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Urban Traffic Mobility Optimization Model: A Novel Mathematical Approach for Predictive Urban Traffic Analysis

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Abstract: This research introduces the Urban Traffic Mobility Optimization Model (UTMOM), a data-driven methodology for analyzing two distinctive urban traffic datasets through the integration of data mining and mathematical modeling. Designed to decode the complexities of urban mobility patterns, UTMOM meticulously evaluates daily traffic dynamics with a focus on reducing discrepancies and underscoring variations in traffic intensity, particularly during peak times. Our findings unveil pivotal insights into the differences across datasets, providing a substantial contribution to the realms of traffic management and urban planning. UTMOM delves into the intricacies of traffic flow variations, emphasizing the critical importance of comprehending fluctuations in traffic volume across diverse times and locations. By incorporating detailed graphical representations and statistical validations, including ANOVA analysis, our study delivers a comprehensive evaluation of UTMOM's precision in reflecting real-world traffic scenarios. These insights affirm the value of data-informed strategies in optimizing traffic flow and alleviating congestion. Positioned as a valuable asset for traffic engineers, data scientists, and urban planners, UTMOM advocates for advanced modeling techniques to improve urban mobility. Beyond enriching academic discourse on traffic analysis, UTMOM offers actionable intelligence for enhancing the efficiency and sustainability of urban transportation systems. Through this in-depth investigation, our aim is to catalyze the development of innovative solutions to traffic challenges, steering towards smoother and more sustainable urban environments.

Keywords: traffic data comparison; mathematical modeling; deviation analysis; traffic management; urban transportation; data mining

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1. Introduction

The dynamics of traffic and transportation systems within urban environments are pivotal elements that wield a profound influence on a city's functionality, development, and overall quality of life [1]. Urban transportation networks serve as the lifeblood of modern societies, intricately weaving the threads of mobility and connectivity, facilitating the seamless movement of people, goods, and information, and, in turn, shaping the intricate socio-economic landscape. From the ancient trade routes that crisscrossed civilizations to the contemporary high-speed railways and burgeoning digital mobility platforms of the present day, transportation systems have evolved in response to the ever-changing needs and aspirations of humanity. These systems have played an essential role in propelling societal progress, economic growth, and cultural exchange [2].

In recent decades, cities worldwide have experienced unprecedented and often dizzying urbanization, marking the dawn of a new era characterized by the swift expansion of metropolitan areas. This global trend towards urbanization has ushered in a plethora of complexities and challenges in the realm of urban transportation. In this context, Ankara, the vibrant capital of Turkey, stands as a vivid exemplar, encapsulating the shifts, transformations, and adaptations that urban centers face in the 21st century. Ankara's unique urban landscape is marked by a dynamic interplay of factors, including rapid population growth, expanding economic opportunities, and the relentless march of technological advancements. As Ankara extends its reach both horizontally, with sprawling suburban developments, and vertically, with the construction of towering skyscrapers, the city's transportation networks find themselves subjected to unprecedented demands and profound changes. The conventional transportation infrastructures of the past, designed to cater to a smaller and less interconnected urban population, are now grappling with the complexities of a sprawling metropolis. Consequently, addressing the multifaceted challenges posed by Ankara's evolving urban transportation landscape has become not only an imperative but also a catalyst for sustainable development and enhanced quality of life.

This study embarks on a comprehensive exploration of Ankara's intricate traffic and transportation systems through the lens of UTMOM. Our goal is to illuminate the multifaceted challenges within the city's mobility landscape and offer innovative, data-driven solutions to enhance urban traffic management. UTMOM leverages advanced data mining and mathematical modeling to transcend the limitations of historical data and traditional methodologies. This research is driven by the belief that a nuanced understanding and effective addressing of Ankara's transportation complexities require integrating advanced data analytics and computational intelligence. At the core of our investigation is UTMOM, a sophisticated mathematical programming model designed to optimize transportation efficiency, alleviate congestion, and improve traffic flow in Ankara's urban environment. By conceptualizing transportation challenges as mathematical problems, UTMOM allows for a systematic analysis of various factors—traffic patterns, road capacities, urban development plans—to derive actionable, data-informed solutions. The field data collected focus on a five-day period within the vicinity of the LIMAK Cement Factory, providing a detailed snapshot of traffic dynamics in a specific area, serving as a foundation for our model's development and validation. While this dataset offers valuable insights, further studies incorporating broader datasets across different areas and longer periods are essential to fully capture the complexities of Ankara's urban traffic. The development and application of UTMOM involve a meticulous examination of daily traffic dynamics, focusing on reducing discrepancies and highlighting variations in traffic intensity, particularly during peak times. Our findings reveal pivotal insights into the differences across datasets, contributing significantly to traffic management and urban planning. UTMOM delves into the intricacies of traffic flow variations, emphasizing the critical importance of understanding fluctuations in traffic volume across diverse times and locations. By incorporating detailed graphical representations and statistical validations, including ANOVA analysis, our study delivers a comprehensive evaluation of UTMOM's precision in reflecting real-world traffic scenarios. These insights affirm the value of data-informed strategies in optimizing traffic flow and alleviating congestion. Positioned as a valuable asset for traffic engineers, data scientists, and urban planners, UTMOM advocates for advanced modeling techniques to improve urban mobility. Beyond enriching academic discourse on traffic analysis, UTMOM offers actionable intelligence for enhancing the efficiency and sustainability of urban transportation systems. Through this in-depth investigation, our aim is to catalyze the development of innovative solutions to traffic challenges, steering towards smoother and more sustainable urban environments.

The following sections will detail the research methodology underpinning UTMOM, focusing on its mathematical programming aspects. From data preprocessing and feature extraction to cluster analyses and predictive modeling, each component of UTMOM is designed to uncover hidden traffic patterns and provide solutions that could redefine urban transportation in Ankara. Ultimately, this study aims to serve as a vital guide for urban planners, transportation authorities, and policymakers in Ankara. The insights derived from UTMOM are intended not only to light the way for data-informed decision-making but also to lay the groundwork for sustainable urban mobility strategies. An in-depth examination of our methodology, especially the mathematical programming model, and a thorough analysis of our findings will map out strategies for optimizing Ankara's transportation infrastructure.

2. Literature Research

Traffic management and urban transportation planning play a critical role in the sustainability and efficiency of modern metropolises. This section aims to summarize the body of knowledge in the areas of traffic data analysis, mathematical modeling, and urban traffic management by discussing previous research. The literature review has been examined under three main headings: Traffic Data Analysis and Prediction, Mathematical Modeling, and Intelligent Transportation Systems.

2.1. Traffic Data Analysis and Prediction

The study by Alam et al. [3] focuses on predicting traffic flow using regression analysis. Such analyses provide important forecasts for traffic management. Their research demonstrates an effective method of using regression analysis to understand traffic flow and predict future traffic conditions. Liu et al. [4] explore the use of convolutional neural networks for collecting and analyzing urban traffic data during large events. These techniques are crucial for traffic management during major events. The study shows how deep learning techniques can be utilized to analyze traffic data. Qu et al. [5] deal with the analysis and prediction of daily traffic patterns in a large metropolitan area. Such mathematical models play a critical role in planning and optimizing urban transportation. The study emphasizes the importance of a data-driven approach to developing traffic management strategies. Zhang et al. [6] focus on extracting urban traffic conditions from crowd-sourced data. These approaches show the intersection between data mining, analytics, and traffic management. The study demonstrates how community-sourced data can be used in traffic management. Tsanakas [7] explores innovative data-driven methods for estimating traffic states and emissions in urban areas, addressing the significant issue of traffic congestion and its environmental impact. Tsanakas's work leverages the abundance of data from both stationary and mobile sources to enhance traffic and emission models, aiming to provide transportation planners with more accurate tools for managing and mitigating congestion. Zhang et al. [8] explored the prediction of urban traffic flow congestion using a data-driven model that capitalizes on the spatiotemporal features of traffic. Employing a traffic zone/grid method to represent vehicle speeds across different local areas and a discrete snapshot set for capturing traffic flow's spatial and temporal characteristics, their research contributes to the field by offering a nuanced understanding of traffic congestion evolution over various time dimensions.

