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UTILIZING DISCRETE EVENT SIMULATION TO OPTIMIZE HEADWAY TIMES IN A LIGHT RAIL TRANSIT SYSTEM

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ABSTRACT

Due to recent urbanization and population growth in cities, the passenger transport system is faced with significant congestion and delay problems. In particular, to handle peak-time passenger traffic, railway public transport systems are operated with more frequent trips during the peak hours, and less-frequent train interarrivals are scheduled during off-peak hours to increase the total system utilization. This study proposes a simulation methodology for optimizing the trips of a metro line with variable passenger traffic. A microsimulation model was constructed using the Arena software to create an experimental medium for the optimization phase. The discrete-event simulation concept was utilized for the model building. The passenger flow and train arrival rates were the main input parameters obtained from the passenger origin-destination station matrix and train arrival data. The model was coupled with the artificial bee colony algorithm for determining the optimized train time headways. The optimization study resulted in a decrease of 27.5% and 25.5%in the total number of daily train trips for the normal and increased train capacity scenarios under a zero failed boarding policy. The results of the study were also compared with the literature findings which are discussed in detail.

Keywords: Railway, Train, Simulation, Optimization, Headway.

1 INTRODUCTION

Public transport (comprising services such as buses, railways, ferries, and taxis) plays a vital role in ensuring affordable mobility, mitigating traffic congestion and emissions, and promoting sustainable urban land use. Today, public transportation systems are under mounting pressure to deliver reliable, efficient, and environmentally sustainable services in response to rapid urbanization and global climate commitments, such as those outlined in the United Nations Sustainable Development Goals. For example, Türkiye has experienced a significant urbanization as in 1960, approximately 31% of the population resided in urban areas and by 2023, this figure had risen to 77.5%, with an annual urbanization rate of 1.1% between 2020 and 2025 [1]. İzmir, Türkiye's third-largest metropolitan area, has also reflected national urbanization trends while exhibiting unique regional dynamics. The metropolitan population grew from approximately 1.5 million in 1985 to an estimated 3.15 million in 2025, reflecting an average annual growth rate of 1% to 2% over the past four decades [2]. Population growth has significantly increased urban transport passenger flow, contributing tothe increased utilization of the urban rails and metro lines and especially in developing countries, new rail transport systems are planned as a preferred mode of public transport. For instance, the İzmir Metro serves as a key backbone of urban transportation in İzmir. With an average daily ridership exceeding 250,000 passengers, the system frequently approaches its capacity limits, particularly during morning and evening peak hours [3]. Driven by increasing urbanization, population density, and the growing pressure from private vehicle usage, the metro system faces significant challenges in terms of operational efficiency and service quality. In recent years, simulation-based analyses have been applied to evaluate and enhance system performance. For instance, Öztürk [4] utilized Arena software to simulate passenger volumes and station-level waiting times along the İzmir metro line. Similarly, Yalçınkaya and Bayhan [5] optimized travel times by adjusting parameters such as train speeds and headways. These studies underscore the relevance of model-based decision-support tools for adapting to rising passenger demands in İzmir’s urban rail network.

The growing demand for public rail transport has led to challenges such as congestion, delays, and reduced service quality. Congestion is especially severe during peak hours when sudden travel demand overwhelms the system. To establish a passenger-oriented transport service, managers aim to optimize metro operations to ensure comfort, punctuality, and cost-efficiency However, reducing costs often conflicts with service quality, as maintaining uncrowded and punctual service requires more frequent trains and lowers system utilization. With the global economic crisis and ongoing price inflations, transport costs also significantly increased. In this context, public transport plays an important role in energy conservation, and emission reduction [6]. Not only electricity costs but also maintenance and management of trains, stations, and infrastructure require significant expenditure, impacting ticket prices and passenger trip costs.

Despite extensive research on train scheduling and headway optimization discussed in the literature review section, few studies integrate discrete-event microsimulation with metaheuristic optimization under a failure boarding constraint for metro lines, particularly in the context of mid-sized and developing cities with irregular passenger trip data like İzmir. Considering the conflict between service quality and cost, this study contributes to the literature by proposing a simulation-optimization methodology that aims to:

- Develop a discrete-event simulation model to represent metro operations, using İzmir's urban rail system as a case study.
- Integrate the simulation model with an optimization framework based on the Artificial Bee Colony algorithm to optimize train headway times.
- Generate an optimized timetable by incorporating passenger origin-destination data and line characteristics, aiming to reduce operational costs through the minimization of total daily trips while ensuring zero failed passenger boardings.

2 LITERATURE REVIEW

Railway capacity analysis has received considerable attention in the literature where mathematical models, analytical methods, and simulation techniques have been used to determine line capacity or schedule train timetables. Although there is a vast body of literature on analytical and mathematical approaches, in practice, some of these approaches have been applied for determining the line capacity such as the UIC-406 analytical method [7], which has been extended for further needs [8]. An event-driven simulation model was proposed, and it was applied to a multi-line metro infrastructure for investigating different train operating strategies [9]. The model was developed in the MATLAB environment using an object-orient modeling approach. Salido et al. [10] proposed analytical and simulation techniques for assessing the robustness of a single railway line with a given schedule considering the primary and secondary delays and timetable disruption. Discrete-event simulation modeling was implemented for analyzing rail line performance using a speed profile and energy consumption concepts [11]. In addition to event-based simulation but the coupled optimization methods were used for improving the performance of the ride-sharing systems [12]. Grube et al. [9] implemented an event-based dynamic multi-line metro simulator for evaluating the practical application of different operating strategies. Wales and Marinov [13] used event-based simulation for evaluating the delays of the rail lines in metropolitan areas by applying several delay mitigation techniques. The simulation modeling was also used for the assessment of the utilization levels of rail lines for urban freight movement [14], scheduling of the freight trains in the shared railway lines [15] evaluating the performance of autonomous shuttle freight trains [16], planning and evaluation of the passenger evacuation for the metro lines [17], [18]. Yalçınkaya and Bayhan [5] implemented Arena simulation and response-surface methodology approach for passenger travel time optimization for Izmir metro line. Apart from modifying the restricted train speeds, the travel times were optimized by arranging the train headways. Yalçınkaya and Bayhan [19] also developed a train timetable scheduling tool using Arena discrete event simulation for modeling a railway corridor considering truck failure and maintenance events. Beyond general simulation frameworks, specialized railway simulation tools have also been employed to analyze existing or proposed railway timetables. Tischer et al. [20] used OpenTrack simulation software for analyzing the line capacity of railway lines in the Czech Republic considering the properties of station sidetracks, and the size of block sections by implementing a headway calculator.

