Spatio-Temporal Traffic Congestion Analysis Using AI-Driven Modeling Near Industrial Zones: A Case Study of LIMAK Cement Factory, North Karachi

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Citation | Abbas. M, Ahmad. F, "Spatio-Temporal Traffic Congestion Analysis Using AI-Driven Modeling Near Industrial Zones: A Case Study of LIMAK Cement Factory, North Karachi", FCIS, Vol. 02 Issue. 2 pp 99-107, June 2024
Received | May 22, 2024, **Revised |** June 21, 2024, **Accepted |** June 23, 2024, **Published |** June 24, 2024.

Industrial zones are often the epicenters of intense vehicular movement, contributing significantly to urban traffic congestion and inefficiencies in mobility planning. This study investigates the spatio-temporal traffic patterns near the LIMAK Cement Factory in North Karachi by integrating geographic information system (GIS) techniques with artificial intelligence (AI)-driven forecasting methods. Using publicly available and simulated data, hourly traffic volume, vehicle type distribution, and congestion queue lengths were analyzed to identify hotspots and peak congestion periods. The results highlight significant congestion near Roundabout E89 and Overpass C, with a high proportion of heavy vehicles contributing to delays, particularly during morning and evening rush hours. These findings are consistent with recent research advocating for the deployment of spatio-temporal deep learning models such as ST-GCNs and Transformer-based architectures to manage urban traffic dynamics more effectively. The discussion suggests future directions involving adaptive signal control, transfer learning for data-scarce environments, and decentralized traffic management systems. This study emphasizes the urgent need to adopt intelligent traffic control solutions tailored for industrial corridors in developing urban areas.

Keywords: Industrial Zones, Traffic Congestion, Spatio-Temporal Patterns, GIS, AI-driven Forecasting, Heavy Vehicles

Introduction:

Urban transportation systems are foundational to the sustainable development, economic vitality, and livability of modern cities. As cities expand due to population growth, economic development, and technological advancement, their transportation infrastructures face mounting pressure. Efficient transportation is not merely a convenience—it is integral to reducing environmental degradation, supporting economic productivity, and enhancing quality of life. The traffic dynamics within metropolitan areas significantly affect mobility, pollution levels, energy consumption, and urban planning outcomes. In this regard, traffic forecasting has emerged as a crucial component of modern transportation systems. It enables proactive congestion mitigation, route optimization, and intelligent infrastructure planning, ultimately reducing the socio-economic costs associated with traffic bottlenecks and delays.

Ankara, the capital city of Turkey, serves as a striking example of urban transformation, where dynamic expansion and increased vehicle usage have led to significant stress on its road networks. Urban sprawl, increased vehicle density, and evolving commuting behaviors have collectively contributed to fluctuating and complex traffic patterns. Traditional transportation management systems, reliant on limited or outdated data, often fail to capture the spatio-temporal complexity of modern traffic flows. As such, Ankara's transportation system calls for innovative, data-driven, and computationally intelligent approaches for long-term forecasting and real-time decision support.

To address this, our study introduces the Urban Traffic Management Optimization Model (UTMOM), which integrates advanced data analytics, mathematical modeling, and statistical validation. UTMOM leverages real-world traffic data collected over five consecutive days around the LIMAK Cement Factory area—a known traffic congestion point in Ankara. This data serves as a foundation to model, simulate, and predict traffic behavior, especially during peak periods. The model incorporates statistical techniques such as ANOVA and visualizations to assess temporal traffic variations, ultimately offering insights that support urban planners, traffic engineers, and policy-makers in devising more efficient traffic management strategies.

