



Supplier Congestion Identification and Assessment via a Slack-Based-Measure of DEA (A Case Study)

Maedeh GholamAzad^{1*}, Alireza Eydi²

¹ Post-Doctoral Researcher, Department of Industrial Engineering, University of Kurdistan, Sanandaj, Iran

² Professor, Department of Industrial Engineering, University of Kurdistan, Sanandaj, Iran

Abstract

Supplier selection significantly impacts supply chain cost, reliability, and sustainability. This study uses Slack-Based Measure (SBM) Data Envelopment Analysis (DEA) to identify and evaluate supplier congestion in a cosmetic supply chain, which negatively impacts cost, reliability, and sustainability. The SBM-DEA model assesses suppliers based on input excesses and output shortfalls, distinguishing between efficient, inefficient, and congested suppliers—a state where increased inputs lead to decreased outputs. A case study evaluating 10 suppliers across 9 criteria identified resource congestion in one supplier due to overutilization. Of the suppliers studied, 4 were efficient, and 6 were inefficient. This framework offers practical insights for optimizing supplier selection and resource allocation to improve supply chain efficiency, reduce costs, and enhance performance. The findings underscore the importance of congestion analysis in supplier evaluation, enabling data-driven decision-making and providing theoretical and practical contributions to supply chain management by helping procurement managers address supplier inefficiencies.

Keywords: Supplier selection; SBM-DEA; Congestion; Efficiency.

1. Introduction

Supplier selection, a critical aspect of supply chain management, involves choosing suppliers for necessary goods and services and significantly impacts an organization's costs, quality, and overall performance [1]. Supplier selection research utilizes various methods, including MCDM, mathematical modeling such as DEA, and machine learning [1, 13, 14]. Each supplier selection method has pros and cons, and DEA is a widely used method in supply chain and supplier selection due to its ability to evaluate the relative efficiency of similar decision-making units (DMUs). Originally introduced by Charnes et al. (1978) with the CCR model [2], DEA has been extended by numerous models, including the SBM [3]. Unlike radial DEA models that assume proportional input and output changes, SBM is a non-radial approach that directly addresses input excesses and output shortfalls to identify inefficiencies without requiring proportional adjustments [3].

A DMU is considered congested when increasing an input led to decreased output, indicating inefficiency. Congestion arises from various factors, including overutilization of inputs, poor management or coordination, capacity constraints, improper input mix, and external factors. In DEA, congestion signifies that a DMU is not operating at its optimal scale [4]. In the context of supplier selection, congestion occurs when increasing inputs (e.g., cost, lead time, labor) results in no improvement or even a decline in outputs (e.g., quality, delivery performance, customer satisfaction). Identifying and understanding the causes of congestion provides valuable insights for enhancing efficiency and resource allocation [14]. For this purpose, this study evaluates the impact of congestion on supplier selection. First, the SBM model is applied to all suppliers (DMUs). Inefficient DMUs (those consuming excess input resources) are then identified, and their surplus rate is removed before re-running the SBM model. A DMU efficient after this process is deemed congested, implying congestion caused its initial inefficiency. Conversely, a DMU remaining inefficient is considered technically inefficient, indicating no congestion. This process was applied to a cosmetic supply chain with 10 suppliers, using 9 criteria including price, lead time, manufacturing cost, defect rate, shipping cost, availability, products sold, revenue generated, and customer reach. Results revealed congestion in some DMUs, suggesting they should optimize resource consumption to enhance efficiency.

Evaluating supplier congestion using the SBM significantly contributes to supplier selection and supply chain optimization. These contributions can be categorized into theoretical, methodological, and practical implications:

* Corresponding Author ISSN: 1735-8272, Copyright © 2025 JISE. All rights reserved

1. Theoretical Contributions:

- ✓ Extends DEA for supplier evaluation by incorporating SBM-based congestion analysis, providing a more comprehensive efficiency assessment than traditional DEA models which often overlook congestion.
- ✓ Introduces congestion as a KPI in supplier evaluation, allowing for the identification of efficient, inefficient, and congested suppliers and assessment of waste due to excess inputs.
- ✓ Advances understanding of inefficiencies by employing the SBM model to simultaneously analyze input slacks and output shortfalls, offering a non-radial and unit-invariant efficiency measurement for more accurate supplier analysis.