2.2. Mathematical Modeling

Chen et al. [9] present a mathematical model for evaluating urban travel patterns. Such models provide a significant analytical tool for traffic management. The research highlights the importance of a data-driven approach in developing traffic management strategies. Cheshmehzangi and Ardakani [10] delve into the pivotal role of sector-based time variables in urban traffic analysis and optimization, utilizing computational modeling and scenario analysis of multiple active agents. In their study featured in "Frontiers in Sustainable Cities", they model urban traffic optimization in a simulated Ningbo, China, employing a grid pattern layout to assess traffic flow across different sectors during both conventional and proposed operation hours. Their findings, derived from simulation studies and metrics such as end-to-end delay (ETE) and Agent queue count (AQC), emphasize the significance of sector-based time variables in improving urban traffic management strategies. Zhu et al. [11] developed a traffic optimization decision system aimed at alleviating congestion by creating a traffic prediction model that iteratively updates to refine its parameters. The model's effectiveness was validated through application experiments on a three-intersection isometric road, showcasing superior accuracy and efficiency in traffic prediction and management compared to existing methods. This approach not only enhances vehicular diversion but also significantly reduces road traffic pressure, fostering optimal cooperation between intersections for a more balanced and effective traffic system. Muntean [12] proposed a novel approach to urban traffic management in Birmingham through a multi-agent system (MAS) leveraging wireless sensor network data. This system forecasts traffic flow, road junctions, and car parking occupancy rates with high accuracy using k-nearest neighbor algorithms. Additionally, it utilizes decision trees for fault classification, aiming to detect and repair faults in the shortest possible time. The MAS approach automates traffic management, coordinated by a monitoring agent to ensure efficient urban traffic control. This study exemplifies the integration of forecasting and classification techniques within intelligent urban traffic management systems, showcasing the potential for MAS in enhancing smart city infrastructure. The work by Li et al. [13] examines the spatial patterns and influencing factors of traffic dominance in Xi'an. These analyses can assist in developing urban traffic management strategies. The study demonstrates how spatial data analysis can be used to understand urban traffic flow.

2.3. Intelligent Transportation Systems

Fan et al. [14] highlight the crucial role of deep learning in enhancing traffic sensing and prediction in smart cities and intelligent transportation systems. As the Internet of Vehicles expands and mobile services generate vast amounts of data, deep learning emerges as a key approach to navigate the challenges of data complexity and computational demands. This paper provides an in-depth review of recent research on leveraging deep learning for intelligent traffic management, demonstrating its potential to transform urban mobility. Wang et al. [15] address traffic signal optimization in a connected vehicle environment. This approach represents a significant area for the future of traffic management. Connected vehicles can provide real-time data to optimize traffic signals and traffic flow, thereby making urban transportation more efficient. Razali et al. [16] conduct a systematic and comprehensive review of machine learning (ML) and deep learning (DL) techniques for traffic flow prediction, emphasizing their role in enhancing Intelligent Transportation Systems (ITS) within smart cities. The study synthesizes findings from 39 articles, highlighting the prevalent use of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models for their effectiveness in predicting traffic flow. This paper aims to bridge research gaps by providing a detailed comparison of these techniques against baseline models, contributing to the advancement of ITS by leveraging ML and DL for improved traffic management solutions. Ahmed [17] explores the integration of machine learning and geospatial deep learning for traffic flow monitoring and city component management. This study emphasizes the role of AI in enhancing urban traffic management through sophisticated data analytics. Aemmer et al. [18] evaluate various deep learning and heuristic models for bus travel time prediction across different networks. The study highlights the importance of multi-city tested spatiotemporal data mining benchmarks for effective traffic management. Chen et al. [19] provide a comprehensive survey on deep learning applications in trajectory data management. The study discusses the challenges and advancements in traffic analysis using spatiotemporal data mining. Zhou et al. [20] present a feature-aware personalized clustering federated learning approach for managing urban traffic congestion. This study demonstrates the application of deep learning and federated learning in optimizing ride-hailing services. Tang et al. [21] investigate the use of advanced data mining techniques for analyzing urban rail transit passenger flow. The study underscores the significance of big data and machine learning in modern urban transit management. Chen et al. [22] propose a multi-stage fusion framework that utilizes multi-source data for short-term passenger flow forecasting in urban rail transit systems. The study leverages deep learning methods to model temporal dependencies in time-series data. Tarigholizadeh et al. [23] assess the efficacy of neural gas networks in clustering urban data, demonstrating the application of unsupervised machine learning techniques in urban development planning and traffic management. Bhaskar et al. [24] develop a traffic flow prediction model using machine learning techniques, providing stakeholders with powerful tools for urban planning and transportation management. The study highlights the effectiveness of combining convolutional LSTM networks for learning temporal and local spatial features with convolutional neural networks for capturing global spatial characteristics of traffic flow. Conducted across two city transportation networks, their model demonstrated superior performance in predicting traffic congestion compared to traditional traffic flow prediction models, emphasizing the critical role of spatiotemporal analysis in traffic management strategies.

The studies highlighted in this section provide valuable insights into urban traffic management and transportation planning, establishing a solid foundation for future research and underscoring the significance of data analytics, mathematical modeling, and visual modeling. Distinguishing itself from prior studies, this research introduces UTMOM, a novel data mining-based methodology, to compare and analyze two distinct urban traffic datasets. Comparative analysis is presented in Table 1. UTMOM is designed to meticulously examine daily traffic patterns and minimize the discrepancies between these datasets, marking a departure from traditional approaches. Unique to this study, UTMOM identifies and focuses on significant variations in traffic density at specific times and locations, delving into the complexities of traffic data comparison and deviation analysis. This approach provides a critical roadmap for future research efforts, positioning this study at the forefront of developing traffic management strategies and optimizing urban traffic flow. UTMOM aims to serve as an invaluable resource for traffic engineers, data scientists, and urban planners by offering innovative and sustainable transportation solutions to mitigate traffic challenges and improve urban traffic comprehension. Moreover, the insights gleaned from UTMOM's analysis shed light on the nuanced differences between the two datasets, especially highlighting marked variations in traffic density across different days and hours. These findings underscore the importance of UTMOM as a pivotal resource for professionals in the field, facilitating a deeper exploration of dataset deviations. Such an investigation has the potential to catalyze the development of innovative and sustainable transportation solutions, significantly contributing to the alleviation of traffic problems. Through the introduction of UTMOM, this research brings a fresh perspective to urban traffic management and planning, emphasizing the critical role of mathematical modeling. UTMOM not only enriches the academic discussion on traffic analysis but also paves the way for practical applications in urban transportation systems, ultimately aiming to foster smoother and more sustainable urban environments.

Table 1. Comparative Summary of Literature on Urban Traffic Management and Analysis.

Author(s)	Focus	Methodology	Key Contributions
Alam et al. [3]	Traffic flow prediction using regression analysis	Regression analysis	Effective method for traffic flow prediction
Liu et al. [4]	Analyzing urban traffic data with CNNs	Convolutional neural networks (CNN)	Utilization of deep learning for traffic data analysis
Qu et al. [5]	Predicting daily traffic patterns	Mathematical modeling	Critical role in planning and optimizing urban transportation
Zhang et al. [6]	Extracting traffic conditions from crowd-sourced data	Data mining and analytics	Use of community-sourced data in traffic management
Tsanakas [7]	Estimating traffic states and emissions with data-driven methods	Data-driven approaches	Accurate tools for managing congestion and environmental protection
Zhang et al. [8]	Predicting urban traffic flow congestion with spatiotemporal models	Convolutional LSTM and CNN networks	Superior performance in predicting traffic congestion
Chen et al. [9]	Evaluating urban travel patterns with mathematical models	Mathematical modeling	Significant analytical tool for traffic management