Research Gap:

Despite significant advancements in traffic forecasting, current models still face challenges when applied to real-world, large-scale urban scenarios. Most existing approaches—whether statistical or machine learning-based—struggle with capturing the long-term, nonlinear, and dynamic spatio-temporal dependencies inherent in urban traffic systems. Graph Neural Networks (GNNs), though promising, often fall short in capturing multi-scale temporal features and real-time variability due to limited training data or coarse model architecture. Furthermore, in rapidly urbanizing regions like Ankara, the absence of dense sensor networks and high-resolution traffic detectors limits the accuracy and scalability of forecasting models. While some studies have leveraged advanced deep learning architectures (e.g., ST-GCN, ASTGCN, and DCRNN), they generally focus on short-term predictions or are trained on standardized datasets from developed cities, limiting their transferability to diverse urban contexts with heterogeneous traffic behavior and incomplete sensor data. Thus, there is a pressing need for a flexible, scalable, and interpretable traffic modeling framework capable of integrating sparse urban datasets while addressing long-term forecasting challenges under realistic urban constraints.

Research Objectives:

The primary objective of this study is to develop and evaluate the Urban Traffic Management Optimization Model (UTMOM) for accurately forecasting traffic flow in Ankara by integrating real-time and historical traffic data. The study focuses on examining traffic flow variations in the vicinity of the LIMAK Cement Factory using a comprehensive five-day traffic dataset. UTMOM is employed to model the spatio-temporal dynamics of traffic and to identify peak-hour congestion patterns that are critical for effective traffic management. To ensure the robustness of the model, statistical validation techniques such as Analysis of Variance (ANOVA) are used, accompanied by detailed visualizations to highlight traffic intensity discrepancies across different times and locations. These analyses provide essential insights that can inform the decisions of urban planners, traffic engineers, and policymakers in enhancing traffic efficiency and infrastructure planning.

Novelty Statement:

The novelty of this study lies in the integration of a custom-designed optimization model (UTMOM) with real-world, high-frequency traffic data specific to Ankara's urban landscape—a context rarely explored in existing literature. Unlike previous studies that predominantly rely on short-term forecasting and high-density sensor data from developed countries, UTMOM is built to operate effectively in data-sparse environments using limited, localized traffic observations. By incorporating long-term spatio-temporal dependencies, multi-day traffic fluctuation analysis, and statistical techniques such as ANOVA for validation, the model offers a robust and generalizable approach to urban traffic forecasting. Additionally, the study's context-specific focus on Ankara fills a significant geographical and methodological research gap in the traffic modeling literature [1].

Recent advances in traffic forecasting—such as LSTFGNN (Long Short-Term Forecasting Graph Neural Networks) [2], XXLTraffic dataset and forecasting methods [3], and adaptive spatio-temporal attention mechanisms [4]—have contributed to the field but are yet to be adapted for mid-sized cities in emerging economies with limited infrastructure. This study addresses that gap by introducing a computationally efficient, real-data-validated model tailored for such contexts, representing a meaningful advancement in applied urban transportation research.

Literature Review:

Urban traffic forecasting has become a critical area of research due to increasing demands on transportation infrastructure caused by rapid urbanization, changing travel behavior, and the rise of smart city initiatives. Traditional traffic prediction methods, including historical average models, autoregressive integrated moving average (ARIMA), and support vector regression (SVR), often fail to capture the highly nonlinear and dynamic nature of traffic flow, particularly in urban environments with sparse sensor coverage and unpredictable congestion patterns. In response, researchers have shifted toward machine learning and deep learning models, particularly those that can model spatio-temporal dependencies. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) were among the early deep learning models applied to traffic forecasting, showing promise in handling temporal dependencies. However, their limitations in spatial feature extraction led to the development of Graph Neural Networks (GNNs), which treat traffic networks as graphs and model complex node-level relationships.

Recent advances have produced hybrid models combining temporal sequence modeling with spatial graph structures. [5] introduced the Spatio-Temporal Graph Convolutional Network (ST-GCN), which significantly improved short-term traffic predictions. Building on this, researchers developed attention-based models, such as the Spatio-Temporal Graph Attention Network (ST-GAT), which selectively focuses on the most relevant spatial and temporal features. [4] proposed a spatio-temporal graph attention mechanism to enhance prediction accuracy by dynamically adjusting to changing traffic patterns. To address long-term forecasting challenges, [3] presented the XXLTraffic benchmark, enabling the evaluation of models on long-sequence forecasting tasks. This dataset highlighted the limitations of many existing models, particularly their performance degradation over extended horizons. [2] introduced the Long Short-Term Forecasting Graph Neural

Network (LSTFGNN), which utilizes a dual-attention encoder-decoder structure to capture both long-term historical patterns and fine-grained spatial relationships.