2. Methodological Contributions:

- ✓ Enhanced Supplier Efficiency Assessment: SBM-DEA, unlike CCR and BCC, directly incorporates input/output slacks, improving congestion detection and providing superior supplier discrimination compared to traditional DEA.
- ✓ Quantitative Framework for Congestion Analysis: This study develops a structured framework for evaluating supplier congestion across industries, enabling ranking based on congestion levels and potential efficiency gains.
- ✓ Data-Driven Decision-Making: SBM identifies specific input reductions or output enhancements needed for efficiency, empowering procurement managers to make informed decisions and suggest targeted corrective actions for underperforming suppliers.

3. Practical Contributions:

- ✓ Improves Supplier Selection: Reduces reliance on congested suppliers, leading to cost savings, lower emissions, and efficient resource allocation.
- ✓ Facilitates Supplier Improvement: Offers insights for optimizing supplier processes (e.g., logistics, production, waste reduction) instead of immediate removal. Companies can leverage SBM results to help suppliers improve.

This article is structured as follows: Section 2 details the methodology and calculations, Section 3 presents the case study, and Section 4 concludes.

1.1. Literature review

Shabanpour et al. (2019) introduced a DEA model for identifying input congestion in DMUs. Developed to assess supplier sustainability, the model detects congestion between DMU pairs. An application at Samane Andishmand Pegah (SAP) demonstrated the model's ability to identify congestion and suggest improvements for suppliers [6]. Mehdiloo et al. (2020) developed a production technology, imposing no input disposability, and defined weak and strong congestion measures. Based on their theoretical findings, they developed three algorithms to test congestion in observed DMU samples. Four numerical examples demonstrate these algorithms' superiority over existing congestion identification methods [7]. Ren et al. (2021) reviewed six DEA methods for identifying and evaluating congestion, examining their underlying principles, contributions over previous approaches, and limitations. Their review concluded that current congestion identification and measurement methods remain insufficient [8]. Shadab et al. (2021) introduced a network DEA model to assess congestion in two-stage sustainable supply chains, considering the role of intermediate products. Applying this model to 20 Iranian resin manufacturing companies, they found that companies 1, 2, 8, 14, and 15 were inefficient, while the remainder were strongly efficient [9]. Moosavi and Bagherzadeh (2022) presented novel insights into congestion and non-congestion areas in production technology, along with two mathematical definitions of congestion based on PPS properties. These definitions enable the detection of weak and strong congestion statuses of DMUs, and are applicable to both non-negative and negative data. Their method's reliability was demonstrated in the Chinese textile and auto industries, with results indicating superior accuracy [10]. Saati and Shadab (2023) introduced a linear programming model to identify congested, highly efficient supply chains based on the role of intermediate products. The model, which features scenario-specific variations for detecting strong and weak congestion, was tested on 15 Iranian cement factory supply chains to assess its effectiveness in identifying congestion [11]. Saati et al. (2024) built upon Shadab et al. (2021) to create a fuzzy DEA model for congestion detection, applying it to 15 Tehran hospitals with imprecise data. Their results indicated that 39.9% of the hospitals exhibited congestion, and they quantified the impact of this congestion on performance improvement [12]. Lin and Lu (2024) optimized Apple supplier performance

using a novel framework combining inverse DEA (IDEA) and machine learning. They applied IDEA to recalibrate operational benchmarks for significant CO₂ reduction and used random forest and k-Nearest neighbors' algorithms to predictively guide supplier practices towards Apple's sustainability goals. By distilling unbiased insights from historical data, their methodology provides precise, objective supplier assessments, offering a strategic blueprint for data-driven sustainability implementation in corporate supply chains [13]. Bazyar et al. (2025) introduced a novel DEA model to identify and evaluate congestion, including weak congestion, in sustainable supply chains with undesirable outputs. Applying it to the Iranian water and wastewater industry, they found 4 of 21 suppliers to be congested, offering empirically-based insights for improving efficiency [14]. Tronnebati et al. (2025) presented a comprehensive DEA-based method for evaluating and selecting environmentally sustainable suppliers in the automotive industry. Case studies demonstrate the model's effectiveness in identifying suppliers who meet operational standards and excel in sustainability, underscoring the importance of integrating environmental considerations into supplier selection for automakers seeking to enhance green procurement [15].

