Efficiency-Driven Cost Optimization of Apparel Supply Chain Using Data Envelopment Analysis

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Abstract

Optimizing supply chain costs is essential for maintaining a cost-effective yet efficient operation that can adapt to market changes. This research focuses on optimizing apparel supply chain costs by maximizing overall efficiency through the application of Data Envelopment Analysis (DEA), a linear programming (LP) approach. Yarn suppliers in the complex fabric supply chain are categorized into effective and average frontiers using DEA, providing a comprehensive evaluation of their performance. To assess independent efficiencies for each DMU, we formulated goal functions and constraints using MATLAB software allowing for a nuanced understanding of supplier performance within the selected subset. The collected data reveals crucial insights into yarn supply chain dynamics, emphasizing factors such as lead time, purchase profit, availability, and purchase quantities. The identification of role models within effective frontiers, depicted as convex curves, establishes benchmarks for suppliers seeking to improve efficiency. Ineffective Decision-Making Units (DMUs) within the curve gain insights into their shortcomings and strategies for improvement. Suppliers can identify role models by determining the shortest distance from effective frontiers, promoting the adoption of best practices. These insights serve as a foundation for strategic decision-making, empowering businesses to optimize supplier relationships and cost-effectively enhance overall supply chain efficiency. Furthermore, this study highlights the importance of advanced computational tools in analyzing complex supply chain networks.

Keywords
Data envelopment analysis, decision-making units, apparel supply chain, linear programming, and frontiers.

1. Introduction
The business focus on supply chain management has been influenced by the increasing diversity of customer demands, continued information technology improvements, and growing environmental concerns (Sheffi and J.B. Rice 2005). In the SCM (supply chain management) industry, selecting the right set of suppliers to supply materials and components to your manufacturer or products to your retailer is a common issue that has been a hot topic for decades. In a highly competitive global market, buyers with high expectations often look for supply chains to enhance their end-to-end capabilities, such as cost reduction and increased productivity. On the buyer's side, purchasing department managers are constantly searching for competitive suppliers who can meet their needs and build long-term relationships (Park J et al. 2010). According to Chan (2003), supply chain management aims to gain an advantage in terms of customer service and cost over competitors. Supplier selection refers to the process of identifying, analyzing, and negotiating with suppliers as part of supply chain management. In the dynamic landscape of the apparel industry, where trends change rapidly and consumer preferences are evolving, efficient supplier selection plays a pivotal role in sustaining competitiveness and maximizing profitability. Considering the rapidly changing market conditions and customers seeking the best value, long-term relationships with vendors became very critical in the apparel industry. Therefore, apparel retailers are looking for vendors who can provide the best cost in the fastest way. The selection of suppliers involves intricate decision-making processes, as it necessitates the evaluation of multiple criteria while making the best use of available resources (Boer et al. 2001). The selection of suppliers involves intricate decision-

making processes, as it necessitates the evaluation of multiple criteria while making the best use of available resources (Rashid et al. 2019). Data Envelopment Analysis (DEA), a well-established technique in operations research, offers a systematic approach to evaluate the relative efficiency of suppliers and guide decision-makers towards optimal choices. Data collected from various suppliers for a company designates these suppliers as Decision Making Units (DMUs). Efficiency for these suppliers is measured based on their ability to offer raw materials at lower costs while incurring less transportation expenses for the company. Efficient DMUs are those that provide cost-effective raw materials with minimized transportation costs. The remaining DMUs, represented within the convex hull (Roy et al. 2023), are positioned between the efficient and inefficient frontiers, indicating varying levels of performance and efficiency.

1.1 Objectives

This paper delves into the application of DEA as a strategic tool for cost optimization of supply chain within the context of the apparel business in Bangladesh. The primary objective is to demonstrate the effectiveness of DEA in quantifying the relative efficiencies of suppliers while considering both quantitative and qualitative inputs and outputs. By adopting DEA, businesses in the apparel industry can identify suppliers that provide the most value and operate efficiently, contributing to enhanced supply chain performance and overall business success.