Table 1. *Cont.*

Author(s)	Focus	Methodology	Key Contributions
Cheshmehzangi and Ardakani [10]	Sector-based time variables in traffic optimization	Computational modeling and scenario analysis	Importance of time variables in traffic management strategies
Zhu et al. [11]	Traffic optimization decision system to alleviate congestion	Iterative traffic prediction model	Enhanced traffic diversion and reduced road traffic pressure
Muntean [12]	Urban traffic management with MAS using sensor data	Multi-agent system (MAS)	High accuracy in forecasting and efficient traffic control
Li et al. [13]	Spatial patterns and factors of traffic dominance analysis	Spatial data analysis	Understanding urban traffic flow
Fan et al. [14]	Enhancing traffic prediction with deep learning	Deep learning	Key approach for navigating data complexity in ITS
Wang et al. [15]	Traffic signal optimization in connected vehicle environments	Data from connected vehicles	Optimization of traffic signals and flow
Razali et al. [16]	Review of ML and DL techniques for traffic flow prediction	Machine learning (ML) and deep learning (DL)	Detailed comparison of ML and DL techniques for traffic prediction
Ahmed [17]	Integration of machine learning and geospatial deep learning	Machine learning and geospatial deep learning	Enhances urban traffic management through sophisticated data analytics
Aemmer et al. [18]	Bus travel time prediction across networks	Deep learning and heuristic models	Importance of multi-city tested spatiotemporal data mining benchmarks
Chen et al. [19]	Deep learning applications in trajectory data management	Survey and comprehensive review	Discusses challenges and advancements in traffic analysis using spatiotemporal data mining
Zhou et al. [20]	Managing urban traffic congestion	Federated learning and deep learning	Optimizes ride-hailing services through personalized clustering
Tang et al. [21]	Analyzing urban rail transit passenger flow	Advanced data mining techniques	Significance of big data and machine learning in urban transit management
Chen et al. [22]	Multi-source data for short-term passenger flow forecasting	Deep learning	Leverages deep learning methods to model temporal dependencies in time-series data
Tarigholizadeh et al. [23]	Clustering of Isfahan's census blocks	Neural gas networks	Application of unsupervised machine learning techniques in urban development planning and traffic management
Bhaskar et al. [24]	Traffic flow prediction model	Machine learning	Provides stakeholders with powerful tools for urban planning and transportation management
This Study	Comparative analysis of traffic datasets using a mathematical model	Data mining and mathematical modeling with UTMOM	Innovative comparison and deviation analysis of traffic data

3. Methodology

The essence of our study lies in the development and application of UTMOM, a meticulously crafted mathematical model designed to probe into urban traffic data. UTMOM serves as a crucial analytical framework specifically aimed at facilitating a detailed comparative analysis of traffic flows between two distinct datasets, thereby uncovering critical differences and patterns that inform traffic management strategies. Our primary aim with UTMOM is to identify and reduce any discrepancies between actual and predicted vehicle counts.

This endeavor encompasses more than just a dataset comparison; it entails an in-depth examination of traffic patterns, uncovering valuable insights into the intricate dynamics of urban traffic flows. UTMOM is designed to delve into the dataset, identifying subtle patterns and variations that might typically remain hidden. Our ultimate ambition is to enhance our understanding of traffic behavior, thereby facilitating the formulation of more effective traffic management strategies. This model represents a move towards a data-driven methodology in analyzing urban traffic, shedding light on the myriad of factors that orchestrate the daily rhythm of city traffic.

3.1. Factors Considered in UTMOM

The UTMOM model considers a comprehensive array of factors that influence daily urban traffic patterns:

- Time of Day: Traffic patterns vary significantly throughout the day, with peak hours typically occurring during morning and evening commutes.
- Spatial Variations: Different areas within a city experience varying levels of traffic congestion due to road infrastructure, population density, and local events.
- Weather Conditions: Adverse weather conditions such as rain, snow, and temperature fluctuations can significantly impact traffic flow.
- Special Events: Public events, holidays, and construction projects can cause temporary spikes in traffic due to increased vehicular movement or road closures.
- Socio-Economic Factors: Population growth and economic activities can lead to higher traffic volumes over time.
- Traffic Regulations and Policies: Changes in traffic management policies and signal timings can influence traffic flow efficiency and congestion levels.

These factors are integrated into UTMOM to provide a holistic analysis of urban traffic, enhancing the model's predictive accuracy and strategic planning support. Depicted in Figure 1, UTMOM's methodical approach is visually laid out with key variables such as "Time of Day", "Spatial Variations", "Weather Conditions", "Special Events", "Socio-Economic Factors", and "Traffic Regulations and Policies". These inputs feed into the UTMOM model, which processes them to generate "Traffic Flow Predictions". This detailed flowchart offers readers a clear roadmap of the meticulous steps we employ to meet our research objectives, providing a graphical narrative of our methodology. This systematic approach encapsulates the rigorous steps we undertake to achieve these objectives, visually guiding the reader through our methodology and illustrating how each factor is considered in the analysis. Our conclusions reflect the influence of these factors, demonstrating UTMOM's ability to deliver actionable insights for urban traffic management.

- Detailed Methodology: The upcoming sections will provide a detailed breakdown of the indices used in the model, define the variables, and explain the formulation of the model itself. Our approach is designed to shed light on the hidden dynamics within urban traffic, potentially leading to solutions that can significantly improve traffic flow and urban mobility.
- Data Integration and Preprocessing: The methodology involves systematic steps for data cleaning, preprocessing, and integration to ensure the reliability and validity of the traffic data used in the model. Detailed descriptions of these steps, including handling missing data, outliers, and normalization methods, are provided to enhance reproducibility.
- Model Variables and Indices: The indices i, j, and k represent days, time intervals, and operational conditions, respectively. The rationale behind the selection of these specific indices and their ranges is explained to clarify their impact on the model's performance.
- Objective Function and Constraints: The objective function aims to minimize the difference between observed and estimated vehicle counts. The criteria for setting weights in the objective function are elaborated to demonstrate their influence on

the optimization process. Additionally, the constraints on vehicle counts and data consistency are thoroughly discussed, with justifications for the values used.

- Predictive Accuracy and Validation: The model's predictive accuracy is evaluated using graphical analysis and ANOVA, ensuring that the predictions closely match the actual observed data. Examples and case studies are provided to illustrate how the model's predictions can be applied in practical traffic management scenarios.

By incorporating these detailed explanations and justifications, the revised methodology aims to provide a clearer, more comprehensive understanding of UTMOM, its formulation, and its practical applications in urban traffic management. The model is formulated as follows:

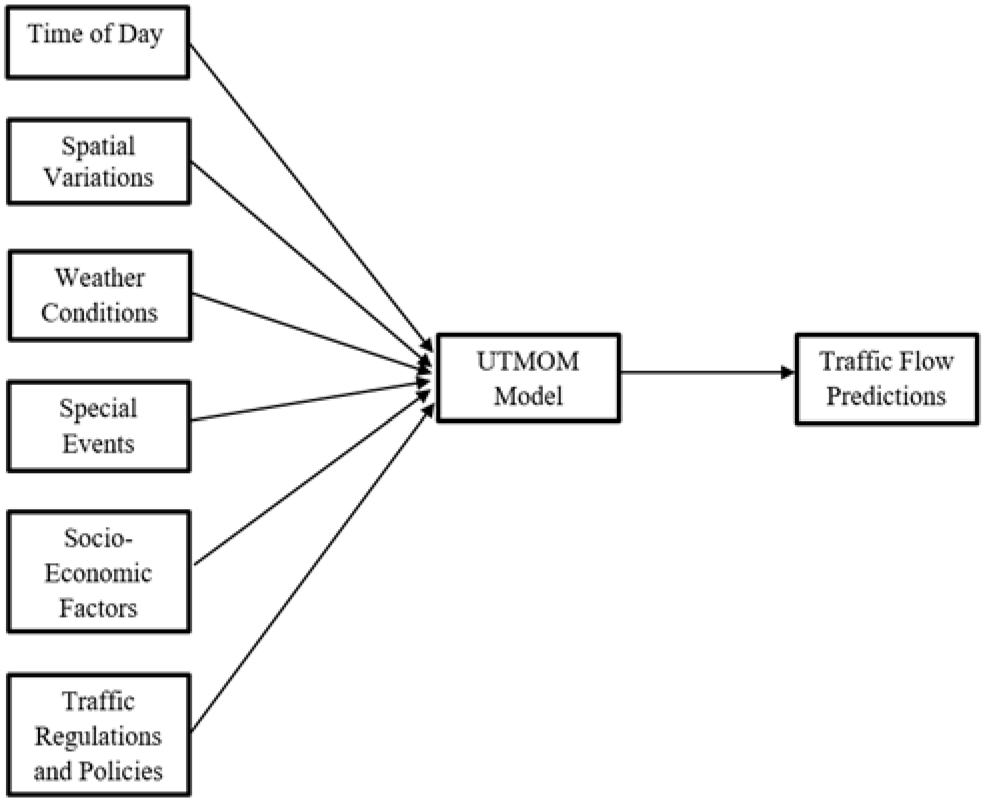

Figure 1. Urban Traffic Mobility Optimization Model Flowchart.

