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Efficiency Analysis of Commercial Bank Branches Using a Common Set of Weights in DEA

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Abstract

This study investigates the operational efficiency of 375 commercial bank branches during the fiscal year 2017 by employing advanced Data Envelopment Analysis (DEA) methodologies. Each branch is considered a Decision Making Unit (DMU) consuming multiple inputs to generate outputs. To address the multi-dimensional nature of performance evaluation, both the lexicographic method and a weighted linearized approximation of the Common Set of Weights (CSW) DEA model are applied. The lexicographic approach prioritizes objectives sequentially, reflecting decision-makers' preferences, while the weighted linearized model allows simultaneous consideration of all objectives with adjustable importance weights. The weighted model mitigates computational and feasibility challenges inherent in the lexicographic approach, enabling efficient analysis of large-scale data. The results provide valuable insights into relative branch efficiency, identify best-performing units, and offer a practical framework for resource allocation and performance improvement in the banking sector.

Keywords: Data envelopment analysis, Common set of weights, Bank branch performance.

1 | Introduction

Over the past few decades, the banking industry has faced growing demands for transparency, efficiency, and accountability. In response, performance evaluation tools have become increasingly vital for regulators, stakeholders, and policymakers. Among these, Data Envelopment Analysis (DEA) has emerged as one of the most widely applied non-parametric methods for measuring the relative efficiency of Decision Making Units (DMUs), especially in financial institutions such as banks. Its ability to handle multiple inputs and outputs without requiring a predefined functional form makes it especially suitable for complex environments like the banking sector.

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Despite its strengths, a major limitation of classical DEA models lies in their flexibility in weight selection. Each DMU is allowed to choose a set of input and output weights that maximizes its efficiency score. While this approach ensures each unit is evaluated in the most favorable light, it also reduces the comparability and discriminatory power of the results. In particular, several units may appear equally efficient, making it difficult to distinguish the truly high-performing banks from those that are merely optimizing under favorable weight schemes.

To address this concern, researchers have proposed the use of Common Set of Weights (CSW) models, which restrict all DMUs to be evaluated under a single, uniform set of input and output weights. This approach enhances the fairness and consistency of the rankings, offering a more realistic basis for performance comparison. Additionally, various extensions such as cross-efficiency, super-efficiency, and distance-based models have been developed to improve ranking quality, especially among efficient units.

This study aims to review the evolution of CSW models and compare them with other prominent DEA-based ranking methods. We apply these methodologies to a dataset of 375 commercial banks in 2017, with the goal of identifying the most robust and interpretable ranking technique. By reviewing past contributions and implementing these models on real-world data, this research provides insight into best practices for performance assessment in the banking industry.

Recent developments in DEA reflect a substantial shift toward integrating multi-objective, network-based, and fuzzy frameworks for capturing real-world complexities. In particular, studies such as Mozaffari et al. [1] and Ostovan et al. [2] present advanced DEA-R and two-stage DEA models capable of dealing with undesirable outputs, fuzzy inputs, and multi-layer network structures. Additionally, Gerami et al. [3] propose slacks-based and additive measures to improve the reliability of non-radial value efficiency models. These extensions significantly enhance the applicability of DEA in environmental and stochastic contexts, as further shown in stochastic DEA-R models for two-stage systems and ratio-based multi-criteria two-stage models [4], [5].

A complementary direction focuses on the use of Multi-Objective Linear Programming (MOLP) and goal programming structures within DEA. Foundational studies by Lotfi et al. [6], [7] and Kamyab et al. [8] illustrate how MOLP can uncover efficient hyperplanes or enable centralized resource allocation. Similarly, Olfati et al. [9] integrate goal programming to solve multi-objective DEA problems more flexibly. These algorithmic perspectives offer promising tools for performance analysis under conflicting objectives, especially in public service and supply chain environments. Moreover, the inverse DEA-R models and ratio-based interactive benchmarking demonstrate new possibilities for input/output estimation and decision support in dynamic systems [10], [11].

