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Discrete Event Simulation and Data Envelopment Analysis to Evaluate and Improve Efficiency: A Case Study of Commercial Bank Branches

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Abstract

Performance measurement, encompassing efficiency and effectiveness, is fundamental to organizational dynamics and achieving strategic goals. This study proposes an integrated model utilizing Discrete Event Simulation (DES) and Data Envelopment Analysis (DEA) to evaluate the performance and efficiency of commercial bank branches. The primary research question addressed is: How can the performance of bank branches be assessed and improved using Arena simulation software and DEA? The study focuses on estimating key branch outputs—namely, the number of customers served, value-added, and employee productivity—which are difficult to measure precisely in real-world settings. These outputs are derived from simulating branch operations using Arena software, considering customer priority, service process, and service duration factors. After validating the simulation model, statistical analysis is performed on various scenarios. The generated outputs are then used as inputs for the DEA model (Specifically, the BCC model) to assess the relative efficiency of the branches Decision-Making Units (DMUs). The results identify the efficiency frontier, inefficient units, and potential causes of inefficiency. Furthermore, the integrated approach facilitates the analysis of improvement scenarios by modifying simulation parameters and re-evaluating efficiency through DEA. A case example demonstrates how identifying and addressing a bottleneck in an inefficient branch (DMU_6) leads to a significant improvement in its efficiency score. This research highlights the practical utility of combining DES and DEA for data-driven performance evaluation and improvement in service organizations like commercial banks.

Keywords: Bank efficiency, Data envelopment analysis, Decision-making units, Discrete event simulation, Performance evaluation.

1 | Introduction

Effective performance evaluation is a cornerstone of organizational success, enabling managers to understand the extent to which objectives are met and identify areas for improvement. In dynamic and complex

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environments, a robust evaluation system is crucial for assessing resource utilization, strategic alignment, and personnel effectiveness. For service organizations, such as commercial banks, the efficiency and effectiveness of frontline units like branches directly impact overall organizational performance and customer satisfaction. Evaluating the performance of bank branches is challenging due to the multifaceted nature of inputs (e.g., staff, cost) and outputs (e.g., number of transactions, value generated, service quality).

Traditional performance evaluation methods often rely on readily available metrics, which may not fully capture the complexity of service processes or the dynamic interactions within a system. Data Envelopment Analysis (DEA), introduced by Charnes, Cooper, and Rhodes (CCR) [1], is a non-parametric method widely used for evaluating the relative efficiency of Decision-Making Units (DMUs) that consume multiple inputs to produce multiple outputs. While powerful, DEA requires precise input and output data. Obtaining accurate and dynamic output measures, such as the actual number of customers served under varying conditions or the precise value added by specific processes within a bank branch over a given period, can be difficult.

Discrete Event Simulation (DES) is a modeling technique used to represent the behavior of a system over time as a sequence of distinct events [2]. DES is particularly well-suited for analyzing complex service systems characterized by queues, resource constraints, and variability, such as bank branches. Simulation allows researchers to model processes, experiment with different scenarios, and estimate performance measures that are difficult to obtain from real-world observations alone. Simulation has been applied in various service contexts, including healthcare [3–7], manufacturing [8–11], and logistics.

Integrating DES and DEA offers a synergistic approach where simulation can provide the necessary data, particularly challenging output measures, for DEA analysis. This combined methodology allows for a more dynamic and comprehensive evaluation of efficiency, enabling managers to understand the impact of process changes, resource allocation, or operational strategies on performance before implementing them in the real system. While integrated DES-DEA approaches have been explored in various fields, their specific application to generating dynamic operational outputs for bank branch efficiency evaluation presents a valuable research opportunity.

This study aims to develop and apply an integrated DES and DEA model to evaluate and improve the operational efficiency of commercial bank branches. Specifically, the research seeks to answer the question: "How can the performance of bank branches be evaluated and improved using Arena simulation software and DEA?" The study utilizes DES to estimate key operational outputs of bank branches and subsequently employs DEA to assess their relative efficiency based on these simulated outputs and observed inputs.

The findings are expected to provide bank managers with a data-driven framework for identifying inefficient branches, understanding the root causes of inefficiency, and evaluating potential improvement strategies.

The remainder of this paper is structured as follows: Section 2 provides a review of relevant literature on DEA, DES, and their integrated applications. Section 3 details the research methodology, including data collection, the simulation model development and validation, and the DEA model formulation. Section 4 presents the results of the simulation and DEA analysis, including the identification of inefficient units and an example of an improvement scenario. Section 5 discusses the findings, their implications, and limitations. Section 6 concludes the study and suggests avenues for future research.

2 | Literature Review

This section reviews existing literature on DEA, DES, and studies that combine these two methodologies for performance evaluation, particularly in service settings.

2.1 | Data Envelopment Analysis

DEA is a non-parametric frontier method for measuring the relative efficiency of a set of DMU_s with multiple inputs and outputs. The efficiency of a DMU is defined as the ratio of the weighted sum of its outputs to the weighted sum of its inputs, where the weights are determined by solving an optimization problem that maximizes this ratio for each DMU, subject to the constraint that the efficiency of all DMUs is less than or equal to one.

