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RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

Evaluation of an Urban Bus Transportation Network for COVID-19 Pandemic

COVID-19 Pandemisi için Şehir içi Otobüs Taşımacılığı Ağının Değerlendirilmesi

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Abstract

The COVID-19 pandemic adversely affected urban transportation networks, necessitating real-time monitoring and optimization to meet passenger loads under rising demand while maintaining public health and safety. This study proposes a novel optimization model to evaluate the performance of an urban bus transportation network in a Turkish municipality during the pandemic. The model uses manual passenger counts from four primary bus lines during peak hours to determine the optimal number of bus trips required to accommodate demand, considering seated and standing passenger reduction factors. The model is implemented with Google OR-Tools and compares actual trip counts with optimal values, avoiding subjective design decisions. Findings indicate that trip numbers during the data-collection period were sufficient to meet demand and protect public health; however, comfort could be improved by adding a small number of additional trips. By adjusting trip counts in both overloaded and underloaded scenarios, the model enables decision-makers to improve network performance under varying demand and emergency conditions. The study also evaluates environmental impacts, with a focus on carbon emissions. The proposed technique offers an objective, data-driven framework for assessing and enhancing urban transportation networks, providing critical insights for responding to extraordinary circumstances—such as pandemics—while prioritizing passenger safety and comfort.

Keywords: *Linear Goal Programming, Urban Transportation, COVID-19 Pandemic, Transportation Efficiency, Operations Research*

Öz

COVID-19 salgını, artan talep altında yolcu yükünü karşılamak ve aynı zamanda halk sağlığını ve güvenliğini korumak için gerçek zamanlı izleme ve optimizasyon gerektiren kentsel ulaşım ağlarını olumsuz etkiledi. Bu çalışmada, pandemi sırasında Türkiye'deki bir belediyede kentsel otobüs ulaşım ağının performansını ölçmek için yeni bir Optimizasyon modeli önerdik. Model, oturan ve ayakta yolcu azaltma faktörleri dikkate alınarak yolcu yüklerini karşılamak için gerekli olan optimum otobüs seferi sayısını belirlemek için yoğun saatlerde dört ana otobüs hattından manuel yolcu sayma verilerini kullanır. Model, Google OR-Tools ile uygulandı ve öznel tasarım kararlarından yoksun, gerçek otobüs seferi sayımları optimum sayımlarla karşılaştırıldı. Bulgular, veri toplama süresi boyunca gerçekleştirilen sefer sayısının hem yolcu yükünü karşılamak hem de halk sağlığını sağlamak için yeterli olduğunu, buna karşın seferlerin konfor seviyesinin biraz daha fazla sefer eklenerek iyileştirilebileceğini gösterdi. Modelin hem aşırı kalabalık hem de yetersiz kalabalık senaryolarında sefer sayılarını değiştirme yeteneği, karar vericilerin değişen yolcu sayıları ve acil durumlarda ağ performansını iyileştirmelerini sağlar. Bu çalışma ayrıca optimize edilmiş ağın karbon emisyonlarıyla ilişkili çevresel etkisini de değerlendirdi. Önerilen teknik, kentsel ulaşım ağlarını değerlendirmek ve geliştirmek için nesnel, veri odaklı bir çerçeve sunarak, karar vericilerin pandemiler gibi olağanüstü durumlara yanıt vermesi, yolcu güvenliği ve konforunu önceliklendirmesi için kritik içgörüler sağladı.

Anahtar Kelimeler: *Lineer Hedef Programlama, Kentsel Ulaşım, COVID-19 Pandemi, Ulaşım Verimliliği, Yöneylem Araştırması*

1. Introduction

Transportation is a fundamental element of daily life and ranks among the essential necessities alongside housing and basic public utilities. Urban transportation systems should be designed to deliver high service levels, adhering to principles of accessibility, reliability, and environmental sustainability [1]. However, increasing population density and urbanization have significantly amplified transportation challenges, particularly in developing countries. These shifts have increasingly rendered existing urban transport infrastructure inadequate, stimulating greater private-vehicle use. This surge has led to adverse outcomes, including air pollution, traffic accidents, and congestion [2]. To address this issue, local administrations are integrating new transportation models and expanding public-transport capacity through investments in vehicles and network coverage. Nevertheless, public-transport design and implementation face constraints that limit the viability of certain plans in developing nations. A key constraint is the substantial cost of infrastructure investments. For example, metro infrastructure is far more expensive than bus services, which are therefore favored in many developing countries. Metro systems require extensive fixed guideways, necessitating significant investment. These requirements can be unsuitable for mountainous or otherwise challenging terrain, or they require extensive—and costly—tunneling. In contrast, bus-based public transportation offers flexibility, adapting to diverse topography at substantially lower cost. Owing to their operational simplicity, versatile applicability, and cost-effectiveness, bus systems continue to be one of the most widespread and accessible modes of transportation globally.

Designing effective public transport involves three core elements: passenger-load assessment, vehicle selection based on

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technical specifications, and driver assignment aligned with capacity. Passenger-load assessment is pivotal to operational performance. It determines the required number of buses and initial network coverage and informs ongoing improvements to the system. Passenger load can be measured via travel-behavior surveys combined with automatic and/or manual passenger counting—techniques also used in other modes such as metro systems. After estimating passenger load, decision-makers calculate the optimal number of routes and trips, subject to constraints such as bus and driver availability. As highlighted by Murat, because bus and driver assignments depend directly on the schedule, passenger-load assessment is central to public-transport design [1].

