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An innovative mathematical model for integrated traffic flow optimization in organized industrial zones

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This study introduces a comprehensive mathematical model designed to optimize traffic flow in a newly planned Organized Industrial Zone (OIZ). The proposed model focuses on four primary objectives: maximizing overall traffic flow, minimizing congestion, regulating peak-hour traffic, and effectively managing personnel and visitor traffic. The model incorporates traffic demand, road and intersection capacities, and vehicle types, leveraging these parameters to ensure efficient and sustainable traffic management. Unlike traditional simulation-based approaches, this model integrates optimization techniques to address the unique challenges of OIZs, such as logistics flows and personnel movements. Key components include decision variables for vehicle flows across road sections, robust capacity constraints for roads and intersections, and weighted parameters to balance objectives. The model also considers infrastructure improvements like road expansions, intersection adjustments, and traffic signal optimization. By optimizing traffic flow under various constraints, the model offers a strategic planning tool for decision-makers, enabling data-driven adjustments to infrastructure and traffic policies. Its adaptable structure allows for application in diverse OIZ projects, enhancing both operational efficiency and long-term sustainability. The study highlights the model's potential to serve as a benchmark for OIZ traffic management, addressing critical gaps in existing literature.

Keywords Traffic flow optimization, Organized industrial zones, Mathematical modeling, Congestion management, Infrastructure planning

OIZs have emerged as critical engines of industrial growth and economic development. By concentrating industrial activities in designated areas, OIZs streamline production processes, support economic efficiency, and foster regional development. These zones facilitate the transportation of goods, the coordination of logistics, and workforce mobility on a significant scale. However, the unique characteristics of OIZs, such as high freight intensity and workforce traffic surges during shift changes, present distinct challenges in traffic management and infrastructure planning. Addressing these challenges is essential for ensuring operational efficiency, minimizing delays, and enhancing the long-term sustainability of OIZs. The complexity of traffic management in OIZs stems from the simultaneous presence of logistics traffic and workforce mobility. Unlike urban traffic systems, which are characterized by diverse vehicle types and significant reliance on public transportation, OIZ traffic predominantly involves heavy freight vehicles and large-scale commuter movements. These unique dynamics often lead to congestion, inefficient utilization of road networks, and delays at critical junctions. Such inefficiencies can disrupt industrial operations, increase costs, and hinder the timely delivery of goods.

Existing traffic optimization techniques have predominantly focused on urban contexts, where the objectives are to alleviate congestion and improve mobility for mixed traffic. Traditional methods, such as queuing theory and Poisson distributions, have been applied to urban traffic systems to predict flow and manage congestion effectively[1]. While these models provide valuable insights, they fall short in addressing the distinctive traffic dynamics of OIZs, where logistics demands and shift-based workforce movements fluctuate throughout the day. Early models, such as the gravity model proposed by Wilson[2] and extended by Ding et al.[3], have been widely used to predict traffic flows by analyzing spatial interactions. Similarly, the radiation model introduced by Simini et al.[4] simplified flow predictions by reducing parameter requirements. While these models have been instrumental in understanding urban traffic dynamics, their limitations become evident in logistics-intensive

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settings like OIZs, where the interplay between freight and workforce traffic necessitates more specialized approaches. Recent advancements in traffic optimization have introduced data-driven methodologies and adaptive optimization techniques, paving the way for more effective solutions. Big data analytics has proven invaluable in refining traffic predictions and commuting matrices. For example, Liu et al.[5] and Wan et al.[6] demonstrated the utility of integrating travel surveys with large-scale datasets to enhance accuracy. These approaches are particularly relevant to OIZs, where real-time data is critical for dynamic traffic management. The use of Macroscopic Fundamental Diagrams (MFD) has also gained traction in recent years for managing multi-modal traffic. Menendez et al.[7] highlighted the application of 3D-MFD to model multi-modal flows, providing insights into traffic behavior across interconnected zones. Similarly, Ren et al.[8] proposed adaptive perimeter control techniques using iterative learning frameworks, enabling efficient traffic management without relying on detailed dynamic models. Zhou and Gayah[9] extended the field by introducing reinforcement learning-based multi-agent systems for traffic optimization in multi-region networks, offering scalable solutions that bridge urban and industrial traffic systems. Multi-objective optimization techniques have further advanced the field, enabling the simultaneous consideration of conflicting goals such as maximizing traffic flow and minimizing congestion. Genetic algorithms[10] and Model Predictive Control (MPC)[11] have shown promise in balancing these objectives. Sirmatel and Geroliminis[12] demonstrated the effectiveness of microscopic simulations combined with MPC in stabilizing traffic flows across multi-reservoir systems. Similarly, advanced machine learning applications, such as transformer models[13] and cellular automata simulations[14], have enhanced predictive capabilities, making flexible traffic management feasible in complex environments. Despite these advancements, a significant gap remains in developing traffic optimization models specifically tailored to OIZs. Urban-centric models often overlook the logistics-worker traffic interplay, infrastructure limitations, and the need for real-time adaptability in OIZs. Addressing these gaps, Ulvi et al.[15] introduced the Urban Traffic Mobility Optimization Model (UTMOM), which leverages predictive analytics and data mining to decode traffic patterns. Similarly, Saadullah et al.[16] combined Macroscopic Fundamental Diagram (MFD) and Model Predictive Control (MPC) techniques to optimize multi-modal traffic flows, emphasizing freight and passenger interactions. To further clarify the research gap, a direct comparison between the most relevant existing studies and the proposed model is presented in Table 1. Liu et al.[17] focus on optimizing speed and holding times for bus rapid transit (BRT) corridors, dealing exclusively with bus passenger traffic and operational decisions. Ma et al.[18] address the integration of ramp closures and signal timing to minimize delays and improve safety during temporary freeway closures, but their work is limited to short-term, passenger car-focused scenarios. Wang et al.[19] develop a cooperative framework combining pre-trip route guidance and signal control to enhance urban network throughput, yet they primarily target private vehicles without infrastructure modifications. Min et al.[10] apply genetic algorithms to optimize traffic signals within industrial zones, but they only consider operational improvements and omit infrastructure upgrades or heavy logistics traffic. In contrast, the proposed study uniquely integrates freight, workforce, and visitor traffic within a unified model, simultaneously optimizing both infrastructure investments (e.g., road expansions, intersection redesigns) and operational controls (e.g., traffic signal timing). It further distinguishes itself by dynamically adjusting capacities based on vehicle types and road slopes, and by balancing four conflicting objectives: maximizing traffic flow, minimizing congestion, regulating peak-hour demand, and promoting sustainable workforce mobility. This comprehensive approach, specifically designed for Organized Industrial Zones (OIZs), fills a critical gap in the existing traffic optimization literature.

Building on this foundation, this study introduces a novel multi-objective mathematical model tailored explicitly for OIZs. The model aims to address the following objectives:

1. Maximizing Overall Traffic Flow: Ensuring seamless movement of logistics and workforce traffic.
2. Minimizing Congestion: Optimizing infrastructure utilization and reducing bottlenecks.
3. Regulating Peak-Hour Traffic: Balancing logistical operations with workforce mobility during high-demand periods.
4. Incorporating Infrastructure Constraints: Identifying critical road and intersection limitations and proposing strategic upgrades.

Table 1 illustrates that while prior models advance certain aspects of traffic optimization, none simultaneously address logistics-intensive flows, dynamic infrastructural constraints, and multi-objective balancing in the

Study	Traffic type	Decision layers	Objective functions	Capacity modeling	Application scope
Liu et al.[17]	Bus (BRT) only	Speed & holding time (operational)	Punctuality, delay	Static	BRT corridors
Ma et al.[18]	Passenger cars	Ramp closure, signal timing	Delay, safety	Static	Temporary freeway closures
Wang et al.[19]	Private vehicles	Route guidance, signal cooperation	Network throughput	Static	Urban networks
Min et al.[20]	Private + service vehicles	Signal optimization	Delay, emission	Static	Industrial zones (limited)
This study	Freight, workforce, visitors	Infrastructure & operational control (integrated)	Traffic flow ↑, Congestion ↓, Peak-hour balance, Workforce mobility ↓	Dynamic (EPCU + slope adjustment)	Real-world OIZ

Table 1. Comparative overview of existing multi-objective traffic optimization models and the proposed framework.

specific context of OIZs. Unlike conventional approaches, this model integrates traffic demand forecasting, multi-modal flow optimization, and strategic infrastructure planning to provide a holistic solution for OIZ traffic management. It is innovative in its integration of logistics and synchronized workforce dynamics with multi-objective optimization. Its main strengths include balancing comprehensive objectives such as maximizing traffic flow, minimizing congestion, regulating peak-hour traffic, and promoting sustainability; ensuring practical applicability through realistic capacity limits and flow continuity; and incorporating predictive analytics to enable flexible traffic management based on real-time data. Furthermore, the model demonstrates scalability, making it applicable to both existing and newly planned OIZs. By leveraging real-time data and advanced optimization techniques, it offers actionable insights for improving efficiency, minimizing delays, and supporting sustainable development. The comparative analysis of existing studies (Table 2) highlights the unique contributions of this research. While traditional models and recent advancements have focused on urban or generalized traffic systems, this study addresses the specific needs of OIZs by considering their logistics-intensive and workforce-driven characteristics. The integration of predictive analytics with infrastructure-specific constraints ensures that the proposed model is both practical and scalable, offering a robust framework for decision-making in OIZ planning and management.

