

Optimizing the Financial and Service Performance of Distressed BRT Systems in Makassar City

Muhammad Rusman

Department of Industrial Engineering, Universitas Hasanuddin, Makassar, Indonesia
rusman@unhas.ac.id (corresponding author)

Andry Yusdi

Department of Industrial Engineering, Universitas Hasanuddin, Makassar, Indonesia
andryyyusdi@gmail.com

Dwi Handayani

Department of Industrial Engineering, Universitas Hasanuddin, Makassar, Indonesia
dwianda@unhas.ac.id

Mansur Maturidi Arief

Department of Aeronautics & Astronautics, School of Engineering, Stanford University, California, USA
mansur.arief@stanford.edu

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ABSTRACT

Bus Rapid Transit (BRT) systems in developing countries face serious sustainability challenges that can lead to route closures and threaten public access to affordable transportation. This study demonstrates that a Multi-Objective Goal Programming (MOGP) approach can improve the economic viability of BRT operations by allocating a fleet responsive to variations in passenger demand. Optimization of the KM5 Corridor in Makassar reduced fleet requirements from 17 to 13 buses, with a daily deployment of 5–10 buses; transformed a monthly deficit of IDR 18.7 million into a profit of IDR 15.6 million; increased the Benefit-Cost Ratio (BCR) from 0.81 to 1.24; and maintained a load factor above 70%. These findings demonstrate that appropriate operational optimization can support a more sustainable transportation system without additional reliance on subsidies. The proposed model provides a data-driven decision-making framework that balances financial sustainability and service quality. The operational scenarios analyzed also consider the current fleet availability (17 buses), while several additional scenarios are included to illustrate potential performance improvements with future fleet expansion. Further research is proposed to apply the Goal Programming (GP) method to various public transportation routes to optimize the overall fleet distribution and to conduct periodic evaluations of fleet distribution and dynamic passenger demand.

Keywords-benefit-cost ratio; bus rapid transit; load factor; goal programming; emerging economies

I. INTRODUCTION

The performance of transportation services is shaped by social dynamics and population density, making transportation planning and land use crucial components of public policy [1, 2]. However, congestion, pollution, and low utilization of public transport continue to pose significant challenges, negatively affecting both environmental sustainability and quality of life [3]. Land transportation alone accounts for approximately 70% of emissions in the transportation sector [4], and without effective mitigation strategies, these impacts

are likely to intensify [5]. These challenges are particularly complex in developing countries, where limited financial resources and socioeconomic constraints further hinder the development of efficient and sustainable urban transportation systems [6]. In developing countries, public transportation systems face the dual challenge of providing affordable services while maintaining financial sustainability with limited subsidies [7, 8]. These services are widely used by vulnerable groups, such as low-income communities, students, and workers; thus, closing routes that are not financially viable can exacerbate social inequality. This social dimension makes

transportation optimization more complex because the social value of specific routes is often not fully reflected in conventional cost-benefit analyses. Makassar, a major city in South Sulawesi, Indonesia, reflects the challenges of public transportation systems in developing Southeast Asian countries. Its transportation system includes a modern system known as Bus Rapid Transit (BRT), locally branded as Trans Mamminasata [9]. The BRT system has been developed to improve public transport services and is complemented by app-based (online) transportation services. The BRT system operates under a Buy-The-Service (BTS) scheme to enhance efficiency and accessibility [10]. However, the system still faces operational sustainability challenges due to limited fare revenue, high operational costs, and minimal government subsidies. Figure 1 shows the development of Trans Mamminasata passenger numbers on four corridors: K1 (Panakkukang Mall - Galesong Port), K2 (Panakkukang Mall - Sultan Hasanuddin International Airport), K3 (UNHAS Campus - PIP Campus), and K4 (UNHAS Faculty of Engineering, Gowa - Panakkukang Mall) from January to June 2022. Overall, all corridors showed an increasing trend in passenger numbers from month to month, although there were slight fluctuations in some periods.