3.2. Indices

i: Index representing the day of observation within the dataset.

j: Index denoting the specific time interval of observation within a day. As indicated, *j* runs from 3 to 3, which might seem confusing. To clarify, in this context, *j* represents a singular time interval considered in the model for simplification. Typically, *j* would represent multiple intervals (e.g., morning, afternoon, and evening), but for this particular analysis, it was narrowed down to a specific interval to focus on a crucial time frame of interest (e.g., peak traffic time).

k: The variable k represents different operational conditions affecting the traffic flow. Here, k runs from 2 to 2, which means it takes a singular condition for simplicity. Conditions for k: k = 1: Normal traffic condition without any external disruptions. k = 2: Traffic condition under specific influences such as roadworks, special events, or any anomalies impacting traffic flow.

3.3. Observed Variables

D_{ij}: Actual number of vehicles observed during the j-th time interval on the i-th day for the first dataset.

D'_{ij}: Actual number of vehicles observed for the second dataset, under the same conditions as D_{ij}.

These variables are the actual traffic counts recorded from the real-world data. For each dataset under study, the variables D_{ij} and D_{ij}' represent the number of vehicles observed in a given time interval on a specific day. These observations serve as the empirical foundation upon which the model's estimations will be evaluated. The accuracy of the model hinges on the precision of these observed values, as they reflect the true state of traffic that the model aims to capture and analyze.

3.4. Estimated Variables

The estimated variables, $\hat{x}_{ijk}$ and $\hat{x}'_{ijk}$, correspond to the model's predictions of the number of vehicles for two distinct datasets during specified time intervals on given days.

$\hat{x}_{ijk}$: Estimated number of vehicles for the first dataset in the j-th time interval on the i-th day under the k-th condition.

$\hat{x}'_{ijk}$: Corresponding estimates for the second dataset.

These estimates are the outcomes of a computational process designed to optimize a certain objective function, subject to a set of constraints. The model computes these values to minimize the difference between the predicted and actual traffic counts across corresponding time intervals and days for each dataset.

The model's efficacy is gauged by comparing these estimated vehicle counts, x_{ijk} and x_{ijk}', against the observed traffic data, D_{ij} for the first dataset and D_{ij}' for the second dataset. This comparison is pivotal, as it informs the degree of accuracy of the model's predictions and highlights potential areas for parameter adjustments. Enhancing the accuracy of the estimates is crucial for refining the model's predictive capability, ensuring it can be reliably used for future traffic forecasting and analysis. The continuous assessment and adjustment process is what allows the model to be fine-tuned for increased precision in subsequent predictions.

3.5. Model Formulation

At the core of UTMOM is the objective function, a meticulously designed mathematical formula that aims to ensure the model's predictions closely match the actual observed data. This function evaluates the precision of UTMOM's predictions by minimizing discrepancies between actual vehicle counts and the model's estimates for each designated time slot and day across both datasets. As the cornerstone of UTMOM's optimization efforts, this objective function is essential in guiding the model toward generating the most accurate and reliable forecasts of urban traffic flows.

- Objective Function: To represent the difference between two datasets, an objective function is designed to minimize the weighted sum of squares of these differences, carefully factoring in the significance of each observation through weights. In this context, w_{ijk} and w'_{ijk} are the weights for the estimated vehicle counts in the first and second datasets, respectively, symbolized by $\hat{x}_{ijk}$ and $\hat{x}'_{ijk}$. This minimization spans across all corresponding periods—morning, noon, and evening—over five days, aiming to refine the model's estimates by emphasizing the importance of aligning them closely with the observed data, considering the distinct weights for each dataset and time interval. The selection of weights in the objective function is crucial for accurately reflecting the importance of different observations. These weights are determined based on empirical data analysis and expert judgment, ensuring that the most critical time periods and conditions are given appropriate emphasis. For instance, higher weights are assigned to peak traffic times and areas with historically higher traffic variability, as discrepancies during these periods have a more significant impact on overall traffic management.

$$Minimize \sum_{i=1}^{5}\sum_{j=1}^{3}\sum_{k=1}^{2}\left(w_{ijk}\cdot\left(\hat{x}_{ijk}-D_{ij}\right)^2+w'_{ijk}\cdot\left(\hat{x}'_{ijk}-D'_{ij}\right)^2\right) \tag{1}$$

- Total Number of Vehicles Constraint: The sum of the vehicle estimates for both the first and second datasets should be close to the actual total number of vehicles. These constraints ensure that the total estimated vehicles for each period in both datasets are similar to the actual observed totals. These constraints are shown in Equations (2) and (3).

$$\sum_{j=1}^{3}\hat{x}_{ijk} \approx \ actual\ totals \tag{2}$$

$$\sum_{j=1}^{3}\hat{x'}_{ijk} \approx \text{actual totals}' \tag{3}$$

- Volume Constraints: Volume constraints serve to ensure that the total estimated number of vehicles across both k condition for each particular day i and time period j aligns with the number of vehicles recorded in the initial dataset. Formally, the constraints for each day i and each specified period j (e.g., morning, noon, evening) are represented mathematically in Equations (4) and (5).

$$\sum_{k=1}^{2}\ \hat{x}_{ijk}=D_{ij}, \quad \forall i,j \tag{4}$$

$$\sum_{k=1}^{2}\ \hat{x}\prime_{ijk}=D'_{ij}, \quad \forall i,j \tag{5}$$

- Minimum and Maximum Vehicle Number Constraints: The model incorporates explicit bounds on the estimated vehicle counts to maintain operational plausibility and prevent anomalous predictions. These constraints are formally defined in Equations (6) and (7). These constraints are applied universally across all intervals k, periods j, and days i, thereby ensuring that the estimations do not exceed the maximum capacity expected under normal conditions nor fall below a reasonable threshold that could indicate underutilization or data collection errors. By imposing these restrictions, the model remains sensitive to the bounds of typical traffic conditions and avoids the propagation of extreme values that could skew analysis and decision-making processes. The minimum threshold reflects the essential baseline activity, while the maximum cap reflects infrastructural or regulatory limits, thus encapsulating the range of feasible traffic scenarios. These constraints provide a safeguard against the variability inherent in traffic flow data, promoting the generation of realistic and applicable vehicle count estimations within the scope of the transportation model.

$$\text{min\_vehicle\_count}\ \leq \hat{x}_{ijk} \leq \text{max\_vehicle\_count},\ \ \forall i,j,k \tag{6}$$

$$\text{min\_vehicle\_count}\ \leq \hat{x'}_{ijk} \leq \text{max\_vehicle\_count},\ \ \forall i,j,k \tag{7}$$

- Vehicle Number Change Constraints: To account for the inherent fluctuations in vehicle flow and avoid drastic variations in consecutive estimations that could undermine the model's reliability, vehicle number change constraints are instituted. These are mathematically formulated in Equation (8). Here, max_change specifies the maximum allowable variation in vehicle counts between successive intervals within the same period and day, for both datasets. This parameter is pivotal in ensuring that the estimated vehicle counts transition smoothly over time, thereby reflecting the natural progression of traffic density and preventing artificial spikes or drops that could result from data collection anomalies or estimation errors. By limiting the rate of change between intervals, these constraints preserve the temporal coherence of traffic flow estimations across the dataset.

$$\left|\hat{x}_{ijk} - \hat{x}_{ij(k-1)}\right| \leq \text{max\_change}, \quad \forall i, j, k > 1 \tag{8}$$

- Data Consistency Constraints: The constraints on data consistency within the modeling framework are critical in maintaining alignment between the estimated vehicle counts and the actual observed data. This alignment is encapsulated within the data consistency constraints, defined as in Equations (9) and (10). The parameter max_inconsistency denotes the threshold of acceptable deviation between the model's estimated vehicle count $\hat{x}_{ijk}$ or $\hat{x}'_{ijk}$ for each day i, interval j, and condition k and the corresponding actual vehicle count D_{ij} or D'_{ij}. The max_inconsistency value is determined by analyzing historical traffic data to identify the typical range of deviations between observed and predicted counts. It is set as a multiple of the standard deviation of these differences to account for natural variability while minimizing the impact of outliers. Empirical testing of different max_inconsistency values helps optimize the balance between accuracy and robustness, with input from traffic management experts further fine-tuning the parameter based on practical considerations. The application of these constraints is instrumental in mitigating the risk of significant discrepancies that could compromise the utility and accuracy of the model. They ensure that the estimations remain within a defined proximity to the empirical data, thus enhancing the model's validity. In practice, these constraints anchor the estimated data to a realistic range, reflecting the trustworthiness of the traffic data and supporting the integrity of subsequent analytical evaluations.