2. Literature Review

The supplier selection process within the dynamic apparel industry is fraught with multifaceted challenges that demand a holistic approach. These challenges encompass intricate considerations such as supply chain volatility, ensuring consistent product quality, meeting stringent lead time requirements, upholding ethical standards, optimizing cost-efficiency, and fostering supplier diversity and innovation (Smith & Johns 2021) on Addressing these challenges is pivotal for enhancing operational efficiency and sustaining competitiveness. The literature surrounding supplier selection and the utilization of DEA spans various domains, including supply chain management, operations research, and business analytics. Researchers have long emphasized the complexities of supplier selection, which involves striking a balance between diverse and sometimes conflicting criteria. DEA, initially developed by Charnes, Cooper, and Rhodes (1978), has gained prominence as an effective method for assessing the performance of decision-making units within a system. DEA is a non-parametric method that has become an influential approach in measuring the efficiency of a set of comparable entities known as decision-making units (DMUs) (Mahad 2020). Efficiency analysis plays a crucial role in assessing the performance of supplier selection. In this context, the Data Envelopment Analysis (DEA) is utilized as a data-centric approach to gauge the efficiency of a group of Decision-Making Units (DMUs). The DEA successfully transforms various inputs into multiple outputs, with each output being quantified in distinct units of measurement. In particular, Charnes et al. (1978) elucidated that the implementation of DEA necessitates solving individual linear programs for each Decision-Making Unit (DMU). This approach is non-parametric, meaning that it doesn't rely on assumptions of normal distribution concerning inputs and outputs, setting it apart from methods that do. In the context of textile sourcing, Yusuf Ersoy utilized DEA to assess suppliers based on a range of criteria, including material quality, environmental sustainability, and responsiveness. This study underscored the practical applicability of DEA in gauging supplier performance and fostering sustainable supplier relationships.

3. Problem Statements and Methods

The research unfolds in three distinctive phases. In the initial stage, a novel framework is constructed, leveraging the CCR model of Data Envelopment Analysis (DEA). This stage encompasses the intricacies of problem formulation and the creation of a Multiple-Input-Single-Output (MISO) model to assess the efficiency of a given system or process. Moving into the second stage, the focus shifts towards the acquisition of supply chain-related data from the industry. The primary objective is to gauge the efficiency of suppliers who contribute significantly to profitability. This involves a comprehensive collection of data pertinent to supplier performance. The third and concluding stage integrates the data amassed in the second stage into the framework developed during the first phase. Employing DEA analysis, the study evaluates supplier efficiency using key inputs such as transportation cost, raw material cost, and lead time. The output parameter for this assessment is profit, allowing for a robust evaluation of supplier efficiency in the context of the specified factors. This staged approach ensures a thorough and nuanced exploration of the supply chain dynamics, culminating in a comprehensive understanding of supplier efficiency within the given framework.

Figure 1. Flowchart of methodology.

3.1 CCR Model

The Charnes, Cooper, and Rhodes (CCR) model, also known as the Constant Returns to Scale (CRS) model, stands as a pivotal linear programming tool for evaluating the efficiency of decision-making units (DMUs), such as organizations, institutions, or companies. Originating in 1978, this non-parametric linear programming approach by Charnes, Cooper, and Rhodes focuses on efficiency assessment. At its core, the CCR model employs the concept of efficient frontiers to identify the best performing DMU within a given set. Within the broader context of Data Envelopment Analysis (DEA), two primary models emerge: the input-oriented model and the output-oriented model. In the input-oriented model, input variables remain constant, while efforts are directed towards maximizing the output variables (Cooper et al. 2011). Conversely, the output-oriented model maintains the constancy of output variables while minimizing input variables. Notably, the efficiency gains associated with suppliers characterized by lower transportation and raw material costs. To align with the goal of maximizing output, our analysis will leverage the output-oriented model, strategically focusing on minimizing input variables while keeping output variables constant. This approach enables a nuanced exploration of efficiency dynamics, emphasizing resource optimization and cost-effectiveness in the pursuit of organizational excellence.

Assume that there are 'n' number of DMUs need to evaluate where each DMU consumes varying amounts of m different inputs to produce s different outputs. If DMU_j needs x_{ij} of input i to produce y_{rj} of output r, where $x_{ij} > 0$ and $y_{rj} > 0$ and λ_r, λ_i are the multipliers of input and output weights. For a particular DMU the ratio of any single virtual output to single virtual input provides a measure of efficiency that is a function of the multipliers, where Output-oriented model is,

