) passed on to the next stage. In other words, at each stage, "quantity of products" is regarded as an intermediate output. The collected input and output indicators, together with their explanations, are summarized in Table 2. The input and output indicators adopted in each of the four stages are presented in Table 3.

In this evaluation, we intentionally selected a relatively large number of input and output variables in order to capture the target from a multifaceted and comprehensive perspective. In general, it is known that the rule of thumb for DEA analysis is $n \geq 3(m + s)$, where n is the number of DMUs, and m and s are the numbers of input and output variables, respectively (Cook *et al.*, 2014). This guideline is often referred to as a benchmark for ensuring the reliability of DEA results. It is sometimes pointed out that when the number of input and output variables increases, the efficiency scores of all DMUs tend to become 1 (i.e., efficient). In our analysis, although there was a tendency for the efficiency scores to be relatively high, no extreme bias such as all DMUs being evaluated as fully efficient was observed. Moreover, in the discussion based on the results of the numerical experiments, we were able to derive practically meaningful implications. Therefore, although this study does not strictly adhere to the conventional rule of thumb for DEA, we consider that it enabled a more practical and valuable analysis.

3.3. Scenarios for Efficiency Evaluation

Numerous supply chains are subject to evaluation in the structure shown in Figure 3, 4 and 5. Therefore, to align with the research objectives, we established the following five scenarios and conducted evaluation analysis accordingly. The descriptive statistics of the data used in each of the five evaluation scenarios have been summarized and presented in the Appendix.

- **Scenario 1**: Efficiency Comparison of Local Production and Sales (Single Key Parts and General Parts Factory, Figures 3 and 4). This scenario compares the efficiency of 8 supply chains engaged in local production and sales, distinguishing between key parts factories and general parts factories. Since all supply chains conduct local production and sales, the goal is to identify which type of local supply chain is more efficient and to determine the causes of inefficiency.
- **Scenario 2**: Efficiency Comparison of Local Production and Sales (Integrated Parts Factories Configuration, Figure 5). This scenario integrates key parts factories and general parts factories into a unified category and compares 5 supply chains engaged in local production and sales. For countries without a key parts factory (e.g., Thailand, China), it is assumed that they utilize a Japanese key parts factory within the Asia region. All supply chains evaluated here engage in local production and sales.
- **Scenario 3**: Evaluation of Combination of Key Parts and General Parts Factories (Integrated Parts Factories Configuration, Figure 5). While Scenarios 1 and 2 focused only on local production and sales, Scenario 3 considers 15 supply chains formed by combinations of 3 key parts factories and 5 general parts factories. The analysis assumes general parts factories conduct local production and sales, while key parts are procured externally. This scenario supports decision-making regarding which country's key parts factory should be used when one is not available domestically. It also aims to provide guidelines on which indicators should be emphasized for inefficient supply chains in this scenario.
- **Scenario 4**: Evaluation of Combinations of General Parts Factories and Assy Factories (Integrated Parts Factories Configuration, Figure 5). Scenario 4 further extends Scenario 3 by evaluating all possible combinations of key parts factories and general parts factories. It assumes that parts can be procured from any factory, and considers local assembly and sales accordingly. A total of 27 supply chains are evaluated. In particular, the objective is to provide guidance on the selection of the assy factory when key and general parts factories are located in different countries.
- **Scenario 5**: Evaluation of Combinations of Key Parts

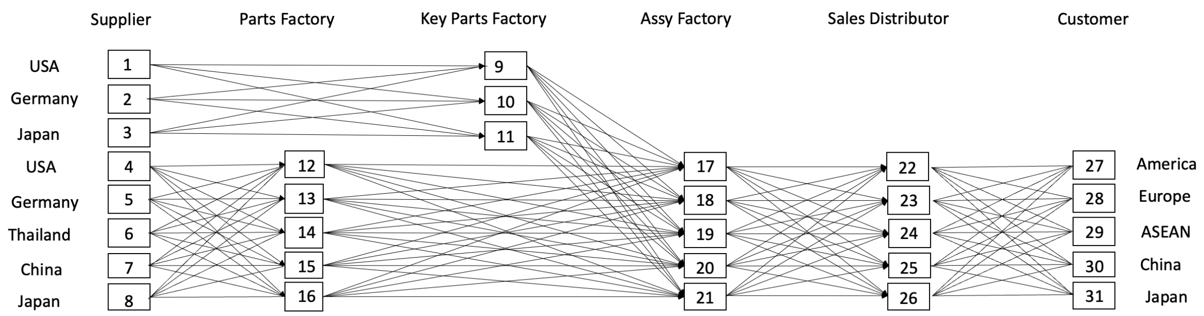

Figure 2 Structure of the Supply Chain Network

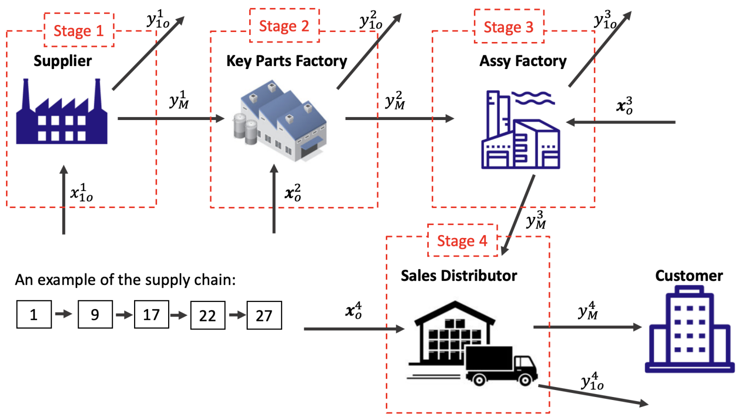

Figure 3 Structure of the Supply Chain Network under Scenario 1: Single Key Parts Factory

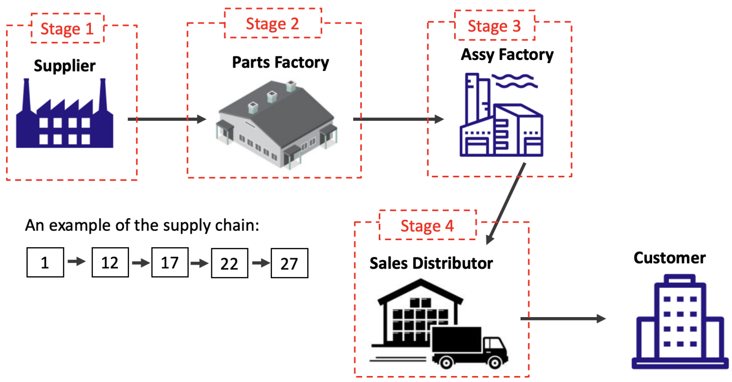

Figure 4 Structure of the Supply Chain Network under Scenario 1: Single General Parts Factory