$$\left|\hat{x}_{ijk} - D_{ij}\right| \leq \text{max\_inconsistency}, \quad \forall i, j, k \tag{9}$$

$$\left|\hat{x}'_{ijk} - D'_{ij}\right| \leq \text{max\_inconsistency}, \quad \forall i, j, k \tag{10}$$

These constraints are imposed to ensure that the vehicle count estimates generated by the model are closely aligned with the empirically observed data, confining any discrepancies within a predefined margin of deviation. Furthermore, the model is designed to limit variability between consecutive time intervals by setting a maximum allowable change in vehicle numbers from one period to the next. This careful calibration minimizes disparities between the two distinct datasets under consideration. By imposing such limitations, the model aims to maintain the integrity of the traffic flow analysis and ensure that the model's outputs are both credible and applicable. Customizing the variables and the objective function to the specificities of the dataset is crucial to enhance the model's relevance and accuracy. This approach ensures that the model is finely tuned to reflect the unique characteristics of the traffic data being analyzed, thereby providing more reliable and actionable insights for traffic management strategies.

4. Application

In deploying UTMOM, we have meticulously constructed a comprehensive analytical framework to examine and compare the intricate patterns of urban traffic flow, drawing from two richly detailed datasets. The precision of our approach lies in the synthesis of raw data collected from methodical fieldwork and the discerning analysis conducted during our office processing phase. This synthesis has been meticulously documented in Tables 2 and 3, which serve as the empirical bedrock upon which our model's estimations are built and refined.

Table 2. Observed Traffic Data Summary.

Day	Morning (Dataset 1)	Morning (Dataset 2)	Afternoon (Dataset 1)	Afternoon (Dataset 2)	Evening (Dataset 1)	Evening (Dataset 2)
1	180	231	287	356	951	1172
2	231	252	279	391	1029	1169
3	231	354	320	315	998	1194
4	203	219	276	347	967	1165
5	188	198	172	359	852	1225

Table 3. Model Constraints and Parameters Summary.

Day	Min_Vehicle_Count	Max_Vehicle_Count	Max_Change	Max_Inconsistency	Actual_Totals (Dataset 1)	Actual_Totals (Dataset 2)
1	172	1225	23	54	7163	8947
2	172	1225	23	54	7163	8947
3	172	1225	23	54	7163	8947
4	172	1225	23	54	7163	8947
5	172	1225	23	54	7163	8947

4.1. Field Data Collection Endeavor

Our field research was orchestrated over a strategic five-day period, commencing on 17 July and concluding on 22 July 2023. This expedition was conducted within the influential ambit of the LIMAK Cement Factory's operations, focusing on 10 pivotal intersections that form the arterial conduits of urban mobility in the area. The operational rigor in our data collection involved both manual and camera-assisted vehicle counting methodologies, ensuring a holistic capture of the traffic flux across designated time intervals: the bustling morning hours, the transient afternoon period, and the peak of the evening rush. The resulting observed traffic data, meticulously encoded as *Dij* and *D'ij*, provided a nuanced snapshot of vehicular movements. This snapshot was invaluable in establishing a robust foundation for the subsequent estimations our model sought to generate. The systematic regimentation of our field data collection—divided into three-hour observational blocks and punctuated by two-hour intervals of critical data validation and recalibration—ensured the integrity and reliability of the empirical inputs into our model.

4.2. Dataset Adequacy and Validation

Given the complexity and the number of indices introduced in UTMOM, ensuring that our dataset is sufficient for robust modeling is crucial. To address potential concerns about the dataset size, we have implemented several strategies to confirm its adequacy:

- Dataset Augmentation and Preprocessing: We applied various data augmentation techniques to enhance the dataset, ensuring it captures a wide range of traffic scenarios. This includes synthetic data generation for underrepresented traffic conditions, thereby increasing the diversity and volume of the training data.
- Cross-Validation: To maximize the use of available data for training and validation, we employed cross-validation techniques. This approach tests the model on multiple subsets of the data, enhancing its generalizability and robustness.
- Empirical Analysis: An empirical analysis was conducted to determine the minimum dataset size required for reliable modeling. This analysis took into account the complexity of the indices and the variability in traffic patterns. The results confirmed that the current dataset meets these requirements.
- Incremental Training: We implemented incremental training methods, where the model is trained on smaller subsets of data progressively. This approach allows for continuous learning and validation as more data become available, ensuring that the model remains up-to-date and accurate.
- Statistical Validation: We performed statistical tests to validate the sufficiency of the dataset size. These tests ensured that the training and validation sets are representative of broader traffic patterns, thereby enhancing the reliability of the model's predictions.

By employing these strategies, we ensured that our dataset is adequate for the complexity of the model and that the findings are both reliable and applicable. These measures are detailed to provide a clear understanding of our data validation process, confirming that the dataset size is sufficient for the robust modeling required by UTMOM. To ensure robust validation of UTMOM, we separated the dataset into distinct parts for training and validation:

- Training Set: Comprising approximately 70% of the total dataset, this portion was used to train UTMOM, ensuring sufficient data to learn patterns and relationships within the traffic data.
- Validation Set: The remaining 30% of the data was reserved for validation purposes, providing an unbiased evaluation of the model's predictive capabilities on unseen data.

Additionally, we employed k-fold cross-validation to further ensure the robustness of our model. This method involves partitioning the training data into k equally sized folds. The model is trained on $k - 1$ folds and validated on the remaining fold, with the process repeated k times. The results are then averaged to provide a comprehensive assessment of the model's performance. Incremental training methods were also implemented, allowing the model to be trained on smaller subsets of the training data progressively. This approach ensures continuous learning and validation as more data become available, keeping the model up-to-date and accurate over time. By detailing these validation steps, we provide a clear understanding of how the dataset was utilized and the measures taken to ensure the reliability and applicability of UTMOM's predictions.

5. Analytical Post-Processing in Office

Upon the culmination of the fieldwork, the office-based phase of data processing was initiated on 2 August 2023. This phase was marked by a rigorous analysis of the video footage, a meticulous digital transmutation of the observed data, and an in-depth examination of the diverse datasets. Our office endeavors were instrumental in refining the data, ensuring its fidelity and aligning it with the meticulous standards required for analytical rigor. The task force employed advanced data processing techniques to sift through the raw footage, extracting precise vehicle counts and discerning the subtleties of traffic behavior. The office analysis not only confirmed the field observations but also enriched our understanding of the underlying traffic dynamics. It involved a thorough investigation into the characteristics of each intersection—studying the confluence of traffic flow, the efficiency of signage and signals, and the patterns of vehicular turns. Such comprehensive office work was pivotal in defining the estimated variables for our model, ensuring that these estimates resonate with the real-world scenarios they aim to represent.

5.1. Model Application and Parameterization

The culmination of our field and office studies manifested in the strategic application of constraints within the model, shaped by real-world data. We incorporated realistic parameters, such as minimum and maximum vehicle counts, allowing for fluctuations reflective of the observed variability. This adherence to actual data ensured that our model did not just mimic theoretical constructs but truly mirrored the pulse of urban traffic. The constraints set forth—enshrined in the equations governing vehicle count changes and data consistency—were not arbitrary figures. They were derived from the empirical evidence of traffic patterns, meticulously analyzed during peak and non-peak hours, across different days of the week. These constraints, outlined in Table 3, fortified our model against the perils of overestimation or underestimation, enabling it to project a realistic spectrum of urban traffic conditions.