Under extraordinary conditions—such as accidents and natural disasters—service quality in urban transport declines markedly [3]. The COVID-19 pandemic illustrated this: many urban transport networks were unable to meet surging demand or adapt to rapidly evolving circumstances. Continuous, effective monitoring is therefore imperative to maintain functionality and responsiveness during critical periods. However, a key limitation of many existing methodologies is over-reliance on subjective judgments, which impedes prompt, effective intervention. This overreliance renders systems more vulnerable during crises.

This study evaluates the performance of a public transport network in a Turkish municipality under extreme conditions, specifically during the COVID-19 pandemic. Within the scope of this research, a manual passenger counting method [4] was employed for passenger load assessment. Four primary bus lines were selected as pilot routes, and passenger load was measured during the peak period between 07:00 and 09:00. A Linear Goal Programming (LGP) model was developed to determine the optimal number of trips required to meet demand. The model was implemented using Google OR-Tools, an open-source, fast, and portable suite for combinatorial optimization that provides algorithms and wrappers for problems such as vehicle routing, scheduling, and resource allocation [5]. An objective evaluation free from subjective design choices was provided by comparing actual trip counts with the optimal counts. The primary contribution of this research is an approach for obtaining optimal trip counts under extraordinary circumstances. To this end, a novel methodology was integrated into the optimization model. This innovative approach allows separate adjustment of seated and standing passenger capacities, giving decision-makers flexibility to fine-tune trip counts in both overloaded and under-utilized scenarios. Consequently, the performance of the urban bus transportation network under extreme conditions was comprehensively assessed using the developed optimization model. Model results support in-depth inferences about network efficiency and enable “what-if” analyses under varying loads and emergency scenarios. Furthermore, the outcomes of the developed method were rigorously evaluated from the perspective of environmental factors.

The remainder of the paper is structured as follows. Section 2 reviews the literature on public-transport optimization. Section 3 presents the model and details the experimental design and case study. Section 4 analyzes the results. Section 5 concludes and outlines future work.

Original Contributions of this Paper

This research addresses a gap in the literature by providing an objective, data-driven methodology to evaluate public-transport network performance, particularly under extraordinary conditions such as a pandemic. The primary contributions are as follows:

1. A novel Linear Goal Programming (LGP) model was developed to determine the optimal number of bus trips objectively, thereby surpassing the limitations of methods that rely on subjective assessments by decision-makers.
2. The model adjusts seated and standing capacities separately, allowing precise control of trip counts in both overloaded and underutilized scenarios—crucial for maintaining service quality and safety during crises.
3. By comparing actual and optimal trip counts, this study provides a comprehensive, objective basis for evaluating network efficiency under extreme conditions.
4. Model outputs support in-depth inferences and “what-if” analyses across emergency scenarios and passenger loads, aiding strategic planning and crisis management.

2. Literature Review

Optimization problems in transportation are recognized as complex but solving them can improve access to opportunities for cities and regions and enhance operational efficiency. Various methodological approaches have been used in research to address these problems, each offering distinct advantages. These approaches can be broadly grouped into mathematical programming, heuristic and metaheuristic algorithms, and data-driven or simulation-based methods.

Mathematical programming focuses on finding optimal solutions through precise, structured formulations of transportation problems. For instance, Luathep et al. formulated mixed (continuous/discrete) transportation network design problems as equilibrium-constrained mathematical programs (MPEC) and solved them using mixed-integer linear programming (MILP) with a global optimization algorithm [6]. Ceder et al. modeled bus-stop placement as a two-level optimization problem, incorporating topographic effects—such as slope—on walking speed and the attractiveness of access paths [7]. Shen et al.’s review of electric-vehicle service operations found that mathematical optimization models are widely used for charging-infrastructure planning and vehicle routing [8]. Similarly, Tong et al. addressed the design of customized bus services—optimizing passenger assignment and vehicle routing simultaneously—through a mathematical programming model and developed a Lagrangian decomposition algorithm for large-scale instances [9]. In driver scheduling, Esquivel-González et al. modeled the bus-driver assignment problem for a Spanish public transport company using integer programming and proposed strategies to improve solution times in optimization software such as CPLEX [10]. Carey presented a model for determining optimal timetable durations in public transport, accounting for delays and operator behavioral responses, illustrating the potential of such models to improve operational efficiency [11]. Although these approaches clearly define problem structures, achieving optimal solutions in complex real-world scenarios—particularly for NP-hard problems—often requires substantial computational resources.

To overcome this computational complexity, heuristic and metaheuristic algorithms are used to find “good-enough” solutions for large-scale and dynamic transportation problems within practical timeframes. Żak et al. formulated the bus-vehicle assignment problem as a multi-objective combinatorial optimization problem and obtained Pareto-optimal solutions using the Pareto Memetic Algorithm and Light Beam Search methods [12]. Semedo improved the performance of algorithms for solving the Public Transport Bus Assignment (PTBA) problem by applying parallel Ant Colony Optimization (ACO) and constraint-based local search techniques [13]. In integrated optimization, Sargut et al. modeled the crew-rostering and vehicle-assignment problem as a multi-objective set-partitioning problem and proposed a new multi-objective tabu search algorithm to obtain approximate Pareto-optimal solutions [14]. Tóth and Krész proposed a flexible solution approach for bus-driver scheduling problems that includes heuristic techniques such as “pre-shift” creation and “cutting,” aiming to produce feasible solutions despite complex real-world constraints [15]. These methodologies, particularly for multi-objective optimization problems, serve as practical decision-support tools by presenting decision-makers with a range of approximate Pareto-optimal solutions that illustrate trade-offs among objectives. However, a key limitation of these approaches is their inability to guarantee optimality and their dependence on algorithm design and parameter tuning.