2. Methodology

The slacks-based approach, measuring performance using slacks rather than radial distances from the origin, is non-radial. While existing in various forms, it is commonly referred to as a slacks-based measure (SBM) model following Tone (2001) [3]. Consider a set of n DMUs, where each DMU_j utilizes m inputs ($X_{ij}, i = 1, \dots, m$) to produce s outputs ($Y_{rj}, r = 1, \dots, s$). The SBM model can be mathematically expressed as [3]:

$$\begin{aligned} \min \quad Z &= \frac{1 - \frac{1}{m} \sum_{i=1}^m s_i^- / X_{io}}{1 + \frac{1}{s} \sum_{r=1}^s s_r^+ / Y_{ro}} \\ \text{s.t.} \quad &\sum_{i=1}^m \lambda_j X_{ij} + s_i^- = X_{io}, \quad i = 1, \dots, m \\ &\sum_{r=1}^s \lambda_j Y_{rj} - s_r^+ = Y_{ro}, \quad r = 1, \dots, s \\ &\lambda_j, s_i^-, s_r^+ \geq 0, \quad j = 1, \dots, n, \quad i = 1, \dots, m, \quad r = 1, \dots, s. \end{aligned} \quad (1)$$

Where s_i^- and s_r^+ be input and output slacks, respectively, for the evaluated DMU_o . DMU_o is efficient (on the DEA frontier) if and only if $s_i^- = s_r^+ = 0$ at optimality; otherwise, it is inefficient, possibly due to congestion. Congestion occurs when excessive variable input relative to fixed input diminishes output. Ignoring this effect understates the true efficiency of DMUs in this region [4]. Different models can be used to evaluate the congestion. One of these approaches for measuring the effect of congestion, proposed by Cooper et al. (1996) [5], is to separate the input slack into those due to weak efficiency and congestion in an additive form. For this purpose, let λ_j^* be the optimal solution, then the projection point is:

$$\hat{X}_{io} = \sum_{i=1}^m \lambda_j^* X_{ij}, \quad i = 1, \dots, m; \quad \hat{Y}_{ro} = \sum_{r=1}^s \lambda_j^* Y_{rj}, \quad r = 1, \dots, s \quad (2)$$

The input slack, $s_i^{-*} = X_{io} - \hat{X}_{io}$, reflects the combined effect of weak inefficiency and congestion. By fixing outputs at their projected values, the maximum total input slack quantifies the difference between weak and strong efficiency. Congestion is calculated using the following mathematical model [5]:

$$\begin{aligned} \max \quad &\sum_{i=1}^m \delta_i^- \\ \text{s.t.} \quad &\sum_{i=1}^m \lambda_j X_{ij} - \delta_i^- = \hat{X}_{io}, \quad i = 1, \dots, m \\ &\sum_{r=1}^s \lambda_j Y_{rj} = \hat{Y}_{ro}, \quad r = 1, \dots, s \\ &\sum_{j=1}^n \lambda_j = 1, \\ &\delta_i^- \leq s_i^{-*}, \quad i = 1, \dots, m \\ &\delta_i^-, \lambda_j \geq 0, \quad j = 1, \dots, n, \quad i = 1, \dots, m. \end{aligned} \quad (3)$$

The aggregate slack s_i^{-*} minus the slack associated with weak efficiency δ_i^{-*} is the slack associated with congestion, $s_i^c = s_i^{-*} - \delta_i^{-*}$.

2.1. Supplier congestion assessment

This section presents the proposed algorithm for identifying and evaluating supplier congestion.

Step 1. Identify Efficient and Inefficient Suppliers using DEA

- ✓ Rank suppliers by efficiency scores using an SBM-DEA model.
- ✓ Determine input slacks (excess inputs).

Step 2. Identify Congested Suppliers

Employ a two-stage DEA approach:

1. Initial SBM-DEA. Calculate efficiency using actual data.
2. Second SBM-DEA. Minimize inputs while maintaining constant outputs.
3. Assess congestion.
 - ✓ If efficiency increases after reducing inputs, congestion exists.
 - ✓ If efficiency remains the same, there is no congestion.

Step 3. Remove Congested Suppliers

- ✓ Congested Suppliers: These suppliers waste resources, making them less desirable.
- ✓ Non-Congested & Efficient Suppliers: These are the best choices for selection.

Step 4. Rank Suppliers Based on Congestion-Adjusted DEA Scores

- ✓ Suppliers with high congestion (excess input usage) should be reconsidered.
- ✓ Suppliers with low congestion and high efficiency are the best choices.

Figure 1 schematically illustrates the proposed algorithm.

