Towards Street-Level Traffic Analysis Using Waze Crowdsourced Data

Magdaléna Ondrušková, Jiří Hynek, Radek Burget

***Abstract*—Traffic congestion represents a global challenge, significantly impacting the quality of life for urban residents. As a result, one of the main goals for traffic engineers is to optimize urban traffic flow. Advances in technology have introduced new diverse sources of traffic data, such as IoT-based sensors, mobile network operators, and crowdsourced platforms like Waze and Google Maps. This paper uses crowdsourced data from the Waze navigation application, obtained through the Waze for Cities program, to associate traffic congestions and incidents with specific street segments. The methodology is demonstrated through a usage scenario in Brno, employing two Waze datasets—Traffic Congestion and Traffic Incidents—alongside a municipal street network dataset. The proposed approach systematically maps traffic events to street segments, offering a detailed and citywide perspective on traffic conditions. To illustrate the application of this method, traffic events, and congestion levels are visualized along a computed route between two distinct locations. The route is generated using an optimized A* algorithm, modified to enhance calculation speed and efficiency.**

***Index Terms*—Waze, Waze for Cities, Traffic analysis, Data processing, Route planning**

I. Introduction

Personal transportation plays a pivotal role in urban life, significantly influencing the quality of life for city residents. Current estimates indicate that 40% of the global population commutes at least one hour per day [1]. As of 2018, 55% of the world's population resides in urban areas—a proportion anticipated to increase to 68% by 2050. By mid-century, metropolitan regions are projected to house an additional 2.5 billion people due to the combined effects of global population growth and the ongoing migration of individuals from rural to urban areas, underscoring the growing importance of effective and sustainable urban transportation systems [2].

As urban populations grow and the demand for personal transportation increases, traffic congestion has become a pressing global challenge. Congestion, characterized by significant delays compared to free-flowing traffic [3], arises when the volume of vehicles exceeds the physical capacity of road infrastructure [4], [5]. The maximum throughput of a road—the greatest number of vehicles it can handle within a given timeframe—becomes a critical threshold. Once this capacity is surpassed, roads transform into bottlenecks. Contributing factors to such bottlenecks often include poorly designed intersections, frequent merging from secondary roads, and inadequately planned infrastructure [6].

Traffic incidents are another major contributor to traffic delays, often stemming from accidents, severe weather conditions, poorly timed traffic signals, or ongoing road maintenance and construction. Beyond disrupting regular traffic flow, such incidents can trigger behavioral adaptations, such as increased reliance on public transportation or route deviations during extreme weather events like snowstorms [6].

The implications of traffic congestion extend far beyond simple delays, posing significant challenges for urban environments.

One of the most serious effects is the rise in greenhouse gas emissions and worsening air pollution, both of which have major environmental and health impacts [7], [8]. Additionally, congestion increases the likelihood of accidents due to reckless or aggressive driving behaviors and contributes to heightened stress and anxiety among commuters [9]. Economically, traffic congestion reduces overall productivity by causing delays in goods and services delivery, including critical services such as emergency medical response, ultimately impairing urban economic performance [10].

Though a comprehensive solution is doubtful, there are several reducing techniques for traffic congestion. Promoting safer driving habits, such as avoiding actions that worsen traffic, such as improper overtaking or ignoring traffic signals, is one of these strategies [11]. Additionally, urban authorities can promote congestion-reducing practices like ridesharing and the installation of high-occupancy vehicle lanes for buses or automobiles carrying several people [12]. Other approaches include improving traffic management through infrastructure upgrades and restricted parking systems [13].

While increasing road capacity by adding more lanes may seem like a straightforward solution, it is often impractical and counterproductive. This approach typically leads to the phenomenon of induced demand, where the additional capacity attracts more vehicles, ultimately restoring or even worsening pre-existing traffic levels [13]. In expanding metropolitan areas, it is widely recognized that no number of lanes will suffice to eliminate congestion entirely. A notable example is the Katy Freeway expansion in Texas, which, despite becoming the world's widest highway, led to a 30% increase in morning and 55% in afternoon peak-hour commuting times within four years, exceeding pre-expansion levels [14]. Modern traffic engineering instead emphasizes advanced control systems to optimize existing infrastructure [15].