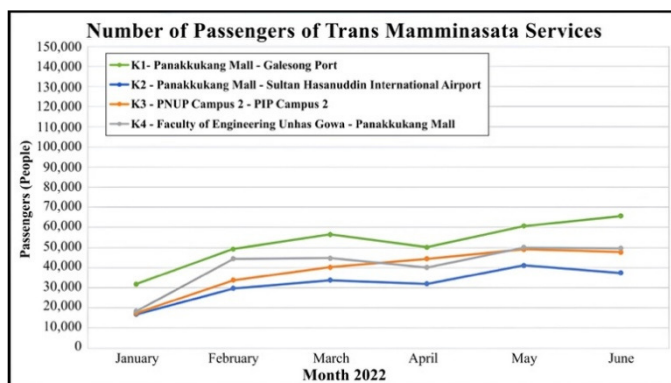


Fig. 1. Number of passengers on BRT KM 5 Makassar services.

The financial sustainability challenges of Makassar's BRT system are illustrated by the closure of Corridor 4, which, despite having the second-highest passenger demand, was unable to cover operational costs due to a low fare policy. Corridor KM5 presents a significant opportunity for intervention to avoid a similar outcome. This 54-km route connects the UNHAS campuses in Tamalanrea and Gowa, serving a large population of students, lecturers, and staff. Passenger demand varies considerably with the academic calendar, with daily ridership reaching approximately 2500–3500 on weekdays and declining to 1500–2000 on weekends. However, the current fixed allocation of 15 buses/day fails to reflect these fluctuations, leading to operational inefficiencies and a mismatch between costs and revenue. As a result, the long-term sustainability of this vital educational corridor is at risk, potentially restricting access to higher education for thousands of students in South Sulawesi. Route closures due to financial unsustainability are widespread and have a significant impact on vulnerable groups in developing countries [8, 11]. The COVID-19 pandemic has further exposed the fragility of public transport systems, with many operators facing

bankruptcy without government intervention [12]. These challenges are compounded by exchange rate volatility, limited fleet financing, and regulations that prioritize social access over commercial viability. These conditions place operators in a poverty trap, where low fares limit revenue, reduce service quality, and ultimately reduce passenger numbers.

Although the research on transportation planning and optimization has been growing, the literature still lacks multi-objective optimization models that simultaneously account for time-demand fluctuations, cost efficiency, and service quality in resource-constrained BRT systems in developing countries [13, 14]. Existing approaches generally use single-objective models developed for transportation systems in developed countries, thus failing to capture socioeconomic trade-offs that affect operational sustainability, such as social responsibility, budget and subsidy constraints, service quality demands, and the risk of route closures impacting vulnerable groups. Several studies have developed optimization models for public transportation systems that generally focus on a single operational objective, such as improving schedule efficiency or operational performance. Authors in [15] optimized bus schedules to improve operational efficiency, while authors in [16] emphasized route and schedule optimization to improve transportation system performance. Although more recent studies, such as [17], have begun to adopt a multi-objective approach, most existing models still focus on a single performance indicator. This approach is considered insufficient to represent the trade-off between socio-economic factors and service quality faced by BRT operators, especially in developing countries. This research addresses a significant gap by developing a Multi-Objective Goal Programming (MOGP) framework for financially constrained BRT systems in developing countries. The proposed optimization model simultaneously minimizes unserved passengers and maximizes operational profitability, enabling a balance between service quality and financial sustainability. It incorporates fleet size and trip scheduling through binary variables to better reflect real-world operational conditions, while integrating fleet optimization with financial analysis to evaluate service feasibility. Unlike prior studies that typically focus on a single objective, this approach captures the trade-offs between operational efficiency and social service provision. Although Goal Programming (GP), an extension of linear programming, is well-suited for handling such conflicting objectives, its application in public transportation remains limited, with most studies concentrated in production planning contexts [18, 19]. The proposed framework optimizes daily fleet allocation by considering key operational constraints, including fleet availability, vehicle capacity, and cost structure, while using deviation variables to manage competing objectives. Its application to the KM5 Corridor is expected to enhance operational efficiency, mitigate financial risks, and establish a sustainable BRT operating model that can be replicated in other developing-country contexts.

