# Multidimensional Efficiency Evaluation of Bus Routes in Indore, India: Using Data Envelopment Analysis

Madhav Angham, Rupam Fedujwar and Amit Agarwal
Indian Institute of Technology Roorkee
Correspondance: amitfce@iitr.ac.in

**Abstract.** The present study evaluates the efficiency of public transport services on different routes for Indore, India, using Data Envelopment Analysis (DEA). A total of 36 bus routes are analyzed to assess their performance based on multiple input and output variables. The analysis considers four dimensions of efficiency- overall, operational, service, and technical. The study employs both constant and variable returns to scale DEA models tailored to different performance goals. The findings reveal significant variation in route-level efficiency, indicating opportunities for targeted improvements in fleet allocation, scheduling, and service design. A sensitivity analysis further identifies the impact of bus fleet adjustments on efficiency scores. The study provides actionable insights for transit authorities and lays a foundation for data-driven urban transport planning in India.

*Keywords:* Public transport; Route Efficiency; DEA;

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## 1 Introduction

Public transportation plays a vital role in shaping the mobility, accessibility, and sustainability of urban environments. In rapidly growing cities, particularly in developing countries such as India, efficient public transport systems are essential to reduce traffic congestion, minimize environmental impacts, and improve the quality of urban life. However, with increasing operational complexity and limited resources, evaluating the performance of individual routes becomes necessary to ensure optimal service delivery and efficient use of public resources [3]. For that, transit agencies must balance cost containment with service quality, requiring careful allocation of buses, design of stops and schedules, as well as responsiveness to passenger needs. While city-level performance indicators are often used to plan budgets or compare systems across regions, these aggregate measures can conceal substantial variation in efficiency between individual routes. Decisions about fleet assignment, stop spacing, and scheduling are fundamentally made at the route level. Without a clear understanding of route-level efficiency, operators risk over-supplying low-demand corridors while neglecting high-potential ones, leading to financial losses and poor service quality. This study addresses this critical planning need by applying Data Envelopment Analysis (DEA) to evaluate the efficiency of 36 city bus routes in Indore using detailed operational data from Electronic Ticketing Machines (ETMs). Unlike traditional, single-dimensional approaches, this analysis evaluates four distinct efficiency dimensions-overall, operational, technical, and service efficiency, reflecting the diverse goals of cost reduction, service quality, and demand satisfaction. It also incorporates sensitivity analysis to test how operational changes affect efficiency scores. By providing evidence-based, route-level insights, this research aims to support targeted improvements in fleet deployment, stop design, and scheduling strategies, contributing to a more efficient and sustainable urban transport system for Indore.

## 2 Literature review

Measuring efficiency in public transport operations has received extensive academic attention, given the need to maximize service delivery under budget and resource constraints. Data Envelopment Analysis (DEA) has emerged as a preferred method for such studies, valued for its ability to assess relative efficiency among comparable units without assuming a specific production function [2]. Many early DEA applications in transit focused on operator or system-level efficiency. Nolan [6] assessed mid-sized U.S. city bus systems using service hours, fleet size, and ridership. Odeck [7] evaluated Norwegian bus companies, revealing scale effects and management-driven efficiency variations.Such studies provided valuable benchmarks but lacked the granularity needed to guide route-level operational decisions, where issues like over- or under-provisioning of services typically arise. Recognizing this, more recent work has shifted toward route-level analyses. TRAN [8] examined 50 Hanoi bus routes with an output-oriented DEA model, using inputs like trips, stops, and vehicles to assess technical efficiency and operational effectiveness. While that study demonstrated the value of route-level DEA, it relied on annual aggregate data, evaluated only two dimensions of efficiency, and used relatively simple input-output structures. It also omitted financial outputs such as revenue, which are critical for assessing fare-based sustainability, and did not include sensitivity analysis to test the robustness of efficiency scores to operational changes.