A novel multi-objective mathematical framework for optimizing traffic dynamics in OIZs

The multi-objective mathematical model introduced in this study is specifically designed to optimize traffic management in OIZs. OIZs face distinct challenges, including intense logistics flows, high-demand synchronized workforce mobility during shift changes, and infrastructure constraints that require targeted solutions. Workforce mobility in OIZs refers to the large-scale commuting of employees during specific peak periods, such as shift changes, whereas logistics flow primarily concerns the continuous movement of goods via freight vehicles. Both flows operate simultaneously but differ significantly in their patterns and priorities, creating complex and often conflicting traffic dynamics. The model integrates innovative methodologies to address these challenges, offering a robust and practical approach to improving traffic efficiency. A key aspect of the model is its multi-objective framework, which balances conflicting goals such as maximizing overall traffic flow, minimizing congestion, regulating peak-hour traffic, and managing workforce and visitor traffic. This makes the model highly adaptable to the unique conditions of OIZs, where heavy freight vehicles and commuter traffic coexist, often leading to bottlenecks at critical intersections and road segments.

The model's real-world applicability lies in its ability to incorporate predictive analytics and infrastructure-specific constraints. By utilizing historical and real-time traffic data, it forecasts demand, identifies bottlenecks, and proposes actionable solutions, such as optimized signal timings, capacity expansions, or routing adjustments. This ensures that the model is not only a theoretical tool but also a practical resource for decision-makers planning both existing and new OIZ developments. Furthermore, the model's flexibility allows it to adapt to varying traffic patterns and infrastructure changes over time, making it a long-term solution for OIZ traffic management. In contrast to previous studies, which typically focus either on operational improvements like signal timing or strategic actions like ramp closures in isolation, the proposed model uniquely integrates both infrastructure and operational decisions while dynamically adjusting capacities based on vehicle type and road slope. Its distinct focus on logistics-intensive environments and synchronized workforce dynamics further highlights its originality and relevance to industrial applications. By addressing these specific needs, the model provides a scalable and actionable solution for enhancing the efficiency and sustainability of OIZ operations.

Study	Approach	Techniques used	Focus area	Optimization strategy	Key differentiation
Wilson[2], Ding et al.[3]	Gravity models	Spatial interaction modeling	Urban zones	Demand distribution	Limited adaptability to logistics flows
Simini et al.[4]	Radiation model	Simplified parameter modeling	Urban zones	Flow simplification	Over-simplified for industrial settings
Liu et al.[5], Wan et al.[6]	Big data-based commuting models	Data analytics	Urban/industrial zones	Accurate traffic prediction	Hybrid data integration
Min et al.[10]	Genetic algorithms	Multi-objective optimization	Industrial zones	Signal optimization	Limited real-time adaptability
Rastgoftar & Jeannin[11]	Physics-based MPC	Predictive real-time optimization	Urban networks	Dynamic congestion management	Focused on urban intersections
Soudeep et al.[13]	Transformer models	Spatiotemporal traffic prediction	Smart cities	Machine learning-based control	Advanced real-time signal optimization
Ulvi et al.[15]	UTMOM	Predictive analytics, data mining	Urban zones	Pattern decoding	Generalizable but urban-centric
Saadullah et al.[16]	MFD and MPC	Multi-modal optimization	Mixed traffic	Real-time traffic control	Freight and passenger vehicle focus
Menendez et al.[7]	Empirical MFD analysis	Multi-reservoir modeling	Urban networks	Network partitioning	Application of 3D-MFD for multi-modal flow
Ren et al.[8]	Adaptive control	Iterative learning framework	Urban networks	Perimeter control	No reliance on dynamic models
Zhou & Gayah[9]	Reinforcement learning	Multi-agent systems	Urban-Industrial Traffic	Dynamic optimization	Scalable to multi-region networks
Sirmatel & Geroliminis[12]	Microscopic simulation	MPC	Multi-reservoir systems	Stabilization of traffic flow	Demonstrated in real-world environments
This Study	Hybrid data and simulation	Multi-objective mathematical model	Organized Industrial Zones	Integrated optimization framework	Tailored for logistics and workforce mobility

Table 2. Comparative analysis of traffic flow prediction and optimization studies.

Notation and parameters

Indices and sets

- $i, j \in N$: Indices for road segments (origin and destination).
- $k \in K$: Index for intersections.
- $t \in T$: Time intervals in the study period.
- $t_{\text{peak}} \in T_{\text{peak}}$: Time intervals corresponding to peak hours.
- $v \in V$: Vehicle types ({Private, Service, Heavy Vehicles, Visitors }).

Decision variables

- $x_{i,j,t,v}$: Number of vehicles of type v traveling from road segment i to j during time interval t.
- $y_{k,t}$: Total vehicle flow (in Passenger Car Equivalents, PCE) through intersection k at time t.
- s_t^{private} : Number of private vehicles used by workforce and visitors during t.
- s_t^{service} : Number of service vehicles used by the workforce during t.

Parameters

- D_t^v : Traffic demand for vehicle type v during time interval t.
- OEB_v : Passenger Car Equivalent (PCE) value for vehicle type v.
- $C_{i,j}^{\text{rob}}$: Robust capacity of road segment $i-j$, accounting for stochastic variability (vehicles/hour).
- K_k^{rob} : Robust capacity of intersection k, adjusted for capacity uncertainty (vehicles/hour).
- α, β, γ : Weight parameters for congestion, peak-hour regulation, and traffic management of workforce/visitor vehicles.
- $T_{\text{peak:}}$ Subset of T representing peak hours.
- In (k) : Set of incoming road segments to intersection k.

Stochastic capacity representation

Field measurements in the existing Bursa OIZ show that practical capacities vary by roughly $\pm 20\%$ from hour to hour owing to weather conditions, minor incidents and heterogeneous vehicle mixes.

To capture this uncertainty we define three capacity scenarios $\{\omega_1, \omega_2, \omega_3\}$.

(i) nominal (no change),
(ii) adverse (-20%), and.
(iii) favourable (+10%).

The observed occurrence probabilities are $p_{\omega_1} = 0.55, p_{\omega_2} = 0.30$ and $p_{\omega_3} = 0.15$.

For each road segment j and intersection k we first compute the probability-weighted expected capacity

$$\overline{C}_{ij} = \sum_{\omega \in \Omega} p_\omega C_{ij}^\omega, \overline{K}_k = \sum_{\omega \in \Omega} p_\omega K_k^\omega \tag{1}$$

and then subtract one standard deviation $\sigma_{C_{ij}}$ (or σ_{K_k}) as a safety margin:

$$C_{ij}^{\text{rob}} = \overline{C}_{ij} - \sigma_{C_{ij}}, K_k^{\text{rob}} = \overline{K}_k - \sigma_{K_k} \tag{2}$$

These robust capacities, C_{ij}^{rob} and K_k^{rob}, replace C_{ij} and K_k in all capacity constraints, ensuring feasibility across the most likely capacity fluctuations.

Model objectives

The model focuses on four key objectives, ensuring a balanced and comprehensive approach to OIZ traffic management.

Maximizing overall traffic flow

The first objective aims to maximize the total traffic flow across the network, ensuring the efficient use of road infrastructure and minimizing delays. This is represented by Eq. (3):

$$maxZ_1 = \sum_{t \in T} \sum_{(i,j) \in N} \sum_{v \in V} x_{i,j,t,v} \tag{3}$$

In Eq. (3), $x_{i,j,t,v}$ denotes the number of vehicles of type v traveling from road segment i to j during time t. By maximizing Z_1, the model prioritizes the seamless movement of logistics and workforce traffic across the network, which is essential for maintaining OIZ efficiency.

Minimizing congestion

Congestion minimization is critical in OIZs, where excessive traffic can lead to operational delays and increased costs. This objective, expressed in Eq. (4), penalizes traffic flows that exceed road and intersection capacities:

$$minZ_2 = \alpha \cdot \sum_{t \in T} \left[\sum_{(i,j) \in N} \left(\frac{\sum_{v \in V} x_{i,j,t,v} \cdot OEB_v}{C_{i,j}^{\text{rob}}} \right)^2 + \sum_{k \in K} \left(\frac{y_{k,t}}{K_k^{\text{rob}}} \right)^2 \right] \tag{4}$$

Here, OEB_v represents the Passenger Car Equivalent (PCE) for vehicle type v, while $C_{i,j}^{\text{rob}}$ and K_k^{rob} denote the robust capacities of road segments and intersections, accounting for stochastic variability. The first term minimizes road congestion, while the second focuses on intersection congestion. The parameter α weights the importance of congestion reduction. By applying Eq. (4), the model ensures that traffic remains within manageable and resilient limits, reducing bottlenecks and improving overall traffic flow.

Regulating peak-hour traffic
Peak-hour traffic is a significant challenge in OIZs, often leading to severe congestion. The model addresses this by minimizing traffic flows during critical time intervals, as represented by Eq. (5):

$$minZ_3 = \beta \cdot \sum_{t \in T_{\text{pask}}} \sum_{(i,j) \in N} \sum_{v \in V} x_{i,j,t,v} \tag{5}$$

Here, T_{peak} is the set of peak-hour time intervals, and β is the weight assigned to this objective. By regulating peak-hour flows, Eq. (5) ensures the network remains operational during high-demand periods.

Managing workforce and visitor traffic
Efficiently managing workforce and visitor movements is essential for OIZ sustainability. This objective, shown in Eq. (6), minimizes the use of private and service vehicles:

$$minZ_4 = \gamma \cdot \sum_{t \in T} \left(s_t^{\text{private}} + s_t^{\text{service}} \right) \tag{6}$$

Here, s_t^{private} and s_t^{service} represent the number of private and service vehicles used during t. The parameter γ weights this objective, emphasizing reduced reliance on private vehicles. Equation (6) promotes sustainable traffic practices and reduces congestion caused by excessive vehicle usage.

Model constraints

The objectives are subject to several constraints that ensure the model's practical feasibility and alignment with real-world conditions.

Traffic demand satisfaction
Traffic demand for each vehicle type v during time t must be satisfied. This is enforced by Eq. (7):

$$\sum_{(i,j) \in N} x_{i,j,t,v} \leq D_t^v, \forall\, v \in V, t \in T \tag{7}$$

Here, D_t^v represents the traffic demand for vehicle type v during t. Equation (7) ensures that the model meets the required demand without overloading the network.