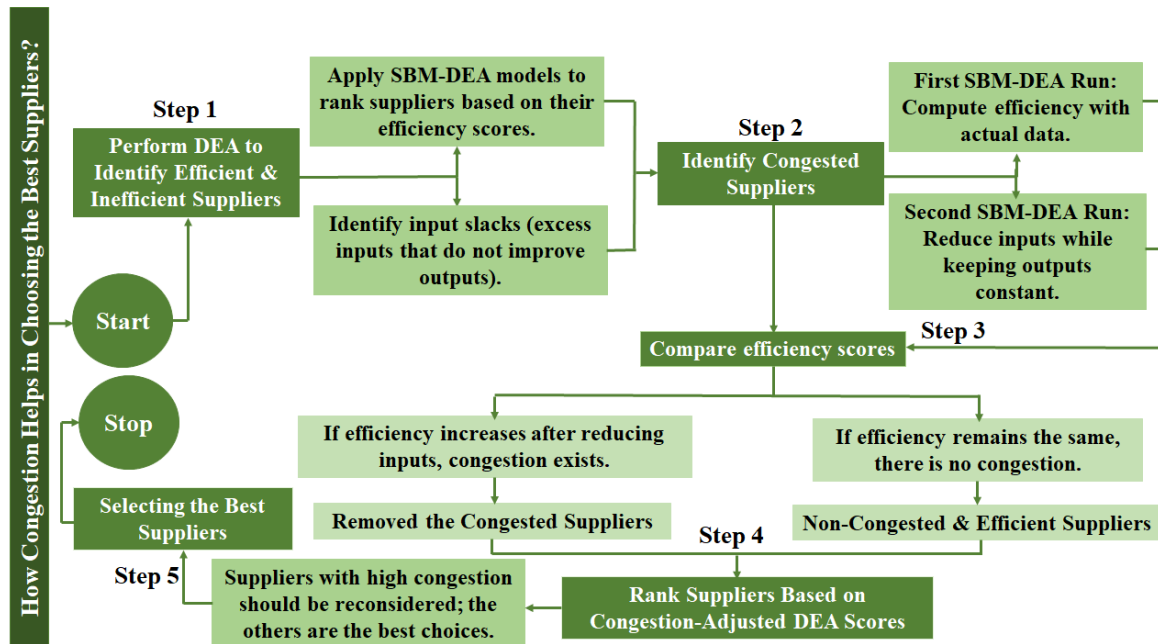


Fig. 1. Supplier congestion assessment algorithm schematic

3. Case Study

The cosmetic supply chain refers to the end-to-end process of producing, distributing, and delivering cosmetic products to consumers. It involves multiple stages, from sourcing raw materials to manufacturing, packaging, distribution, and retail. The cosmetic industry is highly competitive, and successful cosmetics supply chain management necessitates strategic collaboration with suppliers, manufacturers, distributors, and retailers to ensure product quality,

meet consumer demand, and maintain profitability. Cosmetic supply chains depend significantly on suppliers of raw materials, packaging, and machinery. Selecting efficient suppliers is vital for optimizing the overall supply chain. For this purpose, this study examines supplier congestion in a major Iranian cosmetic supply chain involving ten key suppliers. Figure 2 provides a schematic overview of the chain.



Fig. 2. The cosmetic supply chain process

Table 1 presents the key criteria for assessing supplier congestion within this chain.

Table 1. The main criteria and their notations

	Criteria	Notation		Criteria	Notation
1	Price (USD)	x_1	2	Lead time (days)	x_2
3	Manufacturing cost (USD)	x_3	4	Defect rate (%)	x_4
5	Shipping cost (USD)	x_5	6	Availability (%)	y_1
7	Number of product sold	y_2	8	Revenue generated (USD)	y_3
9	Customers reach	y_4			

First, we categorize the criteria as either input and output parameters for the SBM-DEA model. Table 2 indicates inputs with ($x_i, i = 1,2,3,4,5$) and outputs with ($y_r, r = 1,2,3,4$).

Table 2. The inputs and outputs parameters

Suppliers	x_1	x_2	x_3	x_4	x_5	y_1	y_2	y_3	y_4
S1	50	5	200	3	30	95	5000	100000	10000
S2	55	7	220	4.2	40	92	4500	90000	9000
S3	45	6	180	2.5	35	97	5300	110000	11000
S4	60	8	250	5	50	90	4000	80000	8000
S5	48	4	190	3.2	25	96	5200	105000	10500
S6	53	6	210	3.8	38	93	4700	95000	9500
S7	47	5	195	2.8	28	94	5100	102000	10200
S8	52	7	230	4	42	91	4300	87000	8700
S9	49	4	185	3.1	27	95	5250	107000	10700
S10	58	9	240	5.5	55	89	3900	78000	7800

We execute the proposed algorithm step-by-step using the information in Table 2.