Finally, data-driven and simulation-based approaches have created new opportunities to understand and optimize transportation system dynamics, particularly by leveraging large data sources and advanced analytical techniques. Acharya et al. estimated traffic speeds using machine-learning models such as XGBoost to fill missing data in OpenStreetMap (OSM) and computed drive-accessibility scores for the Denver metropolitan region [16]. Gong et al. examined the spatiotemporal dynamics of commuting-cycling activities during the pandemic using various indicators and supervised machine-learning techniques [17]. Wang et al. and He et al. delineated pandemic control zones in cities using community-detection algorithms such as the Leiden algorithm and fast-unfolding algorithm applied to multimodal transportation data [18]. Yıldızhan evaluated the economic and financial feasibility of Bus Rapid Transit (BRT) systems—using metrics such as net present value, benefit/cost ratio, and internal rate of return—under various scenarios [19], [20]. Mitra et al. analyzed bike-lane use and public perception during the pandemic using multinomial logistic regression [19]. Barbieri et al. evaluated the impact of COVID-19 on mobility and perceived risk across ten countries using negative binomial model (NBM) regression [21]. These approaches can improve prediction accuracy and support the development of sustainable, cost-effective, and resilient transportation solutions, particularly under uncertain or changing conditions. However, these approaches depend heavily on data quality and accessibility, which is a notable limitation.

In summary, transportation optimization employs a versatile set of methodological tools, each with unique strengths and weaknesses. Mathematical programming offers theoretical robustness and guarantees optimality for suitable problems, but large-scale, complex real-world scenarios often pose computational challenges. Heuristic and metaheuristic methods provide practical, approximate solutions to these difficulties, enabling their use in large-scale problems; however, they do not guarantee exact optimality. Data-driven and simulation-based approaches excel at understanding system dynamics, making predictions, and evaluating impacts—particularly under uncertain or changing conditions—but they are limited by data availability and quality. Integrating these diverse methodologies facilitates the development of hybrid models, in which the strengths of one approach balance the limitations of another, supporting more comprehensive and adaptable decision-making in urban transportation.

The primary objective of this study is to develop an unbiased method for evaluating urban transportation networks based on the optimal number of trips needed to respond effectively to extraordinary circumstances such as the COVID-19 pandemic. In this context, the model calculates bus occupancy rates using two parameters that separately reduce seated and standing passenger numbers. The study analyzes the impact of these two parameters on factors including public health, safety, and carbon emissions. To demonstrate the model’s practical efficacy, a series of experiments was conducted using real-world data from the urban transportation network in Trabzon, Türkiye. The experiments were implemented using OR-Tools, an open-source, fast, and portable suite for combinatorial optimization that offers algorithms and wrappers for various solvers to address complex problems; it is a widely recognized linear-programming solver developed by Google [5]. The experimental findings indicate that the city's transportation network maintained a sufficient number of trips during the data-collection period. However, comfort levels could be improved by adding a small number of additional trips. Materials and Methods

The model was based on inter-stop passenger-carrying capacity, as this approach allows the mathematical framework to be expanded to handle more complex transportation-planning problems. Accordingly, the objective was to determine the optimal number of bus trips required to transport at least the calculated inter-stop passenger capacity between critical locations. The basic optimization model was enhanced with two adjustable parameters that reduce seated and standing passenger capacities separately. This enhancement allows planners to optimize the total number of trips while accounting for extreme situations such as pandemics. As a final step, the single-objective model—designed to find the optimal number of trips—was extended to a multi-objective model. The extended model determines both the optimal number of trips and the optimal idle time between departure and return trips.

The model is based on passenger numbers in a metropolitan bus network during predefined periods, such as morning and evening peaks. Passenger counts between consecutive stops and total passengers carried on a specific line were chosen as the key performance indicators (KPIs) for model development. Metropolitan bus networks are typically divided into lines during the design phase to simplify planning. Although each line has its own route, some stops are shared by multiple lines. Because one KPI was passenger numbers between consecutive stops, analyzing actual counts identified key stops with higher demand than others in the network. This approach allowed the model to be designed to meet demand at these specific stops.

Mathematical Structure of Goal Programming

Goal programming (GP) is a subset of multi-objective decision-making methods. This technique aims to achieve results as close as possible to the stated goals rather than fully satisfying them. In other words, the aim of GP is to provide efficient and satisfactory solutions to conflicting objectives [22]. Several operations are essential for establishing a GP model. These operations, required in the mathematical formulation of GP, are presented in their general form in Equation 1.

$$Min\ Z = [P_1 w_1(d_i^-, d_i^+) + \cdots + P_k w_k(d_i^-, d_i^+)] \quad (1)$$

Here Z is the final value of the objective function, P_k denotes the priority of deviation variables, and w_k is the weight of deviation variables with the same priority, k is the number of deviation variables, d_i^- and d_i^+ are the deviation variables. This function is created by using the preferences of a decision maker or domain expert based on the problem requirements. Because GP seeks approximate rather than exact results, the degree of goal achievement is measured using deviation variables. The weights and definitions of these variables are also subject to the preferences of decision makers or domain experts. The final model is formulated to minimize the gap between the goal and the model results [1].