According to the literature review, it was shown that several modeling approaches such as dedicated railway simulations and general simulation frameworks were used for modeling the train operations on railway lines. One important contribution of the study is that in contrast to studies utilizing synthetic or assumed origin-destination data, this study is grounded in empirical passenger flow data from İzmir Metro, like Beijing [21], Istanbul [22] and Vienna [23] reflecting actual demand variations across hourly intervals providing a realistic basis for validating the proposed optimization model. More specifically, several studies in the literature consider the Izmir metro line which try to optimize passenger travel time and analyze the metro line's performance. Öztürk [4] used discrete-event simulation with Arena software to analyze the İzmir metro line's performance. The study focused on important performance metrics such as average passenger numbers in trains and station waiting times. The simulation work determined the average number of passengers per train and evaluated the passenger comfort index and average train waiting times. Additionally, the study highlighted the necessity of optimizing the train time headway through simulation optimization for future studies. Based on these outcomes, this study contributes by implementing a heuristic-based Artificial Bee Colony algorithm to optimize train headways, with a focus on a zero-passenger boarding criterion.

3 MATERIAL AND METHOD

In this study, first a DES model for mimicking the operations of a metro line was developed using Arena 14 simulation framework. DES was selected in this study due to its flexibility in modeling complex, dynamic systems where events occur at discrete points in time (such as metro operations with stochastic passenger arrivals and varying train dispatch schedules). Unlike analytical or purely mathematical models (e.g., mixed-integer linear programming or queuing theory), DES can capture real-world randomness and variability without oversimplifying the system. This feature is particularly crucial for modeling urban rail systems, where passenger flows, boarding times, and service delays fluctuate significantly throughout the day. Compared to specialized railway simulation tools like OpenTrack or analytical capacity methods such as [7] and [8], DES allows a more transparent and customizable structure. It enables the integration of detailed operational processes (e.g., station-level boarding logic, dwell time variability) and facilitates the coupling with optimization algorithms, such as the Artificial Bee Colony method used in this study. Moreover, DES has been widely applied in prior studies (as discussed in the literature review section) to evaluate line performance, passenger travel times, and scheduling robustness, validating its suitability for metro system analysis. In contrast to black-box simulation environments, Arena-based DES provides modular visibility and supports seamless interaction with optimization frameworks via external programming tools such as MATLAB. This makes it especially advantageous for developing adaptable, scenario-based models that are both operationally insightful and computationally efficient.

The model directly uses discrete-event simulation methodology and utilizes the modular SIMAN simulation language. Given the extensive literature on the DES approach, readers can refer to [24] and [25] for more detailed theoretical background. The DES model was constructed considering different train operation and passenger transport processes which simultaneously generate train and passenger entities during the simulation execution. The model included several simulation blocks for representing the train routing, passenger arrivals to the station, boarding, and departures. The DES model blocks and the roles in the model are depicted in Table 1. The two separate processes are also synchronized using different SIGNAL blocks and hold modules triggered by the signals. The entity flowcharts of the DES model are depicted in Figure 1.

Table 1. The DES model blocks and the roles in the model.

CREATE	Generates the periodic metro trains at the initial stations
ASSIGN	Assigns passenger and train characteristics (destinations, train capacity, number of traveling passengers)
RECORD	Record train travel times, passenger waiting times, and delays
DISPOSE	Removes trains and passengers from the simulation model
DELAY	Represents the operational delays (train routing, station service, passenger waiting)
DECIDE	Control the passenger and train operations (passenger boarding, passenger deboarding, train routing decisions)
STATION	Acts as a transfer hub for entities and receives entities between submodels
ROUTE	Routes the model entities to a specified station block
SIGNAL	Synchronizes and triggers the train and passenger entity flow during the simulation. (Triggers train deboarding and boarding processes)