In India, DEA has primarily been applied to city- or operator-level benchmarking, comparing systems to inform funding or policy. For example, Vaidya

[9] and Gadepalli and Rayaprolu [4] compared city bus operators to identify macro-level inefficiencies but did not address variations within cities. This leaves a clear gap in evidence-based, route-level planning guidance for transit agencies. This study seeks to fill that gap by applying a multi-dimensional DEA approach to 36 bus routes in Indore, India. It uses high-resolution ETM data to model operational and financial variables at the trip level, evaluating overall, operational, technical, and service efficiency separately to reflect different planning goals. The inclusion of sensitivity analysis offers further practical value by showing how changes in fleet size or stop configurations can influence efficiency outcomes. By doing so, the study delivers actionable, route-specific insights that support more effective, data-driven urban transport planning in the Indian context.

The objectives of the study are to:

- Evaluate the efficiency of 36 city bus routes in Indore using Data Envelopment Analysis (DEA) across four dimensions: overall, technical, operational, and service efficiency.
- Identify high- and low-performing routes to reveal inefficiencies in resource allocation and service delivery.
- Assess the sensitivity of efficiency scores to changes in key operational variables, particularly the number of buses assigned per route.
- Provide actionable, route-specific recommendations for improving scheduling, fleet deployment, and stop design.

## 3 Methodology

Data Envelopment Analysis (DEA) was selected as the methodological framework due to its suitability for evaluating the relative efficiency of service units such as bus routes, which is operate with multiple inputs and outputs. DEA is a non-parametric, frontier-based technique that does not require specification of a functional form, making it especially appropriate when the relationship between inputs and outputs is complex or unknown. Its ability to generate comparative efficiency scores without the need for price or cost data allows for fair benchmarking across heterogeneous routes. Moreover, DEA supports dimensional decomposition, enabling the study to evaluate not just overall efficiency, but also specific dimensions such as operational, technical, and service efficiency, which are critical for informed transit planning.

### 3.1 Data envelopment analysis framework

Data Envelopment Analysis (DEA) is a non-parametric method based on linear programming, widely employed to evaluate the relative efficiency of homogeneous decision-making units (DMUs) [5]. A Decision Making Unit (DMU) is an entity responsible for converting inputs into outputs and is commonly analyzed for efficiency using models like Data Envelopment Analysis (DEA). DMUs should perform similar functions to ensure fair comparison. Examples include schools, hospitals, bank branches, bus operators, and factories. DEA facilitates a comparative assessment of multiple inputs and outputs without requiring an explicit production function. Instead, it constructs a piecewise linear efficiency frontier and measures how closely each DMU performs relative to this benchmark. DEA models can be either input-oriented or output-oriented, depending on the analytical focus. In this research, both orientations are strategically applied to align with specific performance dimensions:

- Input-oriented DEA prioritizes minimizing operational resources, such as travel time, fleet size, or infrastructure (e.g., stops) while maintaining current service levels. This approach is suitable for evaluating overall, operational, and technical efficiency, where the goal is to identify routes that can deliver the same output (e.g., ridership, revenue) with reduced inputs.
- Output-oriented DEA, in contrast, emphasizes maximizing service outcomes, such as passenger demand or revenue, without increasing resource utilization. This is particularly relevant for service efficiency, where enhancing passenger engagement and revenue generation takes precedence over input reduction.

By adopting this dual approach, the study enables a nuanced efficiency analysis tailored to the distinct operational objectives of Indore's public transport system. Furthermore, DEA models can assume different returns to scale:

- Constant Returns to Scale (CRS): Assumes proportional changes in outputs with changes in inputs [2]
- Variable Returns to Scale (VRS): Accommodates increasing or decreasing returns to scale [1]

Both CRS and VRS models are employed in this study. The CRS model (also known as the CCR model) is used for assessing Overall and Technical efficiency, while the VRS model (also known as the BCC model) is applied to evaluate Operational and Service efficiency. This distinction allows for the decomposition of efficiency into technical and scale components.

### 3.2 Mathematical formulation

Let there be $n$ decision-making units (DMUs), indexed by $j = 1, ..., n$, $m$ as the inputs and $s$ as the output.

- $x_{ij}$ and $y_{rj}$ are the input and output values for DMU $j$,
- $x_{io}$ and $y_{ro}$ are the input and output values for DMU $o$,
- $\theta$ is the efficiency score (to be minimized or maximized depending on orientation),
- $\lambda_j$ are weights assigned to peer DMUs.