Another important component of GP is the target constraint, which is an equation that the solution value must satisfy. Equation 2 shows a general form of the target constraint.

$$\sum_{j=1}^{n}\left(a_{ij}X_j\right) + d_i^- - d_i^+ = b_i, (\forall\, i = 1, \dots, m) \quad (2)$$

Here, X_j denotes the decision variables of the model, allowing developers to express problem requirements mathematically, and a_{ij} represents the coefficient of the decision variables. The number and aim of each decision variable are determined by model developers to address a specific part of the problem. Similarly, b_i is the right-hand value and d_i^-, d_i^+ are deviation variables of the target constraint. Each target constraint has deviation variables representing the difference between b_i and the solution value of target constraint. In other words, d_i^- represents negative difference between target constraint and b_i, while d_i^+ represents positive difference between target constraint and b_i. The objective function does not need to include all deviation variables depending on the structure of the related target constraints. For instance, if a target constraint is allowed to exceed its right-hand value, its negative deviation variable should be included in the objective function, while its positive deviation variable indicates the level of satisfaction. Thus, some deviation variables indicate undesired values, while others indicate desired values [23]. GP aims to minimize the values of undesired deviation variables. The type of deviation variable could be determined by the structure of the target constraint, and all possible cases are given in Table 1.

Table 1. All possible target constraint types and definitions.

Constraint Type	Meanings
If $f_i(x) \geq b_i$,	Here, d_i^+ is the desired variable and d_i^- is the undesired variable. The target constraint is expected to exceed right hand value. Objective function should include d_i^-.
If $f_i(x) \leq b_i$,	Here, d_i^- is the desired variable and d_i^+ is the undesired variable. The target constraint is not expected to exceed right hand value. Objective function should include d_i^+.
If $f_i(x) = b_i$,	Here, both d_i^- and d_i^+ is undesired variables. The target constraint should have exact value of right-hand value. Objective function should include both deviation variables.

During the model development, some constraints should be satisfied exactly. These are called system constraints and general form of a system constraint is given in Equation 3.

$$\sum_{j=1}^{n} a_{ij}X_j = b_i, (\forall i = m+1, \dots, m+p) \quad (3)$$

All decision and deviation variables should have non-negative integer values as defined in Equation 4.

$$d_i^-, d_i^+, X_j \geq 0, \forall\, i, j \quad (4)$$

Finally, general GP model given in Table 2.

Table 2. General goal programming (GP) model [23].

Objective Function	$min\, Z = \sum_{i=1}^{m} p_i w_i (d_i^- + d_i^+)$.
Target Constraints	$\sum_{j=1}^{n}\left(a_{ij}X_j\right) + d_i^- - d_i^+ = b_i, \forall i = 1, \cdots, m.$
System Constraints	$\sum_{j=1}^{n} a_{ij}X_j = b_i, \forall i = m+1 \dots m+n.$ $d_i^-, d_i^+, X_j \geq 0, \forall i = 1, \cdots, m, \forall j = 1, \cdots, n$

Data Collection

To evaluate the efficacy of the proposed methodology, the Trabzon Metropolitan Municipality (TMM) was selected as the case study area. Data were collected from four designated bus lines operated by Trabzon Transportation Inc., a subsidiary of the municipality. The selected routes served approximately 30% of the city's total population. A total of 164 bus trips were observed and analyzed during the period from March to April 2021. During this period, the total population of TMM was recorded as 816,684, while the potential ridership for the four selected lines was 238,571. This corresponds to the selected lines collectively having the capacity to serve 29.21% of the total urban population [24].

Data collection was conducted manually due to the absence of the necessary technical infrastructure. Specifically, passenger load data were recorded for trips operating between 07:00 and 09:00, as this period corresponds to the peak travel time for the selected routes. The high passenger volume during these hours is primarily due to their alignment with commuting times for passengers traveling to workplaces or healthcare facilities, as all selected lines serve both the city center and major medical centers [4].

Variable Definitions

This section presents an overview of the variables used in the model, as summarized in Consequently, this enhances the model's extensibility and optimizes its ability to manage congested situations.

Table 3. Initially, the model uses predefined set of bus models and lines denoted as $G = G_0 + G_1 + G_2 + \cdots + G_n$ and $L = L_0 + L_1 + L_2 + \cdots + L_m$, respectively. The decision variables in the model X_{ji} represent the number of trips to be performed by bus group i on line j. However, the model excludes certain line–bus model combinations, as some bus groups are restricted from operating on specific lines; this restriction is represented by LB_j. This approach eliminates unnecessary constraints by using only the essential variables for valid line–bus group combinations, thereby improving solution speed by disregarding irrelevant physical or technical limitations. Another feature of the model is the inclusion of the ideal time interval between two consecutive trips on a given line, represented as decision variable, Δt_j , within a predefined period, T. The methodology integrates decision variables such as total time and number of trips to identify optimal values, thereby enhancing flexibility through the application of constraints on Δt_j values. Ultimately, the key innovation of the model lies in the capacity parameters α_{st} and α_{se} , which allow adjustments to passenger reduction levels, thereby helping decision-makers address emergencies and

prevent overloading. Consequently, this enhances the model's extensibility and optimizes its ability to manage congested situations.