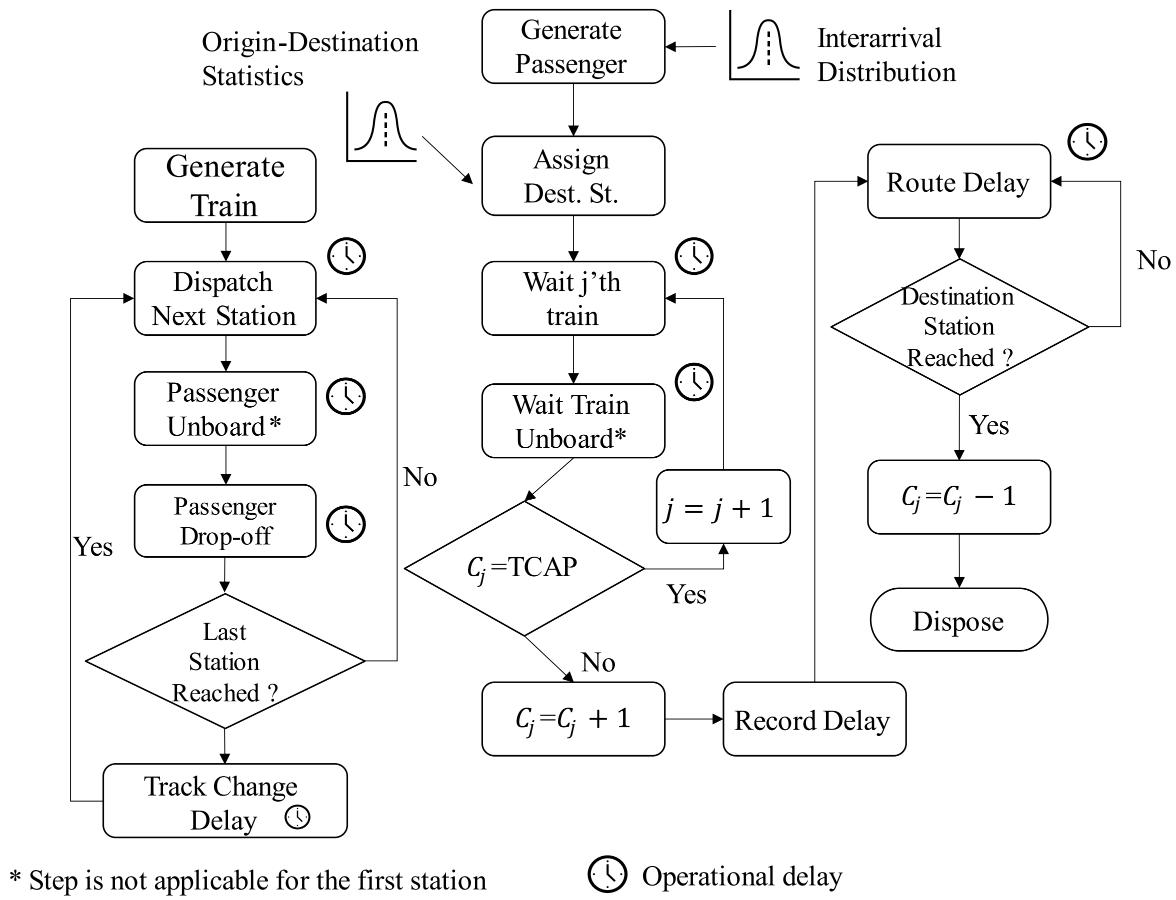

Figure 1. Entity flowcharts for train and passenger operations for the DES model.

The system decomposition technique was used for isolating the system elements into submodels to keep the model structure simple [26]. DES model includes two types of modeling entities (passengers and trains). The model entities are generated using the CREATE block and follow DELAY blocks and HOLD queues for mimicking the station dwelling and routing operations. Each train station was modelled as a submodel with a series of CREATE, DELAY, and DECIDE model blocks to represent passenger arrivals, boarding, and alighting from the train. The model blocks for the simulation of the station operations are depicted in Figure 2 and Figure 3 for Bölge and Basmane station submodels.

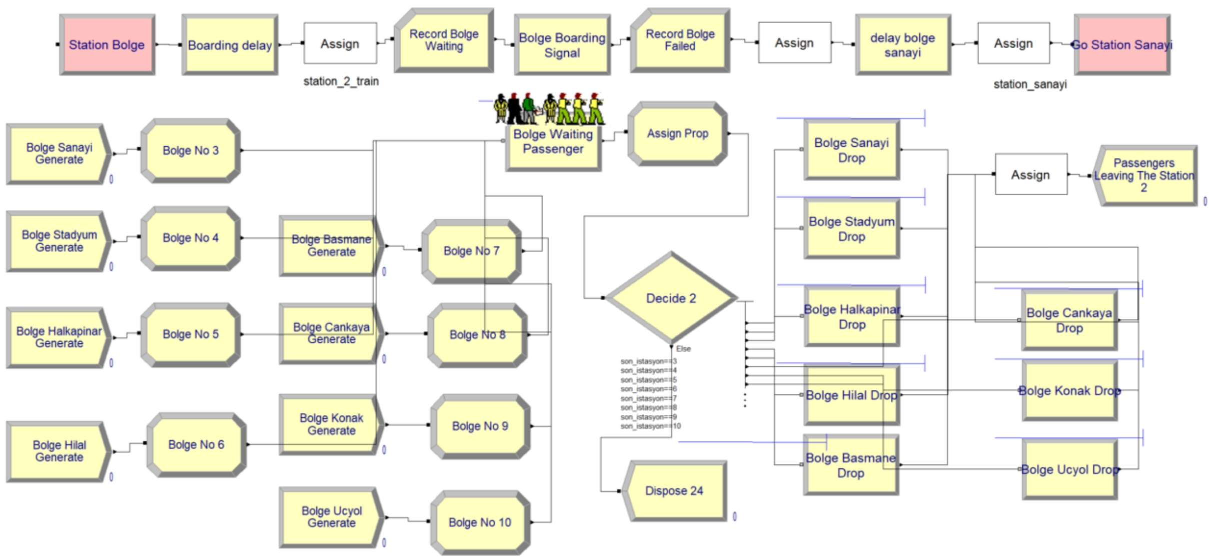

Figure 2. Model blocks for station submodel (Bölge station).