Sustainability and social-environmental integration also emerge as critical areas. Rashidi et al. [12] propose a comprehensive DEA-based framework to evaluate vehicle types, combining undesirable inputs with environmental indicators. Mozaffari et al. [13] extend this sustainability discourse by developing hybrid models—such as a genetic algorithm + DEA ratio-based model—applied to two-echelon supply chains. Additional efforts, such as the handling of missing data and fuzzy transportation problems, further indicate DEA's versatility beyond classic efficiency evaluation [14], [15]. Collectively, these works advance DEA into a multi-faceted analytical tool ready for modern sustainability and optimization challenges.

This paper presents a framework for evaluating the efficiency of DMUs using the CSW approach in DEA. First, the theoretical background and previous studies on CSW are reviewed, highlighting its advantages in the fair ranking of units. Then, two primary methods are introduced: The lexicographic optimization method for prioritizing objectives and a weighted linearized model for more efficient multi-objective problem solving. In the case study, the performance of 375 bank branches is analyzed using these methods, demonstrating that, unlike classical DEA models, the proposed models have a greater ability to discriminate between efficient and inefficient units.

2 | Literature Review

2.1 | Common Set of Weights and Ranking in Data Envelopment Analysis

One of the earliest contributions to the CSW framework was made by Despotis [16], who introduced a global efficiency model to enhance DEA's ability to discriminate between DMUs. By incorporating a multi-objective framework and defining an ideal point of performance, he proposed minimizing the gap between each unit's efficiency and this benchmark. His work laid the foundation for using optimization-based techniques to generate common weights.

Kao and Hung [17] advanced this idea by introducing a compromise solution approach, which aims to derive a set of weights that balances the performance of all units. Their model focused on reducing the deviation from the ideal efficiency value across all DMUs, and they demonstrated its application using data from forest districts. However, they also noted the limitations of using extreme norm-based models, particularly in terms of stability and weight interpretability.

Further refinements were provided by Jahanshahloo et al. [18], who presented a fractional multi-objective model to define common weights with specific goals for each performance criterion. Their approach allowed for partial resolution without solving the whole model, making it computationally efficient. Chen et al. [19] argued for CSW based on three primary advantages: Reduced computational complexity, more vigorous theoretical justification for rankings, and better discrimination. They introduced an inefficiency function and proposed models that aligned closely with multi-criteria optimization principles. Other notable contributions include Saati et al. [20], who integrated CSW with ideal point projections on the efficient frontier, and Chiang et al. [21], who proposed a linear reformulation of fractional models to facilitate practical implementation.

More recently, Sajedinejad and Chaharsooghi [22] revisited CSW within the multi-objective programming framework and emphasized the relevance of aggregate input-output spaces for determining ideal points. In each case, the researchers aimed to address the core challenge of ranking efficient and inefficient units using a unified and transparent evaluation standard.

2.2 | Theoretical Foundation of the Common Set of Weights in Data Envelopment Analysis

In the classical DEA framework, each organization or DMU is given the freedom to select weights that best highlight its performance. This approach, although fair on an individual level, can lead to an unrealistic situation where many units appear fully efficient simply because they have optimized under different criteria. As a result, comparing and ranking these units becomes difficult and sometimes even misleading.

To make the evaluation more equitable and transparent, researchers have proposed using a CSW— a shared set of input and output weights that applies to all DMUs. This idea shifts the focus from self-justification to collective fairness. However, finding such a common set is not an easy task, as it involves balancing multiple objectives across diverse units with different input-output structures. Recognizing this challenge, Kao and Hung [17] suggested a more practical approach: Instead of trying to force an exact solution for everyone, why not minimize the difference between the original DEA efficiency scores and those calculated using a CSW? By using mathematical norms (Called p-norms), they developed a model that gently pulls individual performances toward a shared standard, without losing too much of their unique characteristics.