II. RESEARCH METHODOLOGY

A. Benefit-Cost Ratio (BCR)

The BCR is a key tool for assessing the financial feasibility of public transportation investments, particularly in developing

countries with limited capital allocation [20]. BCR analysis assesses whether a project's benefits exceed its costs by considering time savings, operational efficiency, and social accessibility as indicators of benefit [21, 22]. This method helps determine optimal resource allocation to maximize service benefits and minimize operational costs for long-term sustainability. In BRT applications, the BCR serves to assess the financial feasibility of a route and determine the most efficient operational strategy for passenger demand [23]. The BCR compares annual benefits, such as fare revenue, time savings, and external cost reductions, with annual costs that include operations, maintenance, labor, and capital investment [22, 23]. This evaluation is crucial for transportation projects in developing countries with budget constraints. The BCR value for BRT ranges from 0.6 to 2.4, with financial sustainability generally achieved at a BCR above 1.2 [24]. The mathematical formulation is expressed as:

$$\text{BCR} = \frac{\text{Income}}{\text{Expenditure}} \quad (1)$$

The BCR interpretation provides clear decision criteria: a $\text{BCR} > 1$ indicates that benefits exceed costs and is financially viable, while a $\text{BCR} < 1$ indicates that costs exceed benefits and requires operational optimization or service adjustments. This evaluation is important for policymakers in developing countries to assess profitability and sustainability under budget constraints.

B. Load Factor

Load factor analysis measures the level of vehicle occupancy relative to available capacity as an indicator of resource utilization efficiency and financial sustainability [25, 26]. A load factor above 100% indicates overloading that reduces service comfort and reliability, while a value below 70% indicates inefficient fleet utilization due to excess supply compared to demand [25]. Integrated load factor optimization can increase load levels from below 70% to above 90%, thereby improving passenger satisfaction and operator profitability [27]. Load factor improvements of 14%–37% have been demonstrated through dynamic scheduling and route optimization in developing countries [28]. Optimal management requires 70%–100% load while maintaining operational efficiency and service quality, although variations in demand time and the risk of crush loads pose challenges. Increased load factors also have a positive impact on environmental performance due to improved vehicle fuel efficiency [9]. Effective optimization requires a dynamic fleet allocation strategy based on demand projections to maintain service reliability.

C. Goal Programming

GP is an optimization method for decision-making with multiple conflicting objectives, making it relevant for BRT fleet optimization in developing countries [19, 29]. As an extension of Linear Programming, GP uses deviation variables to accommodate financial, service quality, and social equity objectives [18]. This method focuses on minimizing deviations from established targets, rather than on a single objective. MOGP extends this approach by prioritizing and weighting objectives according to stakeholder and policy preferences

[17]. The application of GP in public transportation can reduce total costs by 15%–25% while improving service quality by considering time variations and capacity constraints [30]. The integration of GP with machine learning improves the quality of solutions for real-time fleet optimization [16]. The relationship between travel time and distance is influenced by traffic conditions, route characteristics, and operational constraints [31]. Various studies have shown the effectiveness of GP in balancing service quality and financial sustainability, including schedule optimization and reducing passenger waiting time [18, 30]. The GP approach is suitable for BRT optimization in developing countries with limited resources and diverse stakeholder demands.

D. Ridership Data

This study utilizes operational data from the Makassar BRT system. Primary data were collected through interviews with BRT operational management, while secondary data consist of daily passenger counts for November 2024, obtained from official records of Perum DAMRI Makassar Branch. These records are routinely compiled during operations and summarized in operational reports, ensuring data reliability. The analysis focuses on the fleet allocation problem for the KM5 Corridor, specifically the route connecting the Hasanuddin University main campus in Tamalanrea, Makassar City, to the Faculty of Engineering campus in Gowa Regency. Based on the BCR, load factor, and operational cost analysis, a GP model is developed and evaluated. Detailed passenger data are presented in Table I and further summarized by day in Table II.

TABLE I. BRT KM5 RIDERSHIP DATA FOR NOVEMBER 2024

Day, date	Passengers/day (people)	Day, date	Passengers/day (people)
Fri, 1/11/2024	2982	Sat, 16/11/2024	1951
Sat, 2/11/2024	2259	Sun, 17/11/2024	1680
Sun, 3/11/2024	1912	Mon, 18/11/2024	1895
Mon, 4/11/2024	2860	Tue, 19/11/2024	2966
Tue, 5/11/2024	3455	Wed, 20/11/2024	2557
Wed, 6/11/2024	3203	Thu, 21/11/2024	3018
Thu, 7/11/2024	2987	Fri, 22/11/2024	2767
Fri, 8/11/2024	3171	Sat, 23/11/2024	1789
Sat, 9/11/2024	2198	Sun, 24/11/2024	1570
Sun, 10/11/2024	1904	Mon, 25/11/2024	2957
Mon, 11/11/2024	3086	Tue, 26/11/2024	3034
Tue, 12/11/2024	3157	Wed, 27/11/2024	1387
Wed, 13/11/2024	3029	Thu, 28/11/2024	2774
Thu, 14/11/2024	2884	Fri, 29/11/2024	2283
Fri, 15/11/2024	2847	Sat, 30/11/2024	1596