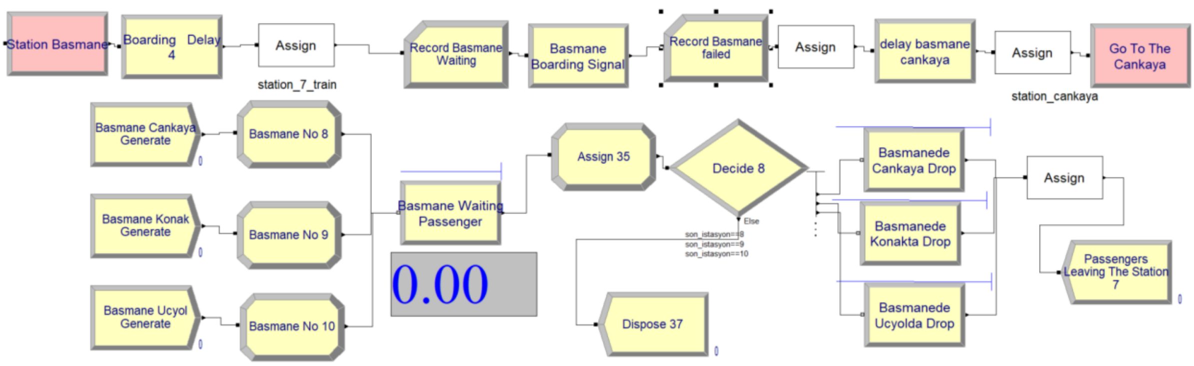

Figure 3. Model blocks for station submodel (Basmane station).

In the DES model, passengers are generated using CREATE blocks based on origin-destination data. Upon arrival at the station, passengers enter a HOLD queue representing the train waiting time. The hold queue is triggered by the arrival of the metro train. Train capacity limits the number of passengers allowed to board. Passengers get onto the train with a FIFO (First in First Out) queue priority and the remaining passengers wait for the next train in line. After the train is dispatched from the station, the DES model records the number of failed passengers boarding the train. The whole process can be shown in the Figure 1. DES model was constructed with several modeling assumptions for simplifying the model structure since more complex systems require more computational efforts. With the increase of the model complexity, the model execution time significantly increased which also increases the optimization phase. The following assumptions were made (1) The passenger arrival scenario was discretized on an hourly basis. The passenger arrival scheme for each hour was kept constant. (2) The train interarrival times were also considered on an hourly basis (3) The passengers boarded the trains using the FCFS queue rule. (4) Upon the arrival of the train at a station, boarding began after the passenger leaves the train. The optimization study was performed using a stand-alone optimization module. The objective function was developed by joining the number of performed metro trips and failed passenger boarding numbers in a serial form as shown in Equation 1.

$$\min f(\vec{x}) = N_T + \emptyset \times N_F \quad (1)$$

where $f(\vec{x})$ is the function to be minimized, and $\emptyset$ is a significantly large real number for guaranteeing the optimization module for locating the solutions corresponds with no failed passenger boarding and applying the optimization constraint and N_F is the number of failed boardings. The $\vec{x}$ is a solution vector corresponding to the train interarrival times for each hourly operation interval and depicted as Equation 2.

$$\vec{x} = (v_1, v_2, v_3, \dots, v_n) \quad (2)$$

where v_i is the train headways between the i-1'th hour and i'th hour. Hence, the vector included control variables evaluated for each model execution. The model optimization cycle is depicted in Figure 4.

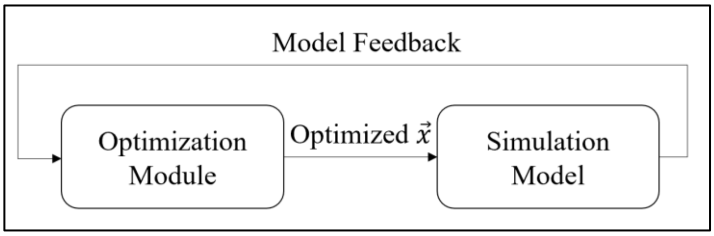

Figure 4. Methodology of the model optimization cycle.

In each optimization cycle, the model uses output from the previous DES execution as input. Based on this evaluation, the optimization module selects a new set of input parameters, which are then passed to the DES model for evaluating the new set of parameters and feeding the optimization module for the next cycle. The iteration process is terminated after a termination criterion is reached (error value, epoch number, or time limit). In this study, the number of epochs was used as the termination criterion.

The Artificial Bee Colony (ABC) algorithm was chosen for its simplicity, global search ability, and effectiveness in solving complex, nonlinear optimization problems with limited parameter tuning. Unlike other metaheuristics, ABC algorithm requires fewer control parameters and is computationally efficient, making it suitable for simulation-based problems. In this study, ABC algorithm optimizes hourly train headways by minimizing a cost function that combines total daily trips and penalties for failed boardings. Each solution generated by the algorithm is evaluated through the DES model, and performance feedback is used to guide subsequent iterations. The algorithms mimic the behaviors of the honeybees for searching and exploiting the profitable food sources in a search space. The extensive methodology of the ABC algorithm can be found in [15]. In the ABC algorithm, a candidate food source is generated using Equation 3.

$$A_{ij} = x_j^{min} + M_r\left(x_j^{max} - x_j^{min}\right) \tag{3}$$

where $i = \{1,2,\ldots,N_s\}$, $j = \{1,2,\ldots,N_P\}$, N_s is the food source number, N_P is the number of the model parameters, x_j^{max} and x_j^{min} are upper and lower limits of the jth parameter and M_r is a number in a range of -1 to 1 assigned as randomly. During the employer bee stage, the bees explore the vicinity of the current food sources, and a new solution vector is generated using Equation 4.