The initial DEA model, the CCR model [12], assumes Constant Returns to Scale (CRS), meaning that increasing inputs proportionally results in a proportional increase in outputs. Banker, Charnes, and Cooper [1] later introduced the BCC model, which assumes Variable Returns to Scale (VRS). The BCC model can identify technical efficiency independent of scale efficiency, making it more appropriate when DMUs operate at different scales, as is often the case with bank branches of varying sizes. DEA models can be input-oriented (Minimizing inputs for given outputs) or output-oriented (Maximizing outputs for given inputs). For performance improvement, an output-oriented model is often preferred as it focuses on increasing desirable outputs.

DEA has been widely applied in the banking sector to evaluate the efficiency of branches or banks themselves [13]. These studies typically use financial data (e.g., deposits, loans) and operational data (e.g., number of employees, operating expenses) as inputs and outputs. However, obtaining precise operational outputs that reflect dynamic service processes can be challenging.

2.2 | Discrete Event Simulation

DES models systems as a sequence of events occurring at discrete points in time. It is a powerful tool for analyzing the behavior of complex systems, especially those involving variability, queues, and resource interactions. DES allows for experimentation with different system configurations, policies, and parameters without disrupting the real system.

Simulation has a long history, with early applications in military and industrial settings. Computer simulation became more accessible with the development of specialized simulation languages and software. Arena, developed by Rockwell Automation, is a widely used DES software that employs the SIMAN simulation language [14], [15] Arena provides a graphical interface with modules representing common system components (e.g., arrival, process, queue, dispose), making it easier to build and visualize simulation models.

Simulation in service systems, including banking, focuses on modeling customer flow, service processes, resource utilization (Staff, tellers), waiting times, and throughput. For example, simulation can estimate the average number of customers served per day, the average waiting time, the utilization of staff, or the impact of adding/removing resources. This dynamic, process-oriented perspective provides valuable insights into system performance.

2.3 | Integrated Simulation and Data Envelopment Analysis

Recognizing the strengths of both methodologies, researchers have combined DES and DEA. In integrated approaches, simulation is often used to:

I. Generate input and output data for DEA, especially when real-world data is scarce or difficult to measure precisely.

II. Evaluate the impact of proposed changes (Simulated scenarios) on DMU efficiency as measured by DEA.

III. Identify potential improvement strategies by analyzing simulation results and DEA efficiency scores.

Studies combining simulation and DEA have been conducted in various domains. Al-Refaie et al. [3] used simulation and DEA to improve the performance of a hospital emergency department. Azadeh et al. [13] integrated simulation optimization with stochastic DEA to model human errors and optimize an emergency department. Liu et al. [5] combined simulation and optimization for calibrating agent-based emergency department models. These studies demonstrate the utility of using simulation to generate data or evaluate scenarios for subsequent DEA analysis.

More recent research continues to explore the integration of simulation and DEA. A study by Ingole [16] combined DES and DEA to optimize resource allocation in healthcare systems, using simulation to model patient flow and resource utilization and DEA to evaluate the efficiency of different resource configurations. Similarly, Wong [17] applied a simulation-DEA framework for assessing the efficiency of supply chain networks under uncertainty, where simulation captured the dynamic behavior and risk propagation, providing performance data for DEA.

In the banking context, a recent paper by Arya and Hatami-Marbini [18] utilized DES to model customer service processes in bank branches and generated key operational metrics, which were then used in a DEA model to benchmark branch performance.

Another relevant study by Tsolas and Charles [19] proposed a simulation-based approach to estimate the impact of digital transformation initiatives on bank branch efficiency, using simulation outputs as inputs for a dynamic DEA model.

These recent studies underscore the growing interest in integrating simulation and DEA for performance analysis in complex systems. However, the specific application of using DES to generate dynamic outputs like customer count, value-added, and employee productivity for DEA evaluation of commercial bank branches and then using this integrated approach to analyze and demonstrate the impact of specific operational changes on efficiency warrants further investigation.

This study contributes to the literature by providing a detailed methodology and case study for such an application in the banking sector.

3 | Methodology

This research employs a mixed-methods approach, primarily quantitative, combining DES and DEA. The study follows a two-stage process: first, developing and running a simulation model to generate key operational outputs for bank branches, and second, using these outputs along with observed inputs in a DEA model to evaluate branch efficiency. The research is applied and developmental, aiming to improve existing processes and develop a practical evaluation framework.

3.1 | Research Scope and Data Collection

The study focuses on evaluating the efficiency of 24 branches of a commercial bank over three months. Due to data confidentiality, the bank's name is not disclosed. The branches vary in size, with staff numbers ranging from 5 to 9 personnel.

Data collection involved observing operations within selected bank branches to understand customer arrival patterns, service processes at different counters (e.g., tellers, customer service, credit), and service durations for various transaction types. This observational data was crucial for building a realistic simulation model. Key data collected included:

I. Customer arrival times.

II. Service times for different transaction types at each service point (e.g., teller, customer service desk).

III. Routing of customers through the branch.

IV. Staff assignments and roles.

The collected data on inter-arrival times and service times were analyzed using statistical tools, such as the input analyzer within Arena software, to determine the appropriate probability distributions that best fit the observed data.