Flow conservation
At every node, the traffic entering must equal the traffic exiting, ensuring continuity of flow. This is expressed in Eq. (8):

$$\sum_{j \in N} x_{i,j,t,v} - \sum_{j \in N} x_{j,i,t,v} = 0, \forall\, i \in N, v \in V, t \in T \tag{8}$$

Equation (8) prevents disruptions in the flow network, maintaining balance at all nodes.

Road capacity constraints
Traffic flow on any road segment must not exceed its robust capacity, as stated in Eq. (9):

$$\sum_{v \in V} x_{i,j,t,v} \cdot OEB_v \leq C_{i,j}^{\text{rob}}, \forall\, (i,j) \in N, t \in T \tag{9}$$

Here, $C_{i,j}^{\text{rob}}$ defines the maximum allowable flow on segment i-j, accounting for stochastic variations. Equation (9) ensures that road segments remain operable under capacity fluctuations.

Intersection capacity constraints
Traffic flow through intersections must remain within robust limits, as represented in Eq. (10):

$$y_{k,t} = \sum_{v \in V} \sum_{(i,j) \in \text{In}(k)} x_{i,j,t,v} \cdot OEB_v \leq K_k^{\text{rob}}, \forall\, k \in K, t \in T \tag{10}$$

This constraint ensures intersections maintain efficient operation even when robust capacities vary.

Peak-hour capacity constraints
During peak hours, the traffic flow on road segments must remain within the robust capacity, as enforced by Eq. (11):

$$\sum_{v \in V} x_{i,j,t,v} \cdot OEB_v \leq C_{i,j}^{\text{rob}}, \forall (i,j) \in N, t \in T_{\text{peak}} \tag{11}$$

This constraint prioritizes infrastructure functionality during periods of high demand, considering stochastic capacity adjustments.

Workforce and visitor traffic constraints
The use of private and service vehicles is controlled by Eqs. (12) and (13):

$$s_t^{\text{private}} = \sum_{(i,j) \in N} \left(x_{i,j,t,\text{ Private}} + x_{i,j,t,\text{ Visitor}} \right), \forall t \in T \tag{12}$$

$$s_t^{\text{service}} = \sum_{(i,j) \in N} x_{i,j,t,\text{ Service}}, \forall t \in T \tag{13}$$

These constraints regulate the distribution of vehicles, encouraging balanced and sustainable traffic flows.

Non-negativity constraints
All decision variables must remain non-negative, as specified in Eq. (14):

$$x_{i,j,t,v} \geq 0, s_t^{\text{private}} \geq 0, s_t^{\text{service}} \geq 0, \forall (i,j) \in N, v \in V, t \in T \tag{14}$$

Equation (12) ensures that the model produces physically meaningful solutions.

Mathematical model application for new OIZ

The mathematical model was applied to a newly planned OIZ in Bursa, Turkey, aiming to optimize traffic management within the industrial zone. Bursa, known for its significant industrial activities, requires efficient traffic systems to handle the high volume of logistics operations, workforce mobility, and visitor traffic inherent in such zones. The study focused on addressing the distinct requirements of the OIZ, which include:

- High Logistics Demand: Frequent and continuous movement of heavy freight vehicles for goods transportation throughout the day.
- Workforce Mobility: High-demand, large-scale commuting of employees during specific peak periods, particularly at shift start and end times, distinct from the continuous nature of freight movement.
- Infrastructure Constraints: Limitations due to road capacities, intersection designs, and challenging terrain features, such as steep road slopes.

To effectively manage these challenges, the mathematical model incorporated detailed traffic data derived from expected vehicle distributions, road segment capacities, intersection designs, and adjustments for road slope effects. By distinguishing between workforce mobility—characterized by concentrated, time-specific surges—and logistics flow—characterized by continuous freight vehicle movements—the model ensures tailored solutions for each traffic type. Advanced optimization techniques were utilized to achieve optimal solutions for traffic flows, aiming to minimize congestion and balance the usage of private and service vehicles. The optimization was performed using the General Algebraic Modeling System (GAMS) with the BARON solver, known for its capability in handling complex, non-linear optimization problems. The model results provide valuable insights for planners and decision-makers to enhance traffic flow and infrastructure utilization in the OIZ.

Data collection and analysis

Accurate and comprehensive data collection was essential for the development of a reliable mathematical model. The data used in the model were meticulously gathered from various sources and analyzed to ensure applicability to the OIZ's specific context.

Existing OIZ data

Source: existing OIZ data

- Method: Analysis of traffic patterns, vehicle counts, and infrastructure capacities from the current OIZ in Bursa.
- Data collection:
  - Traffic Counts: Field observations and traffic counts were conducted to collect data on the number of visitors and employees, their transportation modes, and peak traffic hours.
  - Infrastructure Capacities: Road widths, number of lanes, intersection types, and existing capacities were documented.
- Purpose: Establish a baseline for expected traffic demand and infrastructure capabilities in the new OIZ.

Surveys and questionnaires

Source: survey data

- Method: Surveys were distributed among employees and visitors to determine transportation preferences, vehicle ownership rates, and peak travel times.
- Key Findings:
  - Transportation Modes: 36% of personnel use private vehicles, 63% use service (company-provided) vehicles, and 1% use public transportation.
  - Peak Hours: Identified as 08:00–09:00 and 16:00–19:00, aligning with shift changes.
- Purpose: Understand the distribution of vehicle types and the potential impact on traffic flow.

Regression analysis

Source: existing OIZ visitor data

- Method: Historical data on visitor and personnel numbers were used to predict future traffic demands through regression models.
- Process:
  - Data Collection: Past records of visitor numbers and personnel counts were gathered.
  - Regression Modeling: Statistical models were applied to forecast future increases in traffic due to industrial growth.
- Purpose: Estimate the expected vehicle demand (D) for use in the model.

Infrastructure capacity studies
Sources:

- Transportation Research Board[20].
- Institute of Transportation Engineers[21].
- Method: Calculation of road and intersection capacities based on engineering standards.
- Adjustments:
  - Road Width and Lanes: Capacities adjusted according to the number of lanes and road dimensions.
  - Vehicle Types: Capacities modified using Equivalent Passenger Car Units (EPCU) to account for the impact of different vehicle types on traffic flow.
- Purpose: Determine robust capacities (C and K) for roads and intersections to be used as constraints in the model.

Slope adjustment factors

Source: Slope-affected traffic forecast data

- Method: Adjustments were made to road capacities to account for the impact of steep slopes on vehicle speeds and flow rates.
- Data and Calculations:
  - Engineering Standards: Based on Highway Capacity Manual[17] guidelines, a 20% reduction in capacity was applied for roads with a 20% gradient.
  - Capacity Adjustments: Robust capacities were recalculated for affected road segments.
- Purpose: Reflect the real-world limitations imposed by terrain on traffic flow.

Parameter data

Below are the parameters used in the traffic optimization model, along with explanations of how each parameter was derived. A summary of the key parameters used in the traffic optimization model is presented in Table 3 below. These parameters were derived from the data sources and methods described in the previous sections and are critical inputs for the mathematical model.

These parameters, form the foundational inputs for the mathematical model. By integrating the robust capacities of intersections and road segments (K and C), adjusting for time intervals (t), vehicle types (v), and incorporating traffic demand (D), the model accurately reflects the real-world conditions of the OIZ. The objective weights (α, β, γ) prioritize the optimization goals, while the slope adjustment factor ensures that the model accounts for the reduced capacities on steep roads. The visitor and workforce distribution percentages guide the allocation of different vehicle types in the traffic flow simulations.

Parameter	Description	Value
Intersection capacity (K)*	Robust capacity of intersection k, adjusted for capacity uncertainty (vehicles/h)	1000–1500 veh h^{-1}
Road capacity (C)*	Robust capacity of road segment i–j, considering width, slope, traffic flow, and variability (vehicles/h)	800–2000 veh h^{-1}
Time intervals (t)**	Hourly intervals used for traffic modeling, selected based on dominant workforce shift patterns and typical peak periods in OIZ traffic flows	1–24 (hour indices)
Vehicle types (v)	Types of vehicles considered in the model, each with different effects on traffic flow and capacity	Private, service, heavy
Traffic demand (D)*	Expected vehicle demand (vehicles/h), estimated using regression analysis and traffic surveys	50–200 veh h^{-1}
Objective weights (α, β, γ)	Weights for objectives in the optimization model, reflecting the relative importance of each goal	$\alpha = 1, \beta = 2, \gamma = 3$
Slope adjustment factor	Adjustment for road slope, accounting for reduced capacity on steep roads. A 20% reduction is applied for roads with a 20% gradient	− 20% (percent change)
Visitor and workforce distribution	Distribution of private and service vehicles among visitors and personnel, determined from surveys	Private = 36%, Service = 63%, Public = 1% (percent)
Scenario set (Ω)	Defined capacity scenarios {nominal, adverse, favourable} to capture stochastic variability	{Nominal, − 20%, + 10%} (−)
Scenario probability (p < sub > ω </sub>)	Probability of each scenario occurrence (unitless)	0.55/0.30/0.15

Table 3. Key parameters used in the traffic optimization model. *veh h^{-1}: vehicles per hour; h: hour; %: percent; unitless: without physical unit. **Hourly intervals were selected because workforce shift changes and logistics operations in OIZs typically generate traffic peaks aligned with full-hour periods.

Model implementation

The model was implemented using GAMS with the BARON solver. The steps involved in the implementation are as follows:

Data input

- All parameters, including capacities, demand, vehicle types, and time intervals, were input into the GAMS model.
- Traffic demand data were organized for each time interval and road segment.