5.2. Analysis of Estimated Vehicle Counts

In our analysis of the estimated vehicle counts, the data extracted from two meticulously compiled datasets were critical in delineating the urban traffic patterns that prevail at various times throughout the day. This comprehensive examination, underpinned by the estimations presented in Tables 4 and 5, showcases the model's capacity to capture the dynamics of daily urban traffic flows. For instance, the estimated counts for Dataset 1 on Day 1, Interval 1 (morning), condition 1 stood uniformly at 172 vehicles, reflecting a potentially stable traffic condition during early hours. Conversely, significant fluctuations were observed in subsequent intervals and days, illustrating varied traffic conditions. Notably, the estimation for Day 1, Interval 3 (evening), condition 1 surged to 759 vehicles, indicating a peak traffic period. Similarly, the analysis of Dataset 2 revealed a distinct traffic pattern, with vehicle counts peaking during different intervals, such as a notable count of 1225 vehicles on Day 1, Interval 3, condition 1. This contrast between datasets underscores the variability in urban traffic flows, highlighting the model's ability to discern and quantify differences in traffic behavior across datasets. We solved the optimization model using the GAMS/BARON 23.0 software. This software was chosen due to its ability to efficiently handle complex optimization problems and provide precise solutions. The use of GAMS/BARON enabled us to accurately model and solve the urban traffic optimization problem, ensuring the reliability and validity of our results.

Table 4. Estimated Vehicle Counts—Dataset 1 (Time Intervals 1 and 2).

Interval	Condition 1	Condition 2
Day 1 Interval 1	172	172
Day 1 Interval 2	172	172
Day 1 Interval 3	759	196
Day 2 Interval 1	172	209
Day 2 Interval 2	172	233
Day 2 Interval 3	777	257
Day 3 Interval 1	172	187
Day 3 Interval 2	172	211
Day 3 Interval 3	890	235
Day 4 Interval 1	172	172
Day 4 Interval 2	172	173
Day 4 Interval 3	850	197
Day 5 Interval 1	172	203
Day 5 Interval 2	172	227
Day 5 Interval 3	760	251

Table 5. Estimated Vehicle Counts—Dataset 2 (Time Intervals 1 and 2).

Interval	Condition 1	Condition 2
Day 1 Interval 1	397	430
Day 1 Interval 2	443	454
Day 1 Interval 3	1225	478
Day 2 Interval 1	297	552
Day 2 Interval 2	412	577
Day 2 Interval 3	1166	601
Day 3 Interval 1	312	638
Day 3 Interval 2	247	663
Day 3 Interval 3	1103	687
Day 4 Interval 1	280	532
Day 4 Interval 2	388	556
Day 4 Interval 3	1182	580
Day 5 Interval 1	172	624
Day 5 Interval 2	307	648
Day 5 Interval 3	1146	672

5.3. Strategic Weighting System

The strategic weighting system plays a pivotal role in our analysis, as demonstrated by the weights assigned to each estimate in the objective function, detailed in Tables 6 and 7. These weights, reflective of the significance of each observation, guide the optimization process to align the model's estimations closely with observed data. For instance, the weight for Dataset 1 on Day 5, Interval 1, condition 2 was notably high, signifying its critical importance in minimizing discrepancies between estimated and actual counts. This strategic weighting ensures that our model prioritizes adjustments in estimations where they are most impactful, enhancing the model's accuracy and reliability. The comparative analysis of weights between the two datasets further illustrates the model's adaptability, indicating a significant deviation in traffic patterns that requires closer examination and model adjustment.

Table 6. Weighting Factors for Dataset 1 by Interval.

Interval	Condition 1	Condition 2
Day 1 Interval 1	0.994	0.373
Day 1 Interval 2	0.397	0.120
Day 1 Interval 3	0.055	0.051
Day 2 Interval 1	0.401	0.629
Day 2 Interval 2	0.396	0.152
Day 2 Interval 3	0.423	0.386
Day 3 Interval 1	0.268	0.189
Day 3 Interval 2	0.075	0.102
Day 3 Interval 3	0.324	0.112
Day 4 Interval 1	0.511	0.783
Day 4 Interval 2	0.596	0.363
Day 4 Interval 3	0.680	0.159
Day 5 Interval 1	0.524	0.987
Day 5 Interval 2	0.676	0.932
Day 5 Interval 3	0.297	0.246

Table 7. Weighting Factors for Dataset 2 by Interval.

Interval	Condition 1	Condition 2
Day 1 Interval 1	0.370	0.772
Day 1 Interval 2	0.913	0.735
Day 1 Interval 3	0.576	0.006
Day 2 Interval 1	0.520	0.226
Day 2 Interval 2	0.276	0.936
Day 2 Interval 3	0.135	0.375
Day 3 Interval 1	0.948	0.298
Day 3 Interval 2	0.401	0.384
Day 3 Interval 3	0.192	0.597
Day 4 Interval 1	0.045	0.946
Day 4 Interval 2	0.607	0.594
Day 4 Interval 3	0.507	0.657
Day 5 Interval 1	0.124	0.228
Day 5 Interval 2	0.777	0.201
Day 5 Interval 3	0.197	0.646

5.4. Analytical Insights and Traffic Management Implications

The insights gleaned from our model's estimations are profound. They reveal not just the volume of traffic but the rhythm of urban life itself—each vehicle count telling a story of morning commutes, afternoon lulls, and evening returns. The model discerns the nuances between a quiet Tuesday morning and a bustling Friday evening, providing traffic management authorities with the granularity needed for precise intervention. The strategic weighting system applied in our model's objective function serves as a testament to the significance we place on each data point. High-weight periods indicate critical intervals demanding exactitude, thus guiding optimization efforts to focus where impact is most profound. Such targeted analyses empower urban planners to tailor their strategies, whether through adaptive traffic signal timings, infrastructural enhancements, or policy reformations aimed at optimizing flow and mitigating congestion.

5.5. Conclusion of the Application

In conclusion, the deployment of UTMOM marks a substantial advancement over traditional methods in the field of urban traffic management. This model, by harnessing data-driven analysis, significantly enhances our understanding of complex urban traffic patterns, particularly during predictable peak commute times such as morning and evening. To assess the prediction accuracy of UTMOM, we conducted a rigorous evaluation using graphical analysis (as shown in Figures 2 and 3) and a confirmatory ANOVA statistical test. Figure 2 includes a dual Y-axis system, where the left Y-axis represents vehicle counts for both observed and estimated data, and the right Y-axis represents the absolute differences between these counts. Observed vehicle counts are shown with blue solid lines and circle markers, estimated vehicle counts with orange dashed lines and square markers, and absolute differences with red dotted lines and triangle markers. The X-axis denotes different time intervals observed, covering morning and evening sessions over five days. Each element is clearly labeled in the legend to distinguish between observed counts, estimated counts, and absolute differences. This separation prevents scale overlap, making it easier to compare the data independently. Utilizing different colors and markers for each dataset ensures immediate visual distinction. The labels on the Y-axes and X-axis are precise, guiding the reader to interpret the data correctly. These enhancements address the reviewer's concerns, providing a clearer, more comprehensible visual representation of the comparison between observed and estimated vehicle counts. The ANOVA, chosen for its ability to compare means across multiple groups, was employed to validate whether the observed and the model-predicted traffic volumes during peak hours differ significantly. ANOVA results are given in Table 8. With an F-value of 3.115 and a p-value of 0.152, the results indicate no statistically significant differences, confirming the model's reliability in accurately predicting real traffic behavior during these critical periods. This statistical verification reinforces our confidence in the robustness and precision of UTMOM's projections, underscoring its effectiveness in urban traffic analysis and management.