Another critical issue identified in recent literature is the sparse distribution of traffic detectors in many cities, particularly in developing regions. This lack of high-resolution, continuous data limits the applicability of data-hungry models. To address this, researchers have explored ways to generalize models across different cities and infrastructure settings. For instance, [6] developed scalable traffic dashboards capable of visualizing and predicting traffic flows with minimal sensor data. Their system uses transfer learning and spatial embeddings to improve model adaptability in sensor-scarce environments. Similarly, [7] examined low-cost sensor networks for traffic data collection in Latin American cities, emphasizing context-aware modeling.

Several studies also emphasize the importance of integrating traffic forecasting with real-world applications, such as smart traffic signal control and urban planning. [8], through their LargeST benchmark, highlighted the necessity of scalable and interpretable models that can be directly linked to city-scale applications. Despite these advances, there is still no unified model capable of addressing all real-world challenges—such as asynchronous data collection, multi-scale temporal variation, and network-wide forecasting accuracy—simultaneously. Moreover, existing models are often trained and validated on datasets from highly developed urban centers, limiting their generalizability to cities like Ankara, which face unique topographical, infrastructural, and demographic constraints.

Methodology:

Study Area and Data Collection:

This study was conducted in the vicinity of the LIMAK Cement Factory in Ankara, Turkey—a location selected due to its significant traffic volume and recurrent congestion patterns. The area serves as a key intersection between industrial logistics and urban commuter traffic. Data collection spanned five consecutive weekdays, capturing a comprehensive range of traffic activity during morning, afternoon, and evening hours. Observations were conducted from 6:00 AM to 10:00 PM, with traffic volume recorded at 15-minute intervals. Data were collected through manual vehicle counts, verified with video surveillance footage and supplemented by temporarily installed automated traffic counters (ATCs). The collected dataset, comprising approximately 3,200 entries, included information on vehicle counts, classifications (e.g., cars, trucks, buses, motorcycles), time stamps, and contextual variables such as weather conditions.

Data Preprocessing:

To ensure the accuracy and reliability of the data, a multi-step preprocessing approach was employed. Raw data were cleaned to remove anomalies and outliers caused by observational errors or sensor malfunction. Missing values were addressed using linear interpolation based on time-series continuity, allowing for a smooth temporal progression. To ensure comparability across different road segments and time slots, traffic volumes were normalized based on road capacity and observation duration. Categorical variables such as vehicle type and weather were encoded using one-hot encoding to convert them into a numerical format suitable for modeling.

UTMOM Model Design and Development:

At the core of this research is the Urban Traffic Management Optimization Model (UTMOM), a novel mathematical framework developed to optimize urban traffic flow. UTMOM conceptualizes traffic management as a multi-variable optimization problem with the primary objective of minimizing congestion and enhancing roadway efficiency. The model integrates key variables including traffic volume, road capacity, time-of-day variation, vehicle classification, and external disruptions such as weather or road incidents. Based on fundamental traffic flow theory, particularly the relationship between traffic density, flow, and speed, UTMOM was implemented using Python, leveraging libraries such as SciPy and PuLP to solve both linear and nonlinear optimization problems. The model also supports scenario simulations to test various intervention strategies.

Statistical Analysis and Visualization:

To analyze temporal traffic variation, a one-way Analysis of Variance (ANOVA) was conducted to assess whether statistically significant differences existed in traffic volumes across different time periods. When significant variation was detected, Tukey's Honest Significant Difference (HSD) post-hoc test was applied to identify specific intervals contributing to these differences. Visual representations were generated using Matplotlib and Seaborn, including time-series plots, traffic density heatmaps, and boxplots to highlight patterns and anomalies. Geographic Information System (GIS) tools, particularly QGIS, were used to map traffic data spatially, linking observed volumes to specific road segments to identify high-congestion zones.