$$s_{ij} = x_{ij} + \emptyset_{ij}\left(x_{kj} - x_{ij}\right) \tag{4}$$

where we choose "i" from the set of integers {1, 2, ..., N_s}, j is a parameter randomly chosen from the range of 1 to D, and k is a randomly selected solution other than "I". The cost function is used to evaluate the fitness of the generated solution. If the fitness of the newly generated solution is superior, the algorithm replaces the old solution with the new one. However, if the old solution is better, it remains in place, and a counter is incremented to keep track of the number of exhausted food sources. After the employer bee stage, the algorithm moves to the onlooker bee stage, where profitable food sources are chosen using a roulette wheel rule. The selection probability of a food source r_i is determined by the fitness value of each solution, as calculated using Equation 5.

$$r_i = \frac{fit_i}{\sum_{j=1}^{n} fit_j} \tag{5}$$

During the onlooker bee stage, food sources are selected by comparing a uniformly random real number, ranging from 0 to 1, with r_i for each food source. If the random number is less than r_i, the onlooker bee finds another food source using Equation 3. If the new solution is superior, it replaces the existing solution in the food source population. After the employer bee stage, the counters for food sources are examined. If a threshold is exceeded, the food source is marked as exhausted, removed, and replaced with a new solution. The cycle of the ABC algorithm continues until specific halting criteria are met. The onlooker bees select food sources by comparing a randomly generated number between 0 and 1 to the food source's probability value, r_i. If the generated number is smaller than r_i, the onlooker bee searches for another food source. If the new food source is better than the previous one, it is added to the population. Following the employer bee stage, the food source counters are evaluated, and if a predetermined limit is reached, the food source is considered exhausted and removed, and a new solution is generated. This process of the ABC algorithm continues until specific halting criteria are satisfied.

To integrate with the DES model, the Arena program is linked with the MATLAB framework using a Visual Basic Script (VBS) object. This setup allows the DES model to iteratively generate outcomes based on selected input parameters. The evaluated objective function is passed to the ABC optimization module, which generates new candidate solution vectors. During the epoch, the best solution vector is stored and the algorithm is terminated if a termination criterion is reached. Each candidate solution in the ABC framework corresponds to a vector of hourly train headways (interarrival times), and the fitness of each solution was evaluated using the output of the DES model. The extensive methodology of the ABC algorithm can be found in [15].

4 RESULTS AND DISCUSSION

This study used the previous configuration of an existing metro line in İzmir, Türkiye, to represent a real-world scenario. The İzmir Metro is a key public transportation system connecting the city center with surrounding suburbs. The views of the metro train and Konak station are shown in Figure 5. The characteristics of the metro train are depicted in Table 2.

Figure 5. (a) Metro train (b) View of the Konak station [3].

Table 2. Characteristics of the metro train [3] [27].

Characteristics	Value
Train width	2,650 mm
Owner	Izmir Metro Joint-stock company
Rail Width	1.435 m
Maximum grade	4.80%
Minimum curb radius	250 m
Car length	23.5 m
Car width	2.65 m
Sitting passengers	44
Standing passengers	204 (5 person /m^2)
CER power	400 kW
Acceleration	1 m/s^2
Deceleration	1.1 m/s^2 1.7 m/s^2 (Emergency braking)

Train car capacity is calculated based on both seated and standing passengers. The number of standing passengers for a car estimated using the passenger occupied area approach. The maximum number of standing passengers per square meter is calculated using a standard density of 4 passengers/m^2 [28]. Considering the metro system's operation at or near peak passenger capacity, a density of 5 passengers per square meter is acknowledged for the purpose of determining the permissible number of passengers per train car.

Since an up-to-date origin-destination matrix for passenger flow could not be reached, this study merely considered the previous state of the current metro line. The objective was to demonstrate the efficiency of the proposed method rather than to develop a digital twin of the actual system. The studied section of the metro line with 10 stations is depicted in Figure 6.

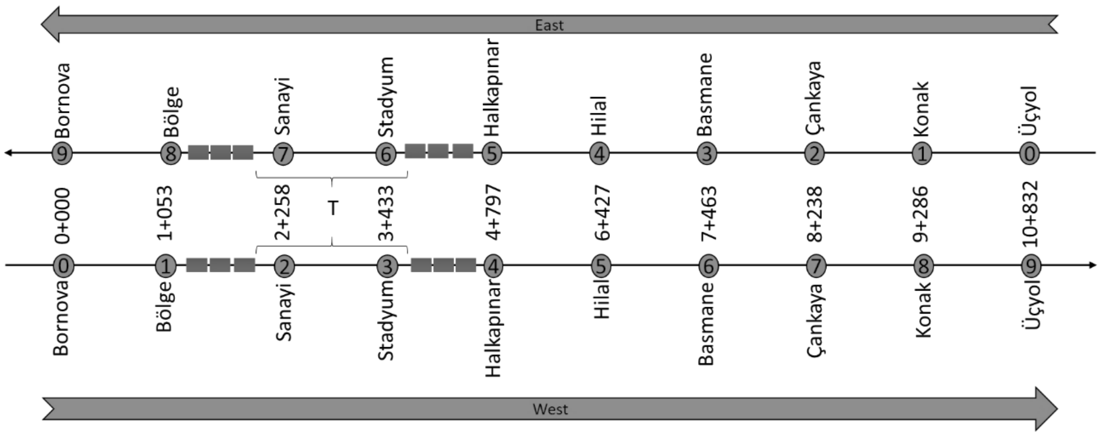

Figure 6. Schematic view of the studied section of the metro line with 10 stations.

In Figure 7, “T” is the train time headway between successive trains determined by the interarrival times of the trains at the first station. Trains depart from Bornova station, travel westward, and reverse direction at Üçyol station to begin a new eastbound trip. The DES model was calibrated using the train route and station dwell times as depicted in Table 3.

Table 3. Train route times between stations and station dwell times.