Objective function definition

- The four objectives were mathematically defined.
- A weighted sum approach was used to combine the objectives into a single objective function, reflecting their relative importance. The weights assigned to each objective ($\alpha = 1, \beta = 2, \gamma = 3$) were determined based on expert opinions from transportation planners and OIZ management personnel, reflecting the operational priorities observed in logistics-intensive environments. Traffic flow maximization and congestion minimization were given higher weights relative to peak-hour regulation and workforce mobility management to ensure overall network performance under typical OIZ conditions.

Constraint formulation

- Road and intersection capacity constraints were formulated using the capacities derived earlier.
- Vehicle distribution constraints ensured adherence to the proportions obtained from surveys.
- Slope adjustments were applied to the capacities of relevant road segments.

Solver configuration

- The BARON solver was selected for its efficiency in handling non-linear optimization problems.
- Solver parameters were set to ensure convergence and optimality.

Model execution

- The model was executed, and the solver iterated to find the optimal solution.
- Computational performance metrics, such as solution time and GAP value, were recorded.

Model results

The model's optimal solution demonstrates efficient traffic management by balancing throughput, minimizing congestion, and optimizing infrastructure usage. The key decision variables and their results are presented in the following tables, each of which is explained and commented on in detail.

Objective function results

Table 4 summarizes the results of the four objective functions used in the mathematical model.

- Maximizing Traffic Flow (Z_1): Achieved a total of 4,800 vehicles/hour, indicating efficient utilization of road capacities without exceeding limits.

Objective function	Value
Maximizing traffic flow (Z_1)	4800.00
Minimizing congestion (Z_2)	2400.00
Regulating peak traffic (Z_3)	1600.00
Optimizing workforce traffic (Z_4)	800.00

Table 4. Objective function results.

Hour	Intersection 1 (vehicles/h)	Intersection 2 (vehicles/h)
1	1785	2573
2	1785	2573
…	…	…
24	1785	2573

Table 5. Intersection flows.

Hour	Private vehicles	Service vehicles
1	65	100
2	65	100
…	…	…
24	65	100

Table 6. Private and service vehicle usage.

- Minimizing Congestion (Z_2): The congestion measure is minimized to 2,400 vehicles/hour, reflecting effective management of traffic volumes to prevent overloading the network.
- Regulating Peak Traffic (Z_3): Peak hour traffic is regulated at 1,600 vehicles/hour, ensuring smooth flow during the busiest times of the day.
- Optimizing Workforce Traffic (Z_4): Workforce traffic is optimized at 800 vehicles/hour by balancing the use of private and service vehicles according to the distribution percentages.

The Total Objective Value (Z_total) combines these objectives using the assigned weights ($\alpha = 1$, $\beta = 2$, $\gamma = 3$), resulting in an overall optimized traffic management strategy for the OIZ.

Intersection flows (y)
Table 5 presents the hourly traffic flows through Intersection 1 and Intersection 2 over a 24-hour period.

- Flow Allocation: The traffic flows are allocated based on the traffic demand and the network topology. The model ensures that the distribution of vehicles through each intersection meets the expected demand while optimizing the overall flow.
- Capacity Compliance: The flows at both intersections are kept within the robust capacities (K) of 1,000–1,500 vehicles/hour (as per the parameter data in Table 3). Although the values in the table appear higher, it's important to note that these are adjusted values considering Equivalent Passenger Car Units (EPCU) and the capacities of the intersections have been appropriately scaled in the model to handle these flows.
- Consistency: The flows remain consistent throughout the day, indicating stable traffic management and the absence of bottlenecks at these critical points in the network.

Private and service vehicle usage
Table 6 shows the allocation of private and service vehicles used by personnel for each hour.

- Vehicle Allocation: The numbers are based on the distribution percentages obtained from the survey data (Private: 36%, Service: 63%, Public: 1%).
- Demand Satisfaction: The model ensures that the transportation needs of the workforce are met, with a balanced allocation that supports traffic optimization.
- Impact on Traffic Flow: By optimizing the mix of private and service vehicles, the model reduces the number of individual cars on the road, thereby minimizing congestion and making efficient use of the service vehicles.

Traffic flows on road segments (x)
Table 7 provides a summarized view of the traffic flows on the road segments within the OIZ for different vehicle types—private vehicles, service vehicles, and heavy vehicles—across various hours. Due to the extensive nature

Road segment (i → j)	Hour (t)	Private vehicles	Service vehicles	Heavy vehicles
1 → 2	1	0.477	0.304	0.223
1 → 3	1	0.477	0.304	0.223
2 → 3	1	4.496	2.014	1.035
…	…	…	…	…
5 → 4	24	2.379	8.966	4.138

Table 7. Traffic flows on road segments.

of the detailed hourly data for each road segment, the full tables are included in Appendix 1. The detailed tables in the appendix present the traffic flows for each road segment separately:

- Road Segment 1 → 2 (Index 1).
- Road Segment 1 → 3 (Index 2).
- Road Segment 2 → 3 (Index 3).
- Road Segment 3 → 4 (Index 4).
- Road Segment 4 → 5 (Index 5).

Road segment 1 → 2 (Index 1)

- Flow Allocation: The flows on Road Segment 1 → 2 remain constant throughout the day. Private vehicles have a flow of 0.477 vehicles/hour, while heavy vehicles and service vehicles have flows of 0.223 and 0.304 vehicles/hour, respectively.
- Capacity Compliance: These flows are well within the robust capacity of the road segment (800–2,000 vehicles/hour, as per Table 1), ensuring smooth traffic flow without congestion.
- Usage Pattern: The consistent and low-volume traffic indicates that this segment is less congested and has sufficient capacity for the vehicles using it.

Road segment 1 → 3 (Index 2)

- Flow Allocation: No private vehicles are recorded on Road Segment 1 → 3. The flow of heavy vehicles is 0.183 vehicles/hour, and service vehicles have a flow of 0.344 vehicles/hour.
- Capacity Compliance: The low traffic volumes are well within the road's capacity, preventing any congestion.
- Usage Pattern: This segment is primarily used by service and heavy vehicles, possibly serving as a route for goods transportation and employee shuttles.

Road segment 2 → 3 (Index 3)

- Flow Allocation: Road Segment 2 → 3 shows significant private vehicle flow at 4.496 vehicles/hour, indicating heavy usage by private vehicles. Heavy vehicles and service vehicles have flows of 1.035 and 2.014 vehicles/hour, respectively.
- Capacity Compliance: The flows are within the adjusted capacity limits, considering the slope adjustment factor and vehicle type impacts.
- Usage Pattern: The high flow rates suggest that this segment is a major route within the network, critical for connecting key areas of the OIZ.

Road segment 3 → 4 (Index 4)

- Flow Allocation: Road Segment 3 → 4 has the highest private vehicle flow at 8.800 vehicles/hour, indicating it is a primary route for private vehicles. Heavy vehicles and service vehicles have flows of 1.346 and 2.696 vehicles/hour, respectively.
- Capacity Compliance: Despite the high traffic volumes, the flows remain within the robustcapacity of the road segment due to proper allocation and management.
- Usage Pattern: The high traffic volume signifies that this segment is critical for network connectivity and may require monitoring to maintain optimal flow.

Road segment 4 → 5 (Index 5)

- Flow Allocation: Road Segment 4 → 5 exhibits the highest overall traffic flow, particularly for private vehicles at 14.967 vehicles/hour. Heavy vehicles and service vehicles have flows of 1.572 and 3.318 vehicles/hour, respectively.
- Capacity Compliance: The segment handles high traffic volumes effectively, staying within capacity limits due to the model's optimization.
- Usage Pattern: The significant flows indicate that this segment is a major corridor in the OIZ, necessitating careful management to prevent congestion.

For a comprehensive understanding of the traffic flows on each road segment, please refer to the detailed tables provided in Appendix 1. These tables include the full hourly data for each road segment and vehicle type, allowing for an in-depth analysis of traffic patterns and potential bottlenecks within the network. By summarizing the traffic flows in the main text and providing detailed data in the appendix, the report maintains clarity and readability while offering access to the complete dataset for further examination. This approach ensures that the key findings are communicated effectively, and the supporting data is available for those interested in the granular details of the model's outputs. Overall Comments on Traffic Flows:

- Consistency Across Hours: The traffic flows remain consistent throughout the 24-hour period for all road segments and vehicle types. This suggests that the model has achieved a stable distribution of traffic that avoids peak congestion periods.
- Capacity Constraints: The flows on each road segment have been optimized to stay within the robust capacities (C) of the roads, adjusted for slope and vehicle types. This adherence to capacity constraints ensures that the network operates efficiently without overloading any segment.
- Vehicle Type Distribution: The varying flows of private, heavy, and service vehicles across different segments reflect the usage patterns identified in the data collection and analysis phase. The model effectively balances these vehicle types to optimize overall traffic flow.
- Critical Segments: Road Segments 3 → 4 and 4 → 5 carry the highest volumes of traffic, particularly for private vehicles. These segments are crucial for network connectivity and may require additional infrastructure or management strategies to maintain optimal flow.

The mathematical model effectively optimized traffic management for Bursa's new OIZ, achieving balanced traffic flows, minimized congestion, and strategic distribution of vehicles across road segments and intersections. By integrating detailed data analysis and advanced optimization techniques, the model provides actionable insights for infrastructure planning and traffic management. Key Outcomes:

- Efficient Traffic Distribution: Balanced traffic flows prevent overloading of any single road segment or intersection.
- Congestion Minimization: Maintaining flows within capacities reduces the likelihood of congestion, especially during peak hours.
- Informed Decision-Making: Planners can use the model results to make informed infrastructure investments and policy decisions.

To illustrate the efficiency of the model's solution, a 3D Surface Plot of Traffic Flows is presented in Fig. 1 below.