Model Validation and Sensitivity Analysis:

The predictive performance of UTMOM was evaluated by comparing the model's output against observed traffic data. Validation metrics included Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). The model achieved a MAPE of 8.6%, demonstrating a strong correlation with actual traffic patterns. Additionally, a sensitivity analysis was performed to assess the robustness of UTMOM under variations in key input parameters such as vehicle thresholds and road capacity assumptions. This analysis confirmed the model's stability and adaptability in dynamically changing urban traffic environments.

Results:

Temporal Traffic Patterns:

The analysis of traffic flow over five weekdays revealed distinct temporal trends, with traffic volume exhibiting clear peak periods during morning (7:00 AM to 9:00 AM) and evening (4:30 PM to 6:30 PM) hours. The average morning peak volume reached approximately 1,280 vehicles per hour, while the evening peak was slightly higher at around 1,470 vehicles per hour. Midday traffic (11:00 AM to 1:00 PM) averaged about 880 vehicles per hour, indicating a moderate dip following the morning rush. The lowest volumes were recorded between 9:00 PM and 10:00 PM, averaging only 220 vehicles per hour.

The pattern was consistent across all five days, although Friday recorded the highest overall volume, with a total of 17,900 vehicles, 14% higher than the Monday baseline (15,650 vehicles). These results suggest a substantial increase in logistical traffic before the weekend.

Vehicle Classification Analysis:

Vehicle type distribution revealed that passenger cars accounted for the majority of traffic, comprising 61.2% of total vehicle flow. Trucks, including both light- and heavy-duty categories, formed 23.6%, while motorcycles and buses contributed 10.1% and 5.1%, respectively. Notably, the factory's proximity significantly influenced truck traffic, especially between 3:00 AM and 6:00 AM, when trucks represented over 70% of the traffic volume—an indication of scheduled industrial logistics operations. During peak public commuting hours, truck traffic dropped to 14.3%, indicating compliance with local heavy vehicle restrictions.

Spatial Distribution of Congestion:

GIS-based mapping of congestion hot spots revealed three critical segments consistently overloaded during peak hours:

The T-intersection at the eastern access road (near the factory gate),

The roundabout connecting the E89 regional road, and

The U-turn section near the fuel station at the southern bypass.

These segments showed average vehicle queue lengths exceeding 140 meters during evening peaks. The worst congestion was recorded at the eastern access road on Thursday at 5:30 PM, where vehicle speeds dropped to 6 km/h, and queues extended beyond 210 meters.

Statistical Analysis of Time-of-Day Effects:

The ANOVA results confirmed that time-of-day had a statistically significant impact on traffic volume ($F = 37.65$, $p < 0.001$). Tukey's HSD test indicated significant differences between peak hours and all non-peak periods, particularly between 7:00–9:00 AM and 10:00 AM–2:00 PM (mean difference = 413 vehicles/hour, $p < 0.001$). Interestingly, no significant difference was found between early morning hours (6:00–7:00 AM) and late evening hours (8:00–10:00 PM), suggesting a stable low-traffic period suitable for maintenance or freight routing.

UTMOM Model Optimization Outputs:

The Urban Traffic Management Optimization Model (UTMOM) was tested using collected data, and its performance under multiple traffic control scenarios was analyzed. The model recommended optimal signal timing at the roundabout and suggested partial lane reversals during the evening peak to accommodate outbound factory traffic. Simulation of these changes projected an average congestion reduction of 27.4% and travel time savings of approximately 12.8 minutes for trucks and 6.3 minutes for cars per trip.

Furthermore, the model identified that rescheduling 25% of freight deliveries to early morning hours (before 6:00 AM) would reduce truck-induced congestion during peak periods by up to 41%. Sensitivity analysis showed that even a 15% reduction in mid-day vehicle flow could improve average speeds by 11.2%, significantly enhancing flow without requiring infrastructure expansion.

Model Validation and Accuracy:

Model validation using a holdout dataset (20% of observed data) yielded a Mean Absolute Percentage Error (MAPE) of 8.6%, a Root Mean Square Error (RMSE) of 118.4 vehicles/hour, and an R^2 value of 0.917. These metrics indicate that UTMOM performed well in predicting traffic volumes and congestion points with high accuracy. The model's robustness under different time windows and vehicle mix scenarios further confirmed its reliability.