First submitted 31.1.2025.

This work was supported by project Smart information technology for a resilient society, FIT-S-23-8209, funded by Brno University of Technology.

Magdaléna Ondrušková is a doctoral student at Brno University of Technology, Brno, 612 00 Czechia (email: iondruskova@fit.vutbr.cz).

Jiří Hynek is with the Brno University of Technology (email: ihynek@fit.vutbr.cz).

Radek Burget is with the Brno University of Technology (email: burgetr@fit.vutbr.cz).

This paper utilizes crowdsourced data from the Waze navigation application to propose a methodological framework for improving urban traffic monitoring and management. The primary goal is to develop a method that links traffic events and congestion to specific street segments, providing a more detailed and actionable understanding of traffic patterns. To test the applicability of the proposed methodology, the Waze data are integrated with a municipal street network dataset, enabling precise mapping of traffic incidents to their corresponding road segments. This implementation validates the methodology and evaluates its potential for practical application in urban traffic management.

In collaboration with the Municipal office of Brno, the proposed methodology was applied in the city of Brno, aiming to assess its effectiveness in actual traffic conditions. The results are intended to support urban residents in navigating traffic more efficiently and assist municipal authorities in developing data-driven traffic management strategies, such as optimizing lane closures or adjusting traffic flow to reduce congestion.

II. Current Solutions

Traffic data can be obtained from multiple sources, including crowdsourced platforms like Google Maps [16], [17] and Waze [18], [19], data from mobile network operators [20] and municipal traffic monitoring systems [21]. One of the most widely used crowdsourced platforms, Waze, in their program Waze for Cities[1], provides detailed traffic data by collecting user-reported incidents and congestion levels in real-time. Case studies from Monaco and Joinville, highlight its effectiveness in improving traffic flow and public transportation. In Monaco[2], Waze data helped manage traffic for 40,000 daily commuters, reducing congestion and air pollution. In Joinville, targeted interventions based on Waze insights, such as constructing a roundabout, improved travel times, and pedestrian safety [22].

Once traffic data is obtained, it must be processed to extract meaningful urban planning and management insights. This processing can be performed at different levels, including entire streets or more granular road segments. By evaluating congestion trends over whole streets, this method is useful for broad urban planning and policy-making. Several papers [23], [24], [25] have employed this approach to detect citywide congestion hotspots and assess the overall efficiency of road networks. However, this method may overlook localized congestion patterns that occur within individual street sections.

More detailed methods based on road segments allow for a finer-grained understanding of congestion patterns and localized traffic dynamics. A study analyzing 45 cities examined traffic patterns using GPS-based road segments to improve data accuracy and congestion assessment [26]. Other research has ranked road segments based on traffic influence [27], identified high-risk accident zones using clustering techniques [28], and applied graph neural networks to improve travel speed predictions while reducing data collection costs [29].

[1]https://www.waze.com/wazeforcities

[2]https://www.waze.com/wazeforcities/casestudies/easing-Monaco-traffic-and-launching-real-time-messaging-for-drivers

Despite their advantages, both street-level and road-segment-based analyses have limitations. Commuters require traffic insights along entire routes rather than isolated street segments. Likewise, city planners benefit from understanding congestion patterns along key transit corridors rather than individual sections. Most current methodologies fail to bridge this gap, focusing either on broad citywide conditions or highly localized traffic patterns without considering full-route dynamics.

Finally, traffic visualization helps interpret complex mobility patterns and support decision-making. Geographic Information Systems (GIS), dashboards, and heatmaps are widely used to depict spatial and temporal trends [30]. Interactive tools like the Trafair Traffic Dashboard integrate real-time sensor data with simulation models, offering dynamic urban traffic insights [31]. Advanced frameworks apply predictive analytics to anticipate congestion and optimize planning [32].

One of the primary challenges is the seamless integration of visualization with larger traffic management frameworks. Many tools focus on specific aspects but lack a unified approach, limiting their ability to provide comprehensive, multi-layered insights [30]. Developing platforms that combine real-time data with interactive, multi-dimensional analysis is crucial for improving urban mobility strategies.