Then the general form of the output-oriented model for a DMU $o$ is:

$$
\begin{aligned}
\max_{\theta,\lambda_j} \quad & \theta \quad (\geq 1) \\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io}, \quad \forall i = 1, ..., m \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq \theta y_{ro}, \quad \forall r = 1, ..., s \\
& \lambda_j \geq 0, \quad \forall \;\; j = 1, ..., n
\end{aligned} \tag{1}
$$

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$$
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\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \quad \forall i \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \quad \forall r \\
& \lambda_j \geq 0, \quad \forall \;\; j = 1, ..., n
\end{aligned} \tag{2}
$$

In Equation (1), the goal is to maximize $\theta$, which represents the potential increase in outputs (e.g., more passengers or revenue), given current inputs. The first set of constraints $\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io}$ ensures that the combination of DMUs does not use more input than the DMU under evaluation. The second set $\sum_{j=1}^{n} \lambda_j y_{rj} \geq \theta y_{ro}$ ensures that the weighted output from peers is at least $\theta$ times the output of the DMU under evaluation; this reflects the goal of increasing outputs. $\lambda_j \geq 0$ are weights assigned to each peer DMU; they form the virtual composite used for comparison.

In Equation (2), the goal is to minimize $\theta$, which represents the proportional reduction in inputs needed to still achieve the same level of output. The constraints ensure that the composite DMU doesn't produce less output than the one being evaluated, while using fewer or equal resources.

### 3.3 Efficiency models and interpretations

Four separate DEA models are constructed to analyze different dimensions of bus route performance:

*Overall Efficiency:* The objective is to evaluate a bus route's overall efficiency in converting total resources into system-wide outcomes. This model considers the combined physical, temporal, and operational inputs to assess how effectively a route delivers core outputs such as ridership and revenue. It assumes that each route operates at an optimal scale and does not account for inefficiencies caused by scale variations (e.g., a few routes have narrower gap between demand and supply than other routes). The input-oriented approach helps determine how much resource consumption (distance, time, fleet size, etc.) can be reduced without reducing service output.

*Operational Efficiency:* Evaluate the managerial effectiveness in resource deployment and scheduling. Operational efficiency isolates the performance of day-to-day operations such as route planning and scheduling. It assumes constant returns to scale, focusing on the proportional relationship between inputs and outputs. The input orientation identifies whether a route could achieve the same operational results using fewer resources through better planning.

*Service Efficiency:* It indicates how effectively a route's service design contributes to attracting passengers and generating revenue, reflecting the impact of features such as schedule quality and stop configuration on passenger satisfaction and fare recovery. It assumes variable returns to scale, allowing for the fact that not all service changes yield proportional output changes. The output orientation reflects the goal of increasing user engagement and fare output given the existing level of operational input.

*Technical Efficiency:* Technical Efficiency assesses a route's inherent ability to transform operational resources into outputs, independent of managerial or environmental influences. It refers to how well inputs are converted into outputs under the assumption of optimal operation. This input-oriented model, under variable returns to scale, evaluates whether existing infrastructure and fleet are being used efficiently, and identifies potential reductions in resource usage without compromising output levels, particularly in non-optimal conditions

### 3.4 Rationale for input and output selection

The selection of inputs and outputs in this study was carefully structured to reflect both operational controllability, service effectiveness, and is consistent with best practices in the public transport efficiency literature. Inputs such as total distance, total travel time, unique buses, and number of stops represent the fundamental operational resources required to deliver bus services. Variables like average travel time per trip, distance per trip, and buffer time index (extra time included in a trip schedule as a percentage of actual trip time) further capture the quality and complexity of service scheduling, accounting for factors such as congestion, stop density, and timetable reliability. On the output side, total passengers and total revenue quantify the primary objectives of public transport, meeting mobility demand and generating fare-based income. In addition, trips per bus, average passenger per trip, average revenue per trip, capacity utilization, and revenue per kilometre reflect productivity, demand alignment, and financial performance per unit of service. These variables have been widely adopted in previous DEA-based studies on urban bus systems, including Nolan [6], Odeck [7], TRAN [8] and among others. Their inclusion ensures that the model captures a balanced view of both input minimization and output maximization goals, providing a comprehensive and policy-relevant assessment of route-level efficiency in the context of Indore's public transport system.