Suppose that n DMUs produce s outputs by consuming m inputs. Also, suppose that in the case where the units are black boxes, $X_j = (x_{1j}, x_{2j}, \dots, x_{mj})$ represents the vector of inputs and $Y_j = (y_{1j}, y_{2j}, \dots, y_{sj})$ represents the vector of outputs of the DMU_j . The fractional model for calculating the relative efficiency of the DMU_o, $o \in \{1, \dots, n\}$, is as follows.

$$\theta_o = \text{Max} \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}},$$

$$\text{s.t.}$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, j = 1, \ldots, n, \tag{1}$$
$$u_r, v_i \geq 0, r = 1, \ldots, s, i = 1, \ldots, m.$$

$U = (u_1, u_2, \ldots, u_s)$ and $V = (v_1, v_2, \ldots, v_m)$ are the weights of the output and input vectors of DMU_o, respectively. *Model (1)* for the evaluation of the DMU_o in the technology of Constant Returns to Scale (CRS) in input-oriented is known as the fractional model. The above fractional model is transformed into the following Linear Programming (LP) model by Charnes-Cooper [23] transformations, which is known as the multiplier CCR model:

$$\theta_o = \text{Max} \sum_{r=1}^{s} u_r y_{ro},$$
$$\text{s.t.}$$
$$\sum_{i=1}^{m} v_i x_{io} = 1, \tag{2}$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, j = 1, \ldots, n,$$
$$u_r, v_i \geq 0, r = 1, \ldots, s, i = 1, \ldots, m.$$

The multiplier CCR model is used to calculate the efficiency score of each DMU using a flexible set of weights. By solving *Model (2)*, for each DMU, different weights for inputs and outputs are obtained. On the other hand, due to the fact that the efficiency in the DEA is defined as the weighted sum of the outputs to the weighted sum of the inputs in the input-oriented approach, we have the problem of zeroing the weights, for which the non-Archimedean epsilon number for this problem is used.

Finding the CSW in DEA, that is, in the case that we want to obtain a CSW for all DMUs, the following multi-objective fractional programming model is used.

$$\text{Max}\left\{\frac{\sum_{r=1}^{s} u_r y_{r1}}{\sum_{i=1}^{m} v_i x_{i1}}, \frac{\sum_{r=1}^{s} u_r y_{r2}}{\sum_{i=1}^{m} v_i x_{i2}}, \ldots, \frac{\sum_{r=1}^{s} u_r y_{rn}}{\sum_{i=1}^{m} v_i x_{in}}\right\},$$
$$\text{s.t,}$$
$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, j = 1, \ldots, n, \tag{3}$$
$$u_r, v_i \geq \varepsilon, r = 1, \ldots, s, i = 1, \ldots, m,$$

Model (3) is a fractional multi-objective programming problem in which (u_r, v_i) are the CSW related to the input and output vectors of all DMUs, and it cannot be solved simply. Therefore, in recent years, many studies have been done to find the CSW vectors, which are briefly mentioned in several methods. Based on the idea of Kao and Hung [17], the minimum deviation model of the difference between relative efficiency (Resulting from classic DEA models in the input-oriented CRS technology, which is equal to E_j^*) and $\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}$ is considered as follows.

$$\text{Min}\Big(\sum_{j=1}^{n} (E_j^* - \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}})^p\Big)^{\frac{1}{p}},$$
$$\text{s.t.} \tag{4}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, j = 1, \dots, n,$$
$$u_r, v_i \ge \varepsilon, r = 1, \dots, s, i = 1, \dots, m.$$

Therefore, *Model (4)* is used to measure the minimum deviation between $\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}$ and E_j^* using P-norm.

This section highlighted the shift from flexible, unit-specific DEA models to a unified CSW approach. By using p-norm-based deviation minimization, CSW models provide a practical and fair method for ranking DMUs under a common evaluation standard.

3 | Methodology

3.1 | Lexicographic Method for Multi-Objective Data Envelopment Analysis Models

In evaluating multiple performance criteria simultaneously, the lexicographic approach offers a structured way to prioritize objectives. Initially developed in the context of multi-objective optimization, the lexicographic method solves a sequence of optimization problems by focusing on the most crucial objective first. Once the optimal value for this primary objective is determined, it is fixed, and the next most important objective is optimized under this constraint. This process continues until all objectives have been addressed in a strict priority order.

When applied to the DEA context—particularly for solving a multi-objective CSW model—this method enables decision-makers to emphasize certain aspects of performance, such as input minimization or output maximization, before considering less critical dimensions. It reflects a human-centered decision style: we don't try to do everything at once, but instead, we solve problems step by step, based on what matters most.