In summary, existing approaches to traffic data analysis provide valuable insights but often lack integration between citywide and route-based perspectives.

III. Requirements

Developing an effective traffic analysis system requires addressing several key challenges in existing navigation applications. While modern routing applications such as Google Maps and Waze excel at route selection, they typically lack transparency in their decision-making process and do not provide users with detailed traffic insights beyond immediate navigation. Most of these systems do not allow users to examine traffic conditions along specific streets or access historical traffic data, limiting their usefulness for long-term traffic planning and analysis. These shortcomings highlight the need for a system that not only integrates crowdsourced traffic data but also enables comprehensive citywide traffic monitoring and decision-making support.

To define the key requirements for an effective traffic analysis system, insights were gathered from the commuters and staff within Brno's data analysis and traffic management department. These requirements address the limitations of existing navigation applications and establish the foundation for a system capable of integrating and analyzing crowdsourced traffic data. The following points outline the essential criteria necessary to enhance urban mobility solutions:

1. *Historical Traffic Data Analysis.* In order to spot reoccurring trends and make appropriate plans, users need to be able to examine and evaluate past traffic data for particular streets and routes.

2. *Street Monitoring.* A citywide traffic analysis must include the capability to evaluate traffic conditions at the street level.
3. *Route Monitoring.* An effective traffic analysis system should comprehensively evaluate traffic conditions along selected routes. This capability is essential for assessing both historical and real-time congestion patterns, allowing commuters to make informed decisions and optimize travel planning.
4. *Critical Road Section Identification.* To support both commuters and urban planners, the system should be capable of identifying high-risk road segments characterized by frequent congestion or traffic incidents.
5. *System Accessibility and Usability.* An effective traffic analysis system should be designed for efficiency, scalability, and ease of use. It must support processing of large traffic datasets while remaining accessible to a broad range of users, ensuring practical applicability in diverse urban environments.

Finally, the solution must be scalable and flexible, allowing for implementation across multiple cities with minimal modification, provided the appropriate datasets are available

IV. Proposed Solution

The proposed method (Fig. 1) for urban traffic analysis integrates crowdsourced Waze data with a structured street network. Users can analyze traffic through two approaches: *Route-based analysis*, where a computed route between at least two points serves as a filtering tool to highlight relevant street segments, and *Street-based analysis*, where an entire street is selected directly. In both cases, the input is decomposed into individual street segments—road sections between two consecutive intersections. Traffic conditions are then analyzed per segment using Waze datasets, enabling a structured and scalable approach to congestion and incident detection.

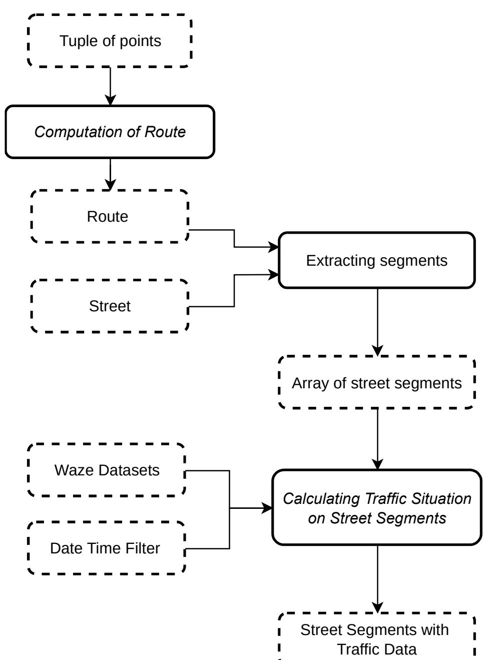

Fig.1: Simplified overview of proposed solution. The primary solution comprises of two methods: *Computation of the Route* and *Calculating Traffic Situation on Street Segments.*

Computation of Route

The route computation process serves as a preparatory step for traffic visualization. As illustrated in Fig. 2, the method involves optimizing the road network dataset before applying an A* algorithm to compute the shortest path. The figure outlines the key preprocessing steps that simplify the dataset while preserving essential connectivity. Before constructing the graph, the road network dataset underwent two key optimizations:

1. *Data Reduction.* The original road network, represented as MultiLineString objects, was decomposed into individual LineString segments. Only each segment's start and end points were retained, significantly reducing data complexity.
2. *Filtering Isolated Segments*. Road segments not connected to intersections were removed, eliminating dead-end streets and unmarked roads that do not contribute to significant traffic flow.