Table 3. Variables used in the model and their descriptions.

Variable	Description
a_{st}	Reducing factor for standing passengers
a_{se}	Reducing factor for seated passengers
N_B	Total Number of Busses
N_L	Total Number of Lines
T	Sampling duration in minutes
G_i	The bus group i
N_i	Total number of busses of group i
Se_i	Seated passenger capacity of bus group i
St_i	Standing passenger capacity of bus group i
BC_i'	Modified capacity of bus group i
L_j	The line j
D_j	Departure time of the trips performed on line j
I_j	Idle time of the trips performed on line j
R_j	Returning time of the trips performed on line j
T_j	Duration of the one trip performed on line j
LC_j	Total number of passengers carried on line j
LB_j	Banned bus groups of line j
CS_k	Consecutive bus stop pair k
BL_k	Bus lines passing through the consecutive bus pair k
PD_k	Passenger load of consecutive bus stops k
N_{ji}	Total number of required busses belonging to bus group i on line j
X_{ji}	Decision variable representing the number of trips performed by bus group i on line j
Δt_j	Delay between two successive trips of line j
d_T^-	Total number of unused busses
d_T^+	Total number of required busses
d_i^-	Total number of unused busses belonging to group i
d_i^+	Total number of required busses belonging to group i
d_j^-	Total amount of early completion time of all trips of line j
d_j^+	Total amount of late completion time of all trips of line j

Reducing Factors

A key performance indicator for urban bus transportation systems is the level of crowdedness on bus trips. This indicator is measured as the number of passengers per square meter. Bus crowdedness is commonly calculated using the overall dimensions of the bus and the total number of passengers. Although it may appear correct to use the total passenger count in the crowdedness formula, the space occupied by seated passengers is significantly greater than that occupied by standing passengers. For example, five standing passengers may occupy one square meter, whereas only one seated passenger may occupy the same space. Therefore, a more accurate crowdedness measure can be obtained by considering the space occupied by both seated and standing passengers separately. In this study, a new metric is introduced to measure crowdedness more precisely by accounting for seated and standing passengers separately. Since the crowdedness values of seated and standing passengers form a ratio, a new formula based on the harmonic mean has been developed in this study, as shown in Equation 5.

$$Crw_{bus} = \frac{2}{\frac{n_{st}}{A_{st}} + \frac{n_{se}}{A_{se}}} = 2\frac{A_{st}A_{se}}{A_{se}n_{st} + A_{st}n_{se}} . \quad (5)$$

Here, $\boldsymbol{n_{st}}$ and $\boldsymbol{n_{se}}$ represent seated and standing passengers, respectively; and $\boldsymbol{A_{se}}$ and $\boldsymbol{A_{st}}$ are the total space of seated and standing passengers, respectively.

During the COVID-19 pandemic, urban bus transportation systems were regarded as significant contributors to the spread of the disease. Consequently, several regulations were implemented in urban bus transportation systems to prevent or slow the spread of the disease. One of the measures adopted by authorities was the reduction of passenger numbers. The extent of the reduction was determined by social distancing requirements and measured in terms of bus crowdedness. The actual crowdedness limits during this period ranged between 1.3 and 2.0 persons per square meter [25], [26].

Urban bus transportation authorities typically use total passenger counts to adjust crowdedness levels to desired thresholds. As noted earlier, actual crowdedness can be more accurately assessed by measuring seated and standing passengers separately. Therefore, it is more effective to adjust the numbers of seated and standing passengers individually, rather than reducing the overall passenger capacity of buses. Integrating this approach into the planning process can enhance both passenger comfort and public health safety in urban transportation systems. Accordingly, two reduction factors were defined to adjust bus capacity: $\boldsymbol{\alpha_{se}}$ and $\boldsymbol{\alpha_{st}}$; representing the reducing factors for seated and standing passengers, respectively. Consequently, the adjusted passenger capacity of a bus is represented by Equation 6.

$$BC' = \alpha_{st}n_{st} + \alpha_{se}n_{se} . \quad (6)$$

In this context, BC' represents the reduced number of bus capacities in terms of α_{st} and α_{se}. A sample calculation is demonstrated for a city bus accommodating 26 seated and 77 standing passengers. According to the conventional approach, authorities operated only 40%–60% of the fleet during the pandemic, without differentiating between seated and standing capacity constraints [4]. In addition, this approach provides a more fine-grained control of passenger load, as presented in Table 4.

This example calculation illustrates how the parameters α_{st} (standing passenger reduction factor) and α_{se} (seated passenger reduction factor) affect total bus passenger capacity. Increments of 0.1 on the axes correspond to 10% steps in passenger capacity. The values in Table 4 report the ***adjusted total passenger capacity*** for each factor combination.

Table 4. Seated and standing passenger load with reduction factors.