Objective function,

$$min\ q = \sum_{r=1}^{s} v_i x_{i0} \qquad 1$$

Subject to,

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0 \qquad 2$$

$$\sum_{r=1}^{s} \mu_r y_{ro} = 1 \qquad 3$$

$$\mu_r, v_i \geq 0 \qquad 4$$

4. Data Collection

The two common methods used for producing fabrics are Knitting and weaving. In our selected Aboni knit Wear only knitted fabric is produced. Knitting is a process of producing fabric by the joining or interlinking of loops of one set of yarn. Knitted fabrics are very popular and produced from yarn. Different types of yarn which are used for fabric production are assumed as the raw material for our study. We have selected Aboni Knit Wear Ltd, Bangladesh to identify supplier selection process. The data for this study was collected from historical information of Aboni Knit Wear Ltd on yarn purchases and deliveries from different suppliers in the fabric yarn knitting supply chain spanning from December 2021 to February 2023. The data sources included purchase records and invoices from the company`s internal records kept as yarn pipeline status.

In the expansive fabric supply chain network, comprising 35 diverse suppliers involved in the knitting process, a strategic decision was made to focus our analysis on a subset of suppliers for a more targeted examination. Seven suppliers were selected based on their substantial contributions, collectively representing the largest portion within the total yarn supply chain network. The selected yarn suppliers, referred to as Supplier 1, Supplier 2, Supplier 3, Supplier 4, Supplier 5, Supplier 6, and Supplier 7, play a crucial role in the yarn supply chain. The anonymized references (Supplier 1 through Supplier 7) allow for a comprehensive evaluation of the supply chain dynamics while maintaining confidentiality regarding the specific identities.

In the context of our study, where yarn prices exhibit variation across different types, the determination of raw material costs necessitates a meticulous consideration of the yarn procurement timeline. We have identified distinct types of yarn, each associated with specific booking placement times. In the intricate web of our supply chain network, yarn suppliers communicate the commencement and conclusion of yarn in-house periods based on the Time and Action (TNA) plans proposed by our customers. For this analysis, the availability of raw materials is derived from the actual yarn in-house date and the yarn in-house commitment date. It is noteworthy that manufacturers formulate their production plans in alignment with the yarn in-house commitment date, which serves as a critical parameter in the Time and Action plan. However, our observations reveal a nuanced aspect of the process — a slight variation that occasionally exists between the yarn commitment time and the actual yarn in-house date across different suppliers. This variation can be attributed to a multitude of reasons. To quantify the total raw material cost, we meticulously calculate the quantity and types of yarn punches from suppliers. This approach not only captures the diversity in yarn types but also accounts for the temporal dynamics in the yarn supply chain, offering a comprehensive understanding of the raw material cost landscape within our manufacturing framework. To streamline the analysis and mitigate the complexities associated with the dynamic nature of yarn prices, a fixed yarn price was selected as of January 2023. This decision provides a stable reference point for the duration of our study and facilitates a more focused examination of supplier selection. By adopting this approach, we aim to isolate the impact of lead time, cost and order quantity without being influenced by the day-to-day fluctuations in the yarn market. In our cost analysis, transportation expenses are crucial, and intricately tied to supplier locations. Calculating transportation costs involves factoring in the distance from each supplier to our manufacturing facilities. Acknowledging the profound impact of logistics on the supply chain, we use geographical distance as a fundamental component in our cost model.

4.1 Data Pre-Processing

The data preprocessing phase was a crucial step in ensuring the reliability and consistency of the collected information for the yarn supply chain analysis. To enhance the quality of the data, an initial step involved filtering and organizing the information using Excel. This process aimed to eliminate any redundancies and ensure that the dataset was focused on relevant and distinct yarn supplier details. Subsequently, the data underwent a meticulous cleaning process within the Excel environment. This involved the identification and removal of duplicate entries to prevent the skewing of results. Additionally, errors within the dataset, such as inaccuracies in dates or inconsistent formats, were rectified to maintain the accuracy of the information. Standardizing data formats was another integral aspect of the preprocessing phase. This step aimed to create a uniform structure for the dataset, facilitating a seamless analysis and interpretation of the collected information. By systematically addressing inconsistencies and discrepancies, the data preprocessing phase laid the foundation for robust and reliable analytical outcomes in the subsequent stages of the yarn supply chain analysis.

Table 1. Pre-processed data

DMU	Input			Output
	Raw material cost	Transportation cost	Lead time	profit
Supplier 1	3683	2150	5	100
Supplier 2	2828	3135	6	100
Supplier 3	3588	7500	5	100
Supplier 4	3622	2915	1	100
Supplier 5	4189	8500	1	100
Supplier 6	3075	1390	2	100
Supplier 7	3994	2570	4	100

6. Analysis and Results

The DEA analysis is performed in multiple phases: problem formulation phase and MISO model analysis. Table-1 displays the data for each subject as well as the input and output of the DEA model.

