USING AI TOOLS TO MODEL PASSENGER FLOW IN PUBLIC TRANSPORT

Jaroslaw Senko[1], Mikolaj Szyca[1], Przemyslaw Rumianek[1], Maciej Jurewicz[2]
[1]Warsaw University of Technology, Poland;
[2]Warsaw University of Life Sciences, Poland
jaroslaw.senko@pw.edu.pl, mikolaj.szyca.dokt@pw.edu.pl,
przemyslaw.rumianek@pw.edu.pl, maciej_jurewicz@sggw.edu.pl

Abstract. Effective management of public transport requires matching vehicle availability to passenger flows. Public transport needs vary depending on the time of day, day of the week, and season. Therefore, there is a need for continuous automated monitoring of the availability of transport and for the active adjustment of public transport availability in the context of current or one-off events. In this study, the authors present a methodology for monitoring passenger flows based on APC (Automatic Passenger Counting). The process of passengers boarding and alighting from trams was recorded using video cameras installed at stops. The recorded image was processed using a YOLO (You Only Look Once) classifier. Unlike solutions based solely on passenger counting, the developed classifier enables temporal and spatial analysis of the passenger exchange process, which is crucial for capacity studies. Using our own recordings of passenger flow between the tram and the stop, we developed and verified software that enables semi-automatic analysis of passenger movement both inside vehicles and in their immediate surroundings (door area, platform, stop). The ability to conduct analyses in real operating conditions, without interfering with the vehicle infrastructure, is an alternative to costly measurement systems. The use of AI algorithms to monitor passenger movement at the individual user level also enables a detailed study of behavior during boarding and alighting. Passenger flow studies conducted using CFD simulations show that non-compliant behavior (e.g., boarding before disembarking is complete) significantly increases transaction time, especially during rush hour. The use of CFD simulations to extend the study of passenger flow dynamics allows for the design of tram entrance spaces that more effectively manage passenger flow.

Keywords: public transport; passenger flow, artificial intelligence, YOLO.

Introduction

Monitoring passenger flow in public transportation has long been a key area of interest for public transit planners and operators. The traditional approach focused on aligning transport capacity with demand for public transit services, which required analyses of passenger flows at both the network and route levels [1-3]. This led to the optimization of schedules, fleet size, and vehicle frequency, particularly in highly urbanized areas [4-7].

Over time, issues related to service provision costs began to play an increasingly important role, including the efficient use of the fleet, reducing empty runs, and minimizing operating costs while maintaining an acceptable level of service quality [4; 8-10]. Research on the quality of sustainable urban transport shows that well-organized public transport directly affects residents' quality of life and perceptions of urban space [11-13].

In recent years, amid growing safety requirements and the need for resilient transport systems, the need for more detailed monitoring and identification of public transport users has come to the fore, for both operational and safety reasons [14-16]. Precise tracking of passenger flows is becoming a tool that supports not only transport planning but also the design of stop infrastructure and vehicles [17-19].

A particularly important area of analysis is the flow of passengers through the doors of public transport vehicles, such as trams and buses (Fig.1). Information on the number and dynamics of boarding and alighting passengers is of direct relevance to engineers designing vehicle interiors, including seat layouts, handrails, and standing areas, as well as to operators responsible for organizing passenger exchange at stops [20-22]. Smooth boarding and alighting depend, among other things, on the width and design of the doors, the way they open, and passenger movement patterns inside the vehicle; local crowding near the doors leads to longer stop times, reduced throughput, and decreased travel comfort [23-25].

The way passengers move inside a tram shows significant similarity to fluid flow in channels with variable cross-sections, featuring local constrictions and obstacles. It has been repeatedly demonstrated in the literature that pedestrian flows exhibit phenomena analogous to saturated flows, bottlenecks, and local congestion, which depend on the door width and the geometry of passageways [2; 23]. Recognizing this analogy, two-dimensional fluid flow can be used as a model for passenger flow inside a vehicle, particularly in the area around doors and adjacent passageways, and CFD analysis of such flow allows for the identification of areas with increased "flow resistance," local congestion, and zones particularly sensitive to increases in passenger flow density [26; 27].