		α_{st}									
		1.0	**0.9**	**0.8**	**0.7**	**0.6**	**0.5**	**0.4**	**0.3**	**0.2**	**0.1**
α_{se}	**1.0**	*103*	*95*	*88*	*80*	*72*	*65*	*57*	*49*	*41*	*34*
	0.9	*100*	*93*	*85*	*77*	*70*	*62*	*54*	*47*	*39*	*31*
	0.8	*98*	*90*	*82*	*75*	*67*	*59*	*52*	*44*	*36*	*29*
	0.7	*95*	*88*	*80*	*72*	*64*	*57*	*49*	*41*	*34*	*26*
	0.6	*93*	*85*	*77*	*70*	*62*	*54*	*46*	*39*	*31*	*23*
	0.5	*90*	*82*	*75*	*67*	*59*	*52*	*44*	*36*	*28*	*21*
	0.4	*87*	*80*	*72*	*64*	*57*	*49*	*41*	*34*	*26*	*18*
	0.3	*85*	*77*	*69*	*62*	*54*	*46*	*39*	*31*	*23*	*16*
	0.2	*82*	*75*	*67*	*59*	*51*	*44*	*36*	*28*	*21*	*13*
	0.1	*80*	*72*	*64*	*57*	*49*	*41*	*33*	*26*	*18*	*10*

Constraints

The proposed model uses passenger load data from a specific period to determine the optimal number of bus trips. This approach is necessary due to the significant fluctuations in passenger demand observed within a single day. For example, passenger demand during morning and evening hours is substantially higher than at other times of the day, primarily due to the large number of individuals commuting to their workplaces.

A constraint was imposed to limit the total number of buses across groups, due to physical limitations and the fact that transportation agencies have a predefined number of buses for each group. This constraint is formally defined in Equation 7.

$$\sum_{j\in L, i\in G} X_{ji}\frac{T_j}{T} + d_T^- - d_T^+ = N_B\,. \tag{7}$$

Here, the term $\frac{T_j}{T}$ shows how much time is consumed for one trip per line j and the decision variable is X_{ji} which is representing the number of trips performed by bus group i on line j. Since this constraint must not exceed N_B, the undesired deviation variable is d_T^+, which represents the additional number of buses. As a result, d_T^- shows the total number of unused buses.

Although Equation 7 limits the total number of buses, it does not restrict the number of buses in each group. This issue was addressed by adding bus group constraints, as defined in Equation 8.

$$\sum_{j\in L} X_{ji}\frac{T_j}{T} \leq N_i, \forall i \in G\,. \tag{8}$$

Here, N_i represents the total number of buses in group i. In addition, two capacity constraints were applied to ensure that passenger demand is met. The first constraint, presented in Equation 9, ensures that the total trip count meets the daily passenger capacity of the line, while the second constraint, presented in Equation 10, ensures that the trip count is sufficient to meet the passenger load between each pair of consecutive bus stops.

$$\sum_{i\in G} BC_i' X_{ji} \geq LC_j\,. \tag{9}$$

$$\sum_{i\in G, j\in BL_k} BC_i' X_{ji} \geq PD_k\,. \tag{10}$$

The model's passenger reduction parameters, a_{st} for standing passengers and a_{se} for seated passengers, allow decision-makers to address emergencies and prevent overcrowding. Thus, BC_i' represents the modified capacity of each bus group, LC_j represents the total number of passengers carried on each line, and PD_k represents the passenger load between each pair of consecutive bus stops.

Additionally, the model was extended to determine the optimal inter-trip waiting duration for each line, as defined in Equation 11.

$$\textstyle\sum_{i\in G} \Delta t_j X_{ji} + d_i^- - d_i^+ = T, \forall j \in L\,. \tag{11}$$

This constraint is non-linear due to $\Delta t_j X_{ji}$ term. However, since both Δt_l and X_{ji} are positive, this constraint can be relaxed using McCormick Inequalities [27], [28]. Finally, the objective function of the model is defined in Equation 12.

$$\min Z = d_0^+ + \sum_{1\leq i\leq N_L} (d_i^+ + d_i^-) - d_0^-\,. \tag{12}$$

The general form of the proposed model is presented in Table 5.

Table 5. Developed general goal programming (GP) model of the proposed model [4].

Total Bus Count Constraint	$\sum_{j\in L, i\in G} X_{ji}\frac{T_j}{T} + d_T^- - d_T^+ = N_B\,.$
Group Based Bus Count Constraints	$\sum_{j\in L} X_{ji}\frac{T_j}{T} \leq N_i, \forall i \in G\,.$
Capacity Constraint 1	$\sum_{i\in G} BC_i' X_{ji} \geq LC_j\,.$
Capacity Constraint 2	$\sum_{i\in G, j\in BL_k} BC_i' X_{ji} \geq PD_k\,.$
Interval Constraints	$\sum_{i\in G} \Delta t_j X_{ji} + d_i^- - d_i^+ = T, \forall j \in L\,.$
Objective Function	$\min Z = d_0^+ + \sum_{1\leq i\leq N_L} (d_i^+ + d_i^-) - d_0^-\,.$

3. Case Study

The Trabzon Metropolitan Municipality (TMM) was selected to evaluate the accuracy of the approach, and data were collected from four bus lines operated by Trabzon Transportation Inc., a subsidiary of the municipality. The selected lines carried approximately 30% of the city's population. Data were collected from 164 trips that conducted between March and April 2021. During the data collection period, the total population of TMM was 816,684, and the potential passenger count for the four selected lines was 238,571 [4]. Thus, the selected lines had the capacity to serve 29.21% of the total city population [24].

Data were collected manually due to the lack of necessary technical infrastructure. Specifically, passenger load data were gathered from bus trips operating between 07:00 and 09:00, as this period represents the peak demand for the selected lines.