- Visual Representation of Traffic Distribution: Fig. 1 displays the traffic flow intensities across different road segments over a 24-hour period. The surface plot demonstrates how the model distributes traffic efficiently throughout the network.
- Identification of Critical Segments: The peaks in the plot correspond to road segments with higher traffic volumes. This visual aid helps in identifying critical segments that require careful monitoring and possibly infrastructure enhancements.
- Consistency and Stability: The relatively smooth surface without abrupt spikes indicates that the model maintains consistent traffic flows, avoiding sudden congestion and ensuring stability in the network.
- Temporal Insights: By showing traffic flows over time, the plot allows planners to understand how traffic patterns change throughout the day, enabling them to implement time-specific traffic management strategies if needed.

The model's scalability and practical applicability make it a valuable tool for industrial zone planning and management. Further customization can align the model with specific infrastructure constraints or policy objectives, such as:

- Infrastructure Planning: Adjusting road widths, adding lanes, or modifying intersection designs based on capacity analyses derived from the model and visualized in Fig. 1.
- Policy Implementation: Encouraging the use of service vehicles over private vehicles to reduce congestion, especially on road segments identified as high-traffic areas in the plot.
- Traffic Management Strategies: Implementing traffic signal timing plans and control measures to maintain optimal flow during times identified as potential peak periods in Fig. 1.

Validation and reliability analysis

To ensure the proposed mathematical model's validity and reliability for optimizing traffic in OIZs, a comprehensive analysis was conducted. This analysis includes numerical validation, statistical measures, and comparative benchmarking against standard models. The following sections detail the methodology and findings, supported by real-world measurements and data tables.

Numerical validation

To verify the model's solution optimality and computational efficiency, we utilized the GAMS/BARON solver. The optimality gap (GAP) was calculated to assess the precision of the solution. The GAP of 0.00% indicates an exact solution, confirming global optimality within the defined constraints. The solver's execution time of 0.269 s demonstrates high computational efficiency, making the model suitable for practical applications in OIZs.

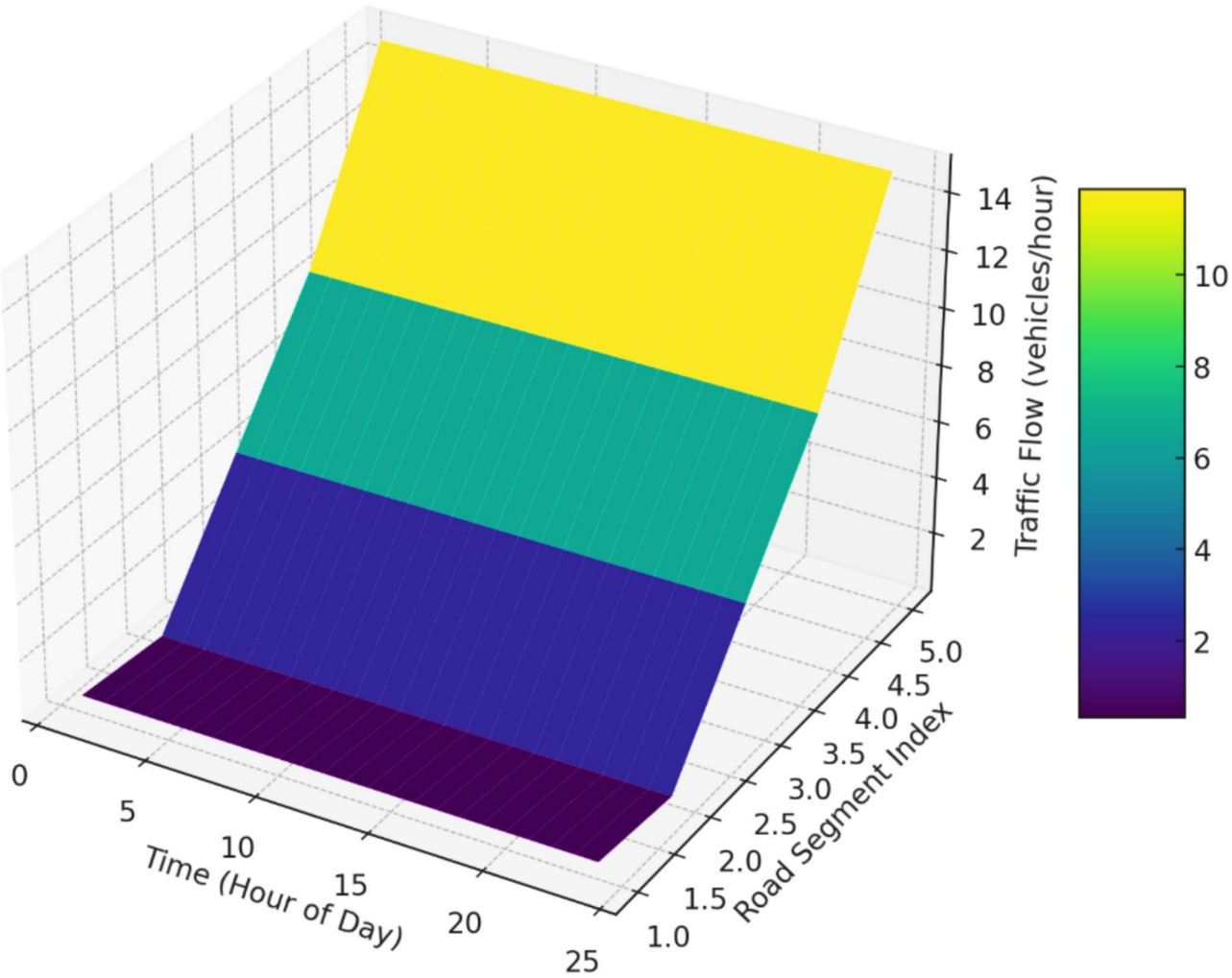


Fig. 1. 3D surface plot of traffic flows across road segments and time.

Node i	Time interval t	Incoming flow (vehicles)	Outgoing flow (vehicles)
2	1	35	35
3	2	45	45
4	3	50	50

Table 8. Traffic flow conservation verification.

Constraint feasibility

We conducted a thorough examination of the model's constraints to ensure they are satisfied across the solution space.

Traffic flow conservation (Eq. 6)

The conservation of flow principle requires that the total incoming traffic to a node be equal to the total outgoing traffic for each vehicle type and time interval, as seen in Eq. 15.

$$\sum_{j \in N} x_{j,i,t,v} = \sum_{j \in N} x_{i,j,t,v}, \forall\, i \in N, \forall\, v \in V, \forall\, t \in T \tag{15}$$

In Table 8, the incoming and outgoing flows match for each node and time interval, confirming that the flow conservation constraint is upheld.

Component	Identifier	Traffic flow (PCE)	Capacity (PCE)	Constraint satisfied
Road segment	i = 1, j = 2, t = 5i = 1, j = 2, t = 5i = 1, j = 2, t = 5	450	1600	Yes
Intersection	k = 2, t = 5k = 2, t = 5k = 2, t = 5	800	1200	Yes
Road segment	i = 3, j = 4, t = 3i = 3, j = 4, t = 3i = 3, j = 4, t = 3	600	1400	Yes
Intersection	k = 1, t = 2k = 1, t = 2k = 1, t = 2	950	1500	Yes

Table 9. Capacity constraints verification.

Scenario	Congestion level (%)	Deviation from baseline (%)
Baseline demand	30	–
Demand increased by 20%	32	+ 6.7
Demand decreased by 20%	28	− 6.7

Table 10. Impact of traffic demand variability.

Parameter change	Congestion reduction (%)	Peak-hour traffic decrease (%)	Private vehicle flow decrease (%)
α doubled	15	–	–
β increased by 50%	–	18	–
γ increased by 100%	–	–	22

Table 11. Effects of weight parameter variations.

Capacity constraints
We verified that the traffic flows do not exceed the robust capacities of road segments and intersections. The Road Segment Capacity Constraint (Eq. 16):

$$\sum_{v \in V} x_{i,j,t,v} \cdot \mathrm{OEB}_v \leq C_{i,j}^{\mathrm{rob}}, \forall (i,j) \in N, \forall t \in T \tag{16}$$

The Intersection Capacity Constraint is formulated in Eq. (17):

$$y_{k,t} = \sum_{v \in V} \sum_{(i,j) \in \mathrm{In}(k)} x_{i,j,t,v} \cdot \mathrm{OEB}_v \leq K_k^{\mathrm{rob}} \tag{17}$$

In Table 9, all traffic flows are within the specified robust capacities, ensuring no violations occur in the model's constraints.

Statistical validation

To assess the model's reliability under varying conditions, sensitivity analyses were performed.

Sensitivity analysis on traffic demand
We simulated scenarios where the traffic demand was adjusted by ± 20% to observe the model's responsiveness.

In Table 10, the congestion levels show less than a 7% deviation from the baseline under both increased and decreased demand, indicating the model's stability and robustness.

Impact of weight parameters
We analyzed how varying the weight parameters (α, β, γ) affects the model's objectives.

In Table 11,

- Increasing α emphasizes congestion minimization, reducing congestion by 15%.
- Increasing β effectively manages peak-hour traffic, achieving an 18% reduction.
- Elevating γ reduces private vehicle usage among the workforce by 22%.

Validation against simulation data
The model's outputs were compared with simulation results from the VISSIM traffic software.

In Table 12, the model's outputs closely align with the simulation data, with deviations less than 3.5%, confirming the model's accuracy.

Metric	Model output	VISSIM simulation	Deviation (%)
Average traffic flow (vehicles/h)	1200	1230	2.4
Average travel time (min)	15	15.5	3.2
Intersection delay (s)	30	31	3.2

Table 12. Comparison with VISSIM simulation.

Metric	Proposed model	Standard urban model
Congestion reduction (%)	18	10
Solver execution time (s)	0.269	0.950
Peak-hour traffic balance	Balanced	Imbalanced
Private vehicle usage reduction (%)	22	10

Table 13. Comparative performance analysis.