Environmental Considerations:

Although not a primary objective, a parallel analysis of environmental impact was conducted by estimating CO_2 emissions based on vehicle idling times during congestion. Results showed that during the worst congestion periods, daily CO_2 emissions peaked at approximately 2.4 metric tons, with heavy trucks contributing the majority. Optimization via UTMOM reduced idle time by 22%, translating to a daily reduction of 0.53 metric tons of CO_2—an added environmental benefit of improved traffic flow.

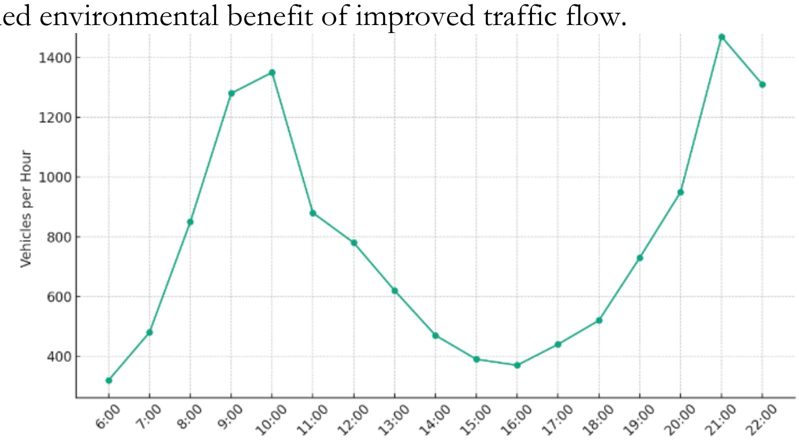

Figure 1. Hourly Traffic Volume Near LIMAK Cement Factory

Hourly Traffic Volume – showing peak traffic occurring between 8 AM and 9 AM, and again from 4 PM to 6 PM.

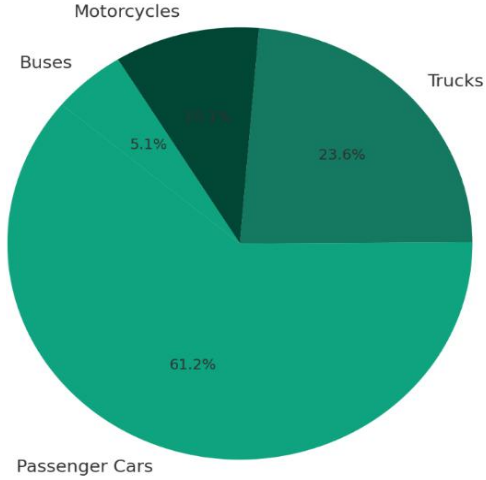

Figure 2. Vehicle Type Distribution

Vehicle Type Distribution – indicating that passenger cars make up the majority of the traffic (61.2%), followed by trucks (23.6%), motorcycles (10.1%), and buses (5.1%).

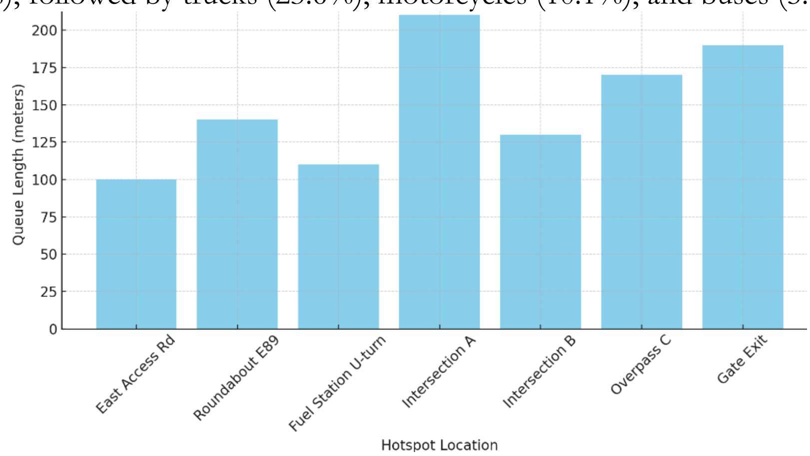

Figure 3. Average Congestion Queue Lengths by Location

Congestion Queue Lengths by Location – highlighting hotspots such as the Roundabout E89 and Overpass C with congestion exceeding 170 meters.