6.1 Multiple Input Single Output Model Analysis

Multiple Input Single Output (MISO) model is a type of DEA model that measures the relative efficiency of DMUs with respect to multiple inputs and single output. In the MISO model, each DMU takes multiple input and produces an output. The goal of the model is to find the weights of the inputs that maximize the efficiency of each DMU while keeping the output constant. The efficiency of a DMU is calculated as the ratio of its weighted sum of inputs to the weighted sum of outputs of the most efficient DMU in the sample.

6.2 Raw Material & Transportation Cost

For multiple-input- single-output (MISO) model analysis takes raw material cost and transportation cost as input and profit as output for the left side. As a result, the linear programming model for the first DMU's (subject) on input efficiency is, by applying the data of Table 2 in equations 1, 2, 3, and 4.

Table 2. Multiple-input- single-output DEA model (Raw material cost & Transportation cost)

DMU	INPUT		OUTPUT
	Raw material cost	Transportation cost	Profit
DMU 1	3683	2150	100
DMU 2	2828	3135	100
DMU 3	3588	7500	100
DMU 4	3622	2915	100
DMU 5	4189	8500	100
DMU 6	3075	1390	100
DMU 7	3994	2570	100

Objective function, $min\, z = 3683 * \lambda_1 + 2150 * \lambda_2 + 0 * \lambda_3$

Subject to,

$$\begin{gathered}
-3683\lambda_1 - 2150\lambda_2 + 100\lambda_3 \leq 0 \\
-2828\lambda_1 - 3135\lambda_2 + 100\lambda_3 \leq 0 \\
-3588\lambda_1 - 7500\lambda_2 + 100\lambda_3 \leq 0 \\
-3622\lambda_1 - 2915\lambda_2 + 100\lambda_3 \leq 0 \\
-4189\lambda_1 - 8500\lambda_2 + 100\lambda_3 \leq 0 \\
-3075\lambda_1 - 1390\lambda_2 + 100\lambda_3 \leq 0 \\
-3994\lambda_1 - 2570\lambda_2 + 100\lambda_3 \leq 0 \\
0 * \lambda_1 + 0 * \lambda_2 + 100 * \lambda_3 = 1 \\
\lambda_1, \lambda_{2,} \lambda_3 \geq 0
\end{gathered}$$

Results from the DEA model, using MATLAB and the fmincon function, indicate that DMU-1 operates at 82.05% efficiency compared to the most efficient DMU while keeping its output constant. Individual efficiencies for each DMU were obtained through separate goal functions and constraints, with efficiencies ranging from 67% to 100% shown in Table 3. DMUs with efficiencies of 100% are considered to be efficient and operate at the minimum possible level given their inputs and outputs. Suppliers who provide materials with low cost and has lower transportation cost tend to be more efficient.2nd, and 6th subjects are the efficient shown in Table 3. The remaining DMUs are operating at varying levels of efficiency compared to the most efficient DMUs.

Table 3. Efficiency of DMUs

DMU	1	2	3	4	5	6	7
Efficiency (%)	82.05	100	78.82	81.09	67.51	100	75.08

Plotting data from Table 2 onto Figure 2 reveals DMUs 2 and 6 as outperformers in terms of raw material and transportation costs. Connecting data points with a convex curve forms the efficient frontier (green curve), designating DMUs on it as 100% efficient. Those outside the frontier are inefficient. The graph highlights potential role models (red curve) for inefficient DMUs, offering insights to improve profitability. This visual representation simplifies identification of optimization areas and emulation of best practices for enhanced performance.