Step1. First, the SBM-DEA model identifies efficient and inefficient suppliers. These suppliers are then ranked by efficiency scores, separating inefficient suppliers from efficient ones. Finally, the excess inputs of the inefficient suppliers are determined. Table 3 displays these results.

Table 3. The results of the SBM-DEA model

Suppliers	z	s_{i1}	s_{i2}	s_{i3}	s_{i4}	s_{i5}	s_{r1}	s_{r2}	s_{r3}	s_{r4}	Reference set
S1	0.89	1.67	0.67	15.83	0.00	1.67	0.33	258.33	750.00	750.00	s_3, s_9
S2	0.65	6.00	3.00	35.00	1.10	13.00	3.00	750.00	17000.00	1700.00	s_9
S3	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	s_3
S4	0.51	11.00	4.00	65.00	1.90	23.00	5.00	1250.00	27000.00	2700.00	s_9
S5	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	s_5
S6	0.73	4.00	2.00	25.00	0.70	11.00	2.00	550.00	12000.00	1200.00	s_9
S7	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	s_7
S8	0.63	3.00	3.00	45.00	0.90	15.00	4.00	950.00	20000.00	2000.00	s_9
S9	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	s_9
S10	0.48	9.00	5.00	55.00	2.40	28.00	6.00	1350.00	29000.00	2900.00	s_9

Table 3's second column presents the efficiency scores of 10 suppliers. Columns 3-7 display input surplus slacks (excess inputs), while columns 8-11 show output shortage slacks. The final column indicates the reference set for each supplier, suggesting pathways to improvement based on benchmark suppliers. Table 3 reveals that 4 of the 10 suppliers

(S3, S5, S7, and S9) are efficient, exhibiting zero shortage and surplus slacks. The inefficiency of the remaining suppliers requires further investigation to determine if it stems from congestion or technical factors.

Step 2. Following the initial step, the first sub-level is executed (Table 3). The second sub-level is then applied to one inefficient supplier (S1, in this case, with the process being similar for others). This involves removing S1's inputs ($s_{i1} - s_{i5}$) while keeping its outputs constant, and then rerunning the SBM-DEA model. The resulting efficiency score of one for S1 (without affecting other suppliers' efficiency) indicates congestion, as shown in Table 4. Consequently, S1 would become efficient if outputs ($s_{r1} - s_{r4}$) were increased to accommodate the excess inputs ($s_{i1} - s_{i5}$). This interpretation applies to all inefficient suppliers.

S1 calculations:

Supplier	x_1	x_2	x_3	x_4	x_5	y_1	y_2	y_3	y_4
S1	48.33	4.33	184.17	3	28.33	95	5000	100000	10000

Table 4. SBM-DEA model results after congestion evaluation

Suppliers	z	s_{i1}	s_{i2}	s_{i3}	s_{i4}	s_{i5}	s_{r1}	s_{r2}	s_{r3}	s_{r4}	Reference set	Ranks
S1	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	s_1	7
S2	0.87	0.00	0.00	0.00	0.00	0.00	3.00	750.00	17000.00	1700.00	s_9	3
S3	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	s_3	1
S4	0.79	0.00	0.00	0.00	0.00	0.00	5.00	1250.00	27000.00	2700.00	s_9	5
S5	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	s_5	1
S6	0.91	0.00	0.00	0.00	0.00	0.00	2.00	550.00	12000.00	1200.00	s_9	2
S7	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	s_7	1
S8	0.85	0.00	0.00	0.00	0.00	0.00	4.00	950.00	20000.00	2000.00	s_9	4
S9	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	s_9	1
S10	0.78	0.00	0.00	0.00	0.00	0.00	6.00	1350.00	29000.00	2900.00	s_9	6

Step 3. Eliminating excess inputs, as shown in Table 4, reveals that only supplier 1 achieves full efficiency, indicating it suffered from congestion. The other suppliers improve but remain inefficient, suggesting technical inefficiencies. Consequently, supplier 1 is an undesirable choice for the SCM due to resource wastage, while efficient suppliers are the preferred alternative.

Step 4. Rank suppliers by congestion-adjusted SBM-DEA scores, prioritizing efficient suppliers with low congestion (as shown in Table 4). Reconsider suppliers with high congestion (excess input usage).