Also, the chosen inputs and outputs are based on data availability and contextual relevance to public transportation systems in Indore. DEA's flexibility allows for alternative or additional variables depending on the study's goals. The structure and the inputs and outputs for the present study are shown in Table 1.

Table 1: Efficiency model structures

| **Efficiency type** | **Inputs** | **Outputs** |
|---|---|---|
| Overall | total distance in km, total travel time in hours, unique buses, number of stops | total passengers, total revenue |
| Technical | distance per trip, average travel time per trip, unique buses | trips per bus, total passengers |
| Operational | distance per trip, average travel time per trip, number of stops, buffer time index | trips per bus, average capacity utilization |
| Service | distance per trip, average travel time per trip, number of stops | average passenger per trip, revenue per km, total passengers |

## 4 Case study: Indore

The Indore, India, the cleanest city, was selected as the study area for the study. As Madhya Pradesh's largest city and one of India's fastest-growing tier-2 urban centres, Indore has implemented a wide range of public transport reforms, including the introduction of Electronic Ticketing Machines (ETMs), Intelligent Transport Systems (ITS), and a limited-scale Bus Rapid Transit System (BRTS). These features provide a rich operational dataset and an evolving transit landscape that is well suited for route-level efficiency analysis. Moreover, Indore exhibits diverse urban characteristics ranging from dense commercial corridors to emerging residential zones, which makes it a representative case for medium-sized Indian cities undergoing similar transit modernization. The method examines the fixed-route bus services operated by Atal Indore City Transport Service Limited (AICTSL). AICTSL, established in 2005, is the primary transit provider throughout Indore city, in Madhya Pradesh. With its 36 bus routes, the city bus network serves as a vital mode of transportation in Indore, catering to a population of over 2 million residents. These routes cover diverse geographical areas and serve different purposes, from local commuting to intercity travel, reflecting the varied needs of commuters in Indore. The city bus network includes air-conditioned (AC) and non-AC buses to accommodate passenger preferences and budget constraints. This assessment becomes particularly crucial as Indore continues to expand and develop, with increasing urbanization putting pressure on the existing public transportation infrastructure.

The dataset used in this study originates from the Electronic Ticketing Machines (ETMs) deployed across public buses operating in Indore, India. ETMs automatically capture rich, operational, and service data, including trip-level details, timestamps, route identifiers, passenger counts, and revenue information. The data includes 36 active bus routes, each treated as a DMU in the DEA models. The data used for this study covers the period from April 1, 2024, to April 30, 2024, encompassing one full month of route-level public transportation operations. Table 2. summarizes the variables used, their descriptions, and whether they serve as an input or output in any of the four DEA models.

Table 2: Factors considered in the study

| **Variable** | **Description** | **Type** |
|---|---|---|
| Total Passengers | Total number of passengers transported | Output |
| Total Revenue | Total ticket revenue generated | Output |
| Total Distance km | Sum of kilometers traveled across all trips | Input (overall), output (operational) |
| Total Travel Time (hours) | Total time spent on the road across trips (in hours) | Input |
| Unique Buses | Count of different buses serving the route | Input |
| Number of Stops | Number of stops on the route | Input |
| Average Travel Time Per Trip | Average time per trip (in hours) | Input |
| Distance Per Trip | Length of a single route trip (in km) | Input |
| Trips per Bus | Average trips made per bus per day | Output |
| Average Passenger Per Trip | Ratio of total Passenger by number of trips | Output |
| Average Revenue Per Trip | Ratio of total revenue by number of trips | Output |
| Average Capacity Utilisation | Ratio of avg passenger per trip by bus capacity (assuming thirty-five) | Output |
| Revenue per km | Ration of avg revenue per trip by distance | Output |
| Average Buffer Time Index | Schedule buffer as a percentage of trip time | Input |