TABLE II. DAYS OF WEEK RIDERSHIP SUMMARY

Day	Number of passengers (people)					Average number of passengers (people)
	Week 1	Week 2	Week 3	Week 4	Week 5	
Mon	2860	3086	1895	2957	N/A	2700
Tue	3455	3157	2966	3034	N/A	3153
Wed	3203	3029	2557	1387	N/A	2544
Thu	2987	2884	3018	2774	N/A	2916
Fri	2982	3171	2847	2767	2283	2810
Sat	2259	2198	1951	1789	1596	1959
Sun	1912	1904	1680	1570	N/A	1767

E. Operational Parameters

Table III summarizes the system's key operational specifications, including fleet allocation, service capacity, route characteristics, and fare structure. Current operations deploy 15 of the 17 buses, each with a capacity of 40 passengers, on four daily trips along a 54-km corridor. This configuration yields a theoretical system capacity of 4800 passengers/day (15 buses × 4 trips × 40 passengers × 2 directions).

TABLE III. OPERATIONAL PARAMETERS

Route	Route length (Km)	Number of buses (SO)	Number of buses (SGO)	Capacity bus (people)	Number of trips	Fare price (IDR)
KM5	54	15	17	40	4	4600

F. Cost Components

The system's total operational cost includes both fixed and variable costs. The breakdown is:

1) Fixed Cost

Fixed costs are expenses that remain constant regardless of how often the bus operates. These costs include vehicle depreciation, vehicle tax, and driver salaries. The information is detailed in Table IV. The daily fixed cost/bus, whether in operation or not, is IDR 415559.

TABLE IV. FIXED COST

Fixed cost	Cost (IDR)	Time period	Cost/day (IDR)
Vehicle depreciation	1000000000	7 years	273972
Vehicle tax	1188000	1 years	3254
Vehicle drivers	4000000	1 month	133333
Cleaning	150000	1 month	5000
Total			415559

2) Variable Cost

Variable costs vary with the level of bus operations and include expenses such as fuel consumption, tire usage, cleaning, and maintenance. As shown in Table V, the variable cost is IDR 2264/km. Given that the KM5 route spans 54 km, the cost /rip is IDR 122256. With four trips/day, the total daily variable cost/bus amounts to IDR 489024.

TABLE V. VARIABLE COST

Variable cost	Cost (IDR)	Expenditure	Usage distance (Km)	Cost/Km (IDR)
Fuel oil	6800	1 Liters	4500	1511
Tire use	2200000	6 Pieces	24000	550
Transmission oil	30000	1 Liters	5000	6
Differential oil	200000	1 Liters	5000	40
Oil filter	200000	1 Pieces	5000	40
Diesel filter	200000	1 Pieces	5000	40
Air filter	85000	1 Pieces	5000	17
Engine oil	100000	1 Liters	5000	20
Chassis grease	200000	1 Pieces	5000	40
Total				2264

G. Benefit Cost Ratio Calculation

This financial analysis aims to evaluate the operational efficiency of the BRT service on Route KM5, which operates with 15 buses. Expenditures and income are summarized in Table VI.

TABLE VI. FINANCIAL ANALYSIS CALCULATION BRT OF THE KM 5 ROUTE

Day	Average number of passengers (people)	Expenditure (IDR)	Income (IDR)
Monday	2700	14400252.42	12420000
Tuesday	3153	14400252.42	14503800
Wednesday	2544	14400252.42	11702400
Thursday	2916	14400252.42	13413600
Friday	2810	14400252.42	12926000
Saturday	1959	14400252.42	9011400
Sunday	1767	14400252.42	8128200
Total		100801766.94	82105400

Calculating the BCR using (1), we obtain:

$$BCR = \frac{\text{Income}}{\text{Expenditure}} = \frac{\text{IDR } 82105400}{\text{IDR } 100801766.94} = 0.81$$

It should be noted that the operational costs exceed the expected revenue. This result indicates that the route, under current operations, is not financially viable and thus risks discontinuation.