For example, customer arrivals might follow an exponential distribution, while service times might follow Weibull, Gamma, or other distributions, as illustrated in the original text's *Fig. 1* (Weibull distribution for Branch Manager service) and *Fig. 2* (Gamma distribution for Banker 1 service).

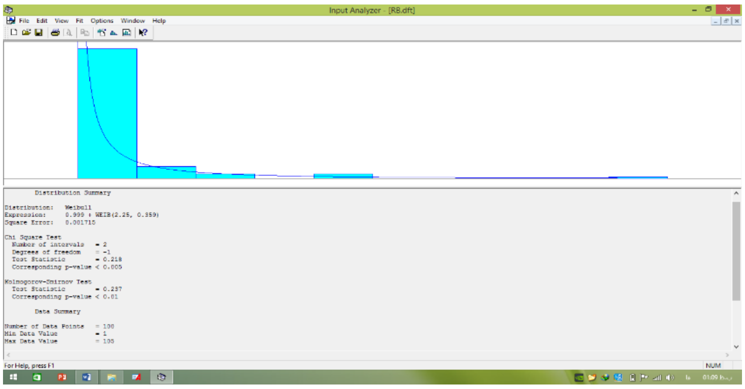

Fig. 1. Weibull statistical distribution graph of bank manager service times to customers.

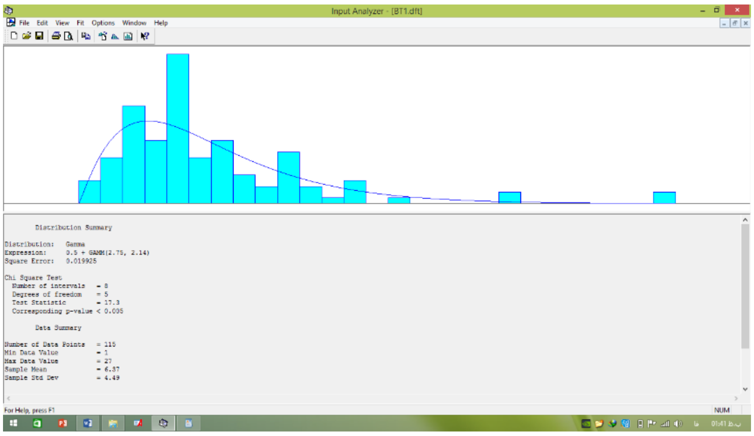

Fig. 2. Gamma statistical distribution of Banker 1's service times to customers.

Inputs for the DEA model were collected directly from the bank's records for the three months:

Input 1 (X1): Number of personnel in the branch.

Input 2 (X2): Branch operating cost (e.g., rent, utilities, salaries excluding base personnel count).

Outputs for the DEA model were generated through the simulation model:

Output 1 (Y1): Total number of customers served during the simulated period.

Output 2 (Y2): Value added, estimated based on the volume and type of transactions processed during the simulated period. This metric was derived from simulation outputs reflecting transaction throughput.

Output 3 (Y3): Employee productivity, calculated within the simulation as the average utilization or throughput per employee.

3.2 | Simulation Model Development and Validation

DES models were developed for each of the 24 bank branches using Arena 14 software. Each model represented the flow of customers through the branch, including arrival, queuing for different services, processing at service counters by staff, and departure. The models incorporated the probability distributions fitted to the collected real-world data for arrival times and service durations. Resource modules in Arena represented the staff at different service points.

Different simulation models were created based on the number of personnel (5, 6, 7, 8, or 9 staff) and the specific layout and service configuration of the branches. The original text shows examples of models for 9 and 8 staff branches (*Fig. 3* and *Fig. 4*).

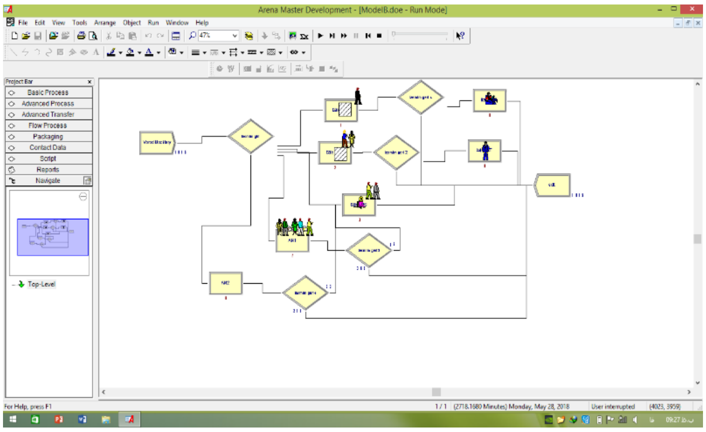

Fig. 3. Simulation of a bank branch with 9 Staff.