However, the lexicographic approach is not without its limitations. First, it assumes that the decision-maker is capable of clearly ranking the objectives in strict order of importance—something that may not always be realistic, especially in complex systems like banking or healthcare. Second, because this method locks in the solution from one stage to the next, it can lead to suboptimal compromises in lower-priority objectives. Additionally, the computational complexity grows as more objectives are introduced and as the number of DMUs increases.

In summary, while the lexicographic method offers a clean theoretical structure and aligns with intuitive human decision processes, it may limit flexibility in balancing competing objectives. It can become computationally intensive in real-world applications. In this section, *Model (3)* is solved using the lexicographic method as follows. Based on the optimal solution obtained from each stage, the subsequent model is solved by imposing constraints derived from the previous optimal solutions. The following model captures this sequential structure to calculate the CSW.

$$Z_k^* = \text{Max}\left\{\frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}\right\},$$
$$\text{s.t.}$$
$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, j = 1, \dots, n, \tag{5}$$
$$u_r, v_i \ge \varepsilon, r = 1, \dots, s, i = 1, \dots, m,$$
$$Z_{k-1}^* = \frac{\sum_{r=1}^{s} u_r y_{rk-1}}{\sum_{i=1}^{m} v_i x_{ik-1}}.$$

However, the lexicographic method presents two significant challenges. First, the model may become infeasible during the sequential optimization process, mainly when the constraints imposed by previous stages overly restrict the feasible region. This infeasibility prevents finding a valid solution for subsequent objectives. Second, even if the model is feasible, it may encounter unbounded optimal solutions, where the objective function can improve indefinitely without reaching a finite optimum.

3.2 | Weighted and Linearized Approximation of the Common Set of Weights Model

To overcome the limitations of the lexicographic approach and to provide a more practical solution method, this study proposes a weighted and linearized version of Model 3. The key idea is to transform the original fractional and non-linear multi-objective model into a single-objective linear program by assigning predefined weights to each objective. This allows for all objectives to be considered simultaneously, but in a way that reflects their relative importance.

The proposed model aggregates the deviations between the CSW and the classical DEA scores across all DMUs, applying a weight to each deviation term. By adjusting these weights, decision-makers can reflect their preferences or strategic priorities while maintaining a tractable and solvable model. This approach not only simplifies computation but also enhances the model's interpretability.

$$\text{Max}\left\{\sum_{j=1}^{n} w_j \left(\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij}\right)\right\}, \tag{5}$$

s.t.

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij}) \leq 0, j = 1, \ldots, n,$$
$$u_r, v_i \geq \varepsilon, r = 1, \ldots, s, i = 1, \ldots, m.$$

Furthermore, the linearized structure enables efficient implementation using standard optimization solvers, even when dealing with large-scale datasets—such as our case involving 375 commercial banks. Unlike the lexicographic method, the weighted model offers greater flexibility and a more balanced compromise across multiple objectives, making it well-suited for real-world performance evaluation and ranking.

4 | Case Study: Efficiency Analysis of 375 Commercial Bank Branches

This study examines the operational efficiency of 375 commercial bank branches during the fiscal year 2017. Each branch is treated as a DMU that consumes multiple inputs to generate various outputs. The primary goal is to evaluate the relative efficiency of these branches, identify best practices, and offer actionable recommendations for resource management and performance improvement.

The input variables represent the resources and costs consumed by each branch in its operations. These include personnel expenses, which cover salaries, benefits, and other labor-related costs, constituting a significant portion of total expenses. Non-Performing Loans (NPLs) reflect the volume of delinquent loans or at risk of default, serving as an indicator of credit risk and asset quality.

Other inputs include the price of funds, capturing the cost incurred in securing financial resources; price of capital, which represents the cost of long-term investments and fixed assets; and price of labor, reflecting unit labor costs such as wage levels and workforce productivity. Additional cost-related inputs include the price of loans, price of securities, and price of NPLs, which account for expenses associated with lending, securities management, and provisioning for risky assets.