Fig. 1. **Example of how the proprietary object classifier works – doors of rail vehicles**

A prerequisite for reliable modelling of passenger movement in a CFD model is the proper definition of boundary conditions, particularly the rates of passenger entry and exit and their temporal distribution. This requires access to reliable data on door flow rates over time, accounting for variable geometric and operational conditions [2; 28; 29]. Currently used passenger counting systems are most often based on two types of solutions: sensors detecting movement in the door area (e.g., infrared barriers, 3D sensors) and video monitoring systems with automatic image processing, with the latter – supported by AI tools – showing the greatest potential for development [30; 31].

The study aimed to develop and validate an approach to modeling and analyzing the functioning of a smart city using data and simulation tools. Particular attention was paid to one of the key urban areas, namely mobility and service infrastructure. The authors developed a methodology for integrating data from various sources, including sensors, urban systems, and historical data. This data is then used to build a model reflecting the actual processes occurring in the city [7; 32].

The article assumes that user behavior and the dynamics of the urban system can be mapped using appropriate algorithms and simulation scenarios. This approach enables the analysis of various variants of the transportation system's operation and the assessment of their effectiveness. A key element of the study is a case study in which the proposed methodology was applied to a specific urban problem. This allowed for the identification of limitations in existing solutions and potential areas for improvement.

The authors emphasize that the quality of the input data and the proper selection of model parameters are key. The results obtained can support decision-makers in planning and optimizing urban transport operations using artificial intelligence tools [33].

AI tools in passenger flow analysis

The development of intelligent transportation systems has led to the widespread use of artificial intelligence tools – particularly deep learning and image analysis methods – in monitoring passenger traffic in public transportation [26; 34]. The literature increasingly features studies on automatic passenger counting, short-term passenger flow prediction, and traffic flow reconstruction based on data from APC and AFC systems as well as video recordings [3; 27; 29; 35].

Typical image-based solutions use object detection models from the YOLO family or related methods, combined with multi-object tracking algorithms, enabling the simultaneous detection of passengers, assignment of identifiers, and recording of their trajectories as they pass through the door zone [24; 25; 30]. In parallel, deep learning models are being developed to predict passenger flows at the network level, based on LSTMs, convolutional networks, or graph models that integrate data from multiple sources [27; 31].

In the context of designing doors and entrance areas, studies of saturated flows are particularly important for understanding the relationships among door throughput, door width, entrance geometry, and local spatial conditions, such as the location of handrails or the presence of obstacles [2; 22; 23; 35]. The integration of AI methods with classical pedestrian flow models and CFD analysis allows for a shift from a purely aggregate description of “passenger numbers” to a description of trajectories and traffic density in time and space, which is of significant importance for studies of throughput and travel comfort [2; 23; 26].

The research conducted by the authors aligns with these global trends, bridging the gap between classical macro-scale demand models and micro-scale descriptions of actual passenger behavior in direct contact with station infrastructure and the vehicle interior. Of particular importance is the combination of empirical measurements, AI-based image analysis, and numerical modeling analogous to fluid flow, which enables not only passenger counting but also a quantitative description of the passenger exchange process [22; 23; 27].

YOLO model for detecting doors and passengers

The first key component of the developed solution is an object classifier based on the YOLO algorithm, trained to automatically recognize public vehicle doors and passengers in video surveillance footage (Fig.2). Models from the YOLO family are widely used for near-real-time object detection, making them particularly useful in transportation applications where both processing speed and object localization accuracy are critical [2; 26; 30].

The proposed approach accounts for the simultaneous detection of doors and passengers, treating doors as reference areas that define the boarding and alighting zones. This allows for unambiguous assignment of passenger trajectories to a specific door zone and the subsequent correlation of their movement with vehicle design parameters and conditions at the stop [22; 23; 35].