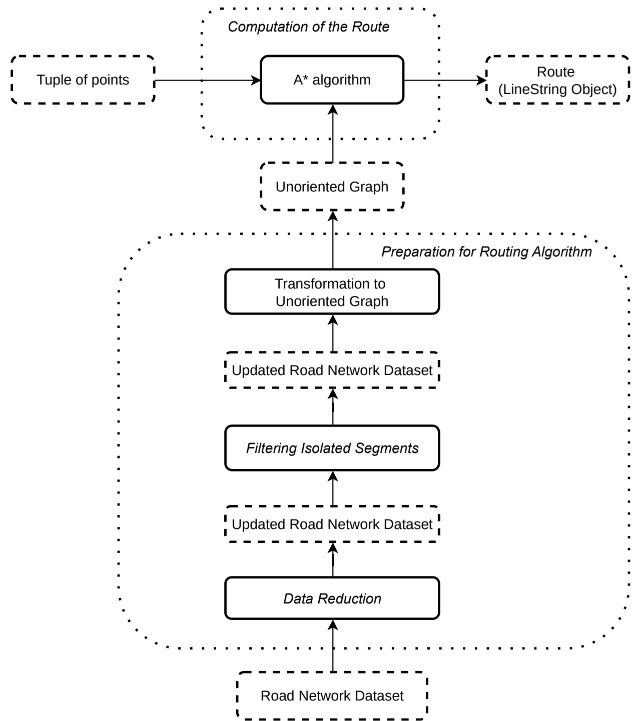

Fig.2: Schema illustrating the route calculation between two points (start point A, endpoint B). Schema also shows that optimization was applied to the road network dataset.

The A* algorithm was then applied to compute the shortest path, improving efficiency by dynamically expanding elliptical boundaries until a valid route was found. These optimizations significantly reduced computation time while ensuring accurate and reliable pathfinding.

Calculating Traffic Situation on Street Segments

Once a route is computed or a concrete street is selected, it must be mapped onto individual street segments to analyze traffic conditions effectively. Fig. 3 illustrates this process, showing how Waze datasets are integrated with the street segments, ensuring accurate assignment of traffic information.

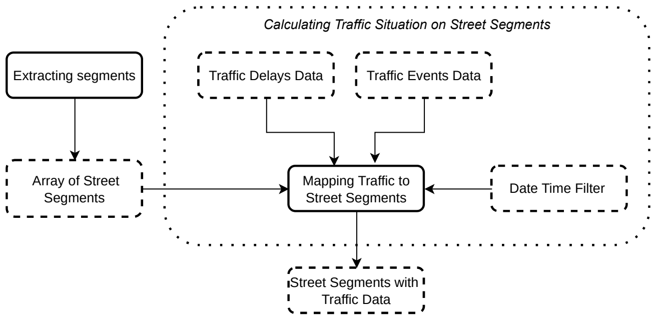

Fig.3: Schema showing the sequence of steps applied on array of street segments to assign corresponding traffic delays and traffic incidents from Waze datasets.

The input data is first represented as a single LineString object, whether a selected street or a computed route. To enable precise traffic analysis, this object is divided into street segments, defined as road sections between two consecutive intersections or crossroads. These segments form the basic units for assessing traffic conditions.

The traffic situation was determined through a two-step process, utilizing two Waze datasets and considering the selected start and end dates (DateTime window). These steps are described as follows:

1. *Traffic Incident Analysis:* User-reported traffic incidents, including accidents, road closures, weather hazards, etc., are mapped to their corresponding street segments.
2. *Traffic Congestion Analysis:* System-generated traffic delays were calculated for each street segment using congestion data, represented as a series of geolocated points that may span multiple segments. Since the starting and ending points of congestion often do not align with the start and end of street segments, a linear overlap method was employed to map each congestion instance to the affected segments accurately. This approach ensured that congestion events passing through intersections were assigned correctly, preventing erroneous attribution to all segments meeting at a crossroad.