## 5 Results and Discussion

After implementing the DEA models using route-level data for the city of Indore, efficiency scores were obtained across four dimensions: overall, operational, service, and technical efficiency, based on carefully selected input-output variables for each model. The overall, operational, and technical efficiency models are executed using an input-oriented approach. In contrast, service efficiency was assessed using an output-oriented approach. For input-oriented models, efficiency scores range from 0 to 1, where a score of 1 indicates an efficient route that lies on the efficient frontier, and a score below 1 suggests potential for input reduction without sacrificing outputs. For output-oriented models, scores are generally greater than or equal to 1, with a score of 1 indicating that no further proportional increase in outputs is possible given the current level of inputs.

### 5.1 Overall Efficiency:

It reflects the comprehensive capability of a bus route to convert all available inputs, such as fleet size, total travel time, and supporting infrastructure, into desired performance outcomes like ridership and revenue. An efficiency score of 1 indicates that a route is operating on the efficient frontier, making optimal use of its resources. Routes such as *C2-(16)*, *M-38*, *M-6*, etc., consistently demonstrate such optimal performance, signifying well-balanced resource allocation and demand responsiveness. In contrast, routes like *M-23*, *M-11*, and *R-17*, etc., exhibit significantly lower efficiency scores, suggesting that they consume more inputs than necessary to produce their current output levels. These inefficiencies may stem from operational redundancies, low ridership, or infrastructure underutilization—areas where targeted interventions could yield substantial improvements.

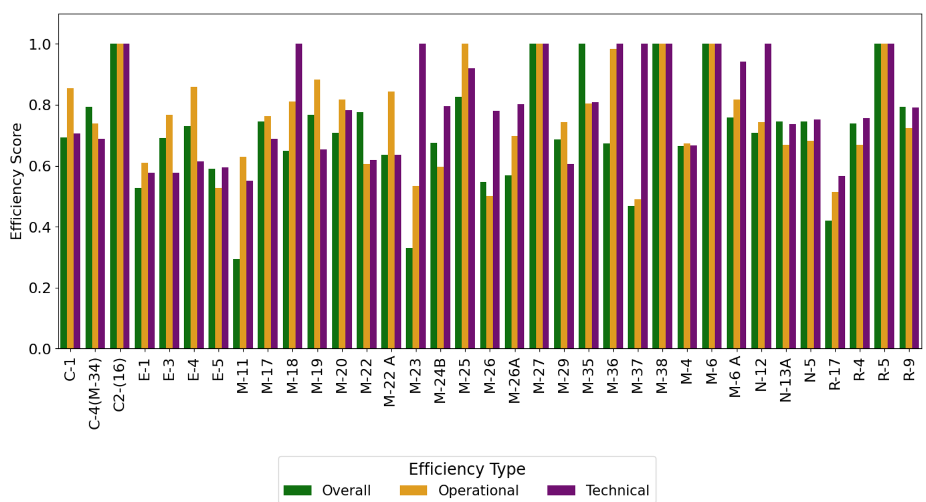


Fig. 1: Overall, operational and technical efficiencies of different routes

### 5.2 Operational Efficiency:

This metric assesses how efficiently each route uses controllable operational inputs, primarily the number of buses and the frequency of service, to produce outputs like distance covered and in-service hours. Routes such as *C2-(16)*, *M-6*, *M-5*, etc. exhibit full efficiency, indicating that no reduction in these inputs is possible without reducing output. Conversely, routes including *R-17*, *M-26*, and *M-37* fall significantly below the efficiency frontier, suggesting operational overuse or misalignment, possibly due to excessive service frequency or fleet size relative to the output achieved. This implies that input adjustments could enhance cost-effectiveness and resource utilization without compromising performance.

### 5.3 Technical Efficiency:

Technical efficiency captures the overall input-output conversion ability, assuming all routes operate at an optimal scale. High-scoring routes such as *C2-(16)*, *M-23*, *M-18*, etc. are technically efficient, indicating they maximize outputs (e.g., ridership or revenue) relative to physical and temporal inputs (e.g., route length, travel time). On the other hand, routes such as *E-3*, *R-17*, and *M-11* demonstrate substantial inefficiencies. These may arise from factors such as underutilized routes, poorly designed travel paths, or suboptimal scheduling, where inputs are not being translated into proportional output. Improving these would require a reevaluation of routing logic or better matching of resources to demand patterns.