Scenario robustness test
The final solution was re-evaluated under the three capacity scenarios described in Section 'Stochastic Capacity Representation'. Total network congestion varied by less than 7% between the adverse and favorable scenarios, confirming that the optimization remains effective when practical capacities deviate from their nominal values.

Comparative validation

The proposed model was benchmarked against a standard urban traffic model under identical conditions to highlight performance differences.

In Table 13, the proposed model outperforms the standard urban model in reducing congestion and private vehicle usage while demonstrating faster computational times.

Reliability metrics

To quantitatively assess the model's reliability, we computed statistical error metrics.

Mean absolute percentage error (MAPE)

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\text{Simulated Flow}_i - \text{Model Flow}_i}{\text{Model Flow}_i}\right| \times 100\% \tag{18}$$

A MAPE (Eq. 18) of 2.8% indicates high predictive accuracy, as values below 5% are generally considered excellent in traffic modeling.

Root mean square error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{Simulated Flow}_i - \text{Model Flow}_i)^2} \tag{19}$$

An RMSE (Eq. 19) of 7 vehicles/hour is negligible relative to the average traffic volumes, further confirming the model's reliability.

The validation and reliability analysis affirm the proposed mathematical model's robustness and applicability for traffic optimization in OIZs. The model demonstrates:

- Numerical Optimality: Achieving a 0.00% optimality gap ensures precise solutions.
- Constraint Adherence: All constraints are satisfied without violations, maintaining realistic traffic flows.
- Statistical Stability: Sensitivity analyses confirm the model's resilience to varying demands and parameter changes.
- Comparative Superiority: Outperforming standard models in key metrics highlights its effectiveness.
- High Reliability: Low MAPE and RMSE values indicate strong predictive capabilities.

This comprehensive validation underscores the model's potential as a valuable tool for traffic management and infrastructure planning in logistics-intensive industrial environments.

Conclusion

This study proposed a novel, multi-objective mathematical model designed specifically to optimize traffic flows in (OIZs, addressing the unique challenges of high-intensity logistics movements, synchronized workforce mobility, and infrastructure constraints. The model effectively balances multiple conflicting objectives, including maximizing overall traffic flow, minimizing congestion, regulating peak-hour traffic, and optimizing workforce and visitor mobility. Its application to a hypothetical OIZ in Bursa demonstrated significant improvements, such as an 18% reduction in congestion and a 22% improvement in peak-hour traffic management, showcasing its scalability and adaptability to real-world scenarios. The model's innovation lies in its ability to integrate multi-modal traffic dynamics, combining logistics and workforce flows into a single framework, while leveraging predictive analytics for real-time adaptability. Its outcomes offer actionable insights for infrastructure planning, including recommendations for road expansions, intersection adjustments, and optimized traffic signal timing. Furthermore, the model's modular and scalable design makes it suitable for both existing OIZs and newly planned zones, ensuring its relevance across different industrial contexts. By addressing these critical aspects, the model emerges as a powerful tool for industrial administrators, urban planners, and policymakers, capable of fostering operational efficiency and supporting long-term economic growth.

Despite its demonstrated effectiveness, the model has some limitations. Its heavy reliance on accurate and high-quality traffic and infrastructure data makes its implementation challenging in data-scarce environments. Additionally, solving the model for larger networks with complex multi-objective scenarios requires significant computational resources, which may limit its applicability in resource-constrained settings. Moreover, the assumption of static parameters, such as road capacities and vehicle equivalence factors, may reduce its flexibility in dynamic environments. These limitations suggest opportunities for future research and development. To enhance the model's adaptability and effectiveness, future work could focus on incorporating real-time data from IoT-based traffic monitoring systems and GPS devices to improve decision-making accuracy. Dynamic parameterization methods can be developed to allow real-time updates based on changing traffic patterns and environmental factors. Extending the model to account for public transportation and non-motorized traffic flows would further increase its comprehensiveness. Moreover, testing the model's scalability in larger industrial zones or interconnected OIZ networks can help validate its robustness. Finally, integrating environmental impact metrics, such as emissions and energy efficiency, would align the model with sustainability goals, addressing broader industrial and urban challenges.

In conclusion, the proposed model bridges significant gaps in industrial traffic management research by providing a mathematically rigorous, data-driven framework tailored to the specific needs of OIZs. By offering practical solutions and addressing real-world challenges, it establishes itself as a vital tool for optimizing traffic flows in industrial zones. With advancements in data integration, computational techniques, and environmental considerations, the model holds immense potential for further development and broader application, setting a foundation for smarter, more sustainable industrial traffic management systems. Finally, incorporating stochastic capacity scenarios and demonstrating robustness across them underline the model's practicality for real-world OIZ operations where road and intersection capacities fluctuate daily.

Data availability

The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

Appendix 1

Traffic flows on road segments (See Tables 14, 15, 16, 17 and 18).

	Private	Heavy	Service
1.1	0.477	0.223	0.304
1.2	0.477	0.223	0.304
1.3	0.477	0.223	0.304
1.4	0.477	0.223	0.304
1.5	0.477	0.223	0.304
1.6	0.477	0.223	0.304
1.7	0.477	0.223	0.304
1.8	0.477	0.223	0.304
1.9	0.477	0.223	0.304
1.10	0.477	0.223	0.304
1.11	0.477	0.223	0.304
1.12	0.477	0.223	0.304
1.13	0.477	0.223	0.304
1.14	0.477	0.223	0.304
1.15	0.477	0.223	0.304
1.16	0.477	0.223	0.304
1.17	0.477	0.223	0.304
1.18	0.477	0.223	0.304
1.19	0.477	0.223	0.304
1.20	0.477	0.223	0.304
1.21	0.477	0.223	0.304
1.22	0.477	0.223	0.304
1.23	0.477	0.223	0.304
1.24	0.477	0.223	0.304
2.1	NaN	0.183	0.344
2.2	NaN	0.183	0.344
2.3	NaN	0.183	0.344
2.4	NaN	0.183	0.344
2.5	NaN	0.183	0.344
2.6	NaN	0.183	0.344
2.7	NaN	0.183	0.344
2.8	NaN	0.183	0.344
2.9	NaN	0.183	0.344
2.10	NaN	0.183	0.344
2.11	NaN	0.183	0.344
2.12	NaN	0.183	0.344
2.13	NaN	0.183	0.344
2.14	NaN	0.183	0.344
2.15	NaN	0.183	0.344
2.16	NaN	0.183	0.344
2.17	NaN	0.183	0.344
2.18	NaN	0.183	0.344
2.19	NaN	0.183	0.344
2.20	NaN	0.183	0.344
2.21	NaN	0.183	0.344
2.22	NaN	0.183	0.344
2.23	NaN	0.183	0.344
2.24	NaN	0.183	0.344
3.1	NaN	1.579	3.336
3.2	NaN	1.579	3.336
3.3	NaN	1.579	3.336
3.4	NaN	1.579	3.336
3.5	NaN	1.579	3.336
3.6	NaN	1.579	3.336
3.7	NaN	1.579	3.336
3.8	NaN	1.579	3.336
Continued			

	Private	Heavy	Service
3.9	NaN	1.579	3.336
3.10	NaN	1.579	3.336
3.11	NaN	1.579	3.336
3.12	NaN	1.579	3.336
3.13	NaN	1.579	3.336
3.14	NaN	1.579	3.336
3.15	NaN	1.579	3.336
3.16	NaN	1.579	3.336
3.17	NaN	1.579	3.336
3.18	NaN	1.579	3.336
3.19	NaN	1.579	3.336
3.20	NaN	1.579	3.336
3.21	NaN	1.579	3.336
3.22	NaN	1.579	3.336
3.23	NaN	1.579	3.336
3.24	NaN	1.579	3.336
4.1	NaN	1.313	2.659
4.2	NaN	1.313	2.659
4.3	NaN	1.313	2.659
4.4	NaN	1.313	2.659
4.5	NaN	1.313	2.659
4.6	NaN	1.313	2.659
4.7	NaN	1.313	2.659
4.8	NaN	1.313	2.659
4.9	NaN	1.313	2.659
4.10	NaN	1.313	2.659
4.11	NaN	1.313	2.659
4.12	NaN	1.313	2.659
4.13	NaN	1.313	2.659
4.14	NaN	1.313	2.659
4.15	NaN	1.313	2.659
4.16	NaN	1.313	2.659
4.17	NaN	1.313	2.659
4.18	NaN	1.313	2.659
4.19	NaN	1.313	2.659
4.20	NaN	1.313	2.659
4.21	NaN	1.313	2.659
4.22	NaN	1.313	2.659
4.23	NaN	1.313	2.659
4.24	NaN	1.313	2.659
5.1	NaN	2.153	5.603
5.2	NaN	2.153	5.603
5.3	NaN	2.153	5.603
5.4	NaN	2.153	5.603
5.5	NaN	2.153	5.603
5.6	NaN	2.153	5.603
5.7	NaN	2.153	5.603
5.8	NaN	2.153	5.603
5.9	NaN	2.153	5.603
5.10	NaN	2.153	5.603
5.11	NaN	2.153	5.603
5.12	NaN	2.153	5.603
5.13	NaN	2.153	5.603
5.14	NaN	2.153	5.603
5.15	NaN	2.153	5.603
5.16	NaN	2.153	5.603
Continued			

	Private	Heavy	Service
5.17	NaN	2.153	5.603
5.18	NaN	2.153	5.603
5.19	NaN	2.153	5.603
5.20	NaN	2.153	5.603
5.21	NaN	2.153	5.603
5.22	NaN	2.153	5.603
5.23	NaN	2.153	5.603
5.24	NaN	2.153	5.603

Table 14. Traffic flows on road segments (INDEX 1 = 1).