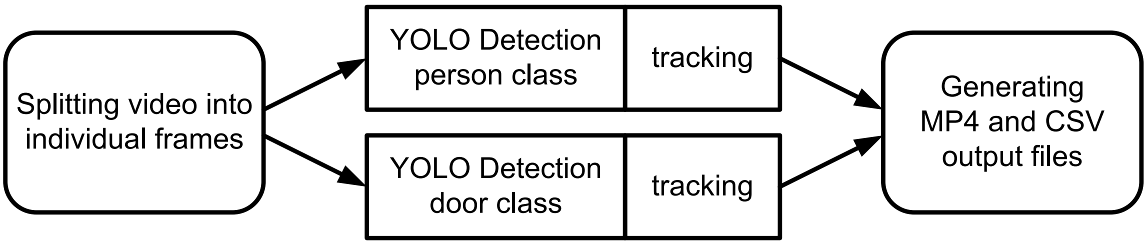

Fig. 2. **Diagram of the object classifier and object tracking system**

The collected dataset comprised tens of thousands of images with annotations regarding doors and passengers, divided into training, validation, and test subsets, which is consistent with the practice in building deep learning models for object detection in transportation [27; 30]. The obtained quality metrics, including detection error matrices for doors and people (Fig. 3), confirm the possibility of reliably applying the classifier to analyze passenger flow under varied lighting conditions and with varying vehicle occupancy.

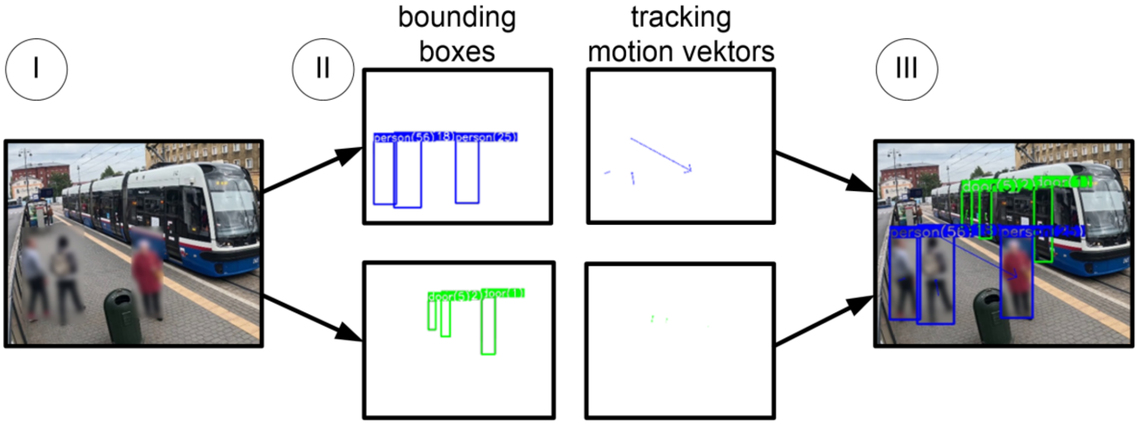

Fig. 3. **Graphical representation of how the object classifier and position tracking work**

The detection module built in this way serves as the basis for further data processing – in particular, for tracking passenger movement over time and identifying the start and end times of boarding and alighting processes. This enables a transition from simply counting passengers to a more comprehensive description of the passenger exchange process, accounting for duration, direction of movement, and local crowding [2; 3; 27].

Semi-automated analysis of passenger flows

Based on the developed (Fig.4) classifier, software was created to enable semi-automated analysis of passenger flows in urban spaces. This solution is part of a trend toward using video data and AI tools to monitor pedestrian and passenger traffic at stations, stops, and transfer hubs [20, 25, 35, 36].

The analysis algorithm flowchart includes: loading video recordings, detecting doors and passengers using the YOLO model, tracking object trajectories over time, defining virtual counting cross-sections, and calculating quantitative metrics such as the flow rate, the number of passengers entering and exiting, and door crossing times. Similar concepts are used in predictive models based on APC/AFC data, where the correct reconstruction of the spatiotemporal distribution of traffic loads is of key importance [21, 29, 31].