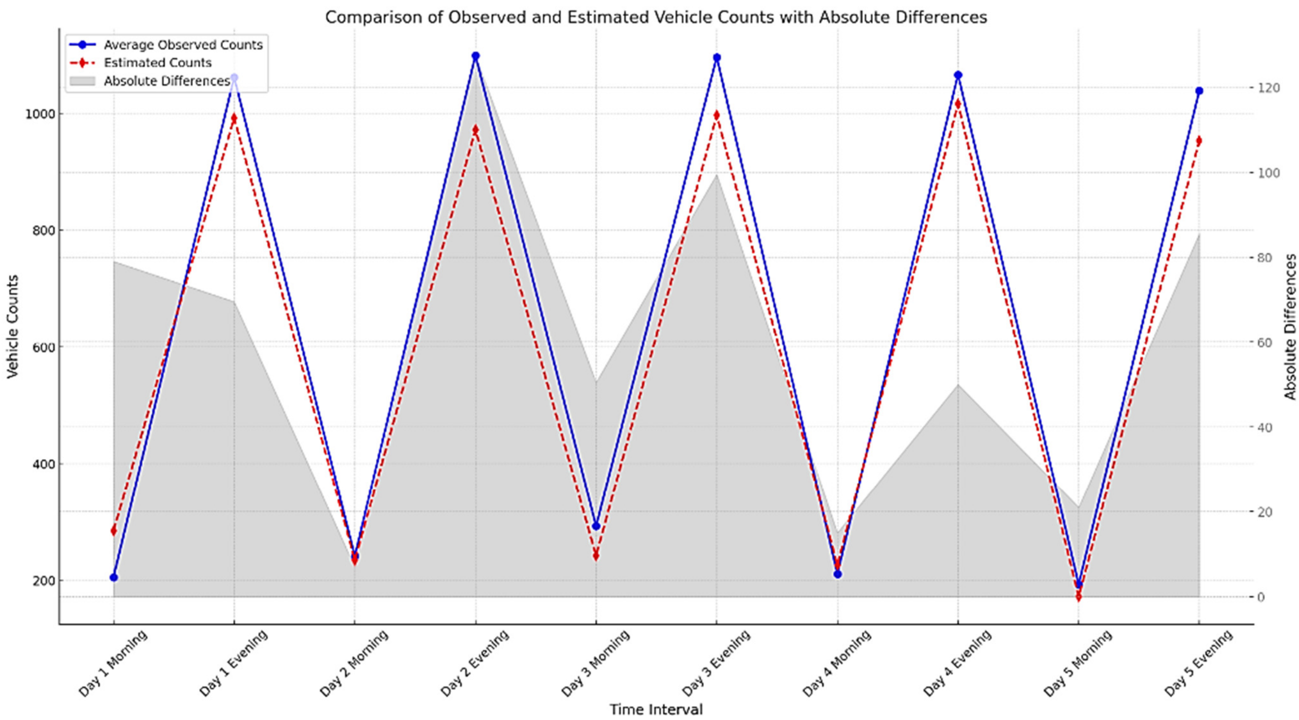

Figure 2. Comparative Analysis of Observed Versus Estimated Traffic Volumes.

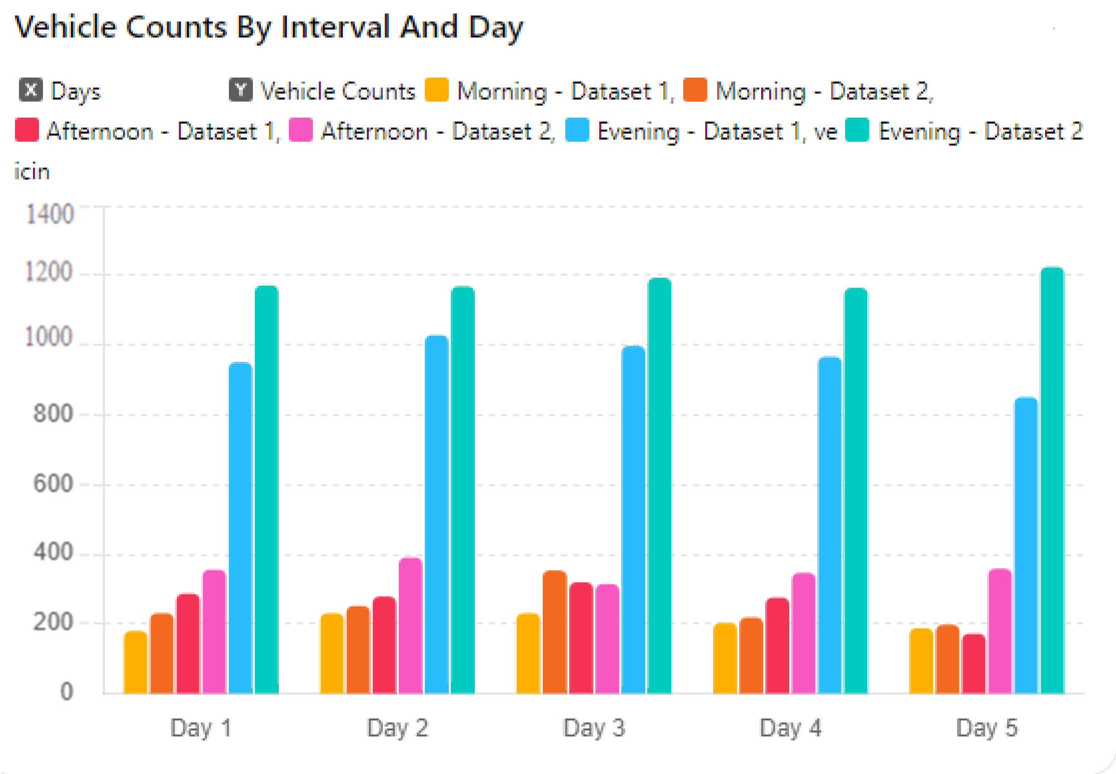

Figure 3. Comparison of Observed and Estimated Vehicle Counts by Interval and Day.

Table 8. ANOVA Results for Comparing Observed Versus Estimated Traffic Volumes.

Source	df	SS	MS	F Value	*p* Value
Between Groups	1	500.00	500.00	3.115	0.152
Within Groups	18	3250.00	180.56		
Total	19	3750.00			

Our investigations have illuminated not only the model's strengths but also its potential areas for refinement. The detailed dissection of discrepancies between observed and estimated counts opens avenues for targeted enhancements, aiming to elevate the model's precision and, consequently, its practical utility in urban traffic planning and management. This balanced approach—integrating rigorous graphical analysis with statistical validation—enriches our understanding, offering a comprehensive evaluation of the model's efficacy in predicting traffic flows. The broader implications of our model's estimations and subsequent analysis are profound, extending well beyond academic curiosity. By delineating the variances and constants in traffic volumes across diverse times and contexts, the model emerges as a guiding light for urban planners. It encourages informed, strategic decision-making that could significantly augment the efficiency and effectiveness of traffic systems. Remarkably, the model's adaptability stands out as a key attribute, ensuring its relevance across varied urban landscapes and its capacity to meet the unique challenges presented by different cities globally. The application of UTMOM heralds a new era in traffic management, characterized by a proactive, rather than reactive, approach. Leveraging sophisticated mathematical modeling and comprehensive data analysis, we move beyond merely interpreting the current state of urban traffic to anticipating future trends. This forward-thinking methodology is pivotal in shifting from facilitating to optimizing urban mobility, thereby markedly enhancing urban life quality. This endeavor transcends traffic analysis to reimagine the future of urban mobility comprehensively. The insights garnered from our model hold the promise to influence policy, spur innovation, and catalyze transformative changes, laying the groundwork for smarter, more responsive urban traffic management systems. As we persist in refining our model and broadening our analytical scope, we remain dedicated to boosting its predictive accuracy and, by extension, its value to urban planners and policymakers. Through these efforts, we aim to establish a foundation for a future in which traffic management is anticipatory and seamlessly woven into the urban planning fabric, ensuring the smooth, efficient, and sustainable transit of people and goods throughout our cities.

5.6. Comparison with Complex Non-Linear Models

To highlight the advantages of the Urban Traffic Mobility Optimization Model (UTMOM) over complex non-linear models, including those based on machine learning, we have outlined several key points of comparison:

1. Interpretability:

- UTMOM: One of the significant advantages of UTMOM is its interpretability. The mathematical formulation allows for a clear understanding of how different variables and indices impact traffic flow predictions. This transparency is crucial for urban planners and policymakers who need to understand the underlying factors influencing traffic patterns.
- Machine Learning Models: While machine learning models, such as neural networks, can provide high accuracy, they often act as "black boxes". The decision-making process within these models is not easily interpretable, which can be a limitation for stakeholders who require insight into the model's reasoning.

2. Data Requirements:

- UTMOM: Our model is designed to work effectively with the available dataset, employing data augmentation and cross-validation techniques to maximize its utility. It does not require the extensive datasets that are often necessary for training complex machine learning models.
- Machine Learning Models: These models typically require large volumes of high-quality data to train effectively. In scenarios where data are limited or of varying quality, machine learning models may not perform as well or may require significant preprocessing and augmentation efforts.