Total interest expenses and non-interest expenses further capture the branch's financial outflows related to interest payments and operational overheads, respectively. Finally, Loan Loss Provisions, including Provisions for General Loans (LLPGL), gross losses from Non-Performing Loans General Loans (NPLGL), and total Loan Loss Provisions (LLP), provide measures of risk mitigation against potential credit defaults. On the output side, variables reflect the branch's productive achievements and financial performance. Total deposits indicate the branch's ability to attract and retain customer funds, while fixed assets represent tangible resources supporting branch operations.

Gross loans capture the volume of credit extended by the branch, and total securities denote the value of securities held or managed. Total assets sum the overall resources under management, providing a scale measure of branch operations. Income variables include net interest income, which is interest revenue minus interest expenses, other interest income capturing additional interest-related revenues, and non-interest income representing earnings from non-interest activities such as fees and commissions. This section presents a detailed numerical analysis of the financial and operational data collected from 375 bank branches. The assessment highlights the variability and distribution patterns of key performance indicators essential for evaluating branch efficiency.

Firstly, the variable total deposits exhibits an extensive range, varying from a minimum of 6.38 units to a maximum of 3,266,469 units. The mean value is approximately 118,465 with a considerable standard deviation of 340,842, indicating a high degree of dispersion and heterogeneity among branches. In other words, some branches have deposits below 10 units, while others exceed three million units. This wide variance reflects significant differences in the capacity of branches to attract financial resources and their operational scale.

The variable gross loans shows a similar distribution, ranging from 25.23 to 2,185,860 units. The mean loan amount is 95,143 units with a standard deviation of 239,667, again suggesting the presence of both substantial and tiny branches. Additionally, NPL range between 0.69 and 63,155 units, with an average of approximately 3,257 units. Such substantial variation may indicate differences in credit risk management and regional economic conditions. Regarding costs, personnel expenses vary from 1.19 to 17,653 units, with a mean of 1,263 and a standard deviation of 2,756, showing that some branches incur minimal labor costs while others have substantial expenditures. This pattern is similar for fixed assets, which range from 0.03 to 38,046 units, with a mean of 1,276 and a standard deviation of 3,854.

In terms of income, net interest income spans from 1.45 to 80,227 units, with a mean of 3,142 and a standard deviation of 8,311. This wide variation reflects the diversity in branch activities and scale. Additionally, total interest expenses range from 0.05 to 52,140 units (Mean: 2,767; standard deviation: 6,977), and non-interest expenses vary from 2.08 to 34,884 units (Mean: 2,404; standard deviation: 5,119), highlighting the critical role of expense management in branch performance. The efficiency score (Eff_AP) ranges from 0.30 to 11.49, with a mean of 1.18. Most branches operate near the optimal efficiency level (Close to one), yet the presence of significantly higher values may indicate outliers or exceptionally efficient units. The standard deviation of 1.08 further signifies noticeable variation in branch efficiency.

The dataset, collected for 375 branches in 2017, underwent thorough preprocessing to address missing values and outliers. Financial figures were standardized and normalized where necessary to ensure comparability across branches of varying sizes and operational contexts. This comprehensive set of inputs and outputs forms the foundation for implementing DEA models to assess relative efficiency, identify high-performing branches, and guide strategic improvements in resource allocation and operational management.

The table presents the performance evaluation of the first 20 bank branches based on five distinct DEA-based models:

I. teta_ccr: Classical CCR model under CRS.

II. teta_bcc: BCC model under Variable Returns to Scale (VRS).

III. Eff_AP: Efficiency score from the proposed model using CSW.

Eff_Maj and Eff_jlk: Composite efficiency measures derived from multi-objective aggregation approaches. In many cases (e.g., DMUs 1 through 7), the values of both CCR and BCC efficiency are equal to 1, indicating that these units are technically efficient under classical DEA assumptions. However, the efficiency scores obtained from advanced models (Eff_AP, Eff_Maj, Eff_jlk) are often greater than 1, reflecting refined measures of performance when using common weights or multi-objective formulations. For example, DMU 3 has an Eff_AP of 2.63, suggesting exceptionally high performance when evaluated through the proposed framework, although it is also rated efficient (Value = 1) in the traditional CCR model.