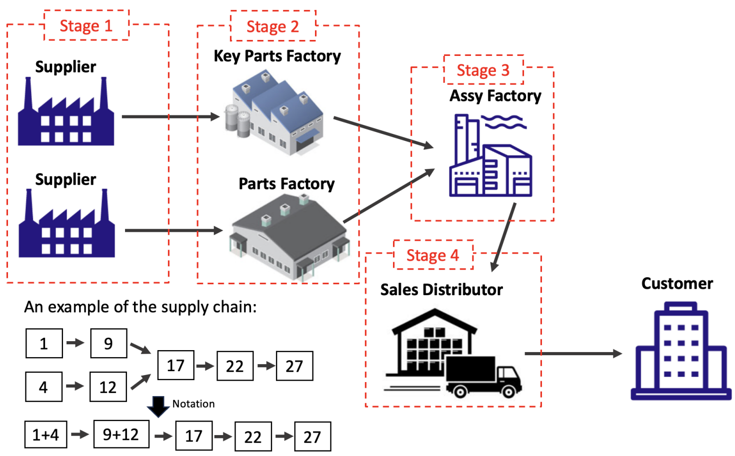

Figure 5 Structure of the Supply Chain Network under Scenarios 2 – 5: Integrated Parts Factories Configuration

Table 2 Description of Inputs and Outputs

Indicator	Description
x_1	Transportation cost: demand × corresponding unit transportation price.
x_2	Procurement cost: revenue from the previous stage.
x_3	Corporate tax: (revenue − total cost) × corporate tax rate.
	Total cost includes transportation, procurement, fixed and variable production costs.
x_4	Tariff: procurement cost × tariff rate.
x_5	Fixed production cost: fixed production unit cost × demand.
x_6	Variable production cost: variable production unit cost × demand.
y_1	Revenue: demand × corresponding transaction price.

Table 3 Inputs and Outputs in Each Stage

Stage	x_1	x_2	x_3	x_4	x_5	x_6	y_1
Stage 1	✓						✓
Stage 2	✓	✓	✓	✓	✓	✓	✓
Stage 3	✓	✓	✓		✓	✓	✓
Stage 4	✓	✓	✓				✓

Notes: A checkmark indicates that the corresponding indicator is used in that stage.

Table 4 Results of scenario 1

No.	Supply Chain	Efficiency
1	1 → 9 → 17 → 22 → 27	1
2	2 → 10 → 18 → 23 → 28	0.998
3	3 → 11 → 21 → 26 → 31	0.993
4	4 → 12 → 17 → 22 → 27	1
5	5 → 13 → 18 → 23 → 28	1
6	6 → 14 → 19 → 24 → 29	1
7	7 → 15 → 20 → 25 → 30	0.989
8	8 → 16 → 21 → 26 → 31	0.988

Table 5 Results of scenario 2

No.	Supply Shain	Efficiency
1	1 + 4 → 9 + 12 → 17 → 22 → 27	0.999
2	2 + 5 → 10 + 13 → 18 → 23 → 28	0.964
3	3 + 6 → 11 + 14 → 19 → 24 → 29	1
4	3 + 7 → 11 + 15 → 20 → 25 → 30	0.993
5	3 + 8 → 11 + 16 → 21 → 26 → 31	1

Factories and General Parts Factories(Integrated Parts Factories Configuration, Figure 5). In this scenario, Scenario 2 is further extended by assuming that the general parts factories can be sourced externally. The evaluation takes the parts factories as the reference point, while production and sales are conducted locally. As a result, 25 supply chain configurations are included in the analysis. While Scenario 4 aimed to investigate the impact of selecting different assy factories on overall supply chain efficiency, the purpose of the present scenario is to examine whether the selection of the parts factory can improve the efficiency of supply chains if they were previously identified as inefficient due to local production and local sales in Scenario 2.

3.4. Results and Discussions

The efficiency scores of the 8 supply chains in Scenario 1 are shown in Table 4. Among the cases where both the Key Parts Factory and the Parts Factory follow a "local production for local consumption" model, only the United States (No. 1 and 4) achieved efficiency. Stage 1 (between Supplier and Parts Factory) was identified as the most influential factor leading to inefficiency. For instance, local production and consumption in the Key Parts Factory were found to be inefficient in Germany and Japan, mainly due to high transportation costs. In the case of the Parts Factory, although Thailand (No. 6) achieved efficiency under local production and consumption, other Asian countries such as China and Japan were inefficient. This was attributed to the overwhelmingly low demand in those markets, resulting in limited sales.

In Scenario 2, 5 supply chains were evaluated by integrating the Key Parts Factory and the Parts Factory, and their efficiency scores are presented in Table 5. Under this integrated evaluation, Thailand (No. 3) and Japan (No. 5) were found to be efficient under local production and consumption. Although Thailand does not have a domestic Key Parts Factory, it was evaluated as efficient overall. This can be explained by low domestic production costs, low transportation costs and minimal tariff impact when procuring Key Parts from Japan, as well as high sales revenue. In contrast, China was rated as inefficient due to low demand and sluggish sales, combined with increased procurement costs for Key Parts from Japan. Considering future demand growth, establishing a domestic Key Parts Factory in China may be a viable option. The United States (No. 1), which was efficient in both the Key Parts Factory and Parts Factory under local production and consumption in Scenario 1, was deemed inefficient in the integrated evaluation due to low sales in Stage 1. This suggests that the integrated evaluation places greater weight on sales performance. In Germany (No. 2), the primary causes of inefficiency were identified as procurement and transportation costs in Stage 4. This may be attributed to the distribution not only within Germany but also across the entire European region in this supply chain.

The efficiency scores of the 15 supply chains in Scenario 3 are shown in Table 6. This scenario includes a variety of production and sales configurations beyond the local production and consumption model. Although local production and consumption generally tended to be efficient, the United States (No. 1) and Germany (No. 7) were found to be inefficient. These supply chains also appeared in previous scenarios, and their causes of inefficiency have already been discussed. In Scenario 3, the combination of Key Parts Factory and Parts Factory can be flexibly adjusted. It was suggested

Table 6 Results of scenario 3

No.	Supply Chain	Efficiency
1	1 + 4 → 9 + 12 → 17 → 22 → 27	0.999
2	1 + 5 → 9 + 13 → 18 → 23 → 28	1
3	1 + 6 → 9 + 14 → 19 → 24 → 29	1
4	1 + 7 → 9 + 15 → 20 → 25 → 30	0.980
5	1 + 8 → 9 + 16 → 21 → 26 → 31	0.997
6	2 + 4 → 10 + 12 → 17 → 22 → 27	1
7	2 + 5 → 10 + 13 → 18 → 23 → 28	1
8	2 + 6 → 10 + 14 → 19 → 24 → 29	1
9	2 + 7 → 10 + 15 → 20 → 25 → 30	0.988
10	2 + 8 → 10 + 16 → 21 → 26 → 31	0.998
11	3 + 4 → 11 + 12 → 17 → 22 → 27	0.955
12	3 + 5 → 11 + 13 → 18 → 23 → 28	0.965
13	3 + 6 → 11 + 14 → 19 → 24 → 29	1
14	3 + 7 → 11 + 15 → 20 → 25 → 30	0.994
15	3 + 8 → 11 + 16 → 21 → 26 → 31	1

that using Thailand's Parts Factory could improve efficiency in the U.S. and German supply chains. In other words, rather than adhering strictly to local production, producing parts at Thailand's Parts Factory and processing and selling them domestically in Thailand may yield higher profits. These findings reaffirm Thailand's attractiveness as a production and market base.