To enhance clarity in visualization, a color-coded system[3] was developed to categorize traffic conditions along the route:

- Green (Low congestion). Minimal or no recurring congestion detected.
- Orange (Moderate congestion). Noticeable slowdowns, but traffic remains manageable.
- Red (High congestion). Frequent or severe congestion, indicating significant delays.

This classification helps users quickly assess road conditions. By presenting traffic data in this format, the system provides a clear and actionable overview of road conditions, supporting commuters and urban planners in making informed decisions.

V. USAGE SCENARIO: BRNO

Brno, the second-largest city in the Czech Republic, presents a complex traffic environment due to its mix of historical streets and modern road infrastructure. Key congestion points, such as Vídeňská and Jihlavská, frequently experience traffic bottlenecks. Brno offers a relevant environment for analyzing traffic delays and suggesting data-driven mobility solutions because of its approximately 400,000 residents and continuous infrastructure improvements. With its global user base exceeding 100 million active users as of 2018 [33], Waze is one of the most popular navigation applications worldwide. In Brno, around 6,000 users actively use Waze daily (2025, Wazestats[4]), generating valuable crowdsourced real-time data on traffic conditions.

This usage scenario leverages two key datasets from the Waze for Cities program:

- *Traffic Congestion Dataset:* This dataset captures real-time generated congestions, represented as geolocated points along roads. It provides a detailed view of traffic slowdowns and their intensity.
- *Traffic Incidents Dataset:* This dataset includes various traffic events, such as accidents, road closures, and hazards, reported by Waze users.

Both datasets cover a one-year period, ensuring sufficient data for traffic analysis. Each data point includes timestamps, geolocation, and other attributes.

The data was processed, cleaned, and prepared using Python with FastAPI framework, ensuring efficient handling of large datasets. The web application[5], built with TypeScript and React, retrieves data via an API from FastAPI, allowing for real-time traffic visualization and analysis. The system enables historical traffic data analysis (Requirement 1) by storing and processing long-term congestion and incident trends, helping to identify recurring patterns and critical areas.

To accurately assess traffic conditions, it is essential to compute efficient routes through the road network. Routes were calculated using the A* algorithm, ensuring reliable pathfinding across Brno's streets. As detailed in Section IV., the road network dataset was optimized in two steps (*Data Reduction* and *Filtering Isolated Segments*) to reduce computational complexity, as illustrated in Fig. 4. These enhancements significantly improved performance, reducing the average runtime to approximately 2.5 seconds after 250 test runs while maintaining accuracy.

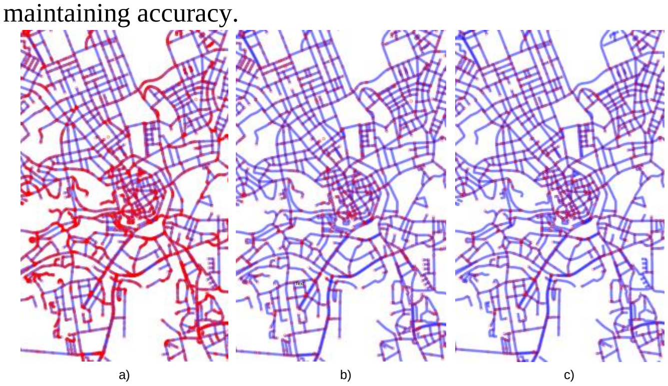

Fig.4: Optimization of the Brno road network for route calculation. The visualization illustrates preprocessing steps from the Proposed Solution chapter, Calculation of the Route section. (a) Shows the original unoriented road graph of Brno. (b) After Data Reduction. (c) After Filtering Isolated Segments.

[3] Based on consultations with a Brno city traffic engineer, specific thresholds were defined for each category. These values may vary across different cities.