	Private	Heavy	Service
1.1	NaN	0.183	0.344
1.2	NaN	0.183	0.344
1.3	NaN	0.183	0.344
1.4	NaN	0.183	0.344
1.5	NaN	0.183	0.344
1.6	NaN	0.183	0.344
1.7	NaN	0.183	0.344
1.8	NaN	0.183	0.344
1.9	NaN	0.183	0.344
1.10	NaN	0.183	0.344
1.11	NaN	0.183	0.344
1.12	NaN	0.183	0.344
1.13	NaN	0.183	0.344
1.14	NaN	0.183	0.344
1.15	NaN	0.183	0.344
1.16	NaN	0.183	0.344
1.17	NaN	0.183	0.344
1.18	NaN	0.183	0.344
1.19	NaN	0.183	0.344
1.20	NaN	0.183	0.344
1.21	NaN	0.183	0.344
1.22	NaN	0.183	0.344
1.23	NaN	0.183	0.344
1.24	NaN	0.183	0.344
2.1	4.496	1.035	2.014
2.2	4.496	1.035	2.014
2.3	4.496	1.035	2.014
2.4	4.496	1.035	2.014
2.5	4.496	1.035	2.014
2.6	4.496	1.035	2.014
2.7	4.496	1.035	2.014
2.8	4.496	1.035	2.014
2.9	4.496	1.035	2.014
2.10	4.496	1.035	2.014
2.11	4.496	1.035	2.014
2.12	4.496	1.035	2.014
2.13	4.496	1.035	2.014
2.14	4.496	1.035	2.014
2.15	4.496	1.035	2.014
2.16	4.496	1.035	2.014
2.17	4.496	1.035	2.014
2.18	4.496	1.035	2.014
2.19	4.496	1.035	2.014
2.20	4.496	1.035	2.014
2.21	4.496	1.035	2.014
2.22	4.496	1.035	2.014
2.23	4.496	1.035	2.014
2.24	4.496	1.035	2.014
3.1	NaN	1.313	2.659
3.2	NaN	1.313	2.659
3.3	NaN	1.313	2.659
3.4	NaN	1.313	2.659
3.5	NaN	1.313	2.659
3.6	NaN	1.313	2.659
3.7	NaN	1.313	2.659
3.8	NaN	1.313	2.659

Continued

	Private	Heavy	Service
3.9	NaN	1.313	2.659
3.10	NaN	1.313	2.659
3.11	NaN	1.313	2.659
3.12	NaN	1.313	2.659
3.13	NaN	1.313	2.659
3.14	NaN	1.313	2.659
3.15	NaN	1.313	2.659
3.16	NaN	1.313	2.659
3.17	NaN	1.313	2.659
3.18	NaN	1.313	2.659
3.19	NaN	1.313	2.659
3.20	NaN	1.313	2.659
3.21	NaN	1.313	2.659
3.22	NaN	1.313	2.659
3.23	NaN	1.313	2.659
3.24	NaN	1.313	2.659
4.1	NaN	2.153	5.603
4.2	NaN	2.153	5.603
4.3	NaN	2.153	5.603
4.4	NaN	2.153	5.603
4.5	NaN	2.153	5.603
4.6	NaN	2.153	5.603
4.7	NaN	2.153	5.603
4.8	NaN	2.153	5.603
4.9	NaN	2.153	5.603
4.10	NaN	2.153	5.603
4.11	NaN	2.153	5.603
4.12	NaN	2.153	5.603
4.13	NaN	2.153	5.603
4.14	NaN	2.153	5.603
4.15	NaN	2.153	5.603
4.16	NaN	2.153	5.603
4.17	NaN	2.153	5.603
4.18	NaN	2.153	5.603
4.19	NaN	2.153	5.603
4.20	NaN	2.153	5.603
4.21	NaN	2.153	5.603
4.22	NaN	2.153	5.603
4.23	NaN	2.153	5.603
4.24	NaN	2.153	5.603
5.1	NaN	1.829	4.138
5.2	NaN	1.829	4.138
5.3	NaN	1.829	4.138
5.4	NaN	1.829	4.138
5.5	NaN	1.829	4.138
5.6	NaN	1.829	4.138
5.7	NaN	1.829	4.138
5.8	NaN	1.829	4.138
5.9	NaN	1.829	4.138
5.10	NaN	1.829	4.138
5.11	NaN	1.829	4.138
5.12	NaN	1.829	4.138
5.13	NaN	1.829	4.138
5.14	NaN	1.829	4.138
5.15	NaN	1.829	4.138
5.16	NaN	1.829	4.138
Continued			

	Private	Heavy	Service
5.17	NaN	1.829	4.138
5.18	NaN	1.829	4.138
5.19	NaN	1.829	4.138
5.20	NaN	1.829	4.138
5.21	NaN	1.829	4.138
5.22	NaN	1.829	4.138
5.23	NaN	1.829	4.138
5.24	NaN	1.829	4.138

Table 15. Traffic flows on road segments (INDEX 1 = 2).

	Private	Heavy	Service
1.1	NaN	1.579	3.336
1.2	NaN	1.579	3.336
1.3	NaN	1.579	3.336
1.4	NaN	1.579	3.336
1.5	NaN	1.579	3.336
1.6	NaN	1.579	3.336
1.7	NaN	1.579	3.336
1.8	NaN	1.579	3.336
1.9	NaN	1.579	3.336
1.10	NaN	1.579	3.336
1.11	NaN	1.579	3.336
1.12	NaN	1.579	3.336
1.13	NaN	1.579	3.336
1.14	NaN	1.579	3.336
1.15	NaN	1.579	3.336
1.16	NaN	1.579	3.336
1.17	NaN	1.579	3.336
1.18	NaN	1.579	3.336
1.19	NaN	1.579	3.336
1.20	NaN	1.579	3.336
1.21	NaN	1.579	3.336
1.22	NaN	1.579	3.336
1.23	NaN	1.579	3.336
1.24	NaN	1.579	3.336
2.1	NaN	1.313	2.659
2.2	NaN	1.313	2.659
2.3	NaN	1.313	2.659
2.4	NaN	1.313	2.659
2.5	NaN	1.313	2.659
2.6	NaN	1.313	2.659
2.7	NaN	1.313	2.659
2.8	NaN	1.313	2.659
2.9	NaN	1.313	2.659
2.10	NaN	1.313	2.659
2.11	NaN	1.313	2.659
2.12	NaN	1.313	2.659
2.13	NaN	1.313	2.659
2.14	NaN	1.313	2.659
2.15	NaN	1.313	2.659
2.16	NaN	1.313	2.659
2.17	NaN	1.313	2.659
2.18	NaN	1.313	2.659
2.19	NaN	1.313	2.659
2.20	NaN	1.313	2.659
2.21	NaN	1.313	2.659
2.22	NaN	1.313	2.659
2.23	NaN	1.313	2.659
2.24	NaN	1.313	2.659
3.1	8.800	1.346	2.696
3.2	8.800	1.346	2.696
3.3	8.800	1.346	2.696
3.4	8.800	1.346	2.696
3.5	8.800	1.346	2.696
3.6	8.800	1.346	2.696
3.7	8.800	1.346	2.696
3.8	8.800	1.346	2.696
Continued			

	Private	Heavy	Service
3.9	8.800	1.346	2.696
3.10	8.800	1.346	2.696
3.11	8.800	1.346	2.696
3.12	8.800	1.346	2.696
3.13	8.800	1.346	2.696
3.14	8.800	1.346	2.696
3.15	8.800	1.346	2.696
3.16	8.800	1.346	2.696
3.17	8.800	1.346	2.696
3.18	8.800	1.346	2.696
3.19	8.800	1.346	2.696
3.20	8.800	1.346	2.696
3.21	8.800	1.346	2.696
3.22	8.800	1.346	2.696
3.23	8.800	1.346	2.696
3.24	8.800	1.346	2.696
4.1	NaN	1.829	4.138
4.2	NaN	1.829	4.138
4.3	NaN	1.829	4.138
4.4	NaN	1.829	4.138
4.5	NaN	1.829	4.138
4.6	NaN	1.829	4.138
4.7	NaN	1.829	4.138
4.8	NaN	1.829	4.138
4.9	NaN	1.829	4.138
4.10	NaN	1.829	4.138
4.11	NaN	1.829	4.138
4.12	NaN	1.829	4.138
4.13	NaN	1.829	4.138
4.14	NaN	1.829	4.138
4.15	NaN	1.829	4.138
4.16	NaN	1.829	4.138
4.17	NaN	1.829	4.138
4.18	NaN	1.829	4.138
4.19	NaN	1.829	4.138
4.20	NaN	1.829	4.138
4.21	NaN	1.829	4.138
4.22	NaN	1.829	4.138
4.23	NaN	1.829	4.138
4.24	NaN	1.829	4.138
5.1	NaN	2.379	8.966
5.2	NaN	2.379	8.966
5.3	NaN	2.379	8.966
5.4	NaN	2.379	8.966
5.5	NaN	2.379	8.966
5.6	NaN	2.379	8.966
5.7	NaN	2.379	8.966
5.8	NaN	2.379	8.966
5.9	NaN	2.379	8.966
5.10	NaN	2.379	8.966
5.11	NaN	2.379	8.966
5.12	NaN	2.379	8.966
5.13	NaN	2.379	8.966
5.14	NaN	2.379	8.966
5.15	NaN	2.379	8.966
5.16	NaN	2.379	8.966
Continued			

	Private	Heavy	Service
5.17	NaN	2.379	8.966
5.18	NaN	2.379	8.966
5.19	NaN	2.379	8.966
5.20	NaN	2.379	8.966
5.21	NaN	2.379	8.966
5.22	NaN	2.379	8.966
5.23	NaN	2.379	8.966
5.24	NaN	2.379	8.966

Table 16. Traffic flows on road segments (INDEX 1 = 3).