Scenario 4 evaluates 27 supply chain configurations, with efficiency scores presented in Table 7. This scenario explores the criteria for selecting the Assy Factory when the Key Parts Factory and Parts Factory are located in different countries, rather than limiting configurations to local production and consumption. Specifically, it examines whether the Assy Factory should be located near the Key Parts Factory or the Parts Factory. For example, a comparison of No. 6 and No. 7 shows that when Key Parts are procured from the USA and Parts from China, assembling and selling in the China (No. 7) is more efficient than doing so in USA (No. 6), as indicated by element (1,5) in Table 9. Similarly, No. 23 and No. 24, which procure Key Parts from Japan and Parts from Thailand, were both efficient regardless of whether the Assy Factory was located in Japan or Thailand (corresponding to element (3,4) in Table 9). Other comparisons are summarized in Table 9, and these analyses and results are expected to offer valuable insights for selecting the suggested location for the Assy Factory.

Table 8 presents the efficiency scores for the 25 supply chain configurations in Scenario 5. In this scenario, the Parts Factory is assumed to be externally sourced and serves as the reference point, while production and sales are conducted locally. Consequently, 25 supply chains with partially local production and local sales are included in the evaluation. In Scenario 4, we examined how the selection of the Assy Factory affects overall supply chain efficiency. While there are various potential strategies for improving inefficient supply chains, such as changing sourcing or production configurations, the choice of factory locations is one of the most actionable levers within our model. Therefore, Scenario 5

Table 7 Results of scenario 4

No.	Supply Chain	Efficiency
1	1 + 4 → 9 + 12 → 17 → 22 → 27	0.996
2	1 + 5 → 9 + 13 → 17 → 22 → 27	1
3	1 + 5 → 9 + 13 → 18 → 23 → 28	0.988
4	1 + 6 → 9 + 14 → 17 → 22 → 27	1
5	1 + 6 → 9 + 14 → 19 → 24 → 29	1
6	1 + 7 → 9 + 15 → 17 → 22 → 27	0.987
7	1 + 7 → 9 + 15 → 20 → 25 → 30	0.991
8	1 + 8 → 9 + 16 → 17 → 22 → 27	0.997
9	1 + 8 → 9 + 16 → 21 → 26 → 31	0.994
10	2 + 4 → 10 + 12 → 17 → 22 → 27	0.992
11	2 + 4 → 10 + 12 → 18 → 23 → 27	0.982
12	2 + 5 → 10 + 13 → 18 → 23 → 28	0.992
13	2 + 6 → 10 + 14 → 18 → 23 → 29	0.981
14	2 + 6 → 10 + 14 → 19 → 24 → 29	1
15	2 + 7 → 10 + 15 → 18 → 23 → 30	0.981
16	2 + 7 → 10 + 15 → 20 → 25 → 30	0.973
17	2 + 8 → 10 + 16 → 18 → 23 → 31	0.994
18	2 + 8 → 10 + 16 → 21 → 26 → 31	0.996
19	3 + 4 → 11 + 12 → 17 → 22 → 27	0.957
20	3 + 4 → 11 + 12 → 21 → 26 → 27	0.954
21	3 + 5 → 11 + 13 → 18 → 23 → 28	0.961
22	3 + 5 → 11 + 13 → 21 → 26 → 28	0.965
23	3 + 6 → 11 + 14 → 19 → 24 → 29	1
24	3 + 6 → 11 + 14 → 21 → 26 → 29	1
25	3 + 7 → 11 + 15 → 20 → 25 → 30	0.994
26	3 + 7 → 11 + 15 → 21 → 26 → 30	0.991
27	3 + 8 → 11 + 16 → 21 → 26 → 31	1

Table 8 Results of scenario 5

No.	Supply chain	Efficiency
1	1 + 4 → 9 + 12 → 17 → 22 → 27	0.999
2	1 + 4 → 9 + 13 → 18 → 23 → 28	0.947
3	1 + 4 → 9 + 14 → 19 → 24 → 29	1
4	1 + 4 → 9 + 15 → 20 → 25 → 30	0.992
5	1 + 4 → 9 + 16 → 21 → 26 → 31	0.984
6	2 + 5 → 10 + 12 → 17 → 22 → 27	0.985
7	2 + 5 → 10 + 13 → 18 → 23 → 28	0.965
8	2 + 5 → 10 + 14 → 19 → 24 → 29	1
9	2 + 5 → 10 + 15 → 20 → 25 → 30	0.990
10	2 + 5 → 10 + 16 → 21 → 26 → 31	0.978
11	3 + 6 → 11 + 12 → 17 → 22 → 27	0.980
12	3 + 6 → 11 + 13 → 18 → 23 → 28	0.981
13	3 + 6 → 11 + 14 → 19 → 24 → 29	1
14	3 + 6 → 11 + 15 → 20 → 25 → 20	0.984
15	3 + 6 → 11 + 16 → 21 → 26 → 31	0.986
16	3 + 7 → 11 + 12 → 17 → 22 → 27	0.986
17	3 + 7 → 11 + 13 → 18 → 23 → 28	0.989
18	3 + 7 → 11 + 14 → 19 → 24 → 29	0.990
19	3+ 7 → 11 + 15 → 20 → 25 → 30	0.996
20	3 + 7 → 11 + 16 → 21 → 26 → 31	0.989
21	3 + 8 → 11 + 12 → 17 → 22 → 27	0.988
22	3 + 8 → 11 + 13 → 18 → 23 → 28	0.980
23	3 + 8 → 11 + 14 → 19 → 24 → 29	0.990
24	3 + 8 → 11 + 15 → 20 → 25 → 30	0.984
25	3 + 8 → 11 + 16 → 21 → 26 → 31	1

Table 9 Suggested selection of assy factory by scenario analysis

Key Parts Factory \ Parts Factory	USA	Germany	Japan	Thailand	China
USA	-	USA	USA	Same	China
Germany	USA	-	Japan	Thailand	Germany
Japan	USA	Japan	-	Same	China