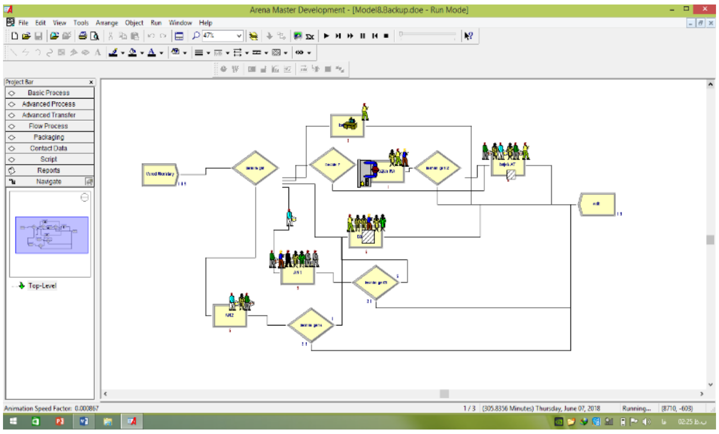

Fig. 4 . Simulation of a bank branch with 8 Staff.

Model verification involved ensuring that the simulation model logic correctly represented the conceptual model of the bank branch operations. This included checking the flow of entities (Customers), resource allocation, queue behavior, and event timing.

Model validation aimed to ensure that the simulation model accurately reflected the behavior of the real system. This was achieved by comparing key performance measures obtained from the simulation runs (e.g., average waiting time, average number of customers served per day) with corresponding data from the actual bank branches over the same period.

Statistical tests (e.g., t-tests) could be used to compare the simulation outputs with real-world data to confirm they are statistically similar. The original text mentions validating the model based on sensitivity analysis and comparing simulated performance measures with the real system. Multiple replications of the simulation runs were conducted for each branch model to account for randomness and obtain stable estimates of the outputs (Y_1, Y_2, Y_3).

3.3 | Data Envelopment Analysis Model

The DEA model was applied in the second stage to evaluate the relative efficiency of the 24 bank branches DMU_s. Given that bank branches operate at different scales (Varying numbers of personnel), the BCC model [1], which assumes VRS, was chosen. An output-oriented BCC model was used, aiming to maximize the outputs (Y_1, Y_2, Y_3) for a given level of inputs (X_1, X_2).

The general formulation for an output-oriented BCC model for a specific DMU_o is as follows:

$$
\begin{aligned}
&\text{Maximize} \quad \theta = \sum_{r=1}^{s} u_r y_{ro} + u_0, \\
&\text{s.t.} \\
&\qquad \sum_{i=1}^{m} v_i x_{io} = 1, \\
&\qquad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + u_0 \le 0, \quad j = 1,\dots,n, \\
&\qquad u_r \ge \varepsilon, \qquad r = 1,\dots,s, \\
&\qquad v_i \ge \varepsilon, \qquad i = 1,\dots,m, \\
&\qquad u_0, \qquad \text{free}.
\end{aligned}
\tag{1}
$$

The dual form of the BCC model, which identifies the efficiency frontier and potential slacks, is often solved using linear programming software. An efficiency score of 1 indicates a relatively efficient DMU, while a score less than 1 indicates inefficiency.

The inputs (X_1, X_2) and outputs (Y_1, Y_2, Y_3) used in the DEA model were those presented in *Table 1* of the original text, where the output values were obtained from the simulation runs of the respective bank branches. The DEA Solver software was used to perform the efficiency calculations.

4 | Results

This section presents the results obtained from the simulation and DEA analysis, including the efficiency scores of the bank branches and an example of an improvement analysis for an inefficient branch.

4.1 | Analysis of Simulation Results to Determine the Outputs for the Data Envelopment Analysis Model

After completing the simulation model design, model verification was performed based on component sensitivity analysis, repeated executions, and a comparison of the obtained results.

Furthermore, validation was conducted by comparing performance metrics in each simulated model with the corresponding real system. Given that our objective in designing the bank branch simulation models was to determine the value added, the number of served customers, and employee productivity, the value added, and the number of customers served were directly obtained from the model execution results.

Employee productivity was calculated using the average utilization of personnel (*Fig. 5*). Subsequently, the inputs and outputs for the DEA model were determined, as presented in *Table 1*, for evaluation using the BCC model.

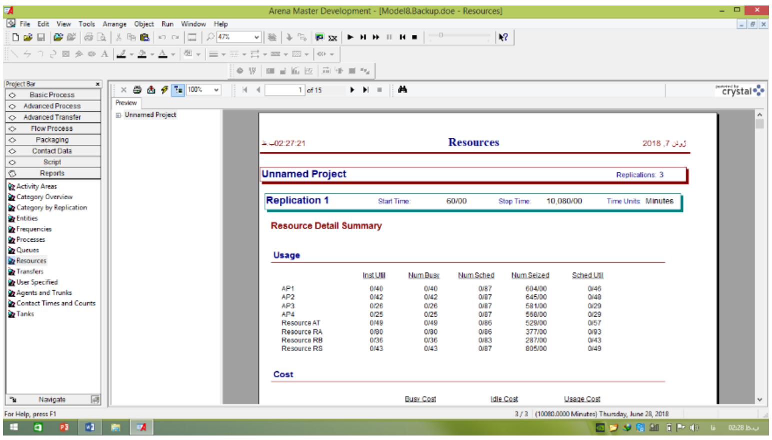

Fig. 5. Sample data output from Arena simulation.

4.2 | Simulation Results and Data Envelopment Analysis Inputs

After developing and validating the simulation models for the 24 bank branches, multiple simulation runs were executed for a simulated period of three months (Equivalent to the real-world data collection period). The outputs of interest—number of customers served (Y_1), value added (Y_2), and employee productivity (Y_3)—were recorded for each branch from the simulation results.