[4] http://wazestats.com/

[5] https://magdalenaondruskova.github.io/waze-data-analysis/

Once the route was computed, route monitoring (Requirement 3) was achieved by mapping it onto individual street segments and enriching each segment with historical and real-time traffic data. This allowed users to analyze congestion and incident trends along their selected paths. Reported incidents were assigned to their respective segments, while congestion levels were classified as light, moderate, or severe using predefined thresholds. A linear overlap method ensured that congestion events spanning multiple segments were accurately mapped, preventing intersectional misattribution.

By providing a detailed, segment-level view of traffic conditions along computed routes, this approach enabled users to anticipate potential delays before travel. The effectiveness of this method is illustrated in Fig. 5, which visualizes congestion and incident data along a selected route.

Fig.5: Visualization of the computed route with traffic analysis from 1 Dec 2024 to 6 Jan 2025. Color-coded segments represent congestion levels, while traffic events are displayed as distinct icons. Events can also be grouped into clusters, with a numeric label indicating each cluster's total number of incidents.

Beyond individual route analysis, the methodology was extended to a citywide scale to enable street monitoring (Requirement 2) and the identification of critical road sections (Requirement 4). By applying congestion classification and incident clustering techniques, high-risk areas were detected based on the frequency and severity of reported disruptions. This approach allowed for a systematic evaluation of traffic conditions across the entire urban road network, highlighting persistent congestion hotspots and streets prone to frequent incidents. These insights are particularly valuable for long-term traffic planning, enabling data-driven decision-making for infrastructure improvements and congestion mitigation strategies. The aggregated results for the broader urban area are visualized in Fig. 6, demonstrating the scalability of the proposed method for full-city traffic assessment.

Fig.6: Citywide traffic analysis in Brno from 1 Dec 2024 to 6 Jan 2025. The visualization represents traffic conditions across the entire road network, incorporating congestion levels and incident reports collected throughout the city during the specified period.

The implementation of this approach in a web application ensures that a comprehensive data analysis tool is available to both commuters and urban planners (Requirement 5). The application lets users to interactively explore traffic conditions, filter data by periods, and identify congestion trends along specific routes or across the city. A dashboard was implemented to enhance further data interpretation, featuring visualizations of key traffic attributes through line charts, bar charts, and other graphical representations. This allows users to gain insights into traffic fluctuations, congestion severity, and incident distributions over time. With a user-friendly interface built in TypeScript with React and powered by an API developed in the FastAPI framework, the system provides a dynamic platform for real-time traffic analysis, making it a practical tool for decision-making in urban mobility management.

Traffic data from 1 Dec 2024 to 6 Jan 2025 was analyzed to evaluate the proposed method's effectiveness. The results revealed clear temporal patterns, with congestion peaking between 07:30–09:00 and 14:30–18:00. During this period, approximately 11,000 congestion events, 900 traffic accidents, and 5,000 hazards were recorded citywide. The most congested streets were Moravské náměstí, Veveří, and Dobrovského, while traffic incidents were most frequent on Vídeňská and Jihlavská. A notable decrease in congestion and incidents was observed from December 24–26, indicating reduced urban mobility during the holiday period. These findings demonstrate the method’s ability to capture seasonal traffic variations, providing valuable insights for urban traffic management.

VI. Discussion

This method demonstrated the effectiveness of integrating crowdsourced traffic data with structured road networks for urban mobility analysis. Unlike existing solutions that primarily focus on broad congestion trends, the proposed methodology offers both a route-specific perspective—analyzing traffic along computed paths and individual street segments—and a citywide perspective by enabling the evaluation of entire streets. Dynamically incorporating real-time and historical traffic data allows for precise congestion monitoring at multiple scales, from localized road sections to full urban corridors. This dual approach enhances situational awareness, providing commuters with live traffic assessments along selected routes while supporting urban planners in identifying persistent congestion patterns across the city. These capabilities make traffic management more responsive and data-driven, improving both short-term navigation and long-term infrastructure planning.

A key advantage over traditional systems is their ability to identify critical road sections based on actual travel patterns rather than generalized congestion zones. Additionally, the provided data analysis tools help traffic engineers evaluate congestion causes and measure the impact of interventions. Compared to infrastructure-heavy solutions that rely on fixed sensors and cameras, this approach is highly scalable, requiring only minimal modifications to be deployed in other cities.