### 5.4 Service Efficiency:

Measures the effectiveness of a route's service design as stop distribution, route length, and travel characteristics, generating key outcomes like ridership levels and fare revenue. This model highlights how design decisions influence user engagement and system performance. Routes like *M-23*, *M-11*, and *R-17* demonstrate very high service efficiency scores, indicating that their current configurations are highly effective in translating service features into desirable outcomes. These routes likely benefit from optimal stop placement, strong demand corridors, and well-matched scheduling. On the other hand, routes such as *M-25*, *M-27*, *R-5*, etc., while relatively close to the efficiency frontier, exhibit lower marginal benefits from further design modifications, suggesting that improvements in these cases may require interventions beyond service configuration, such as demand stimulation or better connectivity.

Figures 1 and 3 provide a clear, color-coded visualization of DEA efficiency scores for all bus routes across the four models, i.e., Overall, Operational, Technical and Service efficiency.

These visual distinctions facilitate quick identification of well-performing and underperforming routes across different efficiency types. Figure 3 provides a clear, color-coded visualization of DEA efficiency scores using Service efficiency model for all bus routes.

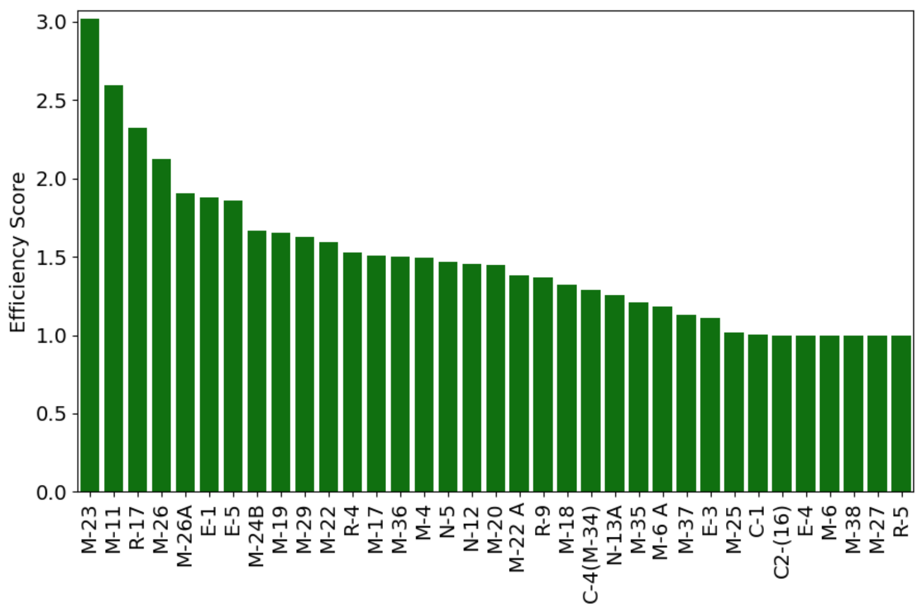


Fig. 2: Service efficiency on different routes

### 5.5 Route-wise Recommendations:

Based on the efficiency scores the following route-specific recommendations are offered:

- High-Efficiency Routes (e.g., C2-(16), M-6, M-38): These consistently scored 0.9 across multiple models and can serve as benchmarks. Their practices e.g., buses scheduling and stop distribution should be studied and emulated for comparable routes.
- Technically efficient but service-inefficient (e.g., M-23, M-26): These routes use inputs efficiently but generate low passenger volumes. Recommendations include realigning stops, improving connectivity to key demand hubs, and refining peak-hour scheduling.
- Operationally inefficient routes (e.g., M-26, M-37): These routes exhibited high input levels with low productivity, primarily due to underutilized capacity during different hours. Hence, it is recommended revisiting trip frequencies and reducing fleet size during different time periods as per need to improve operational efficiency by minimizing empty seat runs and enhancing average capacity utilization.
- Low-Efficiency in All Dimensions (e.g., M-11, R-17): These should be prioritized for route audits, possible mergers with parallel services, or phased withdrawal if demand does not justify operation.