H. Load Factor Analysis

Next, the system's load factor is analyzed to assess bus occupancy levels during operations. Using ridership data from Table I, the load factor is calculated by dividing the total number of passengers/day by the total bus capacity (i.e., 4800 passengers/day). The results are outlined in Table VII.

TABLE VII. LOAD FACTOR DATA BRT OF KM 5 ROUTE

Date	Number of passengers (people)	Load factor (%)	Date	Number of passengers (people)	Load factor (%)
01/11/24	2982	62.13	16/11/24	1951	40.65
02/11/24	2259	47.06	17/11/24	1680	35
03/11/24	1912	39.83	18/11/24	1895	39.48
04/11/24	2860	59.58	19/11/24	2966	61.79
05/11/24	3455	71.98	20/11/24	2557	53.27
06/11/24	3203	66.73	21/11/24	3018	62.88
07/11/24	2987	62.23	22/11/24	2767	57.65
08/11/24	3171	66.06	23/11/24	1789	37.27
09/11/24	2198	45.79	24/11/24	1570	32.71
10/11/24	1904	39.67	25/11/24	2957	61.6
11/11/24	3086	64.29	26/11/24	3034	63.21
12/11/24	3157	65.77	27/11/24	1387	28.9
13/11/24	3029	63.1	28/11/24	2774	57.79
14/11/24	2884	60.08	29/11/24	2283	47.56
15/11/24	2,847	59.31	30/11/24	1596	33.25

For November 2024, most days recorded a load factor below 70%. This consistently low figure indicates that the route is underutilized and has not reached optimal performance in accommodating passenger needs. The disparity between available bus capacity and actual passenger usage highlights inefficiencies in service delivery, and hence the potential for more optimized operational adjustments.

I. Goal Programming Model Development

This study describes the model development of the systems using GP. The main objectives are to minimize the number of underserved (untransported) passengers and to maximize operational profits. The general formulation is:

Objective Function:

$$\text{Minimize } Z = w_1 \sum_{i=1}^I d_i + w_2 \sum_{i=1}^I (T \times (P_i - d_i)) - (FC \times x_i + VC \times y_i) \tag{2}$$

Subject to:

$$d_i \geq P_i - (C \times y_i) \tag{3}$$

$$x_i = \sum_{j=0}^N j \times z_{(i,j)} \tag{4}$$

$$r_i = \sum_{k=0}^{Mxr} k \times w_{(i,k)} \tag{5}$$

$$y_i = \sum_{j=0}^N \sum_{k=0}^{Mxr} (j \times k) \times v_{(i,j,k)} \tag{6}$$

$$\sum_{j=0}^N z_{(i,j)} = 1 \tag{7}$$

$$\sum_{k=0}^{Mxr} w_{(i,k)} = 1 \tag{8}$$

$$\sum_{j=0}^N \sum_{k=0}^{Mxr} (j \times k) \times v_{(i,j,k)} = 1 \tag{9}$$

$$v_{(i,j,k)} \leq z_{(i,j)}, v_{(i,j,k)} \leq w_{(i,k)}, v_{(i,j,k)} \leq z_{(i,j)} + w_{(i,k)} - 1 \tag{10}$$

$$d_i \geq 0 \tag{11}$$

In this model, (3) ensures that the number of underserved passengers is calculated correctly. Equation (4) links the number of buses used to a binary variable indicating whether bus j operates on day i. Equation (5) associates the number of trips on day i with a binary variable that specifies whether trip k is conducted. Equation (6) connects the total number of buses and trips (itineraries) to a binary variable representing the selection of a specific combination of j buses and k trips on day i. Equations (7)-(9) ensure that only one combination of buses and trips is selected for each day. Equation (10) enforces consistency between bus and trip selections: if both the bus and trip are selected (i.e., equal to 1), then their combination is also selected; otherwise, it is not. Finally, (11) ensures that the number of underserved passengers remains nonnegative. The key notations used in the model are summarized in Table VIII.