However, certain limitations remain. The reliability of crowdsourced data depends on user density, meaning areas with fewer active Waze users may produce incomplete datasets. Additionally, external factors such as weather conditions, construction, and special events significantly influence traffic patterns but were not considered in this approach. Weather plays a crucial role in congestion, as heavy rain, snow, or fog can reduce visibility, slow down traffic, and increase accident risks. The absence of such factors may limit the accuracy of congestion assessments, particularly in dynamic urban environments.

Despite these challenges, the method establishes a strong foundation for further development, showcasing the potential of crowdsourced traffic data in urban mobility management. By bridging the gap between citywide monitoring and personalized route optimization, this methodology provides a cost-effective, adaptable solution for traffic analysis. Its ability to combine real-time insights with historical trends makes it a valuable tool for both short-term traffic adjustments and long-term infrastructure planning, ensuring cities can respond proactively to evolving transportation needs.

VII. Conclusion

This approach demonstrated the effectiveness of integrating crowdsourced Waze data with municipal street networks for detailed urban traffic analysis. The proposed methodology provides insights into mobility patterns by mapping traffic incidents and congestion to specific road segments, enhancing traffic monitoring and management. It improves real-time situational awareness for commuters while equipping urban planners with data-driven tools for optimizing infrastructure and mitigating congestion.

Applied to Brno, the method identified critical bottlenecks, particularly on Moravské náměstí, Veveří, and Dobrovského during peak hours. It also captured seasonal variations, such as reduced congestion during holidays, demonstrating its ability to reflect real-world traffic dynamics.

Future research could integrate additional contextual factors, such as weather conditions and police data, to enhance traffic monitoring and analysis. The scalability of this approach suggests its applicability to other urban environments, supporting more adaptive and data-driven traffic management strategies.

References

[1] J. Zhang, F.Y. Wang, K.Wang, W.H. Lin, X. Xu and C. Chen, "Data-Driven Intelligent Transportation Systems: A survey", *IEEE Transactions of Intelligent Transporation Systems*, pp. 1624-1639, 2011, doi: 10.1109/TITS.2011.2158001.

[2] UN, "World urbanization prospects: The 2018 revision", United Nations, 2019.

[3] Lomax, T., Turner, S., Shunk, G., Levinson, H.S., Pratt, R.H., Bay, P.N. and Douglas, G.B. (1997) Quantifying congestion, volume 1 & 2, NCHRP Report 398, Washington, DC: Transportation Research Board

[4] Rothenberg, M.J. (1985) Urban congestion in the United States-what does the future hold, ITE Journal, 55(7), 22-39.

[5] Weisbrod, G., Vary, D., and Treyz, G. Economic Implications of congestion, NCHRP Report 463, 2001, Washington, DC.: Transportation Research Board.

[6] M. Krzyzanowksi, B. Kuna Dibbert and J. Schneider, "Health effects of transport-related air pollution", WHO Regional Office Europe, 2005. ISBN 9789289013734.

[7] C. Systematics, "The Sources of Congestion and Unreliable Travel" *Traffic congestion and reliability solutions to problems*, United States, 2004, pp. 5-10.

[8] K. Zhang and S. Batterman, "Air pollution and health risks due to vehicle traffic", *Science of the total Environment.* Elsevier, 2013, pp. 307-316, doi: 10.1016/j.scitotenv.2013.01.074.

[9] J.A. Zubari, S. Idwan, S.A. Haider and D. Hurtgen, "Smart City Traffic Management for Reducing Congestion", *2022 IEEE 19th International conference on Smart Communities: Improving Quality of Life Using ICT, IoT and AI,* IEEE, 2022, doi: 10.1109/honet56683.2022.10018963.

[10] T. Afrin and N. Yodo, "A Survey of Road Traffic Congestion Measures Towards a Sustainable and Resilient Transportation System", Sustainability, 2020. ISSN 2071-1050.

[11] S. Fadare and B. Ayantoyinbo, "A study of the effects of road traffic congestion on freight movement in lagos metropolis" *European Journal of Social Sciences,* 2010, pp. 429-437.