Employee productivity (Y_3) was calculated as the average utilization rate of the staff resources in the simulation model.

Table 1, reproduced here for clarity, presents the inputs (Number of personnel, branch cost) and the simulation-generated outputs for each of the 24 DMU_s.

Table 1. Inputs and simulation-generated outputs for bank branches (DMU_s).

DMU	X_1	X_2	Y_1	Y_2	Y_3
1	9	16396	3610	6235	0.35
2	9	16408	3677	6015	0.33
3	9	16401	3641	5873	0.32
4	9	16428	3679	6421	0.35
5	9	16392	3661	6161	0.34
6	9	16454	3495	6003	0.33
7	9	16402	3572	6196	0.34
8	9	17231	3787	6569	0.35
9	8	14784	3793	7436	0.43
10	8	14683	3738	7269	0.42
11	8	14753	3837	7207	0.42
12	7	11436	3811	5323	0.47
13	7	11411	3779	4854	0.45
14	7	14424	3493	5242	0.49
15	7	13301	3746	5793	0.39
16	7	13287	3791	5549	0.38
17	7	13297	3760	5541	0.37
18	7	13307	3775	5780	0.39
19	6	12051	3763	6750	0.51
20	6	11995	3755	6566	0.48
21	6	11977	3796	6491	0.48
22	5	10375	3609	5430	0.52
23	5	10364	3537	5182	0.49
24	5	10391	3592	7634	0.65

The simulation models provided dynamic estimates of the operational outputs (Y_1, Y_2, Y_3) for each branch under realistic operating conditions, accounting for variability in customer arrivals and service times. These simulated outputs, combined with the observed inputs (X_1, X_2), formed the dataset for the subsequent DEA analysis.

4.3 | Data Envelopment Analysis Results

Using the inputs and simulation-generated outputs from *Table 1*, the output-oriented BCC model was applied to evaluate the relative efficiency of the 24 bank branches. The DEA Solver software was used for this analysis.

Table 2 presents the efficiency scores for each DMU under the standard BCC model (Assuming VRS) and also explores efficiency under Increasing Returns to Scale (IRS) and Decreasing Returns to Scale (DRS) assumptions within the BCC framework to provide a more nuanced understanding of scale effects.

Table 2. Efficiency scores of bank branches using the BCC model (Output-oriented).

DMU	BCC Score	BCC Efficiency (%)	IRS Score	DRS Score
1	0.6355	64	0.6355	0.6344
2	1.0000	100	1.0000	1.0000
3	0.6442	64	0.6442	0.6389
4	0.6569	66	0.6569	0.6454
5	0.6518	65	0.6518	0.6432
6	0.6304	63	0.6119	0.6304
7	0.6326	63	0.6275	0.6326
8	0.6847	68	0.6847	0.6333
9	0.8014	80	0.8014	0.7410
10	0.7721	77	0.7721	0.7351
11	1.0000	100	1.0000	0.7505
12	1.0000	100	1.0000	0.9580
13	0.9875	99	0.9875	0.9520
14	0.7186	72	0.6962	0.7186
15	0.8546	85	0.8546	0.8100
16	0.8857	89	0.8857	0.8202
17	0.8643	86	0.8643	0.8129
18	0.8740	87	0.8740	0.8157
19	0.9739	97	0.9739	0.9003
20	0.9697	97	0.9697	0.9022
21	1.0000	100	1.0000	0.9130
22	1.0000	100	1.0000	1.0000
23	1.0000	100	0.9811	1.0000
24	1.0000	100	1.0000	1.0000

The results from the BCC model indicate that DMU_s 2, 11, 12, 21, 22, 23, and 24 are on the efficiency frontier, achieving a relative efficiency score of 1.0000. These branches are considered relatively efficient compared to the others in the sample, given their input consumption and output generation.

Analyzing the results under different returns to scale assumptions provides further insight:

I. Under the IRS, DMU_s 2, 11, 12, 21, 22, and 24 are efficient.

II. Under DRS, DMU_s 2, 22, 23, and 24 are efficient.

DMU_s 2, 22, and 24 are efficient under all three assumptions (BCC, IRS, and DRS), suggesting they are consistently high performers regardless of scale effects.

Conversely, several branches exhibit efficiency scores significantly less than 1, indicating relative inefficiency. DMU_6, with a BCC score of 0.6304 (63%), is identified as the least efficient branch among those with nine personnel and the second least efficient overall.

Other branches with low-efficiency scores include DMU_1 (0.6355), DMU_7 (0.6326), DMU_3 (0.6442), DMU_5 (0.6518), DMU_4 (0.6569), and DMU_8 (0.6847), all with nine personnel. Branches with seven personnel also show varying efficiency, with DMU_{14} having a relatively low score of 0.7186.

Identifying inefficient DMU_s is the first step. The next step, facilitated by the integrated approach, is to investigate the causes of inefficiency and propose potential improvements. For inefficient DMU_s, the DEA analysis provides reference sets of efficient DMU_s and potential input/output slacks, suggesting how inputs could be reduced, or outputs increased to reach the efficiency frontier.