## 6 Sensitivity Analysis

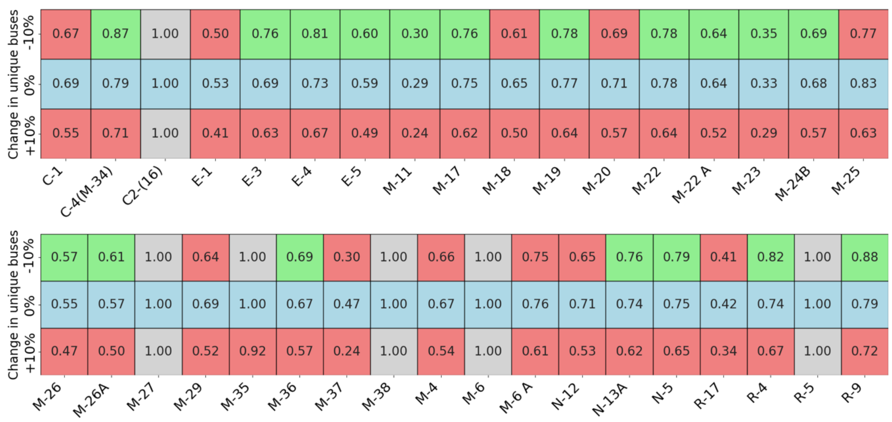


Fig. 3: Fig. 3: Sensitivity analysis of Overall Efficiency (Red: a decrease in efficiency score, Green: an improvement, Blue: the current score.)

A sensitivity analysis is performed to determine the impact of changing the input parameter on the efficiency. Sensitivity analysis introduces controlled perturbations to selected input or output variables to investigate how responsive the efficiency scores are to such changes. This not only enhances the interpretability of the results but also offers valuable insight into which operational parameters most influence route performance.

The study conducted an univariate sensitivity analysis on the DEA-based overall efficiency scores of city bus routes, with a particular focus on the unique buses variable. The number of unique buses running on the routes serves as a key input in the overall DEA model and reflects the operational resource commitment for each route. The number of unique buses for each route was individually varied by $\pm 10\%$, while keeping all other routes and variables constant. This approach allows for isolating the impact of change on a per-route basis without confounding interdependencies.

The sensitivity analysis (cf. Figure 3) for public transport routes provides a comprehensive understanding of operational efficiency by examining how changes in resource allocation impact performance. Among the routes analyzed, such as C2-(16), M-27, M-6, M-38, and R-5, demonstrate stability in efficiency score with $\pm 10\%$ variations in bus numbers, indicating that these routes are fully efficient and robust to small operational changes (gray scale routes in Figure 3). On a 10% increase in the buses, most routes are becoming inefficient, indicating the over-supply. In contrast, other routes reveal inefficiencies that warrant targeted interventions. For instance, routes like C-4(M-34), E-3, E-4, R-9, etc., show improved efficiency when bus numbers are reduced, suggesting they are over-allocated and would benefit from downsizing to enhance resource utilization. Conversely, routes such as E-1, M-18, M-20, M-25, etc., experience a decline in efficiency when buses are removed from the operations, highlighting potential issues where decreasing capacity leads to underutilization. The routes like M-11, R-17, M-23, M-37, etc., already have low baseline efficiency and high sensitivity to changes, particularly when bus numbers are reduced, indicating structural inefficiencies that may require a complete operational redesign rather than simple fleet adjustments.

These findings underscore the value of sensitivity analysis as both a robustness check for efficiency models and a decision-making tool. By identifying which routes are over-resourced or underutilized, transit authorities can prioritize interventions such as relocation of buses, schedule optimization, or redesigning the service on the routes.