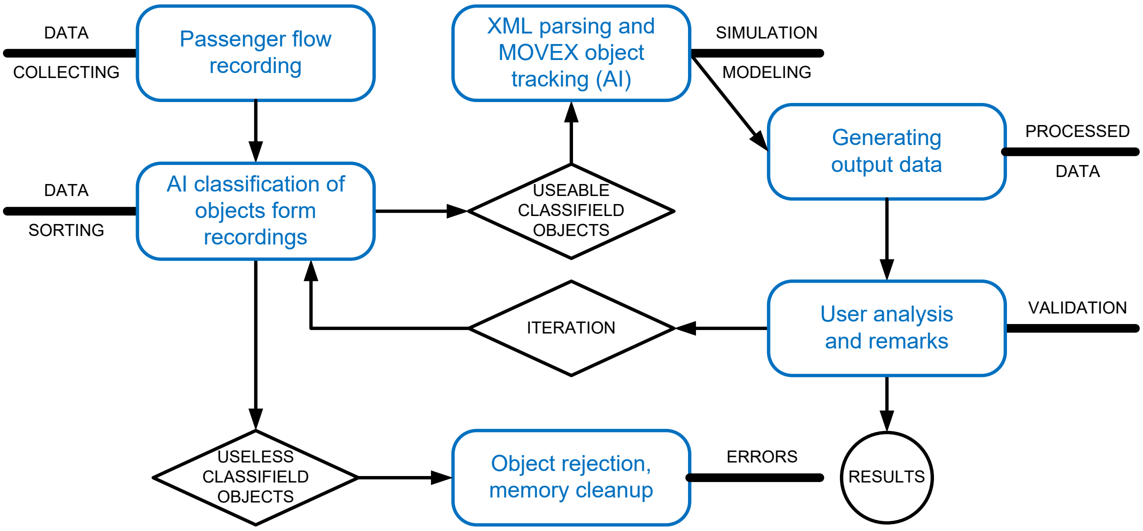

Fig. 4. **Flowchart of the passenger flow analysis algorithm**

A significant advantage of the proposed approach is the ability to conduct analyses under real-world operating conditions without modifying the vehicle's design or installing additional sensors above the doors (Fig.5). The use of existing monitoring systems as measurement tools aligns with trends in intelligent transportation systems, where the goal is to maximize the use of available infrastructure and data [10; 26; 34].

Fig. 5. **Sample screenshot of the counting app in action**

Sample application screens that integrate a video preview with an analytical layer (trajectories, object identifiers, counting results) enable verification of algorithm performance and facilitate interpretation of results by transportation engineers and vehicle designers. Such visual feedback is particularly useful in analyzing boundary conditions, such as saturated flows or local congestion at doors [2; 23; 24].

Passenger traffic results

The application of the developed AI tools to the analysis of real-world recordings enabled verification of several simplifications commonly used in modeling boarding and alighting processes. The results confirmed that the simple, linear relationship between dwell time and the number of boarding and alighting passengers – often assumed in macroscale models – does not fully reflect the system's behavior under conditions of high occupancy and heterogeneous passenger distribution [2; 3; 20; 21].

Analysis of video footage, covering various geometric configurations of vehicles and stops, revealed phenomena analogous to those in fluid mechanics: local congestion, traffic "vortices," heightened sensitivity to minor disturbances, and a significant impact of minor geometric changes on the overall capacity of the door zone. These phenomena are consistent with observations from laboratory studies of pedestrian flows and agent-based simulations of mixed-use systems [2; 23; 24].