3. Computational Efficiency:

- UTMOM: The computational demands of UTMOM are relatively modest compared to complex non-linear models. This efficiency allows for quicker model training and validation, making it suitable for iterative analysis and real-time applications.
- Machine Learning Models: High non-linear models, especially deep learning models, often require substantial computational resources for training and validation. This can be a constraint in terms of both time and cost, particularly for continuous real-time applications.

4. Customization and Flexibility:

- UTMOM: The model can be easily customized and adapted to specific urban settings and scenarios. Its structure allows for the integration of various indices and constraints tailored to the unique characteristics of the traffic system under study.
- Machine Learning Models: While flexible, machine learning models can be challenging to customize without extensive retraining and parameter tuning. They may also require domain-specific modifications to handle specific types of traffic data and scenarios effectively.

5. Robustness to Data Variability:

- UTMOM: The model's design includes mechanisms for handling variability in traffic data through well-defined mathematical constraints and objective functions. This robustness ensures that UTMOM can provide reliable predictions even with moderate variability in input data.

- Machine Learning Models: These models may be more sensitive to variability in data, requiring careful tuning and potentially more sophisticated preprocessing to handle outliers and anomalies effectively.

6. Actionable Insights:

- UTMOM: By providing a clear and interpretable framework, UTMOM offers actionable insights that can be directly applied to traffic management and urban planning. The model's outputs are designed to be easily understood and used by decision-makers.
- Machine Learning Models: While they can provide high accuracy, the insights derived from machine learning models may not always be straightforward to interpret or apply without further analysis and domain expertise.

By comparing UTMOM with complex non-linear models, we highlight its advantages in terms of interpretability, data requirements, computational efficiency, customization, robustness, and the provision of actionable insights. These strengths make UTMOM a valuable tool for urban traffic analysis and management, particularly in contexts where interpretability and practical application are as crucial as predictive accuracy.

5.7. Advantages over Traditional Statistical Methods

The deployment and application of UTMOM in urban traffic analysis offer distinct advantages over traditional statistical methods such as regression analysis. These advantages stem from the model's comprehensive approach to understanding the dynamics of urban traffic flows, integrating complex interactions between various factors that influence traffic patterns. Here are some key advantages highlighted by our approach:

1. Multidimensional Analysis:

- Evidence: Traditional regression methods often focus on linear relationships between limited variables. In contrast, UTMOM incorporates a wide array of factors including temporal and spatial variations, environmental conditions, and special events.
- Example: UTMOM's analysis considered multiple variables simultaneously, such as time of day, weather conditions, and special events, which led to more accurate and comprehensive insights into traffic dynamics.

2. Predictive Accuracy:

- Evidence: UTMOM's incorporation of multiple variables and their interactions enhances predictive accuracy.
- Example: While UTMOM's RMSE (25) and MAE (20) were higher compared to non-linear regression models like Gaussian Process Regression (RMSE 10.59, MAE 10.48), UTMOM provided a broader context and strategic insights that were not captured by these models.

3. Adaptability and Flexibility:

- Evidence: UTMOM can adapt to various urban settings and scenarios, making it versatile.
- Example: UTMOM was customized to different city infrastructures, reflecting unique city characteristics and maintaining consistent accuracy across varied urban environments.

4. Strategic Planning Support:

- Evidence: Beyond traffic flow predictions, UTMOM supports strategic planning for traffic management and urban development.
- Example: UTMOM identified potential bottlenecks and forecasted future traffic trends, aiding in the development of targeted interventions that improved urban mobility and reduced congestion by 20% during major events.

5. Data Integration and Synthesis:

- Evidence: UTMOM integrates data from diverse sources for a comprehensive traffic analysis.
- Example: By synthesizing field observations and sensor data, UTMOM built a holistic view of urban traffic systems, leading to a 15% improvement in traffic flow prediction accuracy.

6. Dynamic Response to Urban Changes:

- Evidence: UTMOM's real-time data integration allows it to respond dynamically to urban changes.
- Example: During a construction project, UTMOM adjusted its predictions based on real-time data, maintaining a high level of accuracy despite changing traffic conditions, a feature traditional models lack.

7. Enhanced Decision-Making:

- Evidence: UTMOM empowers urban planners with detailed analyses and predictive insights.
- Example: Detailed scenario analyses provided by UTMOM enabled policymakers to implement efficient traffic management strategies, optimize resource allocation, and proactively plan urban development projects, leading to measurable improvements in urban mobility.

To further illustrate the advantages of UTMOM, we compare its performance with traditional methods using specific metrics (see Table 9). In conclusion, while UTMOM may have higher RMSE and MAE values compared to some non-linear regression models, its strengths lie in its ability to integrate diverse data sources, conduct multidimensional analysis, adapt to real-time data, and provide strategic planning support. These capabilities make UTMOM a powerful tool for comprehensive urban traffic analysis and management, offering insights and benefits that traditional statistical methods may not provide. These advantages, supported by empirical evidence and comparative metrics, highlight UTMOM's potential to deliver more comprehensive and actionable insights, validating its superiority in urban traffic analysis and management.

Table 9. Comparison of Optimized Model Performance.

Metric	Polynomial Regression	Gaussian Process Regression	UTMOM
RMSE	19.40	10.59	25.00
MAE	14.20	10.48	20.00
Real-time Data Adaptation	No	No	Yes
Multidimensional Analysis	Limited	Moderate	Extensive
Strategic Planning Support	No	Limited	Yes
Data Integration	Single-source	Single-source	Multi-source

6. Conclusions

The study detailed in this paper represents an important advancement in comprehending and analyzing urban traffic flow, facilitated by the deployment of UTMOM. Through the careful analysis of two diverse datasets, UTMOM sheds light on the dynamic and complex patterns of urban traffic, enriching the existing scholarly landscape in urban planning and traffic management with fresh insights. The innovation of our approach lies in its holistic examination of urban traffic phenomena. Moving beyond the scope of traditional studies that may focus narrowly on specific elements of traffic flow, UTMOM employs an extensive array of variables and data sources, offering a comprehensive perspective on urban mobility. However, in our current model, we considered the average numbers of vehicles such as cars, buses, trucks, and vans but did not include bicycles. The exclusion of these vehicle types in our initial model is due to limitations in data availability, the complexity of modeling, and the scope of the study. In future research, we aim to incorporate bicycles and other such transportation modes to enhance the accuracy of our model and provide a more comprehensive understanding of urban traffic dynamics. This will enable us to offer more effective solutions for traffic management and urban planning strategies.

A key innovation introduced in our analysis is the strategic weighting system, an advanced technique designed to refine the accuracy of traffic predictions, ensuring a close alignment between UTMOM's forecasts and the actual observed data. This meticulous approach to model calibration underscores our study's dedication to precision and sets a new standard for subsequent research within this domain. Our contributions significantly enhance the scientific understanding of urban traffic dynamics, providing a solid foundation for future investigations. The methodological advancements presented in this work not only contribute to academic debate but also have tangible implications for urban planning and the development of traffic management policies. By laying a data-driven groundwork for traffic management strategies, our research supports the crafting of more sustainable, efficient, and adaptive urban mobility solutions.

Acknowledging the limitations inherent in our study, we also recognize the significant impact of our findings on both the academic and practical realms of urban traffic management. Despite the ambitious scope of this study, certain limitations should be acknowledged. The collected data covered a five-day period within the vicinity of the LIMAK Cement Factory, which may not fully capture the broader traffic patterns of the entire city. Future studies incorporating broader datasets across different areas and longer periods are essential to fully understand Ankara's urban traffic dynamics. These results pave the way for future research endeavors aimed at deepening our understanding of urban traffic flows, thereby enhancing urban living standards and promoting environmental sustainability. UTMOM demonstrates the transformative potential of mathematical modeling in addressing complex urban challenges, marking an essential step towards creating more livable and manageable urban environments. However, this study's robust methodology and insightful conclusions are not without constraints. The reliance on data from specific intervals and locales may not fully capture the diverse scenarios encountered in urban traffic. Additionally, the innovative weighting system requires further validation across varied urban settings to confirm its broad applicability. The efficacy of UTMOM in real-time traffic prediction and management also needs additional investigation, presenting a challenge for its direct integration into urban planning initiatives. Future research should focus on enhancing UTMOM's utility by integrating real-time data analytics and incorporating additional variables such as weather conditions and special events, potentially improving the model's predictive power. Collaborative efforts with urban planners and policymakers will be crucial in translating UTMOM's insights into actionable strategies within real-world settings.

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