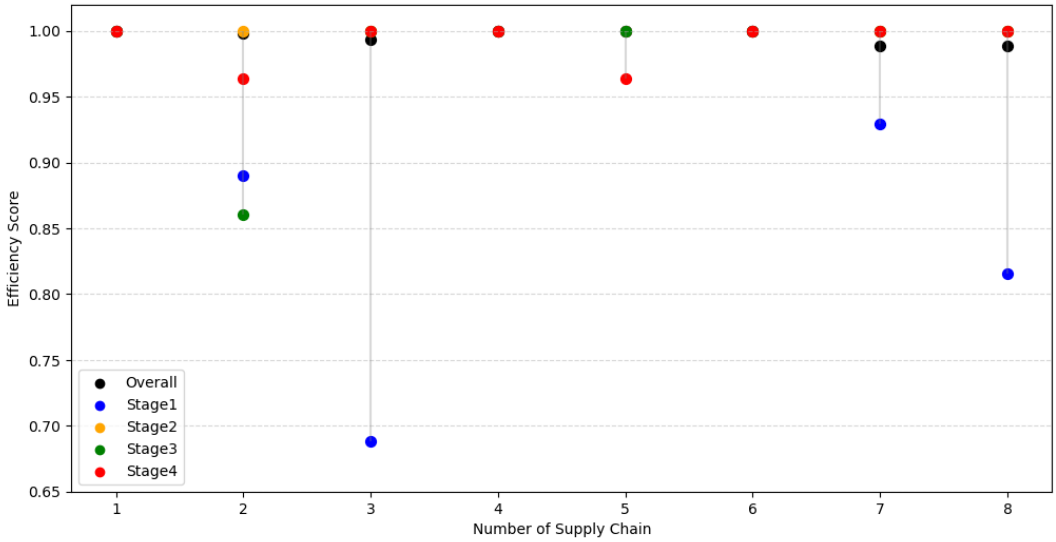

Figure 6 Local vs. Overall Efficiency: Scenario 1

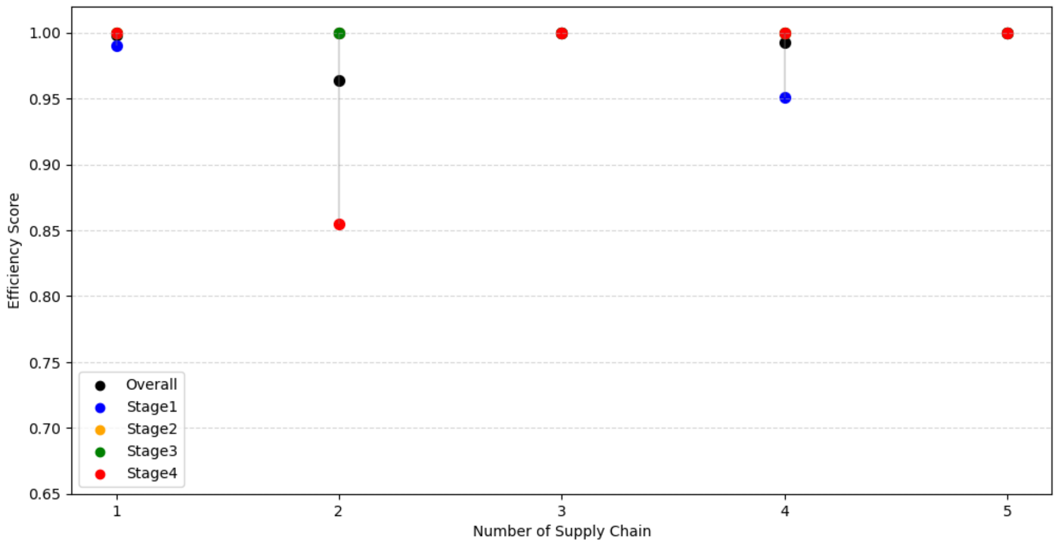

Figure 7 Local vs. Overall Efficiency: Scenario 2

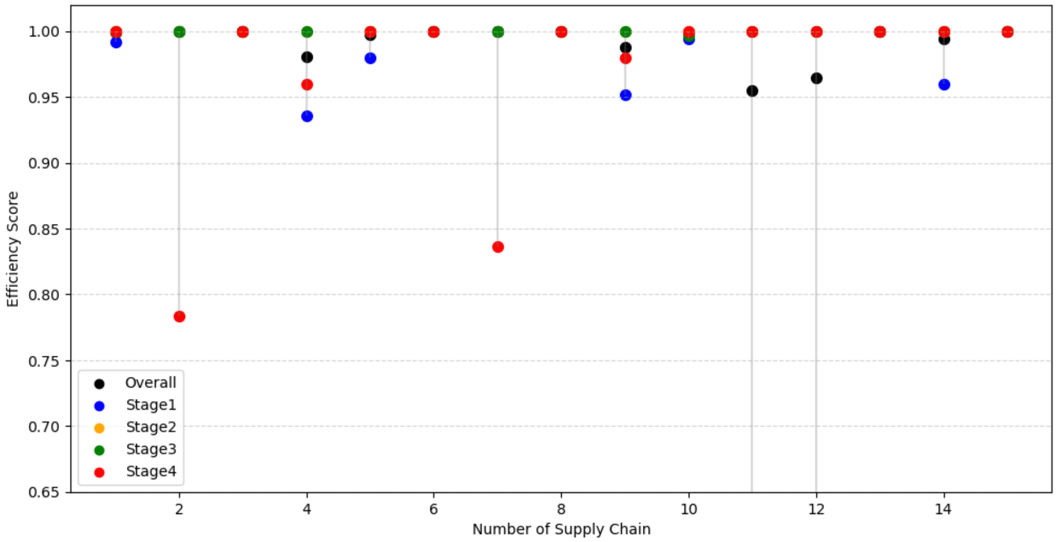

Figure 8 Local vs. Overall Efficiency: Scenario 3

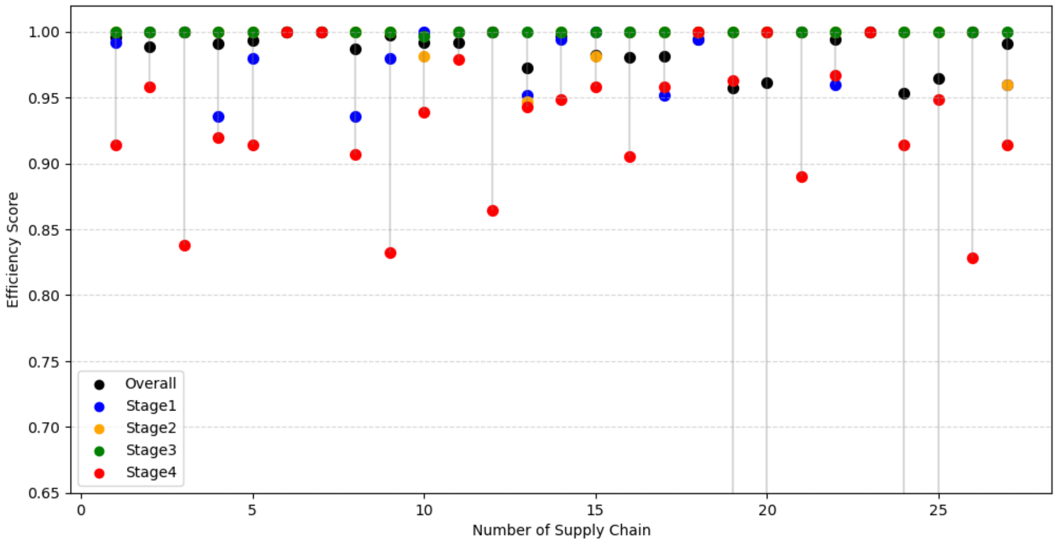

Figure 9 Local vs. Overall Efficiency: Scenario 4

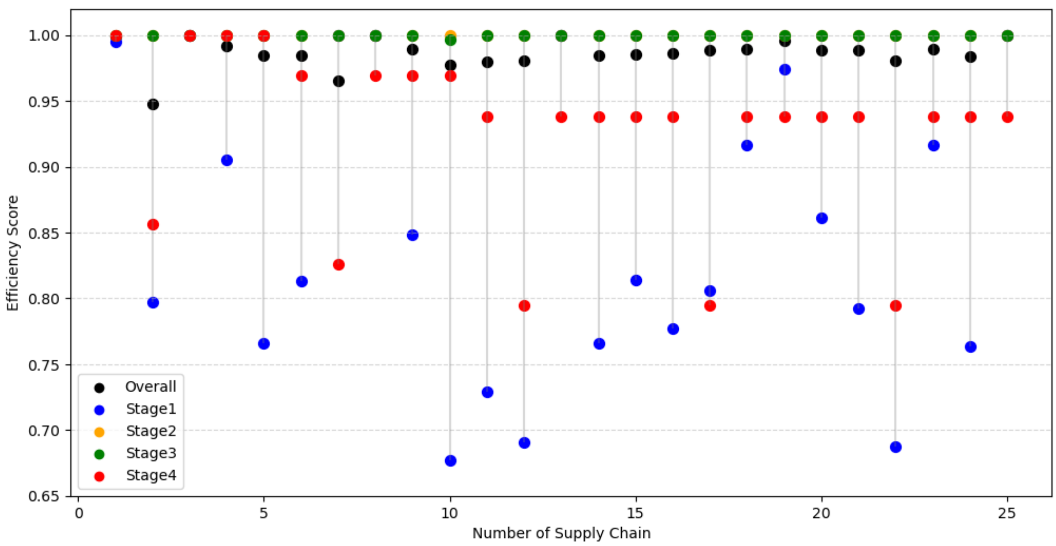

Figure 10 Local vs. Overall Efficiency: Scenario 5

focuses on examining whether the selection of the Parts Factory can improve the efficiency of the supply chains that were identified as inefficient in Scenario 2 due to local production and local sales. For example, in the case of Germany (No.2 in Scenario 2 and No.7 in Scenario 5), Scenario 2 analysis indicated that the primary cause of inefficiency was the procurement and transportation costs in Stage 4. By adjusting the sourcing of parts from Germany and selecting the Parts Factory in Thailand (No.8 in Scenario 5), partially local production and local sales enable the supply chain to achieve efficiency. This scenario analysis demonstrates that, beyond the selection of the Assy Factory, the choice of the Parts Factory can also provide valuable guidance for improving supply chain efficiency. Overall, the analyses in Scenarios 4 and 5 suggest that the proposed model with scenario analysis can offer actionable insights for enhancing supply chain efficiency from multiple perspectives.

3.5. Local vs. Overall Efficiency

To demonstrate the necessity and added value of the proposed multi-stage DEA model, this experiment examines the consistency and discrepancies between the overall efficiency score and the stage-level efficiency scores. By analyzing their relationships, we validate the model outcomes and illustrate why evaluating supply chains solely at the stage level may lead to incomplete or misleading conclusions. The efficiency scores obtained under the 5 scenarios are summarized in Figures 6 – 10. The x-axis represents each supply chain, while the y-axis shows both the stage-level efficiency scores and the overall efficiency score for each supply chain. The results reveal a fundamental characteristic of multi-stage supply chains: local (stage-wise) efficiency does not necessarily imply overall efficiency, and conversely, overall efficiency does not require every individual stage to be fully efficient. This observation aligns with the intrinsic structure of supply chains—systems composed of sequential, interdependent processes. The overall performance depends not only on the efficiency of each individual stage, but also on the flow of intermediate products, the propagation of inefficiencies across stages, and the presence of compensating effects between upstream and downstream operations. Several counterexamples extracted from the numerical experiments illustrate these mechanisms clearly.

- Local efficiency does not guarantee overall efficiency