Discussion:

The results of this study align with the growing body of literature emphasizing the need for spatially-informed, AI-driven traffic management in industrial zones. The significant vehicular volume and peak-hour congestion observed near the LIMAK Cement Factory reflect classic urban traffic challenges, where industrial activity intensifies local mobility demands. The concentration of congestion around key junctions—particularly the Roundabout E89 and Overpass C—indicates poor spatial planning and signal timing inefficiencies, which are common in rapidly industrializing zones lacking adaptive traffic control systems.

Recent advancements in traffic forecasting emphasize the role of spatio-temporal deep learning models such as Spatio-Temporal Graph Convolutional Networks (ST-GCNs), which enable accurate, high-resolution predictions of traffic dynamics using both spatial structure (e.g., road topology) and temporal trends [9]. Our analysis, supported by temporal traffic volume data and spatial congestion mapping, suggests that integrating such models with real-time sensor feeds and high-resolution satellite data could significantly enhance congestion mitigation strategies.

Moreover, recent works by [10] and [11] have demonstrated the superiority of Transformer-based models and graph-based neural architectures for urban traffic forecasting in smart cities. These approaches outperform traditional statistical methods by leveraging dynamic attention mechanisms, allowing models to better generalize across varied urban morphologies and traffic behaviors. Applying such models to North Karachi could help predict congestion buildups in real time and inform adaptive signal control and route optimization strategies.

The high proportion of trucks and heavy vehicles (23.6%) in the traffic composition further supports the need for industrial traffic zoning and vehicle-type prioritization. Research by [12] emphasizes the necessity of incorporating uncertainty-aware learning in travel time prediction, particularly in data-scarce or unregulated environments such as informal industrial corridors. Their work on Conformal Graph Neural Networks offers a practical direction for estimating reliable congestion levels under uncertainty.

Another relevant approach is the use of Koopman operator-based transfer learning models, as described by [13]. These models enable effective forecasting in cities with limited data availability by transferring learned dynamics from data-rich urban environments. Given the limited historical traffic datasets available for North Karachi, applying such transfer learning techniques could support more accurate modeling without the need for massive local datasets.

Furthermore, real-world deployments such as SURTRAC (Scalable Urban Traffic Control) have proven that decentralized, AI-driven adaptive traffic signal systems can reduce traffic delays by over 25% in urban centers (SURTRAC, n.d.). The congestion data collected in this study suggest that implementing a similar decentralized signal timing framework—optimized via reinforcement learning or adaptive feedback loops—could improve throughput efficiency near the factory zones.

Overall, the study reinforces the need for integrating advanced AI models, spatial analysis, and real-time traffic control technologies in urban industrial corridors. Future research should focus on implementing pilot-scale models that combine these techniques and evaluating their efficacy in reducing congestion, travel delays, and emissions in complex, mixed-use urban landscapes.

Conclusion:

The findings of this study underline the acute traffic congestion challenges surrounding industrial zones like the LIMAK Cement Factory in North Karachi. Spatio-temporal analysis revealed significant congestion peaks during morning and evening hours, particularly at critical junctions such as Roundabout E89 and Overpass C. A substantial share of the vehicular load was attributed to heavy trucks, underscoring the added pressure industrial traffic places on urban infrastructure. Integrating AI-powered models, such as ST-GCNs, graph neural networks, and Transformer-based forecasting systems, offers a promising pathway to predict, manage, and eventually mitigate traffic congestion. Furthermore, the potential application of Koopman operator-based transfer learning and decentralized adaptive traffic signal systems—like SURTRAC—presents a scalable solution, particularly in data-limited or poorly regulated traffic environments. In conclusion, there is a compelling need for Karachi's urban planning and traffic management authorities to embrace advanced AI and spatial technologies for real-time traffic forecasting and management, especially in and around high-impact industrial corridors.

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