However, understanding why these slacks exist requires a deeper look at the operational processes, which is where the simulation model becomes invaluable.

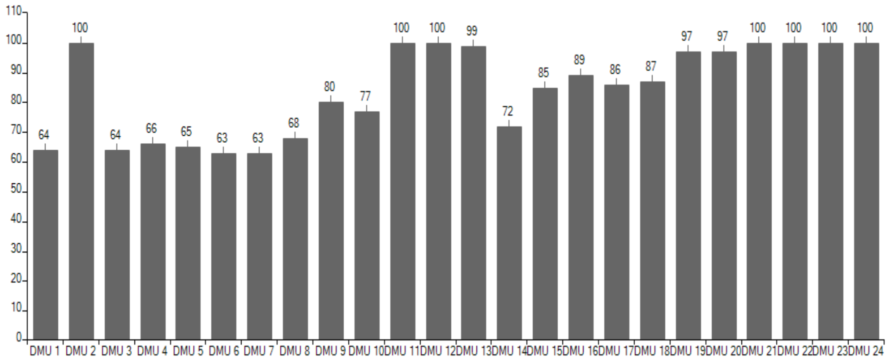

Fig. 6. Efficiency scores of bank branches (BCC Model).

Note: This is a bar chart based on the BCC Score column in *Table 2*, visually representing the efficiency of each DMU.

4.4 | Improvement Scenario Analysis: Case of DMU_6

DMU_6 was identified as one of the least efficient branches (BCC score 0.6304). To understand the reasons for its inefficiency and explore potential improvements, the simulation model for DMU_6 was analyzed in detail. The simulation outputs (e.g., resource utilization, queue lengths, processing times at different service points) provided insights into operational bottlenecks.

Analysis of the simulation results for DMU_6 revealed that Banker 4 (Teller counter) had a high utilization rate (29% as mentioned in the original text, which might be low for utilization but high relative to other tellers or indicative of a specific bottleneck, likely due to high customer traffic or slow processing) and was associated with longer customer queues compared to other service points.

This suggested a bottleneck at this specific service counter, potentially contributing to lower overall customer throughput (Y_1), value added (Y_2), and employee productivity (Y_3) for the branch. Based on this analysis, an improvement scenario was proposed: Reassigning Banker 4 (The teller) to a different role or counter or implementing measures to increase their processing speed (e.g., additional training, process streamlining, or providing incentives).

For demonstration purposes, the scenario involved a hypothetical change in the simulation model for DMU_6, reflecting an improvement in the efficiency or speed of service at the teller counter, potentially through staff reassignment or process optimization. The simulation model for DMU_6 was modified to reflect this proposed change. For instance, this might involve adjusting the service time distribution for the teller counter or reallocating tasks. The modified simulation model was then re-run for the same three-month period.

The outputs (Y_1, Y_2, Y_3) generated from this improved simulation scenario for DMU_6 were then used in the DEA model along with the original inputs (X_1, X_2) and the inputs/outputs of the other 23 branches. *Table 3* shows the results of the DEA analysis after incorporating the outputs from the improved simulation scenario for DMU_6.

Table 3. Efficiency scores after implementing the improvement scenario in DMU_6 simulation.

DMU	BCC Score	BCC Efficiency (%)
1	0.6355	64
2	1.0000	100
3	0.6442	64
4	0.6569	66
5	0.6526	65
6	0.9373	94
7	0.6326	63
8	0.6847	68
9	0.8014	80

Table 3. Contined.

DMU	BCC Score	BCC Efficiency (%)
10	0.7721	77
11	1.0000	100
12	1.0000	100
13	0.9875	99
14	0.7186	72
15	0.8546	85
16	0.8857	89
17	0.8643	86
18	0.8740	87
19	0.9739	97
20	0.9697	97
21	1.0000	100
22	1.0000	100
23	1.0000	100
24	1.0000	100

As shown in *Table 3*, the BCC efficiency score for DMU_6 increased significantly from 0.6304 to 0.9373 after implementing the simulated improvement. This demonstrates the potential impact of addressing the identified bottleneck on the branch's overall operational efficiency, as measured by DEA using the improved simulation outputs. This integrated approach allows bank managers to quantitatively assess the potential benefits of proposed operational changes before actual implementation, reducing risk and optimizing resource allocation for improvement efforts.

5 | Discussion

This study successfully demonstrated the application of an integrated DES and DEA approach for evaluating and improving the operational efficiency of commercial bank branches. By using DES, specifically with Arena software, we were able to generate dynamic and process-driven estimates for key operational outputs (the number of customers served, value-added, and employee productivity) that are often difficult to measure precisely in real-world banking environments. These simulation-derived outputs, combined with readily available input data (Personnel count, branch cost), provided a robust dataset for the subsequent DEA analysis.

The DEA results, using the BCC model, provided a relative efficiency ranking of the 24 bank branches. The identification of efficient and inefficient DMUs offers valuable insights for bank management. Efficient branches represent best practices within the organization and can serve as benchmarks for inefficient ones. Inefficient branches, on the other hand, highlight areas requiring attention and potential intervention.