  For instance, No.7 in Scenario 5, multiple stages are fully efficient (efficiency score of stage 1 – 3 = 1), yet the supply chain as a whole is inefficient (overall efficiency score = 0.9652). The inefficiency arises primarily from the final stage (efficiency score of stage 4 = 0.8258), and this conclusion is further corroborated by the slack analysis conducted for stage 4 using our proposed method. This case shows how inefficiency in a downstream "bottleneck" can dominate the entire system, offsetting the efficiency achieved in earlier stages. Hence, evaluating stages independently may incorrectly classify such a supply chain as highly efficient, overlooking critical downstream issues.
- Local inefficiency does not prevent overall efficiency
  In contrast, No.2 in Scenario 3 and No.3 in Scenario 4 exhibit the opposite pattern. Both supply chains are globally efficient (overall efficiency score = 1) despite having inefficient stages (efficiency score of stage 4 = 0.7832 and 0.8383, respectively). These examples indicate the existence of compensating effects: exceptionally strong performance in certain stages may offset weaker performance in others, allowing the supply chain to remain globally efficient. Such global compensations cannot be detected when analyzing stages in isolation.

Taken together, these findings reinforce the necessity of our proposed multi-stage RAM DEA model. Evaluating each stage separately could result in misleading assessments—either overestimating supply chains that are globally inefficient but possess multiple efficient stages, or underestimating globally efficient supply chains with minor local inefficiencies. By explicitly modeling intermediate links and inter-stage dependencies, the multi-stage DEA framework captures the true operational nature of supply chains and provides a more reliable basis for system-wide decision making. In summary, the comparison between overall and stage-level efficiencies not only validates the multi-stage RAM DEA model but also confirms its critical role in accurately evaluating multi-stage supply chains.

4. CONCLUSION & FUTURE RESEARCH

This study developed a novel network DEA model based on the RAM to evaluate supply chain efficiency from both cost and revenue perspectives. Through an empirical case example involving a global supply chain network—including suppliers, factories, distributors, and customers—we validated the model's capability to benchmark performance under various strategic scenarios. The evaluation not only identified inefficiency factors at different stages but also supported decision-making regarding the selection of sourcing, production, and assembly locations. The results highlight the practical utility of the proposed model in analyzing and improving complex, multinational supply chains. Accordingly, this study makes three primary contributions. First, it introduces a multi-stage network RAM DEA model. Second, it demonstrates its effectiveness in evaluating supply chain efficiency from both cost and revenue perspectives. Third, it illustrates its potential applicability to other multi-stage decision-making structures.