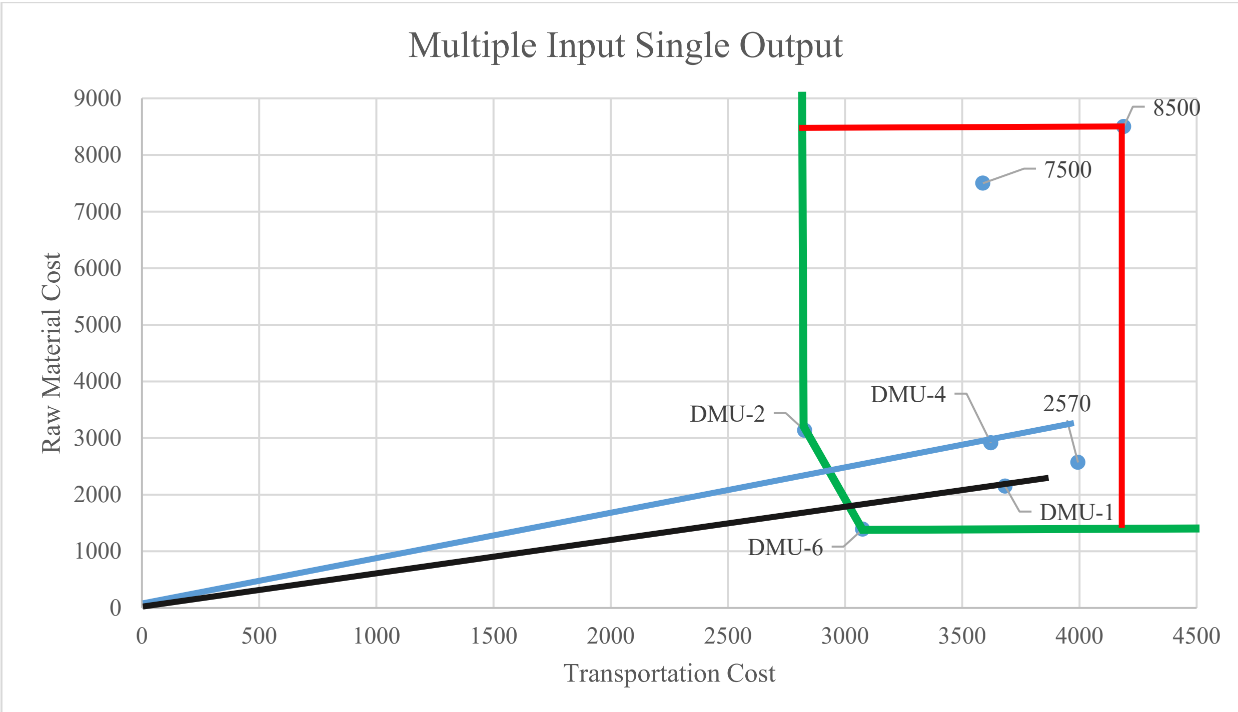

Figure 2. Raw material cost vs Transportation cost

From Figure 2, if we draw a straight line from the basepoint through the DMU-04 we can see that intersect the efficient frontiers convex curve at a specific point, and from that point of intersection, we can say that DMU-02 and DMU-06 are close to DMU-04. But as the DMU-02 is the closest one, this is the role model for DMU-04. Similarly, for DMU-01, DMU-04 is the role model. By drawing a straight line through all other DMUs we can conclude which efficient DMU is the role model for which inefficient DMU.

6.3 Raw Material Cost & Lead Time

Multiple Input Single Output (MISO) model analysis takes trail number as input and elbow joint angle & EMG value of the biceps muscle group as output for the right side. As a result, the linear programming model for the first DMU's (subject) on output efficiency is, by applying the data of Table 4 in equations 1, 2, 3, and 4.

Table 4. multiple-input- single-output DEA model (Raw material cost & lead time)

DMU	Input		Output
	Raw material cost	Lead time	Profit
DMU 1	3683	5	100
DMU 2	2828	6	100
DMU 3	3588	5	100
DMU 4	3622	1	100
DMU 5	4189	1	100
DMU 6	3075	2	100
DMU 7	3994	4	100

Objective function, $min\ z = 3683 * \lambda_1 + 5 * \lambda_2 + 0 * \lambda_3$

Subject to,

$$\begin{gathered}
-3683\lambda_1 - 5\lambda_2 + 100\lambda_3 \leq 0 \\
-2828\lambda_1 - 6\lambda_2 + 100\lambda_3 \leq 0 \\
-3588\lambda_1 - 5\lambda_2 + 100\lambda_3 \leq 0 \\
-3622\lambda_1 - 1\lambda_2 + 100\lambda_3 \leq 0 \\
-4189\lambda_1 - 1\lambda_2 + 100\lambda_3 \leq 0 \\
-3075\lambda_1 - 2\lambda_2 + 100\lambda_3 \leq 0 \\
-3994\lambda_1 - 4\lambda_2 + 100\lambda_3 \leq 0 \\
0 * \lambda_1 + 0 * \lambda_2 + 100 * \lambda_3 = 1 \\
\lambda_1, \lambda_2, \lambda_3 \geq 0
\end{gathered}$$

DEA can evaluate DMUs, and applying DEA equations in MATLAB with the fmincon function allows for efficiency determination. DMUs in this case had efficiencies ranging from 75% to 100%, with DMUs 2, 4, 5, and 6 being most efficient at 100%. DMU-1 was 80.11% efficient, and the remaining DMUs had efficiencies ranging from 75.42% to 82.06% shown in Table 5.