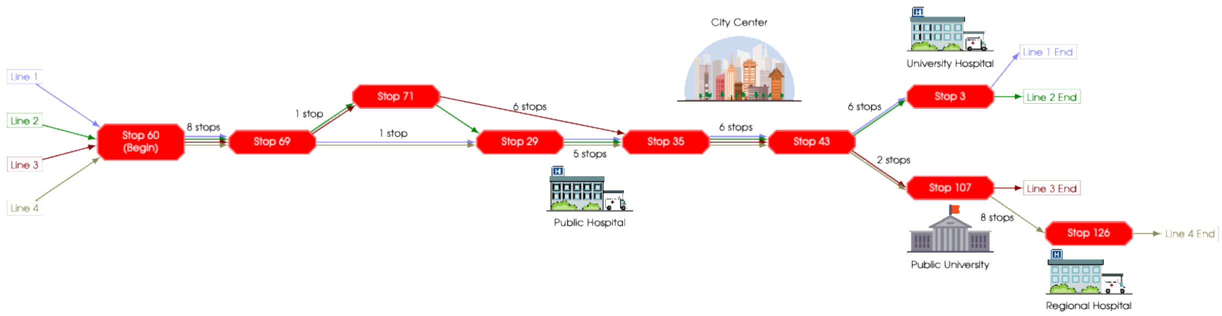

Figure 1. Bus stop network of the selected lines [4].

The high level of crowdedness during these hours is primarily due to passengers commuting to workplaces or medical centers, as all selected lines serve both the city center and major healthcare facilities. Details of the selected lines are presented in

Table 6. Properties of selected lines [4].

Line	Line Lengths (in km)	Number of Stops	Durations (in mins)		
			Departure	Idle	Return
Line 1	8.54	64	40	5	40
Line 2	8.54	64	40	5	40
Line 3	9.25	60	35	5	35
Line 4	13.7	98	55	5	55

Based on the data in the table, a total of 286 bus stops were analyzed. However, the selected lines were found to have a substantial number of overlapping stops. The bus stop network for these lines is illustrated in Figure . The routes of the four lines originate from a single bus station and terminate at different stops. Although Line 1 and Line 2 share identical origins and destinations, they follow distinct routes. Furthermore, several bus lines operate with different timetables for their outbound and return routes due to various operational factors. To identify the primary constraints, the inter-stop passenger-carrying capacity was calculated for each pair of successive bus stops, with the results provided in the following chapter.

The buses used in the experiment were classified into five groups, each with identical technical specifications. After data collection, three scenarios were developed to evaluate the model's performance under varying passenger loads at critical bus stops and along specific lines. These scenarios, referred to as the best, average, and worst cases, represent the minimum, average, and maximum passenger loads, respectively.

Following data collection, a series of experiments was conducted to evaluate the model's performance. The experiments were implemented using OR-Tools, an open-source optimization engine developed by Google. Furthermore, the implementation is solver-independent, enabling seamless integration with various optimization solvers. This design allows the model to be integrated into any type of city management software, enabling decision-makers to incorporate it readily into their planning processes.

4. Experimental Results

All possible variations of the scenarios defined in the case study were examined in the experimental setup to assess the effect of the reduction parameters on the optimization results. A total of 300 experiments was conducted, with the resolution of the reduction parameters set at 10% per increment. This configuration was based on 10 increments for the standing passenger reduction parameter, 10 increments for the seated passenger reduction parameter, and 3 scenarios for each combination of reduction parameters. The results of these experiments are evaluated from multiple perspectives in the following sections.

Trip Counts

The analysis indicated that the optimal number of trips during a two-hour period ranged from 2 to 37. The calculated trip counts are presented in Figure 2. The experimental results show that reducing the number of standing passengers has a significant impact on the required trip frequency, whereas decreasing the number of seated passengers does not produce a comparable effect. For example, when the reduction rate for standing passengers remains constant and the reduction rate for seated passengers increases, the average increase in the required trip count ranges from 27% to 212%. However, when the reduction rate for standing passengers is varied under the same conditions, the trip count increases significantly, ranging from 152% to 519%. This substantial difference is primarily due to the smaller number of seated passengers compared to standing passengers. The calculated trip counts indicate that Line 4 exhibits the highest level of activity among the selected lines. This can be attributed to the presence of multiple stops near the city center, two colleges, and two major medical centers, one of which is the largest in the city. Consequently, Line 4 was the most frequently used among the selected lines. In addition, Lines 1 and 2 display similar trip count patterns due to the substantial similarity between their routes. Finally, Line 3 recorded the lowest number of trips, primarily because it was mainly used by college students who remained in their residences due to compulsory distance learning during the data collection period.

Figure 2 presents four heatmaps, each depicting a sensitivity analysis for one of the four urban transit lines (Lines 1–4). The analysis illustrates how the required number of trips varies in response to adjustments in passenger capacity.

In each heatmap, the *x-axis* represents the reduction factor for *seated passengers* ***(α_{se})***, while the ***y-axis*** represents the reduction factor for ***standing passengers (α_{st})***. These factors range from 10% to 100%, representing the proportion of the original capacity utilized. Cell colors correspond to the number of required trips, with warmer colors (*red*) indicating higher values and cooler colors (*blue*) indicating lower values.

Across all four lines, a clear trend emerges: as the reduction factors for both seated and standing passengers increase (moving from the top-left to the bottom-right of the graphs), the number of required trips decreases. This is expected, as allowing more passengers on each bus (a higher percentage of capacity) means that fewer total trips are needed to meet the same overall demand. The small arrows generally point toward the bottom-right, visually reinforcing the trend of decreasing trip counts as capacity increases.