Future research may extend this work in several directions. First, integrating dynamic or time-series data would allow for the analysis of supply chain performance over time, enabling the evaluation of changes due to demand fluctuations, disruptions, or policy shifts. Second, incorporating stochastic elements or modeling uncertainty—such as variability in tariffs or transportation costs—would enhance the model's robustness and applicability to real-world global supply chains that are often subject to external shocks. Third, further development of a n-stage RAM super-efficiency DEA model could allow for more refined distinction among efficient DMUs, while extending the efficiency definitions for inefficient DMUs would provide a more comprehensive and detailed assessment of supply chain performance. Finally, exploring applications beyond supply chains, such as in healthcare systems, education networks, or service operations, would broaden the impact and versatility of the proposed framework.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to the editor and the two anonymous reviewers for their valuable comments and constructive suggestions, which have greatly improved the quality of this paper. This work was supported by JSPS KAKENHI (Grant Number 23K13518).

REFERENCES

Afonso, G. P., Ferreira, D. C., and Figueira, J. R. (2024) A network-DEA model to evaluate the impact of quality and access on hospital performance. *Annals of Operations Research* 342, 2169–2199.

Alves, C. G. M. d. F., and Meza, L. A. (2023) A review of network DEA models based on slacks-based measure: Evolution of literature, applications, and further research direction. *International Transactions in Operational Research* 30, 2729–2760.

Awasthi, A., Chauhan, S. S., and Goyal, S. K. (2010) A fuzzy multicriteria approach for evaluating environmental performance of suppliers. *International Journal of Production Economics* 126, 370–378.

Banker, R. D., Charnes, A., and Cooper, W. W. (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* 30, 1078–1092.

Charnes, A., Cooper, W. W., Golany, B., Seiford, L., and Stutz, J. (1985) Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. *Journal of Econometrics* 30, 91–107.

Charnes, A., Cooper, W. W., and Rhodes, E. (1978) Measuring the efficiency of decision making units. *European Journal of Operational Research* 2, 429–444.

Chen, Y., Ma, X., Yan, P., and Wang, M. (2021) Operating efficiency in Chinese universities: An extended two-stage network DEA approach. *Journal of Management Science and Engineering* 6, 482–498.

Cook, W. D., Liang, L., and Zhu, J. (2010) Measuring performance of two-stage network structures by DEA: A review and future perspective. *Omega* 38, 423–430.

Cook, W. D., Tone, K., and Zhu, J. (2014) Data envelopment analysis: Prior to choosing a model. *Omega* 44, 1–4.

Cooper, W. W., Park, K. S., and Pastor, J. T. (1999) RAM: A range adjusted measure of inefficiency for use with additive models, and relations to other models and measures in DEA. *Journal of Productivity Analysis* 11, 5–42.

Cooper, W. W., Seiford, L. M., and Tone, K. (2007) *Data envelopment analysis: A comprehensive text with models, applications, references and dea-solver software* (Vol. 2). Springer.

Ebrahimi, F., Saen, R. F., and Karimi, B. (2021) Assessing the sustainability of supply chains by dynamic network data envelopment analysis: A scor-based framework. *Environmental Science and Pollution Research* 28, 64039–64067.

Fu, J. (2018) Two-stage data envelopment analysis with undesirable intermediate measures: An application to air quality improvement in China. *Central European Journal of Operations Research* 26, 861–885.

Govindan, K., Rajendran, S., Sarkis, J., and Murugesan, P. (2015) Multi criteria decision making approaches for green supplier evaluation and selection: A literature review. *Journal of Cleaner Production* 98, 66–83.

Hong, J.-D. (2023) Design of humanitarian supply chain system by applying the general two-stage network DEA model. *Journal of Humanitarian Logistics and Supply Chain Management* 13, 74–90.

Ivanov, D., Dolgui, A., and Sokolov, B. (2019) The impact of digital technology and industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research* 57, 829–846.

Kao, C., and Hwang, S.-N. (2008) Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan. *European Journal of Operational Research* 185, 418–429.

Kenki-parts. (2024) Product and BOM Relationships and Examples of Lean Manufacturing [Last accessed: 2025-08-02]. https://www.kenki-parts.com/hpgen/HPB/entries/22.html

Klibi, W., and Martel, A. (2012) Scenario-based supply chain network risk modeling. *European Journal of Operational Research* 223, 644–658.

Komatsu Ltd. (2025) Komatsu's Annual Financial Reports and Investor Disclosures [Last accessed: 2025-08-02]. https://home.komatsu/jp/ir/library/financial/

Liang, L., Yang, F., Cook, W. D., and Zhu, J. (2006) DEA models for supply chain efficiency evaluation. *Annals of Operations Research* 145, 35–49.

Oliveira, J. B., Lima, R. S., and Montevechi, J. A. B. (2016) Perspectives and relationships in supply chain simulation: A systematic literature review. *Simulation Modelling Practice and Theory* 62, 166–191.

Organisation for Economic Co-operation and Development (OECD). (2025) OECD Corporate Tax Rate Table (Global) [Last accessed: 2025-08-02]. https://stats.oecd.org/Index.aspx?DataSetCode=TABLE_II1

Peng Wong, W., and Yew Wong, K. (2008) A review on benchmarking of supply chain performance measures. *Benchmarking: An International Journal* 15, 25–51.

Ratner, S. V., Shaposhnikov, A. M., and Lychev, A. V. (2023) Network DEA and its applications (2017–2022): A systematic literature review. *Mathematics* 11, 2141.

Soheilirad, S., Govindan, K., Mardani, A., Zavadskas, E. K., Nilashi, M., and Zakuan, N. (2018) Application of data envelopment analysis models in supply chain management: A systematic review and meta-analysis. *Annals of Operations Research* 271, 915–969.

Tavana, M., Mirzagoltabar, H., Mirhedayatian, S. M., Saen, R. F., and Azadi, M. (2013) A new network epsilon-based DEA model for supply chain performance evaluation. *Computers & Industrial Engineering* 66, 501–513.

Tavassoli, M., Ghandehari, M., and Taherinia, M. (2023) Rang-adjusted measure: Modelling and computational aspects from internal and external perspectives for network DEA. *Operational Research* 23, 1–62.

Wang, M., Chen, Y., and Zhou, Z. (2021) Assessing environmental efficiency of China's industry system using two-stage range-adjusted measure model. *Management of Environmental Quality: An International Journal* 32, 1401–1421.

Wanke, P., and Barros, C. (2014) Two-stage DEA: An application to major Brazilian banks. *Expert Systems with Applications* 41, 2337–2344.

Wanke, P., Ostovan, S., Mozaffari, M. R., Gerami, J., and Tan, Y. (2022) Stochastic network DEA-R models for two-stage systems. *Journal of Modelling in Management* 18, 842–875.

World Trade Organization (WTO). (2025) WTO Tariff Analysis Online (TAO) [Last accessed: 2025-08-02]. https://ttd.wto.org/en

Wu, S., Kremantzis, M. D., Tanveer, U., Ishaq, S., O'Dea, X., and Jin, H. (2024) Performance evaluation of the global airline industry under the impact of the COVID-19 pandemic: A dynamic network data envelopment analysis approach. *Journal of Air Transport Management* 118, 102597.