4. Conclusion

The best supplier selection identification involves a comprehensive evaluation of suppliers based on efficiency, resource utilization, and performance metrics. This study highlights the use of the SBM-DEA model as an effective tool for identifying the best suppliers. For this purpose, 4 key steps were presented, including: identify efficient and inefficient suppliers using SBM-DEA, identify congested suppliers, remove congested suppliers, and rank suppliers based on congestion-adjusted SBM-DEA scores.

The validity of the proposed algorithm was tested in the cosmetic supply chain with 10 suppliers and 9 criteria, and suppliers S3, S5, S7, and S9 were identified as the best choices due to their high efficiency and absence of congestion. These suppliers effectively utilize resources, minimize waste, and maximize outputs such as availability, number of products sold, generated revenue, and customers' reach. The results showed that the proposed methodology not only identifies congestion but also offers actionable insights for optimizing resource allocation and improving supplier selection processes. These findings have important theoretical, methodological, and practical implications, enabling companies to enhance supply chain efficiency, reduce costs, and make data-driven decisions. By addressing congestion, organizations can foster better collaboration with suppliers, improve operational performance, and achieve sustainable supply chain management. Future research could extend this approach to other industries and explore additional factors influencing supplier congestion.

References

[1] Gidiagba, J., Tartibu, L., & Okwu, M. (2023). Sustainable supplier selection in the oil and gas industry: An integrated multi-criteria decision making approach. *Procedia Computer Science*, 217, 1243-1255

- [2] Charnes, A., Cooper, W. W., & Rhodes, E., (1978). Measuring the efficiency of decision making units. *European journal of operational research*, 2(6), 429-444
- [3] Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, 130, 498–509
- [4] Kao, C., (2010). Congestion measurement and elimination under the framework of DEA. *Int J Prod Econ*, 123, 257-265
- [5] Cooper, W. W., Thompson, R. G., Thrall, R. M. (1996). Introduction: extension and new developments in DEA. *Annals of Operations Research*, 66, 3–45
- [6] Shabanpour, H., Fathi, A., Yousefi, S., & Farzipoor Saen, R. (2019). Ranking sustainable suppliers using the congestion approach of data envelopment analysis. *Journal of Cleaner Production*, 240, 118190
- [7] Mehdiloo, M., Sahoo, B.K., Zhu, J. (2020). Identification of Congestion in DEA. *International Series in Operations Research & Management Science*, 290. https://doi.org/10.1007/978-3-030-43384-0_4
- [8] Ren, X., Jiang, Ch., Khoveyni, M., Cheng, Z., & Yang, G. (2021). A review of DEA methods to identify and measure congestion. *Journal of Management Science and Engineering*, 6(4), 345-362
- [9] Shadab, M., Saati, S., Farzipoor Saen, R., Khoveyni, M., & Mostafae, A. (2021). Measuring congestion in sustainable supply chain based on data envelopment analysis. *Neural Computing and Applications*, 33, 12477–12491
- [10] Moosavi, S. R., & Bagherzadeh Valami, H. (2022). Congestion and non-congestion areas: identify and measure congestion in DEA. *RAIRO - Operations Research*, 56(4), 2067–2092
- [11] Saati, S., & Shadab, M. (2023). Exploring congestion in intermediate products by DEA: an application on Iranian cement supply chain. *Operational Research*, 23, 60
- [12] Saati, S., Shadab, M., Mohamadniaahmadi, S. (2024). Exploring Congestion in Fuzzy DEA by Solving One Model; Case Study: Hospitals in Tehran. *Decision Making in Healthcare Systems. Studies in Systems, Decision and Control*, 513, 355–372. https://doi.org/10.1007/978-3-031-46735-6_15
- [13] Lin, S. W., & Lu, W. M. (2024). Using inverse DEA and machine learning algorithms to evaluate and predict suppliers' performance in the apple supply chain. *International Journal of Production Economics*, 21, 109203
- [14] Bazyar, A., Ebrahimi, F., & Karimi. (2025). Determining the congestion with undesirable outputs of sustainable suppliers using data envelopment analysis. *OPSEARCH*. <https://doi.org/10.1007/s12597-025-00918-w>
- [15] Tronnebati, I., Jawab, F., & Arif, J. (2025). Innovative Practices for Eco-Friendly Suppliers in the Automotive Industry: Strategies for Sustainable Supply Chains Using DEA Model. *Eco-Logistics and Sustainable Supply Chain Innovations*, 32. DOI: 10.4018/979-8-3693-6175-7.ch018