This optimization model was designed with two main objectives: minimizing the number of underserved passengers and maximizing BRT operational profit. By incorporating these dual goals, the model ensures a balanced decision-making approach that considers both service quality and financial viability through priority weights. The model is then developed in Google Colab. The software used in this study is Google Colab, utilizing the CBC solver through the PuLP library in Python. The parameters employed in the model include the number of passengers, bus capacity, maximum number of trips, fixed costs, variable costs, passenger fares, and the number of available buses. The solution is presented in Table IX, with the optimum route being 4.

TABLE VIII. NOTATION SUMMARY

Notation	Description
w_1	Priority weight to minimize underserved passengers
w_2	Priority weight to maximize profits
P_i	Average number of passengers on day i
C	Bus capacity/trip (40 passengers)
FC	Fixed cost/bus/day (Rp 415559/bus/day)
VC	Variable cost/bus/day (Rp 489024/bus/day)
T	Fare/passenger (Rp 4600/passenger)
N	Number of buses available (17 buses)
I	Number of days considered (7 days)
Mxr	Maximum trips/day (4 trips)
x_i	Number of buses operated on day i
r_i	Number of trips made on day i
y_i	Number of buses operated multiplied by the number of trips on day i
d_i	Number of passengers not transported on day i
$z_{(i,j)}$	Binary variable for selecting the number of buses
$w_{(i,k)}$	Binary variable for selecting the number of trips
$v_{(i,j,k)}$	Binary variable for selecting the combination of the number of buses and trips

TABLE IX. OPTIMUM SOLUTION SUMMARY

Day	Avg. passenger (people)	Fleet (unit)	Load factor (%)	Revenue (IDR)	Cost (IDR)	Profit (IDR)
Mon	2700	8	100	11776000	9314673	2461327
Tue	3153	10	98.53	14503800	10292769	4211031
Wed	2544	8	99.38	11702400	9314673	2387727
Thu	2916	9	100	13248000	9803721	3444279
Fri	2810	9	97.57	12926000	9803721	3122279
Sat	1959	6	100	8832000	8,336577	495423
Sun	1767	5	100	7360000	7847529	487529
Total				80348200	64713666	15634534

Table IX demonstrates significant improvements in operational efficiency through dynamic fleet allocation, as reflected in the model's optimal solution. The optimal solution varies the bus deployment from a minimum of 5 units on Sunday to a maximum of 10 units on Tuesday, using only 13 of the available 17 buses. This variable allocation strategy, maintaining four daily trips across all operational days, generates an optimal monthly revenue of IDR 80348200 while reducing operational expenditures to IDR 64713666, yielding a total profit of IDR 15634534. These results demonstrate the model's effectiveness in transforming Route KM5 from a potentially loss-making operation into a profitable service through data-driven fleet optimization that balances service quality with operational efficiency. The new BCR is now operating at optimal conditions:

$$BCR = \frac{IDR\ 80348200}{IDR\ 64713666} = 1.24$$

This situation demonstrates financial feasibility, with 8, 10, 8, 9, 9, 6, and 5 buses operated from Monday to Sunday, respectively, resulting in a load factor of 97.57%–100%. However, this very high utilization rate has the potential to reduce service quality. With the development of green accounting that assigns financial value to emissions, as summarized in Table X, determining the number of buses for target load factors of 100%, 75%, 50%, and 25% becomes crucial to balance operational efficiency, financial sustainability, and environmental impact [32]. In this analysis, the limited fleet availability of 17 buses was one of the main

operational constraints. Therefore, the scenarios analyzed not only reflect current operational conditions but also include several exploratory scenarios that demonstrate potential improvements in service performance with future fleet expansion.