## 7 Limitations

While this study offers valuable insights into the efficiency of public bus routes in Indore using DEA, it is subject to several limitations:

- Static analysis: The DEA models employed in this study are based on cross-sectional data averages over a one-month period. This approach overlooks temporal variations, such as peak vs. off-peak performance, weekday vs. weekend fluctuations, and seasonal demand shifts. As a result, efficiency scores may misrepresent routes with strong time-dependent patterns (e.g., commuter-heavy or market-based routes), leading to overestimation or underestimation of their true performance across the year. This can be studied as future work.
- Data Constraints: The analysis is restricted to operational and revenue-related variables available from ETM and route-level logs. Key factors such as driver behaviour, vehicle breakdown frequency, fuel consumption, and real-time punctuality were excluded due to data unavailability. These omissions may bias efficiency scores by failing to distinguish between controllable inefficiencies (e.g., poor route planning) and uncontrollable delays (e.g., breakdowns or signal timings). For instance, a technically inefficient route may in fact suffer from operational disruptions not captured in the available data.
- Assumption of Homogeneity: DEA assumes that all Decision-Making Units (DMUs), in this case, bus routes, operate under comparable conditions. However, variations in infrastructure quality, traffic congestion, topography, and passenger behaviour (e.g., boarding delays or fare evasion) can create unequal operating environments across routes. Ignoring these contextual differences may unfairly penalize routes in different landscapes of the city areas or inflate the efficiency of routes in newer, or less congested, corridors.
- No qualitative metrics: DEA is inherently a quantitative technique and does not incorporate qualitative dimensions such as passenger satisfaction, travel

comfort, accessibility for persons with disabilities, or perceptions of safety. Routes may appear technically efficient yet perform poorly in terms of user experience or social inclusion. This limitation restricts the comprehensiveness of the assessment, especially when planning improvements aimed at service equity or customer-centric policies.
- Scale and scope exclusion: This study focuses solely on fixed-route services and excludes the broader network context, such as feeder routes, BRTS corridors, and multimodal integration. As a result, system-level complementarities or inefficiencies, such as duplication of services or poor transfer coordination, are not captured. This may limit the applicability of route-level recommendations for strategic or system-wide planning decisions.

## 8 Conclusion

The present study applied a robust Data Envelopment Analysis (DEA) framework to evaluate the efficiency of bus routes in Indore, India, using a comprehensive dataset derived from Electronic Ticketing Machine (ETM) data. Four distinct DEA models were developed to assess overall, technical, operational, and service efficiencies. The findings revealed significant variability across routes, with some consistently operating near the efficiency frontier, while others exhibited potential for improvement. Notably, service efficiency showed room for enhancement in routes with high stop density but suboptimal passenger engagement. Technical and operational inefficiencies were frequently linked to longer travel times and lower trip frequencies per bus. The modular and adaptable DEA implementation which ensures the reproducibility and extensibility of the analysis. It sets the foundation for integrating advanced techniques such as time-series analysis, bootstrapping, and network DEA in future research. Further, a univariate sensitivity analysis on the DEA-based overall efficiency also performed to determine the impact of changing the input parameter on the efficiency, with a particular focus on the unique buses variable. These findings underscore the value of sensitivity analysis as both a robustness check for efficiency models and a decision-making tool. Ultimately, this research offers actionable insights for transit authorities to reallocate resources, optimize schedules, and improve service delivery. By identifying best-performing routes and benchmarking underperformers, the study contributes to data-driven and equitable public transportation planning.

While the analysis in this study is centered on Indore, the findings have broader applicability to similarly sized cities both within India and globally. Cities such as Bhopal, Surat, and Lucknow face comparable operational constraints, such as mixed-traffic conditions, fluctuating ridership, and limited transit infrastructure, which makes the DEA-based, route-level evaluation approach adopted here particularly relevant. International counterparts like Hanoi (Vietnam) and Medellín (Colombia), with evolving transit systems and data-driven reforms, also mirror Indore's urban transport context. The insights derived from Indore's efficiency patterns and sensitivity to fleet adjustments can thus inform scalable strategies for improving public bus service delivery across a wide range of urban settings undergoing modernization. By establishing a modular, multi-dimensional DEA framework, this study contributes a replicable method that can support performance optimization across diverse public transport networks.

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