The power of the integrated approach is particularly evident in the improvement scenario analysis for DMU_6. By analyzing the simulation results for this inefficient branch, a specific operational bottleneck (Teller counter-performance) was identified. The simulation model allowed us to experiment with a hypothetical improvement scenario (e.g., increasing teller efficiency) and quantify its potential impact on the branch's outputs. Re-evaluating DMU_6's efficiency using DEA with the improved simulation outputs showed a substantial increase in its efficiency score. This provides a data-driven justification for implementing such changes in the real branch.

This methodology offers several advantages over using DEA or simulation in isolation. DEA provides a measure of relative efficiency and identifies targets for improvement (Efficient peers), but it doesn't explain why a unit is inefficient or how to improve it from an operational perspective. Simulation excels at modeling processes, identifying bottlenecks, and evaluating the impact of changes, but it typically focuses on operational metrics (e.g., throughput, waiting time) rather than overall efficiency relative to peers based on multiple inputs and outputs. The integrated approach bridges this gap, using simulation to provide the detailed operational data needed for a comprehensive DEA evaluation and using DEA results to guide the simulation of targeted improvements.

The findings align with the broader literature on combining simulation and DEA for performance improvement in service systems [3], [5], [13]. The recent studies by Ingole [16], Wong [17], Arya and Hatami-Marbini [18], and Tsolas and Charles [19] further underscore the relevance and growing application of such integrated methodologies in various sectors, including healthcare, supply chains, and banking, often leveraging simulation to capture dynamic processes and generate data for DEA. This study contributes specifically to the banking sector by providing a detailed application focused on operational efficiency at the branch level.

However, the study has certain limitations. The accuracy of the simulation outputs depends heavily on the quality and representativeness of the input data collected from the real system (Customer arrivals, service times). While efforts were made to collect data at different times, capturing all sources of variability and ensuring the fitted distributions perfectly represent real-world behavior is challenging.

The definition and measurement of "value added" (Y_2) in a service context can be subjective and complex; the approach taken here, based on transaction volume and type derived from simulation, is an estimation. Furthermore, the DEA results provide relative efficiency within the sample; they do not indicate absolute efficiency. The proposed improvement scenario for DMU_6 was a simplified example; real-world changes may involve multiple factors and interactions.

Despite these limitations, the integrated DES-DEA framework provides a powerful tool for bank managers to gain deeper insights into branch performance, identify root causes of inefficiency, and evaluate the potential impact of operational changes in a controlled, simulated environment before committing resources to actual implementation. This can lead to more effective decision-making and targeted improvement efforts, ultimately enhancing overall bank efficiency and service quality.

6 | Conclusion

This research successfully developed and applied an integrated framework combining DES (Using Arena software) and DEA (Using the BCC model) to evaluate the operational efficiency of commercial bank branches. The study addressed the challenge of obtaining precise operational output data for DEA by generating these measures through realistic simulation models of branch operations.

The two-stage approach allowed for the identification of relatively efficient and inefficient branches within the sample. Furthermore, the integrated methodology facilitated the analysis of potential improvement strategies by simulating changes in operational parameters and assessing their impact on efficiency via DEA. The case study of DMU_6 demonstrated how identifying a bottleneck through simulation and simulating its resolution could lead to a significant improvement in the branch's calculated efficiency.

The findings highlight the utility of this integrated approach for bank managers seeking to enhance operational performance. It provides a quantitative basis for benchmarking branches, diagnosing inefficiencies at a process level, and evaluating the potential benefits of proposed operational changes (e.g., staff allocation, process redesign, technology adoption) in a risk-free virtual environment. By identifying the efficiency frontier and the specific areas where inefficient branches fall short, managers can develop targeted strategies for improvement, potentially leading to better resource utilization, increased customer throughput, and higher value creation.

For future research, several avenues are suggested:

I. Enhanced simulation modeling: Incorporate more detailed aspects of bank operations, such as different customer types (e.g., individual vs. corporate), complex transaction flows, the impact of technology (e.g., online banking, ATMs), and the variability of demand over longer time horizons (e.g., daily, weekly, monthly patterns, as suggested by considering critical periods like month-end or week start).

II. Refining output measurement: Explore alternative or more sophisticated methods for quantifying "Value Added" in a banking context, potentially linking simulation outputs to financial metrics more directly. Consider incorporating qualitative outputs like customer satisfaction, perhaps measured through surveys, and integrating them into a multi-criteria decision-making framework alongside DEA.

III. Advanced DEA models: Utilize other DEA models, such as Slack-Based Measures (SBM), to identify specific input excesses or output shortfalls or dynamic DEA models to evaluate efficiency over time. Investigate advanced techniques like Super-efficiency DEA for ranking efficient units or incorporating undesirable outputs (e.g., customer complaints, error rates) into the analysis.

IV. Optimization within simulation: Integrate optimization techniques directly with the simulation model (Simulation optimization) to automatically search for optimal resource allocations or operational parameters that maximize DEA efficiency or other key performance indicators.

V. Generalizability: Apply this integrated framework to a larger sample of bank branches, potentially across different regions or bank types, to assess its generalizability and identify system-wide patterns of efficiency and inefficiency.

VI. Cost and revenue integration: Develop more sophisticated cost models within the simulation to better integrate financial performance with operational efficiency, potentially using cost DEA models.