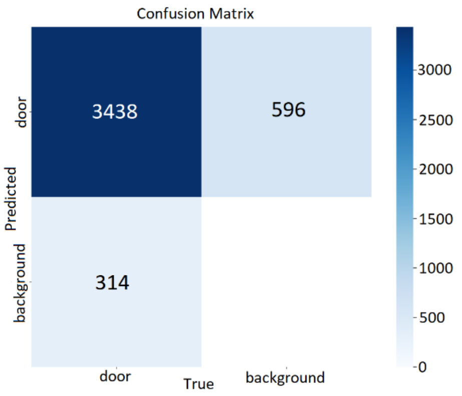

Fig. 6. **Tram door detection model - Door detection error matrix**

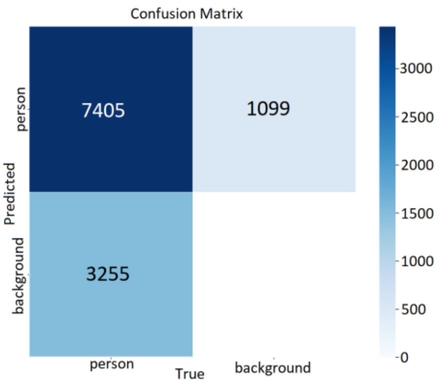

Fig. 7. **Person detection model - Human detection error matrix**

Further data processing allowed us to determine the door (Fig.6) and passenger (Fig.7) detection error matrices and basic classifier quality metrics, which is standard practice in evaluating object detection models used for engineering purposes [2, 23, 24]. The obtained door and passenger detection accuracy values enable the practical use of the system for acquiring input data for numerical passenger flow models and door throughput analysis.

Table 1

Quantitative data from the tram door and passenger detection model for the selected dataset

Parameter	Tram door detection model	Passenger detection model
Training collection	23 031 images with annotations	17 401 images with annotations
Set partitioning	82% training data, 17% validation data, and 1% test data	87% training data, 12% validation data, and 1% test data
Accuracy	70%	62%

These results serve as a starting point for further research on passenger flow modeling using analogies to fluid flows, including CFD simulations, in which passengers are treated as fluid particles in a channel with a variable cross-section. Combining empirical data (trajectories, intensities, densities) with numerical models enables the qualitative and quantitative verification of passenger flow behavior across various vehicle and stop geometry configurations, as well as the comparison of alternative design solutions [23; 26; 27].

Conclusions

The approach presented in this article combines artificial intelligence tools for image analysis with the concept of modeling passenger flow by analogy with fluid flow, thereby enabling a more detailed and operationally useful description of boarding and alighting processes in public transportation than traditional APC-based methods offer. The developed YOLO classifier, integrated with an object-tracking module and quantitative analysis, enables semi-automatic collection of passenger flow data under real-world operating conditions without interfering with the vehicle's design, using only existing monitoring infrastructure. Compared with commonly used counting solutions, the proposed method provides not only aggregated passenger numbers but also time-resolved trajectories and local densities in the door zone, which are directly usable as input data for capacity analyses and CFD models.

Based on the analyses conducted, it was demonstrated that the geometry of the doors and their surroundings – including width, opening mechanism, and the placement of handrails and corridor narrowings – has a significant impact on passenger flow capacity and stability, particularly under high-demand conditions. The results indicate that specific geometric configurations and behavior patterns (e.g., simultaneous boarding and alighting) can lead to local congestion, increased dwell time, and reduced operational robustness, consistent with observations from experimental studies and agent-based simulations and confirmed under real operating conditions in actual tram services. This strengthens the practical applicability of the findings for vehicle interior design and the reconfiguration of door areas in existing rolling stock.

At the same time, the study has several limitations that should be considered when interpreting the results. The analyses were conducted on a limited number of vehicles and stop configurations in a single urban context, limiting the direct transferability of the conclusions to other transport systems and vehicle types. The detection accuracy of current YOLO-based models, while sufficient for engineering applications, still leaves room for improvement, especially under strong occlusion, extreme lighting variation, and very high occupancy. In addition, the CFD model presented is based on a simplified analogy between pedestrians and fluid particles, which does not fully capture individual behavioral differences or passengers' adaptive strategies.

Despite these limitations, the proposed methodology can serve as a practical tool to support vehicle interior design, door-zone optimization, and timetable planning while accounting for the actual dynamics of passenger exchange, rather than relying solely on static assumptions or aggregate demand indicators. Future research should focus on extending the dataset to include different vehicle types, cities, and cultural contexts, improving detection and tracking algorithms (e.g., through multi-camera fusion or 3D methods), and coupling the image-based measurements with more advanced microscopic crowd models. An important direction of development is also the integration of the presented tools with real-time decision-support systems for operators, enabling dynamic adjustment of service parameters (e.g., dwell time control, door usage strategies) in response to current passenger flow conditions, as well as the systematic validation of design variants for new vehicles and stop layouts at the planning stage.