Conversely, several branches (Such as DMUs 18 and 19) exhibit relatively lower performance scores in the CCR model (Below 0.6 and 0.77, respectively), revealing inefficiencies in resource utilization or output generation under DEA assumptions.

Table 1. Comparative efficiency evaluation of the first 20 bank branches.

DMU	CCR	BCC	Eff_AP	Eff_Maj	Eff-1
1	1	1	1.132132	1.003848	1.002730
2	1	1	1.671375	1.015002	1.017839
3	1	1	2.634760	1.080121	1.083502
4	1	1	1.874456	1.015693	1.023179
5	1	1	1.128372	1.004185	1.002872
6	1	1	2.438106	1.000094	1.000052
7	1	1	1.827388	1.018893	1.016402
8	0.959064	0.977110	0.959064	0.999752	1.000000
9	1	1	1.360001	1.003968	1.002701
10	0.885818	0.952490	0.885818	0.999466	1.000000
11	0.817286	0.817472	0.817286	0.998449	1.000000
12	1	1	1.858010	1.008328	1.008385
13	0.929517	0.929567	0.929517	0.998929	1.000000
14	1	1	1.236171	1.005145	1.005680
15	1	1	1.310741	1.006150	1.006110
16	0.898778	0.918747	0.898778	0.999157	1.000000
17	1	1	1.019779	1.000030	1.000010
18	0.577510	0.629979	0.577510	0.999902	1.000000
19	0.760786	0.770065	0.760786	0.995127	1.000000
20	0.987540	0.989085	0.987540	0.999983	1.000000

The results suggest that classical DEA models (CCR and BCC) have limited discriminatory power, as many units receive full efficiency scores. In contrast, the proposed models—particularly those based on standard weights and multi-objective approaches—demonstrate greater resolution and better distinguish between efficient and inefficient branches.

The efficiency scores of the CSW model for various DMUs demonstrate significant variability. Most DMUs show relatively low efficiency scores, with values generally below 0.25. For instance, DMUs 1 (0.3009), 3 (0.2874), 5 (0.2811), 11 (0.3603), 13 (0.2370), and 25 (0.0811) fall within this lower efficiency range, suggesting room for improvement in their resource utilization.

Conversely, a few DMUs exhibit notably higher efficiency values above 1. These include DMUs 30 (1.0355), 40 (1.1334), 41 (1.0170), 47 (1.1412), 69 (1.2741), 239 (1.4825), and 365 (1.3860), indicating superior operational performance, possibly due to better input-output management or scale advantages.

The average efficiency across all DMUs (Excluding negative values) approximates 0.239, with a median near 0.046, demonstrating a skewed distribution where many units have low efficiency and a few perform at a high level. The standard deviation of approximately 0.283 further emphasizes the diverse performance among the DMUs. Low efficiency values close to zero are observed for DMUs such as 6 (0.0017), 8 (0.0244), 10 (0.0278), and 17 (0.0047), highlighting considerable inefficiencies or suboptimal resource use in these units.

Overall, the CSW model effectively distinguishes between low and high-performing units, providing critical insights for benchmarking and resource optimization strategies.

5 | Conclusion

In this study, we evaluated the operational efficiency of 375 commercial bank branches using multi-objective DEA models. Two main approaches were employed: The lexicographic method, which prioritizes objectives step-by-step based on importance, and a weighted linearized model that considers all objectives simultaneously with adjustable weights. Our findings showed that while the lexicographic method offers a structured approach, it can face challenges such as infeasibility and unbounded solutions in some stages. On the other hand, the weighted linearized model overcomes these limitations, providing a more flexible and efficient framework for performance evaluation.

The analysis revealed significant efficiency variations among branches, highlighting top-performing branches that can serve as benchmarks. The ability to adjust weights in the proposed model allows decision-makers to balance different performance criteria according to their strategic priorities, leading to more informed and tailored decisions. This flexibility is crucial in large-scale systems like banking, where competing objectives must be carefully balanced.

Ultimately, our results emphasize that weighted multi-objective DEA models offer a more realistic and reliable way to assess performance. Incorporating decision-makers' preferences through weights makes recommendations more practical and aligned with organizational needs. Future research could expand this framework by including dynamic data and environmental factors, further supporting continuous improvement in branch management.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

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