Origin Station	Destination	L_s (m)	Route Time	Station Dwell Times (sec)
Bornova	Bölge	1053	01:35	25
Bölge	Sanayi	1205	01:38	25
Sanayi	Stadyum	1175	01:34	15
Stadyum	Halkapınar	1364	02:08	25
Halkapınar	Hilal	1630	02:01	25
Hilal	Basmane	1036	01:30	25
Basmane	Çankaya	775	01:22	20
Çankaya	Konak	1048	01:33	25
Konak	Üçyol	1546	02:30	25

L_s :Distance between stations (in meters)

Hourly passenger arrivals were obtained from İzmir Metro Authority and categorized by origin and destination stations. These data were incorporated into the model as entity arrival schedules, as shown in Figure 7. The simulation model was validated using historical origin-destination passenger arrival data collected on an hourly basis. The passenger arrivals were described using an exponential interarrival distribution with hourly passenger arrival means.

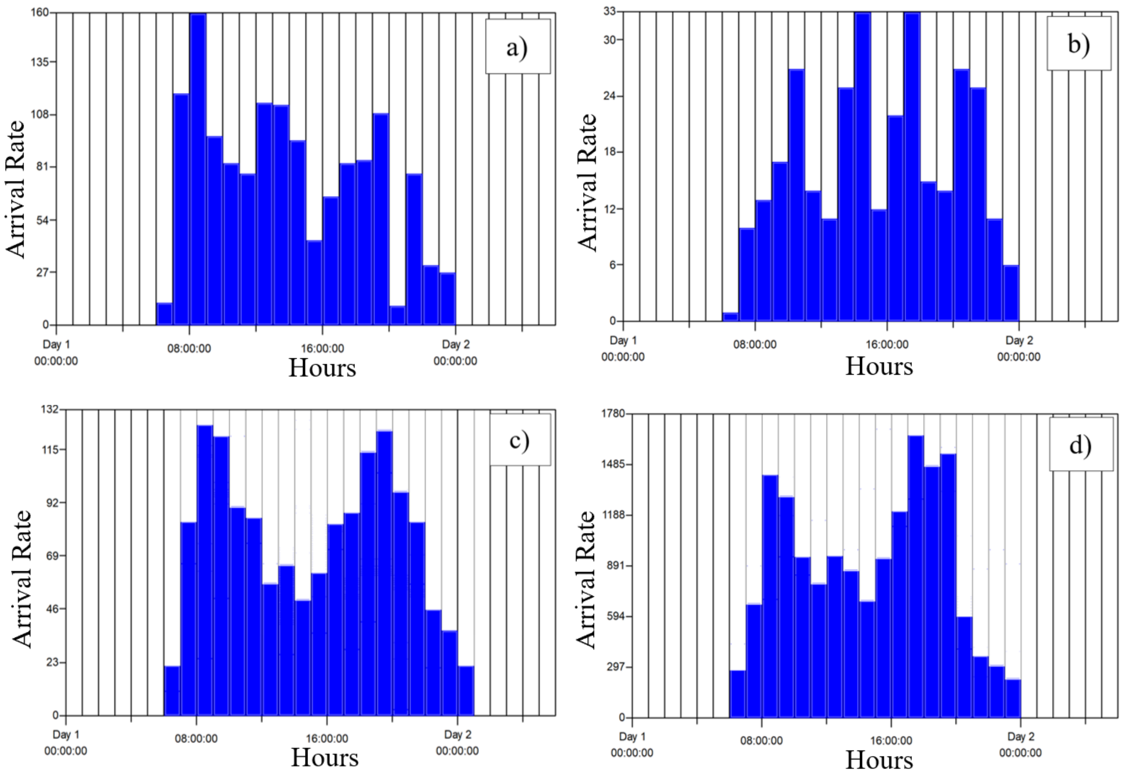

Figure 7. Hourly passenger arrival rates (a) Hilal to Basmane, (b) Bornova to Sanayi(c) Halkapınar to Hilal and (d) Bornova to Halkapınar stations.

The DES model parameters were determined using train specifications, operational constraints, and properties. The train capacity for each trip was assumed as 732 passengers for a rolling stock of 3 attached train cars (244 passengers per car × 3 cars per rolling stock). Specifically, the ABC algorithm was configured with a population size of 60 food sources (candidate solutions), and the maximum number of iterations (epochs) was set to 900. An average of 10 replications were considered for each epoch. The abandonment limit parameter was set to 100, which determines when a food source is replaced due to stagnation. The convergence criterion was defined based on the stabilization of the objective function over 100 consecutive iterations, although the optimization continued until the maximum epoch limit was reached to ensure robustness. The optimization progress and the decrease of the total number of trips for 900 optimization epochs are depicted in Figure 8. Upon examining Figure 8, it is evident that beyond epoch number 300, no discernible enhancement is observed, as indicated by the plateau in the total number of trips. This suggests that the optimization process predominantly converges towards an optimized solution after reaching the specified epoch threshold of 300.