Acknowledgement

This research was fully funded by the National Science Centre under project number 2023/49/N/ST8/03737.

Author contributions

All authors contributed equally to this work. All authors have read and agreed to the published version of the manuscript.

References

[1] Podolski J., Transport w miastach, WKiŁ, Warszawa, 1985.

[2] Zhai H., Cui L., Nie Y., Xu X., Zhang W., A comprehensive comparative analysis of the basic theory of the short term bus passenger flow prediction, Symmetry, 10, 2018, pp. 369.

[3] Baghbani A., Bouguila N., Patterson Z., Short-term passenger flow prediction using a bus network graph convolutional long short-term memory neural network model, Transp. Res. Rec., 2677, 2023, pp. 1331-1340.

[4] Tomczak U., Mielczarek L., Two-level structure for tram and road traffic in the centre of city - Lodz in Poland, Procedia Eng., 142, 2016, pp. 574-581.

[5] Kagramanian A., Aulin D., Trubchaninova K., Caban J., Voronin A., Basov A., Perspectives of multifunctional integrated suburban-urban rail transport development, Sci. J. Silesian Univ. Technol. Ser. Transp., 120, 2023, pp. 105-115.

[6] Gnap J., Dydkowski G., Ondruš J., Synák F., Tariff systems and distance measurement of public passenger transport stops, Commun. Sci. Lett. Univ. Žilina, 25(1), 2023, pp. A26-A39.

[7] Ližbetin J., Pečman J., Hanzl J., Stopka O., Modeling the intelligent transport systems elements functionality testing plan: a case study, Commun. Sci. Lett. Univ. Žilina, 24(4), 2022, pp. F97-F108.

[8] Caban J., A study of eco-driving possibilities in passenger car used in urban traffic, Arch. Automot. Eng. - Arch. Motoryz., 91(1), 2021, pp. 37-48.

[9] Stopka O., Stopkova M., Rybicka I., Gross P., Jeřábek K., Use of activity-based costing approach for cost management in a railway transport enterprise, Sci. J. Silesian Univ. Technol. Ser. Transp., 111, 2021, pp. 151-160.

[10] Caban J., Droździel P., Stoma M., Dudziak A., Vrábel J., Stopka O., Road traffic safety in Poland, Slovakia, and Czech Republic - statistical analysis, in: 2020 XII International Science-Technical Conference Automotive Safety, 2020, pp. 1-7.

[11] Mickiewicz P., Radecka K., Urban transport quality in terms of sustainable development, in: Economic Science for Rural Development 2019, 2019, pp. 185-191.

[12] Szopińska K., Sustainable urban transport and the level of road noise - a case study of the city of Bydgoszcz, Geomatics Environ. Eng., 13(4), 2019, pp. 93-104.

[13] Skorupa J., Toader C.S., Kryszak L., The impact of transport investment on the quality of life for citizens of Bydgoszcz, Lucrari Stiintifice Univ. Stiinte Agric. Med. Vet. Banat Timisoara Ser. I Manag. Agricol, 22(3), 2020, pp. 243-249.

[14] Mamcarz P., Drozdziel P., Gzik A., Rybicka I., Drozdziel P., Characteristics of urban transport users and their level of satisfaction with transport services, Transp. Res. Procedia, 74, 2023, pp. 371-378.

[15] Son T.H., Weedon Z., Yigitcanlar T., Sanchez T., Corchado J.M., Mehmood R., Algorithmic urban planning for smart and sustainable development, Sustain. Cities Soc., 94, 2023, pp. 105562.

[16] Simović S., Ivanišević T., Bradić B., Čičević S., Trifunović A., What causes changes in passenger behavior in South-East Europe during the COVID-19 pandemic?, Sustainability, 13(15), 2021, pp. 8398.

[17] Gnap J., Dydkowski G., Urbanek A., The experience economy in the systems of urban and regional transport, Commun. Sci. Lett. Univ. Žilina, 26(1), 2024, pp. A22-A36.