VII. By pursuing these research directions, the integrated DES-DEA approach can be further refined and extended, providing even more powerful tools for performance evaluation and improvement in the complex and competitive banking sector and other service industries.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

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References

[1] Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, *30*(9), 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078

[2] Banks, J. (2005). *Discrete event system simulation*. Pearson education India. https://www.amazon.com/Discrete-Event-System-Simulation-Jerry-Banks/dp/0136062121

[3] Al-Refaie, A., Fouad, R. H., Li, M. H., & Shurrab, M. (2014). Applying simulation and DEA to improve performance of emergency department in a Jordanian hospital. *Simulation modelling practice and theory*, *41*, 59–72. https://doi.org/10.1016/j.simpat.2013.11.010

[4] Oh, C., Novotny, A. M., Carter, P. L., Ready, R. K., Campbell, D. D., & Leckie, M. C. (2016). Use of a simulation-based decision support tool to improve emergency department throughput. *Operations research for health care*, *9*, 29–39. https://doi.org/10.1016/j.orhc.2016.03.002

[5] Liu, Z., Rexachs, D., Epelde, F., & Luque, E. (2017). A simulation and optimization based method for calibrating agent-based emergency department models under data scarcity. *Computers & industrial engineering*, *103*, 300–309. https://doi.org/10.1016/j.cie.2016.11.036

[6] Farzaneh Kholghabad, H., Alisoltani, N., Nazari-Shirkouhi, S., Azadeh, M., & Moosakhani, S. (2019). A unique mathematical framework for optimizing patient satisfaction in emergency departments. *Interdisciplinary journal of management studies (Formerly known as Iranian journal of management studies)*, *12*(2), 255–279. https://ijms.ut.ac.ir/article_70833_becef4f8225c4250e6d17ece3b360785.pdf

[7] Kuo, Y. H., Leung, J. M. Y., Graham, C. A., Tsoi, K. K. F., & Meng, H. M. (2018). Using simulation to assess the impacts of the adoption of a fast-track system for hospital emergency services. *Journal of advanced mechanical design, systems, and manufacturing*, *12*(3). https://doi.org/10.1299/jamdsm.2018jamdsm0073

[8] Coursol, P., Mackey, P., Morissette, S., & Simard, J. M. (2010). Optimization of the Xstrata Copper-Horne smelter operation using discrete event simulation. *CIM magazine-Canadian institute of mining metallurgy and petroleum*, *10*, 32. https://b2n.ir/my9739

[9] Koch, D. P. (1979). Iron and steel making facilities planning simulation model. *Winter simulation conference, north Holland publishers* (pp. 259–267). IEEE. https://informs-sim.org/wsc79papers/1979_0032.pdf

[10] Chinbat, U., & Takakuwa, S. (2008). Using operation process simulation for a six sigma project of mining and iron production factory. *2008 winter simulation conference* (pp. 2431–2438). IEEE. https://doi.org/10.1109/WSC.2008.4736351

[11] Zhan, W. (2008). A six sigma approach for the robust design of motor speed control using modelling and simulation. *International journal of six sigma and competitive advantage*, *4*(2), 95–113. https://doi.org/10.1504/IJSSCA.2008.020277

[12] Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

[13] Alizadeh, R., Gharizadeh Beiragh, R., Soltanisehat, L., Soltanzadeh, E., & Lund, P. D. (2020). Performance evaluation of complex electricity generation systems: A dynamic network-based data envelopment analysis approach. *Energy economics*, *91*, 104894. https://doi.org/10.1016/j.eneco.2020.104894

[14] Kasales, C. J., & Sturrock, D. T. (1991). Introduction to siman iv. *1991 winter simulation conference proceedings.* (pp. 106–107). IEEE computer society. https://doi.ieeecomputersociety.org/10.1109/WSC.1991.185601

[15] Mandahawi, N., Al-Shihabi, S., Abdallah, A. A., & Alfarah, Y. M. (2010). Reducing waiting time at an emergency department using design for six sigma and discrete event simulation. *International journal of six sigma and competitive advantage*, *6*(1–2), 91–104. https://doi.org/10.1504/IJSSCA.2010.034858

[16] Ingole, P. (2024). Optimizing resource allocation in hospitals using predictive analytics and information systems. *Journal of information systems engineering and management*, *10*, 400–415. http://dx.doi.org/10.52783/jisem.v10i1s.224

[17] Wong, W. P. (2009). Performance evaluation of supply chain in stochastic environment: Using a simulation based DEA framework. *International journal of business performance and supply chain modelling*, *1*(2–3), 203–228. https://doi.org/10.1504/IJBPSCM.2009.030642

[18] Arya, A., & Hatami-Marbini, A. (2025). Productivity analysis of Indian non-bank financial institutes under uncertainty: A dynamic two-stage DEA approach. *Journal of industrial and management optimization*, *1*, 1–25. https://doi.org/10.3934/jimo.2025088

[19] Tsolas, I. E., & Charles, V. (2015). Incorporating risk into bank efficiency: A satisficing DEA approach to assess the Greek banking crisis. *Expert systems with applications*, *42*(7), 3491–3500. https://doi.org/10.1016/j.eswa.2014.12.033