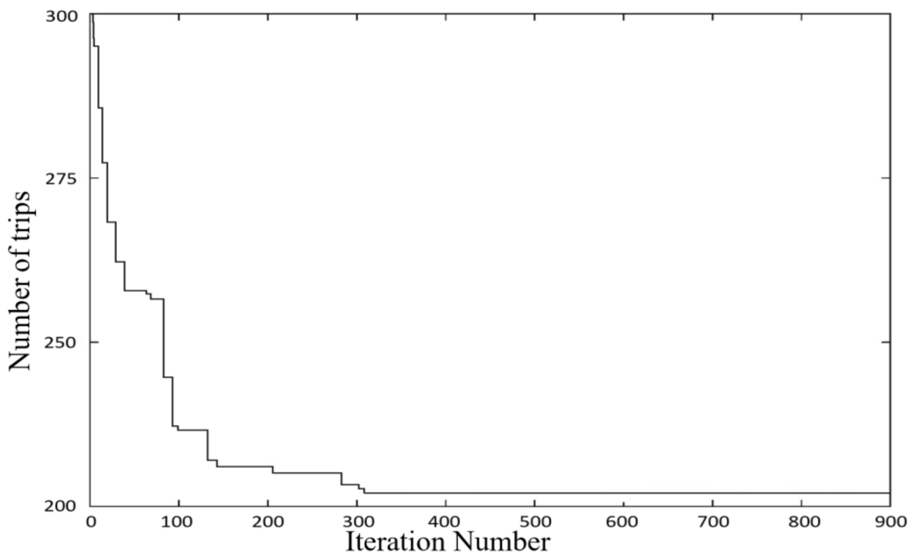

Figure 8. Variation of the daily trips with optimization iteration number.

Following the completion of the optimization study, Table 4 presents the optimized headway values and number of trips with the actual train schedules. After 1000 epochs, the optimization model reached a total of 217 train trips without any failed boarding. However, after epoch number 308, there was no significant drop in the optimized goals, and the goal function was constant until the end of the model execution. Compared to the regular operational scenario the optimized trip parameters yielded a 27.7% reduction in the total number of daily trips (from 300 to 223) while no failed passenger boarding was achieved. In several time intervals (particularly during mid-morning and late evening hours) the optimized headways differ significantly from current operational schedule. These deviations can be attributed to two primary factors: temporal passenger demand fluctuations and the optimization objective focused solely on minimizing daily trip counts under a zero failed-boarding constraint. Longer headways during off-peak periods (e.g., between 10:00–12:00 and after 20:00) reflect an efficient response to lower passenger volumes of the optimization algorithm. Conversely, during high-demand intervals (e.g., 07:00–09:00), the optimized headways remain relatively short (not always as frequent as the existing Schedule). This difference suggests that the current operation may be slightly over-serving demand in some intervals, potentially increasing energy and maintenance costs without proportional gains in service reliability

Furthermore, the study examined the extent to which the optimization of train capacities reflected in the results. To achieve this, the train capacity increased by 20% to reach 878 passengers. In the operational study conducted for this value, the optimum number of trips was found to be 166 trips/day, resulting in a 25.5% reduction. Specifically, the increase in train capacity caused an increase in the train headway time during peak hours.

Table 4. The comparison of the real operational scenario and optimized time headways

#	Time Interval	Existing		TCAP=732		TCAP=878	
		v_i	N_T	v_i*	N_T	v_i*	N_T
1	06:00-07:00	5	12	6	10	9	6
2	07:00-08:00	3	20	3	20	5	12
3	08:00-09:00	3	20	3	20	4	15
4	09:00-10:00	3	20	4	15	6	10
5	10:00-11:00	3	20	7	8	9	6
6	11:00-12:00	3	20	6	10	8	7
7	12:00-13:00	3	20	5	12	6	10
8	13:00-14:00	3	20	4	15	6	10
9	14:00-15:00	3	20	5	12	7	8
10	15:00-16:00	3	20	4	15	6	10
11	16:00-17:00	3	20	3	20	4	15
12	17:00-18:00	3	20	4	15	5	12
13	18:00-19:00	3	20	4	15	4	15
14	19:00-20:00	3	20	10	6	10	6
15	20:00-21:00	8	7	10	6	10	6
16	21:00-22:00	8	7	10	6	10	6
17	22:00-23:00	8	7	10	6	10	6
18	23:00-00:30	8	7	10	6	10	6
		$\sum$	300	$\sum$	217	129	166

*v_i: optimized trip headways for a train capacity of "TCAP" per trip. N_T: Number of trips

5 CONCLUSION AND RECOMMENDATIONS

In this study, a discrete-event simulation (DES) model was utilized to simulate the operations of a metro line, considering passenger boarding, onboarding, and train dispatching. Moreover, the Artificial Bee Colony algorithm was employed for optimizing the model, and its modular integration with the DES model was described in detail. A case study was conducted in Izmir, Türkiye, to demonstrate the advantages of the simulation-optimization approach. The findings of the study showed that DES modeling, coupled with an optimization module, can be effectively utilized to minimize the total daily train trips, and increase system utilization by optimizing the train headways. This approach also ensured a zero failed passenger boarding strategy. The main conclusions of the study are as follows. (1) The DES simulation methodology can successfully be used for simulating both train routing and passenger transport using the principal simulation modeling paradigms and it can be used as a capacity analysis tool for the evaluation of the line capacities. (2) The total reduction of daily train trips was reduced by 27.7% from 300 to 217 daily train trips. (3) A further reduction of the total trips can be achieved by increasing the train capacities by 20% while keeping the other parameters same. With this condition, the optimized train headways resulted in a 25.5% reduction in the total daily trips.

When the results of the study are examined along with the current literature, it can be observed that metaheuristic algorithms can be used to make improvements in railway operations similar to this study. Particularly, genetic algorithms and heuristic algorithms are applied to optimize mixed integer programming mathematical models. Garrisi and Cervello [29] performed train scheduling optimization in railway lines with crowded stations using a genetic algorithm. Als et al. [30] used a genetic algorithm and mixed integer linear programming model for energy-efficient train scheduling for a network consisting of 107 stations and 18 timetables. Without sacrificing other objectives, they achieved up to 3.3% energy savings and a 4.64% reduction in passenger travel time. In a similar vein to this study, Schmaranzer et al. [31] considered station passenger arrivals during peak hours in their headway optimization study for the Vienna metro line using a microsimulation method. They demonstrated that an improvement of 0.79% in operating costs can be achieved with optimized values. Some other headway optimization studies and their findings are tabulated in Table 5.