TABLE X. NUMBER OF BUSES REQUIRED FOR VARIOUS LOAD FACTORS

Days	Number of buses operated at target load factor (unit)			
	100%	75%	50%	25%
Mon	8	11	17	34
Tue	10	13	20	39
Wed	8	11	16	32
Thu	9	12	18	36
Fri	9	12	18	35
Sat	6	8	12	24
Sun	5	7	11	22

III. RESULT AND DISCUSSION

A. Results

Preliminary financial analysis indicates serious sustainability challenges for the KM5 Corridor, with a BCR of 0.81 due to operating costs exceeding fare revenue under the current service scheme. This reflects the financial viability crisis common to BRT systems in developing countries with limited subsidies and demands for affordable fares. The proposed model addresses these challenges through dynamic fleet allocation, reducing the number of operational buses and improving financial performance to a BCR of 1.24, transforming the route from loss-making to profitable. This adjustment aligns with the academic activity-based demand pattern, which exhibits significant temporal variation. These results confirm that efficient fleet management can improve financial sustainability without compromising accessibility. However, implementing dynamic allocation poses operational challenges, necessitating a gradual and socially oriented transition strategy to maintain service reliability and workforce sustainability. The optimizations implemented significantly improved fleet capacity utilization, addressing BRT operational inefficiencies in developing countries. Initially, the load factor was predominantly below 70%, reflecting underutilization due to a mismatch between service frequency and fleet allocation and actual demand. GP implementation increased the load factor to above 70% on all operating days through demand-based fleet adjustments, such as reducing the Friday fleet from 15 to 9 buses to serve an average of 2810 passengers. Scenario analysis revealed a trade-off between efficiency and service comfort. The optimal load factor ranged from 97.57% to 100%, maximizing financial performance but approaching capacity limits and potentially reducing passenger comfort. Conversely, achieving a lower load factor significantly increased fleet requirements; for example, on Mondays, 8 buses were required at 100% occupancy, but reached 34 buses if the load factor was reduced to 25%. These findings provide a basis for decision-makers to determine the contextual balance between operational efficiency and service quality on the KM5 Corridor. The developed model demonstrates a theoretical contribution by addressing key trade-offs in transportation optimization in developing countries that single-objective approaches fail to capture. The model's ability to

simultaneously minimize unserved passengers and maximize operational profitability bridges the tension between social equity and financial sustainability, a key challenge for public transportation with limited subsidies. This approach is significant because it differs from conventional models that separate social and financial objectives, often forcing managers to choose between them.

B. Discussion

The optimization results demonstrate that resource constraints can drive operational efficiency innovation, enabling the KM5 Corridor to transform from a financially distressed to a sustainable one without additional subsidies. Responsiveness to variations in time-of-day demand, with a requirement of 5–6 buses on weekends and 9–10 buses on weekdays, confirms that context-based optimization is more effective than a uniform capacity approach. These findings challenge conventional transportation planning paradigms and demonstrate that BRT systems with unique user characteristics require different operational strategies. Practically, this research offers a replicable framework to prevent route closures while maintaining accessibility for vulnerable groups in developing countries.

IV. CONCLUSIONS

Bus Rapid Transit (BPT) systems in developing countries often face significant sustainability challenges, which can lead to route closures and reduced access to affordable public transportation. This study demonstrates that a Multi-Objective Goal Programming (MOGP) approach can enhance the economic viability of BRT operations by allocating fleet resources in response to variations in passenger demand. Optimization of the KM5 Corridor in Makassar reduced the required fleet size from 17 to 13 buses, with a daily deployment of 5–10 units. This adjustment transformed a monthly deficit of IDR 18.7 million into a profit of IDR 15.6 million, increased the Benefit-Cost Ratio (BCR) from 0.81 to 1.24, and maintained a load factor above 70%. The analysis also considered the current fleet availability (17 buses) and included additional scenarios to illustrate potential performance improvements under future fleet expansion. These findings reveal that appropriate operational optimization can support a more sustainable public transportation system without increasing reliance on subsidies. The proposed model offers a data-driven decision-making framework that balances financial sustainability with service quality. Future research should explore the application of the Goal Programming (GP) approach across multiple public transportation routes to optimize overall fleet distribution, along with periodic evaluations that account for dynamic passenger demand.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no financial interests or personal relationships that could have influenced the results reported in this article.

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DATA AVAILABILITY

The data used in this study were obtained directly through interviews with Makassar BRT managers, including daily operational data such as passenger numbers and fleet allocation. Operating costs were calculated using data gathered during the interviews. The created dataset is available from the corresponding author upon reasonable request to support the reproducibility of the research.

AI USE AND DECLARATION OF GENERATIVE AI USE

In preparing this manuscript, the authors used ChatGPT (OpenAI) to assist with language editing and paraphrasing. The authors reviewed and revised the entire manuscript and take full responsibility for the final version.

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