[18] L'upták V., Pecman J., Assessment of the quality of connections on the rail transport network: a case study, in: Transport Means - Proceedings of the International Conference, 2021, pp. 842-846.

[19] Hurtová I., Sejkorová M., Verner J., Experience operating a trolleybus equipped with traction batteries nLTO, in: Transport Means - Proceedings of the International Conference, 2017, pp. 242-247.

[20] Guo J., Xie Z., Li Q., Zhan S., Xu J., Railway passenger flow recognition algorithm for terminal station based on cost theory and automatic frequency control, IEEE Access, 8, 2020, pp. 26885-26892.

[21] Zhou C., Dai P., Li R., The passenger demand prediction model on bus networks, in: IEEE 13th International Conference on Data Mining Workshops, 2013, pp. 1069-1076.

[22] Sołtysiak A., Migawa K., Sołtysiak R., Maćkowiak P., Time to replace passengers at bus stations in Bydgoszcz, Autobusy Tech. Eksploat. Syst. Transp., 6, 2017, pp. 1078-1083.

[23] Fujii H., Uchida H., Yoshimura S., Agent-based simulation framework for mixed traffic of cars, pedestrians and trams, Transp. Res. Part C Emerg. Technol., 85, 2017, pp. 234-248.

[24] Tang T., Fonzone A., Liu R., Zhu X., Multi-stage deep learning approaches to predict boarding behavior of bus passengers, Sustain. Cities Soc., 69, 2021, pp. 103111.

[25] Zou L., Hu S., Zhu L., Calculation of walking time in metro stations considering the impact of passenger flows based on AFC data, Sustainability, 15, 2023, pp. 6660.

[26] Małek A., Caban J., Dudziak A., Marciniak A., Vrábel J., The concept of determining route signatures in urban and extra-urban driving conditions using artificial intelligence methods, Machines, 11, 2023, pp. 575.

[27] Du B., Peng H., Wang S., Bhuiyan M.Z.A., Wang L., Gong Q. et al., Deep irregular convolutional residual LSTM for urban traffic passenger flows prediction, IEEE Trans. Intell. Transp. Syst., 21, 2020, pp. 972-985.

[28] Ravensbergen L., Van Liefferinge M., Isabella J., Zhang M., El-Geneidy A., Accessibility by public transport for older adults: A systematic review, J. Transp. Geogr., 103, 2022, pp. 103408.

[29] Zhao S.Z., Ni T.H., Wang Y., Gao X.T., A new approach to the prediction of passenger flow in a transit system, Comput. Math. Appl., 61, 2011, pp. 1968-1974.

[30] Pekel E., Soner Kara S., Passenger flow prediction based on newly adopted algorithms, Appl. Artif. Intell., 31, 2017, pp. 64-79.

[31] Wang P., Chen X., Chen J., Hua M., Pu Z., A two-stage method for bus passenger load prediction using automatic passenger counting data, IET Intell. Transp. Syst., 15, 2021, pp. 248-260.

[32] Kalašová A., Čulík K., The micromobility tendencies of people and their transport behavior, Appl. Sci., 13(19), 2023, pp. 10559.

[33] Özuysal M., Tayfur G., Tanyel S., Passenger flows estimation of light rail transit (LRT) system in Izmir, Turkey using multiple regression and ANN methods, Promet Traffic Transp., 24, 2012, pp. 1-14.

[34] Bi L., Zhou S., Ke J., Song X., Knowledge-mapping analysis of urban sustainable transportation using CiteSpace, Sustainability, 15, 2023, pp. 958.

[35] Samaras P., Fachantidis A., Tsoumakas G., Vlahavas I., A prediction model of passenger demand using AVL and APC data from a bus fleet, in: 19th Panhellenic Conference on Informatics, 2015, pp. 129-134.

[36] Petrouš M., Suzdaleva E., Nagy I., Modeling of passenger demand using mixture of Poisson components, in: 16th International Conference on Informatics in Control, Automation and Robotics, 2019, pp. 617-624.

[37] Wei Y., Chen M.C., Forecasting the short-term metro passenger flow with empirical mode decomposition and neural networks, Transp. Res. Part C, 21, 2012, pp. 148-162.