Table 5. The results of the several time headway optimization studies in literature

Study	Properties	Findings
Schmaranzer et al. [31]	Discrete event simulation-based optimization with genetic algorithm, waiting passengers on platforms and within vehicles are subject to capacity restrictions.	Cost reduction of 0.79% and service quality improvement of 3.72%
Chang et al. [32]	The total system cost is composed of the operator costs, the user costs, and the external cost	The optimal length should be longer 2.32 km and the optimal headway should be greater 2.9 minutes
Xu et al. [33]	A particle swarm optimization algorithm is used to search for optimized headways and value of speed limit for a subway line	The minimum headway decreased by 8.3%

As Table 5 is considered, the difference of this study from the literature is the higher rate of improvement since a 27.7% and 25.5% decrease of the number of daily trips was obtained. This is primarily due to the use of a zero failed passenger boarding constraint, instead of the maximum passenger waiting time criterion used in this study. From the operational perspective, the 27.7% reduction in daily train trips directly translates into lower energy consumption, decreased vehicle wear, and potentially reduced labor requirements. These gains may allow operators to allocate maintenance resources more efficiently and reduce operational expenditure, especially in off-peak periods. For passengers, the adoption of a zero failed boarding policy ensures that no passenger is left behind due to vehicle overcapacity, a frequent issue during peak periods. This enhances perceived service reliability and comfort, thereby increasing user satisfaction and potentially encouraging a modal shift from private vehicles to public transit.

Moreover, the studies in literature mainly considered the average waiting time and operational costs as performance measures rather than number of completed train trips that also differentiates the overall results. However, this study successfully demonstrated the applicability of metaheuristic algorithms and microsimulation to optimize the metro train headways considering a particular key performance indicator or zero failed loading constraint.

Although this paper demonstrated the passenger-centric planning and optimization of metro line capacity through microsimulation, it should be considered that there are certain limitations. Firstly, a significant preliminary study is required for calibration and verification of the established model, and a realistic origin-destination passenger matrix needs to be generated over time. For Izmir metro system, obtaining this data is difficult due to the nature of the system where passengers do not tap their cards when exiting the turnstiles, making it impossible to collect destination data. To collect this data, a survey should be conducted with passengers at the stations on a sampling basis for specific days and times, and based on the survey results, an OD matrix should be created. Such a study requires serious project support and fieldwork. Therefore, although the number of stations on the line has increased, there is no OD matrix available for the new stations in this study, and thus the study was conducted based on the old-line configuration.

One notable limitation of the current study lies in the absence of explicit operational constraints typically present in real-world rail systems, such as block signaling logic, safety buffer requirements between successive trains, and minimum headway margins enforced by infrastructure control systems. To improve the practical applicability of future simulation-optimization efforts, it is essential to incorporate these operational constraints directly into the model. For example, integrating block-section logic within the DES framework, accounting for fixed signal positions and inter-train clearance times, would enhance the realism of the model.

Lastly, the modeling assumptions of hourly constant passenger arrivals and uniform interarrival times introduce simplifications that may not fully reflect the real-world variability in metro operations. These assumptions were necessary to ensure computational efficiency during the optimization process, but they may overlook short-term demand fluctuations and queuing effects that typically occur during peak periods.

Not only the operational efficiency, but the optimized headways also have direct implications for passenger comfort and perceived service qualitsy. By enforcing a zero failed-boarding policy for the study, the optimization ensured that no passengers are left behind due to overcrowding which significantly enhances passenger satisfaction, particularly during peak hours. In this sense, the model prioritizes vehicle accessibility and avoids the frustration linked with long platform waits or missed trains due to overcapacity. However, comfort is not solely determined by boarding success. Shorter headways typically lead to less crowded vehicles, more seating availability, and a more comfortable in-vehicle experience. While optimization achieves efficiency by slightly increasing headways in certain peak intervals, this may result in higher occupancy levels, especially if demand predictions deviate from expected values. As a result, although no passenger failed boarding, the passenger experience may involve more standing, limited personal space, and longer exposure to crowding which can reduce overall service satisfaction.

While the case study focused on a specific metro corridor, the developed methodology is applicable to other urban rail systems with similar operational characteristics such as Bus Rapid Transit systems operate on dedicated lanes with scheduled services and passenger boarding dynamics similar to rail systems. The nature of the DES framework and the metaheuristic optimization approach allows adaptation to various system configurations, including different train lengths, station geometries, boarding rules, and demand profiles. However, successful generalization requires system-specific calibration, particularly in terms of passenger arrival patterns and infrastructure constraints. For broader applicability, the methodology can be extended to incorporate additional performance indicators such as energy consumption, operating costs, and average passenger waiting time, thereby enabling multi-objective optimization for diverse transit systems.

In future studies, the DES model is planned to evaluate more realistic operational constraints, such as limiting passenger average station waiting times. Future work will also aim to address the limitations by incorporating finer temporal resolution in passenger arrival modeling, conducting sensitivity analyses on key parameters. Due to institutional and resource limitations, conducting a new field survey or large-scale sampling study was not feasible within the scope of this study. However, future work is planned to include OD matrix updates as part of a funded project proposal. Since the obtained OD matrix is outdated and the authors were unable to obtain up-to-date passenger flow data, a more detailed and up-to-date OD matrix will be collected and implemented to reflect the recent status of the metro network, which will provide more reliable optimization performance based on current data. Furthermore, a cost model that optimizes the number of train sets and energy efficiency will be integrated into the optimization study, in addition to optimizing headways. Operational studies will be conducted regarding different passenger comfort and level of service scenarios.

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Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the authors.

Contributions of the Authors

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