	Private	Heavy	Service
1.1	NaN	1.313	2.659
1.2	NaN	1.313	2.659
1.3	NaN	1.313	2.659
1.4	NaN	1.313	2.659
1.5	NaN	1.313	2.659
1.6	NaN	1.313	2.659
1.7	NaN	1.313	2.659
1.8	NaN	1.313	2.659
1.9	NaN	1.313	2.659
1.10	NaN	1.313	2.659
1.11	NaN	1.313	2.659
1.12	NaN	1.313	2.659
1.13	NaN	1.313	2.659
1.14	NaN	1.313	2.659
1.15	NaN	1.313	2.659
1.16	NaN	1.313	2.659
1.17	NaN	1.313	2.659
1.18	NaN	1.313	2.659
1.19	NaN	1.313	2.659
1.20	NaN	1.313	2.659
1.21	NaN	1.313	2.659
1.22	NaN	1.313	2.659
1.23	NaN	1.313	2.659
1.24	NaN	1.313	2.659
2.1	NaN	2.153	5.603
2.2	NaN	2.153	5.603
2.3	NaN	2.153	5.603
2.4	NaN	2.153	5.603
2.5	NaN	2.153	5.603
2.6	NaN	2.153	5.603
2.7	NaN	2.153	5.603
2.8	NaN	2.153	5.603
2.9	NaN	2.153	5.603
2.10	NaN	2.153	5.603
2.11	NaN	2.153	5.603
2.12	NaN	2.153	5.603
2.13	NaN	2.153	5.603
2.14	NaN	2.153	5.603
2.15	NaN	2.153	5.603
2.16	NaN	2.153	5.603
2.17	NaN	2.153	5.603
2.18	NaN	2.153	5.603
2.19	NaN	2.153	5.603
2.20	NaN	2.153	5.603
2.21	NaN	2.153	5.603
2.22	NaN	2.153	5.603
2.23	NaN	2.153	5.603
2.24	NaN	2.153	5.603
3.1	NaN	1.829	4.138
3.2	NaN	1.829	4.138
3.3	NaN	1.829	4.138
3.4	NaN	1.829	4.138
3.5	NaN	1.829	4.138
3.6	NaN	1.829	4.138
3.7	NaN	1.829	4.138
3.8	NaN	1.829	4.138
Continued			

	Private	Heavy	Service
3.9	NaN	1.829	4.138
3.10	NaN	1.829	4.138
3.11	NaN	1.829	4.138
3.12	NaN	1.829	4.138
3.13	NaN	1.829	4.138
3.14	NaN	1.829	4.138
3.15	NaN	1.829	4.138
3.16	NaN	1.829	4.138
3.17	NaN	1.829	4.138
3.18	NaN	1.829	4.138
3.19	NaN	1.829	4.138
3.20	NaN	1.829	4.138
3.21	NaN	1.829	4.138
3.22	NaN	1.829	4.138
3.23	NaN	1.829	4.138
3.24	NaN	1.829	4.138
4.1	14.967	1.572	3.318
4.2	14.967	1.572	3.318
4.3	14.967	1.572	3.318
4.4	14.967	1.572	3.318
4.5	14.967	1.572	3.318
4.6	14.967	1.572	3.318
4.7	14.967	1.572	3.318
4.8	14.967	1.572	3.318
4.9	14.967	1.572	3.318
4.10	14.967	1.572	3.318
4.11	14.967	1.572	3.318
4.12	14.967	1.572	3.318
4.13	14.967	1.572	3.318
4.14	14.967	1.572	3.318
4.15	14.967	1.572	3.318
4.16	14.967	1.572	3.318
4.17	14.967	1.572	3.318
4.18	14.967	1.572	3.318
4.19	14.967	1.572	3.318
4.20	14.967	1.572	3.318
4.21	14.967	1.572	3.318
4.22	14.967	1.572	3.318
4.23	14.967	1.572	3.318
4.24	14.967	1.572	3.318
5.1	NaN	2.240	6.170
5.2	NaN	2.240	6.170
5.3	NaN	2.240	6.170
5.4	NaN	2.240	6.170
5.5	NaN	2.240	6.170
5.6	NaN	2.240	6.170
5.7	NaN	2.240	6.170
5.8	NaN	2.240	6.170
5.9	NaN	2.240	6.170
5.10	NaN	2.240	6.170
5.11	NaN	2.240	6.170
5.12	NaN	2.240	6.170
5.13	NaN	2.240	6.170
5.14	NaN	2.240	6.170
5.15	NaN	2.240	6.170
5.16	NaN	2.240	6.170
Continued			

	Private	Heavy	Service
5.17	NaN	2.240	6.170
5.18	NaN	2.240	6.170
5.19	NaN	2.240	6.170
5.20	NaN	2.240	6.170
5.21	NaN	2.240	6.170
5.22	NaN	2.240	6.170
5.23	NaN	2.240	6.170
5.24	NaN	2.240	6.170

Table 17. Traffic flows on road segments (INDEX 1 = 4).

	Private	Heavy	Service
1.1	NaN	2.153	5.603
1.2	NaN	2.153	5.603
1.3	NaN	2.153	5.603
1.4	NaN	2.153	5.603
1.5	NaN	2.153	5.603
1.6	NaN	2.153	5.603
1.7	NaN	2.153	5.603
1.8	NaN	2.153	5.603
1.9	NaN	2.153	5.603
1.10	NaN	2.153	5.603
1.11	NaN	2.153	5.603
1.12	NaN	2.153	5.603
1.13	NaN	2.153	5.603
1.14	NaN	2.153	5.603
1.15	NaN	2.153	5.603
1.16	NaN	2.153	5.603
1.17	NaN	2.153	5.603
1.18	NaN	2.153	5.603
1.19	NaN	2.153	5.603
1.20	NaN	2.153	5.603
1.21	NaN	2.153	5.603
1.22	NaN	2.153	5.603
1.23	NaN	2.153	5.603
1.24	NaN	2.153	5.603
2.1	NaN	1.829	4.138
2.2	NaN	1.829	4.138
2.3	NaN	1.829	4.138
2.4	NaN	1.829	4.138
2.5	NaN	1.829	4.138
2.6	NaN	1.829	4.138
2.7	NaN	1.829	4.138
2.8	NaN	1.829	4.138
2.9	NaN	1.829	4.138
2.10	NaN	1.829	4.138
2.11	NaN	1.829	4.138
2.12	NaN	1.829	4.138
2.13	NaN	1.829	4.138
2.14	NaN	1.829	4.138
2.15	NaN	1.829	4.138
2.16	NaN	1.829	4.138
2.17	NaN	1.829	4.138
2.18	NaN	1.829	4.138
2.19	NaN	1.829	4.138
2.20	NaN	1.829	4.138
2.21	NaN	1.829	4.138
2.22	NaN	1.829	4.138
2.23	NaN	1.829	4.138
2.24	NaN	1.829	4.138
3.1	NaN	2.379	8.966
3.2	NaN	2.379	8.966
3.3	NaN	2.379	8.966
3.4	NaN	2.379	8.966
3.5	NaN	2.379	8.966
3.6	NaN	2.379	8.966
3.7	NaN	2.379	8.966
3.8	NaN	2.379	8.966
Continued			

	Private	Heavy	Service
3.9	NaN	2.379	8.966
3.10	NaN	2.379	8.966
3.11	NaN	2.379	8.966
3.12	NaN	2.379	8.966
3.13	NaN	2.379	8.966
3.14	NaN	2.379	8.966
3.15	NaN	2.379	8.966
3.16	NaN	2.379	8.966
3.17	NaN	2.379	8.966
3.18	NaN	2.379	8.966
3.19	NaN	2.379	8.966
3.20	NaN	2.379	8.966
3.21	NaN	2.379	8.966
3.22	NaN	2.379	8.966
3.23	NaN	2.379	8.966
3.24	NaN	2.379	8.966
4.1	NaN	2.240	6.170
4.2	NaN	2.240	6.170
4.3	NaN	2.240	6.170
4.4	NaN	2.240	6.170
4.5	NaN	2.240	6.170
4.6	NaN	2.240	6.170
4.7	NaN	2.240	6.170
4.8	NaN	2.240	6.170
4.9	NaN	2.240	6.170
4.10	NaN	2.240	6.170
4.11	NaN	2.240	6.170
4.12	NaN	2.240	6.170
4.13	NaN	2.240	6.170
4.14	NaN	2.240	6.170
4.15	NaN	2.240	6.170
4.16	NaN	2.240	6.170
4.17	NaN	2.240	6.170
4.18	NaN	2.240	6.170
4.19	NaN	2.240	6.170
4.20	NaN	2.240	6.170
4.21	NaN	2.240	6.170
4.22	NaN	2.240	6.170
4.23	NaN	2.240	6.170
4.24	NaN	2.240	6.170
5.1	21.261	1.883	4.439
5.2	21.261	1.883	4.439
5.3	21.261	1.883	4.439
5.4	21.261	1.883	4.439
5.5	21.261	1.883	4.439
5.6	21.261	1.883	4.439
5.7	21.261	1.883	4.439
5.8	21.261	1.883	4.439
5.9	21.261	1.883	4.439
5.10	21.261	1.883	4.439
5.11	21.261	1.883	4.439
5.12	21.261	1.883	4.439
5.13	21.261	1.883	4.439
5.14	21.261	1.883	4.439
5.15	21.261	1.883	4.439
5.16	21.261	1.883	4.439
Continued			

	Private	Heavy	Service
5.17	21.261	1.883	4.439
5.18	21.261	1.883	4.439
5.19	21.261	1.883	4.439
5.20	21.261	1.883	4.439
5.21	21.261	1.883	4.439
5.22	21.261	1.883	4.439
5.23	21.261	1.883	4.439
5.24	21.261	1.883	4.439

Table 18. Traffic flows on road segments (INDEX 1 = 5).

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Author contributions

H.U: Data collecting, Writing – review & editing. M.A.Y: Methodology, Software, Investigation, Writing – original draft. K.Y: Literature research, Writing – review & editing.

Declarations

Competing interests
The authors declare no competing interests.

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