[12] A. Bull and U. Nations, "Traffic Congestion: The Problem and how to Deal with it", *Economic Commission for Latin America and the Caribbean*, United Nations, 2003. ISBN 9789211214321.

[13] J. Speck, "Understand Induced Demand: Acknowledge that more lanes means more traffic." *Walkable City Rules: 101 Steps to Making Better Places*, pp 64-65, 2018. ISBN 978-1-61091-899-2.

[14] J. Cortright, "Reducing Congestion: Katy Didn't," City Observatory, 2015.

[15] C. Systematics, "Traffic congestion and reliability: Linking solutions to problems". United States, Federal Highway Administration, 2004.

[16] Shearston, Jenni, et al. "Acquisition and Analysis of Crowd-Sensed Traffic Data at Multiple Spatial Scales." *ISEE Conference Abstracts*. Vol. 2022. No. 1. 2022.

[17] Hilpert, Markus, et al. "Acquisition and analysis of crowd-sourced traffic data." in *arXiv preprint arXiv:2105.12235*, 2021.

[18] Hu, Songhua, et al. "Multi-crowdsourced data fusion for modeling link-level traffic resilience to adverse weather events." *International Journal of Disaster Risk Reduction*, 2024.

[19] Sandt, Adrian, et al. "Using crowdsourced data to reduce traffic congestion by improving detection of and response to disabled or abandoned vehicles on Florida limited-access facilities." *Transportation research record*, 2023, pp. 309-323.

[20] Medved, Damir, et al. "Evolution of data sources for integrated data-driven urban mobility management." *Transportation Research Procedia* 64, 2022, pp. 68-75.

[21] Genser, Alexander, et al. "An experimental urban case study with various data sources and a model for traffic estimation." in *Sensors* 22.1, 2021.

[22] Hiroki, Stella Marina Yurí. "Mobility, participation and data: the case study of Waze for Cities Data in Joinville (SC)." *urbe. Revista Brasileira de Gestão Urbana* 13, 2021.

[23] Liu, Feng, et al. "Citywide traffic analysis based on the combination of visual and analytic approaches." *Journal of Geovisualization and Spatial Analysis* 4, 2020, pp. 1-17.

[24] Alkaissi, Zainab Ahmed. "Traffic congestion evaluation of urban streets based on fuzzy inference system and GIS application." *Ain Shams Engineering Journal*, 2024.

[25] Jiang, Bin. "Street hierarchies: a minority of streets account for a majority of traffic flow." *International Journal of Geographical Information Science*, 2009, pp. 1033-1048.

[26] Verendel, Vilhelm, and Sonia Yeh. "Measuring traffic in cities through a large-scale online platform." *Journal of Big Data Analytics in Transportation* 1, 2019, pp. 161-173.

[27] Anwar, Tarique, et al. "Influence ranking of road segments in urban road traffic networks." *Computing* 102, 2020, pp. 2333-2360.

[28] Košanin, Ivan, et al. "A clustering-based approach to detecting critical traffic road segments in urban areas." *Axioms,* 2023.

[29] Ru, Xiaolei, et al. "Critical segments identification for link travel speed prediction in urban road network." *Journal of Advanced Transportation*, 2020.

[30] Chen, Wei, Fangzhou Guo, and Fei-Yue Wang. "A survey of traffic data visualization." *IEEE Transactions on intelligent transportation systems*, 2015, pp. 2970-2984

[31] Bachechi, Chiara, Laura Po, and Federica Rollo. "Big data analytics and visualization in traffic monitoring." *Big Data Research*, 2022.

[32] Picozzi, Matteo, et al. "Traffic visualization-applying information visualization techniques to enhance traffic planning." *GRAPP 2013 IVAPP 2013-Proceedings of the International Conference on Computer Graphics Theory and Applications and International Conference on Information Visualization Theory and Applications*. SciTePress, 2013.

[33] Goodall, Noah, and Eun Lee. "Comparison of Waze crash and disabled vehicle records with video ground truth." *Transportation research interdisciplinary perspectives* 1, 2019.