Xu Wang (PhD) is an Associate Professor in the Faculty of Informatics at Gunma University, Japan. He received his PhD in Engineering from Waseda University. His research interests include efficiency evaluation (such as Data Envelopment Analysis (DEA) and Analytic Hierarchy Process (AHP)), optimization, and operations research.

Qian Huang (PhD) is an Assistant Professor in the Department of Business Design and Management, Graduate School of Creative Science and Engineering, Waseda University, Japan. She received her PhD in Management Engineering from Waseda University. Her research interests include production planning, global supply chain design, and the optimization of production and logistics systems.

Shunichi Ohmori (PhD) is an Associate Professor in the Department of Industrial and Systems Engineering, School of Creative Science and Engineering, Waseda University, Japan. He received both his Master's and PhD degrees in Engineering from Waseda University. His research interests lie in operations research and supply chain management.

Takashi Hasuike (PhD) is a Professor in the Department of Industrial and Systems Engineering, School of Creative Science and Engineering, Waseda University, Japan. He received both his Master's and PhD degrees in Information Science from Osaka University. His research interests lie in operations research and mathematical programming.

A. APPENDIX

A.1. The 4-stage Version of Model 2

$$\hat{\delta} = \underset{s_{i'}^{t-}, s_{r'}^{t+}, s_{k'o}^{t+}, \lambda_j^t}{\text{minimize}} \quad 1 - \frac{\sum_{t=1}^{4}\Big(\sum_{i'=1}^{m^t} \frac{s_{i'o}^{t-}}{R_{i'}^{t-}} + \sum_{r'=1}^{s^t} \frac{s_{r'o}^{t+}}{R_{r'}^{t+}} + \sum_{k'=1}^{k'^t} \frac{s_{k'o}^{t+}}{R_{k'}^{t+}}\Big)}{\sum_{t=1}^{4} m^t + s^t + k^t} \tag{14}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} x_{i'j}^1 \lambda_j^1 = x_{i'o}^1 - s_{i'o}^{1-} \, (i' = 1, 2, \cdots, m^1), \tag{15}$$

$$\sum_{j=1}^{n} y_{r'j}^1 \lambda_j^1 = y_{r'o}^1 + s_{r'o}^{1+} \, (r' = 1, 2, \cdots, s^1), \tag{16}$$

$$\sum_{j=1}^{n} y_{k'o}^1 \lambda_j^1 = y_{k'o}^1 + s_{k'o}^{1+} \, (k' = 1, 2, \cdots, k^1), \tag{17}$$

$$\sum_{j=1}^{n} \lambda_j^1 = 1, \ \lambda_j^1 \geq 0, \ s_{i'o}^{1-} \geq 0, \ s_{r'o}^{1+} \geq 0, \ s_{k'o}^{1+} \geq 0, \tag{18}$$

$$\sum_{j=1}^{n} y_{k'o}^1 \lambda_j^1 \geq \sum_{j=1}^{n} y_{k'o}^1 \lambda_j^2, \tag{19}$$

$$\sum_{j=1}^{n} x_{i'j}^2 \lambda_j^2 = x_{i'o}^2 - s_{i'o}^{2-} \, (i' = 1, 2, \cdots, m^2), \tag{20}$$

$$\sum_{j=1}^{n} y_{r'j}^2 \lambda_j^2 = y_{r'o}^2 + s_{r'o}^{2+} \, (r' = 1, 2, \cdots, s^2), \tag{21}$$

$$\sum_{j=1}^{n} y_{k'o}^2 \lambda_j^2 = y_{k'o}^2 + s_{k'o}^{2+} \, (k' = 1, 2, \cdots, k^2), \tag{22}$$

$$\sum_{j=1}^{n} \lambda_j^2 = 1, \ \lambda_j^2 \geq 0, \ s_{i'o}^{2-} \geq 0, \ s_{r'o}^{2+} \geq 0, \ s_{k'o}^{2+} \geq 0, \tag{23}$$

$$\sum_{j=1}^{n} y_{k'o}^2 \lambda_j^2 \geq \sum_{j=1}^{n} y_{k'o}^2 \lambda_j^3, \tag{24}$$

$$\sum_{j=1}^{n} x_{i'j}^3 \lambda_j^3 = x_{i'o}^3 - s_{i'o}^{3-} \, (i' = 1, 2, \cdots, m^3), \tag{25}$$

$$\sum_{j=1}^{n} y_{r'j}^3 \lambda_j^3 = y_{r'o}^3 + s_{r'o}^{3+} \, (r' = 1, 2, \cdots, s^3), \tag{26}$$

$$\sum_{j=1}^{n} y_{k'o}^3 \lambda_j^3 = y_{k'o}^3 + s_{k'o}^{3+} \, (k' = 1, 2, \cdots, k^3), \tag{27}$$

$$\sum_{j=1}^{n} \lambda_j^3 = 1, \ \lambda_j^3 \geq 0, \ s_{i'o}^{3-} \geq 0, \ s_{r'o}^{3+} \geq 0, \ s_{k'o}^{3+} \geq 0, \tag{28}$$

$$\sum_{j=1}^{n} y_{k'o}^3 \lambda_j^3 \geq \sum_{j=1}^{n} y_{k'o}^3 \lambda_j^4, \tag{29}$$

$$\sum_{j=1}^{n} x_{i'j}^4 \lambda_j^4 = x_{i'o}^4 - s_{i'o}^{4-} \, (i' = 1, 2, \cdots, m^4), \tag{30}$$

$$\sum_{j=1}^{n} y_{r'j}^4 \lambda_j^4 = y_{r'o}^4 + s_{ro}^{4+} \, (r' = 1, 2, \cdots, s^4), \tag{31}$$

$$\sum_{j=1}^{n} y_{k'o}^4 \lambda_j^4 = y_{k'o}^4 + s_{k'o}^{4+} \, (k' = 1, 2, \cdots, k^4), \tag{32}$$

$$\sum_{j=1}^{n} \lambda_j^4 = 1, \ \lambda_j^4 \geq 0, \ s_{i'o}^{4-} \geq 0, \ s_{r'o}^{4+} \geq 0, \ s_{k'o}^{4+} \geq 0. \tag{33}$$

A.2. Descriptive Statistics of the Data

Table 10 Scenario Summary Statistics for Stage 1

Scenario 1	x_1^1	y_1^1
max	10,000.00	120,000.00
min	1,428.57	25,714.29
average	4,000.05	59,107.88
STDEV	3,073.47	32,107.42
Scenario 2		
max	25,714.29	364,285.71
min	10,285.71	171,428.57
average	18,857.14	278,000.00
STDEV	6,180.95	77,338.38
Scenario 3		
max	41,428.57	407,142.86
min	10,285.71	171,428.57
average	22,914.29	290,095.24
STDEV	7,981.17	65,261.23
Scenario 4		
max	41,428.57	407,142.87
min	10,285.71	171,428.57
average	23,555.56	293,333.33
STDEV	7,791.77	62,649.51
Scenario 5		
max	78,714.29	515,714.29
min	10,285.71	152,571.43
average	32,565.71	300,965.71
STDEV	14,877.24	90,747.48