Table 5. Efficiency of DMUs

DMU	1	2	3	4	5	6	7
Efficiency (%)	80.12	100	82.06	100	100	100	75.42

Plotting data of Table 4 onto Figure 3 reveals that DMUs 2, 4, 5, and 6 outperform others in providing raw materials at lower costs and shorter lead times. This set of data points forms the green curve, known as the efficient frontier. DMUs on this curve are considered 100% efficient, while those above it are deemed inefficient. DMU-02 is identified as the closest role model for DMU-03, offering insights for enhanced efficiency. The graph, depicting efficient and inefficient frontiers, aids in discerning performance levels and identifying areas for improvement.

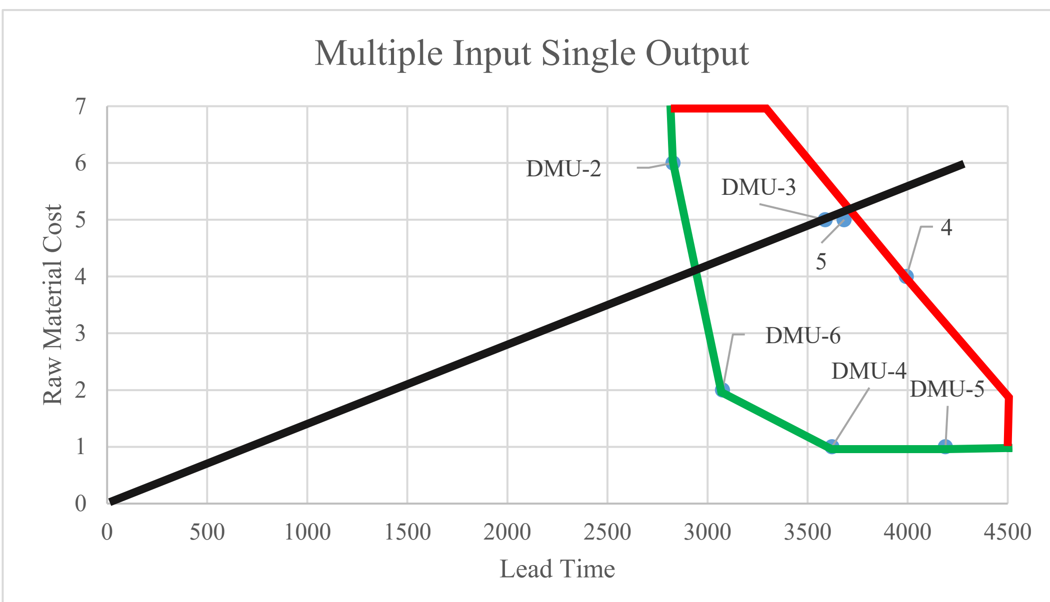

Figure 3. Raw Material Cost vs Lead Time

By altering the output, we can identify the efficient and non-efficient frontiers in every case of such as Transportation cost & lead time as input, transportation cost, raw material cost & lead time as input. This process remains consistent for all input and output levels. All inefficient suppliers from MISO model company may understand how to become more profitable from the efficient supplier and what to do for reducing transportation cost, raw material cost and lead time. By selecting better industry can improve their efficiency, reduce the risk loss, and increase profit.

7. Conclusion

Data Envelopment Analysis (DEA), a liner programming technique or methodology is used to measure efficiency and evaluate the performance of Decision Making Unites (DMU). This is the most popular method for estimating the frontier for assessment of efficiency. DEA may categorize yarn suppliers into effective frontiers and average frontiers, as well as identify role models. All effective frontiers result in a convex curve, while ineffective DMU`s lie inside the curve. Other Supplier can find their role models by determining the shortest distance from these effective frontiers. The frontiers that are less effective can understand the reasons why this is happening and how to become more effective. In addition to this, the management team can learn which supplier to prioritize over others while making cost effective decisions. As a result, this research is aimed at demonstrating the application of DEA through study, showcasing its potential to aid businesses in making well-informed and efficient supplier decisions.

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