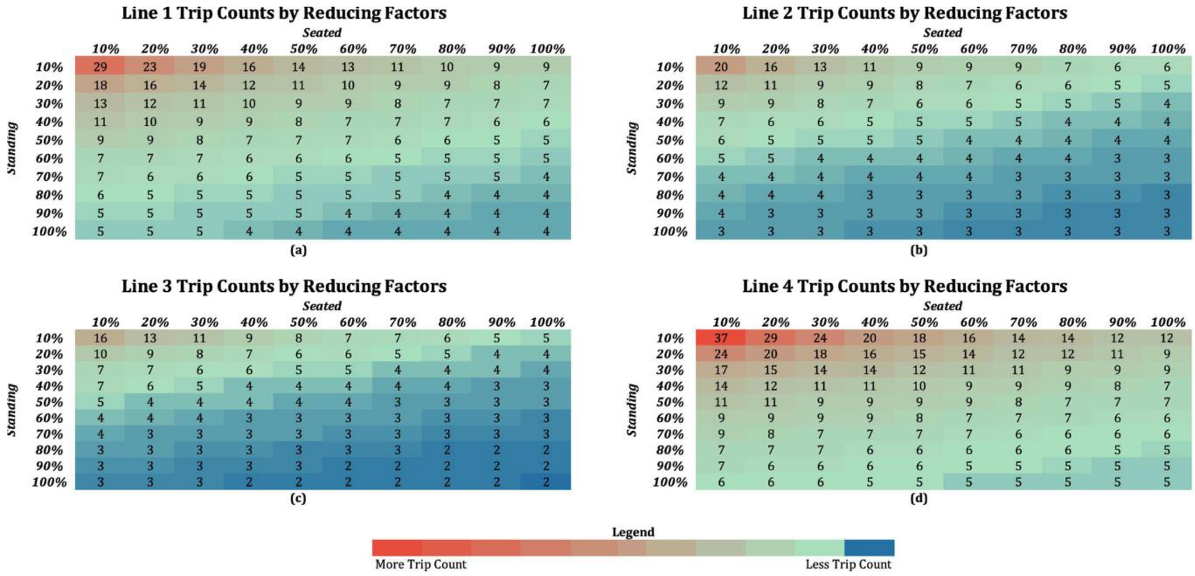

Figure. 2. Sensitivity analysis of the proposed model.

However, the sensitivity to these changes differs across lines. For example, Line 4 exhibits the most pronounced change, with trip counts decreasing from 37 to 12 for $\alpha_{st} = 0.1$. ***Line 1*** also exhibits substantial variation. In contrast, Lines 2 and 3 appear less sensitive, displaying more gradual and less extreme changes in trip numbers across the same range of capacity reductions. This suggests that the operational efficiency of Lines 2 and 3 is less affected by crowding parameters than that of Lines 1 and 4.

5. Discussion and Future Work

This study introduces a novel approach for objectively evaluating an urban bus transportation network, employing the Linear Goal Programming (LGP) method. The proposed methodology incorporates both the total number of seats and number of standing passengers to derive a more precise measure of bus crowdedness within the urban transportation network. Using separate data on seated and standing passengers produces more accurate measurements of persons per square meter. As a result, this method enables decision-makers to conduct precise evaluations and make capacity adjustments, taking into account passenger well-being, safety, and comfort. Current analytical methodologies focus on total passenger counts without distinguishing between the occupied spaces of seated and standing passengers. Furthermore, meetings with the municipality revealed that the standard procedure for determining trip assignments in Türkiye relies on a subjective, experience-based, trial-and-error process rather than on objective data analysis as proposed in this study. This technique clearly enhances the accuracy of existing methodologies.

This study also introduces a novel optimization model for determining the optimal number of bus trips within a specified daily time period, employing the newly proposed bus crowdedness approach. Bus congestion levels are controlled by two new parameters that separately reduce the total numbers of seated and standing passengers. Therefore, the model's outcomes can be used to analyze various scenarios. As an illustrative case, this study provides a thorough examination of the impact of bus overcrowding on resource utilization and environmental outcomes. Thus, the model assists city planners in determining the additional resource allocation required to maintain continuous urban bus service.

A series of experiments was conducted to assess the accuracy and efficiency of the proposed methods. The findings indicate that Trabzon Transportation Inc. provided a satisfactory level of bus transportation service during the data collection period, with appropriate health-related measures implemented to mitigate the transmission of COVID-19. The findings also suggest that service comfort can be improved by adding one or two supplementary trips to each line. The detailed analysis and findings of this study suggest that the approach can be adapted to other urban transportation modes, such as trains and subways. In this context, the model can be used to optimize transportation networks and assess their impacts on various aspects. This approach enables authorities to adapt an entire city's transportation infrastructure to extraordinary circumstances, such as pandemics, while ensuring passenger safety and comfort across all transit modes. Furthermore, the model can support improvements in transportation networks by addressing the travel demand of major attraction centers and identifying additional resource requirements. This aspect is currently being investigated. The outcomes from the model could serve as the basis for a comprehensive transportation planning framework that integrates both bus and driver scheduling, which is the current focus of active research. Integration of nature-inspired optimization models into this approach remains a topic for future study.

Ethics committee approval and conflict of interest statement

This article does not require ethics committee approval. This article has no conflicts of interest with any individual or institution.

Declaration of Generative AI

Generative AI tools were not used in this study.

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