Table 11 Scenario Summary Statistics for Stage 2

	x_1^2	x_2^2	x_3^2	x_4^2	x_5^2	x_6^2	y_1^2
Scenario 1							
max	4,286.00	120,000.00	12,029.41	–	81,052.71	102,857.14	272,547.30
min	1,000.00	25,714.29	2,677.76	–	15,727.24	30,000.00	125,947.66
average	2,321.47	59,107.88	7,082.71	–	51,291.07	60,536.14	204,072.15
STDEV	1,071.16	32,107.42	3,053.95	–	24,901.67	23,915.62	52,833.54
Scenario 2							
max	23,571.43	364,285.71	64,002.80	72,857.14	216,598.40	300,000.00	1,012,118.68
min	3,428.57	171,428.57	25,689.22	0.00	126,666.25	128,571.43	555,221.80
average	12,085.71	278,000.00	50,388.66	22,828.57	177,623.47	228,571.43	806,006.29
STDEV	7,413.17	77,338.38	15,254.74	33,192.45	38,161.43	72,843.14	195,468.58
Scenario 3							
max	38,857.14	407,142.86	98,800.52	111,000.00	322,661.00	380,000.00	1,219,749.13
min	3,428.57	171,428.57	25,689.22	0.00	126,666.25	128,571.43	555,221.80
average	16,847.62	290,095.24	58,800.28	28,727.62	191,770.00	244,571.43	869,105.73
STDEV	9,745.52	65,261.23	18,749.05	39,459.63	50,863.64	67,653.72	176,221.23
Scenario 4							
max	62,428.57	407,142.86	98,800.52	111,000.00	322,661.00	380,000.00	1,225,720.56
min	3,428.57	171,428.57	25,689.22	0.00	126,666.25	128,571.43	555,221.80
average	22,523.81	293,333.33	59,825.63	15,959.79	191,863.36	249,523.81	885,108.17
STDEV	12,816.30	62,649.51	18,295.39	32,404.13	54,538.00	65,914.65	175,301.17
Scenario 5							
max	38,857.14	515,714.29	65,047.74	142,800.00	322,661.00	380,000.00	1,219,749.13
min	3,428.57	171,428.57	25,689.22	0.00	126,666.25	128,571.43	555,221.80
average	16,931.43	299,552.71	42,921.26	29,820.34	178,553.20	227,885.71	814,082.83
STDEV	9,028.12	87,469.09	13,960.21	42,300.30	44,658.26	66,671.50	177,335.68

Table 12 Scenario Summary Statistics for Stage 3

	x_1^3	x_2^3	x_3^3	x_4^3	x_5^3	y_1^3
Scenario 1						
max	3,428.57	272,547.30	154,660.38	85,809.22	102,857.14	1,212,539.90
min	1,428.57	125,947.66	26,603.16	59,447.66	30,000.00	384,892.67
average	2,142.88	204,072.15	75,630.45	75,451.81	57,857.52	670,951.19
STDEV	665.69	52,833.54	40,655.40	9,626.36	23,904.19	265,683.79
Scenario 2						
max	4,285.71	1,012,118.68	64,479.67	174,108.91	140,000.00	1,519,154.19
min	1,714.29	555,221.80	25,689.22	78,760.73	60,000.00	768,769.69
average	3,142.86	806,006.29	35,358.21	129,694.84	102,857.14	1,032,361.02
STDEV	1,030.16	195,468.57	24,298.59	43,749.67	32,324.88	324,157.95
Scenario 3						
max	5,428.57	1,219,749.13	87,292.71	290,181.51	162,857.14	1,924,261.98
min	1,714.29	555,221.80	25,689.22	78,760.73	60,000.00	768,769.69
average	3,371.43	869,105.73	37,075.72	142,490.89	109,714.29	1,285,876.60
STDEV	1,008.41	176,221.23	28,845.58	58,819.34	27,843.80	390,748.30
Scenario 4						
max	28,000.00	1,225,720.56	109,631.49	435,272.27	170,000.00	1,940,101.19
min	1,714.29	555,221.80	25,689.22	78,760.73	60,000.00	768,769.69
average	6,994.71	885,108.17	40,445.50	176,344.76	115,767.19	1,354,394.66
STDEV	8,969.99	175,301.17	30,914.94	81,943.06	28,532.99	361,300.66
Scenario 5						
max	5,428.57	1,219,749.13	87,292.71	290,181.51	162,857.14	1,924,261.98
min	1,714.29	555,221.80	25,689.22	78,760.73	60,000.00	768,769.69
average	3,142.86	814,082.83	33,543.15	131,377.10	102,117.14	1,308,742.83
STDEV	989.74	177,335.68	27,011.98	51,857.03	27,532.05	307,880.77

Table 13 Scenario Summary Statistics for Stage 4

	x_1^4	x_2^4	x_3^4	y_1^4	y_M^4
Scenario 1					
max	3,000.00	1,212,539.90	192,638.08	2,177,444.57	17,142.86
min	1,000.00	384,892.67	45,750.26	585,092.57	4,285.71
average	1,946.44	670,951.20	112,239.19	1,162,041.72	8,750.05
STDEV	767.17	265,683.79	48,097.61	515,057.89	4,142.98
Scenario 2					
max	6,000.00	1,519,154.19	566,468.53	4,354,925.43	34,286.00
min	2,000.00	768,769.61	91,752.05	1,170,263.16	8,572.00
average	3,657.20	1,196,162.16	301,828.65	2,546,045.05	19,428.80
STDEV	1,570.11	324,157.95	177,858.28	1,177,663.77	9,561.74
Scenario 3					
max	6,000.00	1,924,261.98	304,128.86	3,447,620.57	27,142.86
min	1,428.57	768,769.61	91,734.14	1,170,185.14	8,571.43
average	3,400.00	1,285,876.16	213,539.56	2,220,069.12	16,857.14
STDEV	1,403.04	309,478.60	59,823.50	612,481.22	5,042.10
Scenario 4					
max	1,940,110.89	3,711,214.63	453,252.25	3,711,214.63	27,142.86
min	768,769.61	1,170,185.14	84,894.06	1,170,185.14	8,571.43
average	1,354,394.56	2,311,622.50	222,600.21	2,311,622.50	17,248.68
STDEV	312,300.70	639,016.70	82,807.24	639,016.70	4,931.65
Scenario 5					
max	6,000.00	1,519,154.19	566,468.53	4,354,925.43	27,142.86
min	2,000.00	768,769.61	91,752.05	1,170,263.16	8,571.43
average	3,657.20	1,196,162.16	301,828.65	2,546,045.05	15,714.29
STDEV	1,433.31	295,914.37	162,361.65	1,075,055.02	4,948.72