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АНАЛІЗ МЕТОДІВ ПРОГНОЗУВАННЯ РУХУ МІСЬКОГО ГРОМАДСЬКОГО ТРАНСПОРТУ

У статті розглянуто проблему прогнозування руху міського громадського транспорту в умовах зростання мобільності населення, підвищення інтенсивності транспортних потоків та розвитку інтелектуальних транспортних систем. Актуальність дослідження зумовлена необхідністю підвищення точності прогнозування часу прибуття транспорту на зупинку, часу руху між зупинками, інтервалів руху та завантаженості транспортних засобів для покращення якості транспортного обслуговування населення.

Метою роботи є аналіз сучасних методів прогнозування руху міського громадського транспорту, визначення їх переваг і недоліків, а також оцінка перспективних напрямів розвитку систем прогнозування в умовах динамічного міського середовища. Особлива увага приділяється можливості застосування різних підходів залежно від доступності даних, обчислювальних ресурсів та особливостей транспортної інфраструктури.

У роботі проаналізовано статистичні методи прогнозування, зокрема моделі часових рядів, регресійний аналіз, метод ковзного середнього, ARIMA та SARIMA-моделі. Показано, що ці підходи залишаються ефективними для короткострокового прогнозування у відносно стабільних транспортних системах завдяки простоті реалізації, швидкості обчислень і зрозумілій математичній інтерпретації, проте мають обмеження у врахуванні нелінійних залежностей і впливу зовнішніх чинників.

Окремо розглянуто фільтраційні методи, зокрема фільтр Калмана, який застосовується для оцінювання стану транспортної системи в реальному часі на основі даних GPS, AVL та сенсорної інформації. Також досліджено методи машинного навчання, глибокого навчання, нейронні мережі та графові моделі, які забезпечують вищу точність прогнозів за рахунок здатності моделювати складні просторово-часові та нелінійні залежності у транспортних потоках.

Встановлено, що найбільш перспективними є гібридні та просторово-часові моделі, які поєднують переваги статистичних, фільтраційних і нейромережевих підходів. Такі моделі дозволяють досягати високої точності прогнозування в умовах значної варіативності трафіку, адаптуватися до змін транспортної ситуації та працювати з великими обсягами різнорідних даних.

Узагальнено, що вибір методу прогнозування має базуватися на типі транспортної задачі, якості та структурі вхідних даних, а також вимогах до швидкодії та точності системи. Практичне значення роботи полягає у можливості використання отриманих результатів для розроблення інтелектуальних систем підтримки прийняття рішень, удосконалення управління міським громадським транспортом, оптимізації маршрутів і розкладів, а також підвищення надійності та доступності міських перевезень.

Ключові слова: *громадський транспорт, прогнозування тривалості руху, транспортні потоки, часові ряди, машинне навчання, нейронні мережі, фільтр Калмана, гібридні методи, просторово-часові моделі, інтелектуальні транспортні системи.*

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ANALYSIS OF METHODS FOR FORECASTING URBAN PUBLIC TRANSPORT MOVEMENT

The article presents the results of a study the problem of forecasting urban public transport movement under conditions of increasing mobility demand, growing traffic intensity and the need to improve intelligent transport systems. Accurate prediction of vehicle arrival time, travel time between stops, service headways, and vehicle occupancy is essential for route optimization, timetable planning, and improving passenger service quality. The research is motivated by the fact that transport systems operate in a highly dynamic environment influenced by congestion, weather conditions, infrastructure disruptions, and fluctuations in passenger demand.

Analyzed the main methodological approaches used for forecasting urban public transport movement. These include statistical time-series methods (particularly regression analysis, moving average techniques, and ARIMA/SARIMA models), filtering approaches based on the Kalman filter, machine learning and deep learning methods, neural network architectures, hybrid and spatio-temporal models. Particular attention is paid to the strengths and limitations of each approach, their data requirements, computational complexity, and suitability for real-time applications in urban transport systems.

The results show that statistical models remain useful for baseline forecasting due to their simplicity, transparency, and low computational cost, but their ability to capture nonlinear and rapidly changing transport conditions is limited. Kalman filter are effective for short-term real-time estimation when streaming GPS and sensor data are available. Machine learning, deep learning, and graph-based neural network models demonstrate higher predictive accuracy because they can process large-scale heterogeneous data and represent complex temporal and spatial dependencies. Hybrid models that combine statistical and artificial intelligence methods achieve the best overall performance in highly dynamic urban environments.

Keywords: public transport, travel time prediction, traffic flows, time series, machine learning, neural networks, Kalman filter, hybrid methods, spatio-temporal models, intelligent transportation systems.

INTRODUCTION

In the modern urban environment, the growth of population mobility and the constant increase in traffic intensity require the improvement of intelligent transport systems (ITS) for the effective management of urban public transport [1]. Therefore, forecasting urban public transport movement has become a key component for route optimization, timetable planning, and improving the quality of passenger service, including the prediction of vehicle arrival time at stops, travel time between stops, service headways, and vehicle occupancy levels.

With the increasing number of vehicles and passenger demand, as well as the dynamic changes in the urban environment, accurate and timely forecasting becomes critically important for reducing congestion and improving the efficiency of the transport system [2]. The demand for high-precision forecasts is growing alongside changes in demographic structure, urbanization processes, and the increasing requirements for environmentally sustainable development [3].

A serious challenge in the development of forecasting algorithms lies in the high variability and multi-factor nature of transport system parameters. These parameters include temporal and spatial irregularities of traffic flows, the influence of non-recurrent mobility patterns (such as large-scale events or seasonal fluctuations), external factors (weather conditions, traffic incidents, infrastructure maintenance), as well as difficult-to-predict passenger behavior characteristics [4]. Another critical barrier to improving forecasting accuracy is traffic congestion, which disrupts transport schedules in real time and reduces the reliability of planned operational data [5].

Considering the relevance of forecasting urban public transport movement, it is important to highlight the wide range of modern approaches currently applied in this field. These include statistical time-series models (regression analysis, moving average methods, and ARIMA models), filtering techniques for real-time data estimation (Kalman filter), machine learning algorithms, neural networks, hybrid methods, and spatio-temporal models [6-7]. In particular, studies by Antonio Comi and colleagues demonstrate the high potential of time-series approaches and artificial intelligence methods in improving forecasting accuracy and enhancing the adaptability of transport systems [8-10].

Despite significant progress in this area, identifying the most effective methods under specific urban conditions remains a subject of ongoing scientific discussion. Therefore, a comprehensive analysis of modern methodologies and approaches to forecasting urban transport movement is an essential task for ensuring the efficient functioning of transport infrastructure under increasing urbanization.

ANALYSIS OF LITERATURE DATA AND FORMULATION OF THE PROBLEM

Current research in the field of urban public transport forecasting are focused on the development of algorithms capable of addressing the high variability of traffic flows caused by demand uncertainty, traffic congestion, and external factors such as weather conditions. In European countries, considerable attention is given to the integration of machine learning techniques with traditional approaches in order to improve model accuracy and robustness [8; 11].

Time series methods (ARIMA, SARIMA) remain widely used due to their simplicity of implementation and mathematically grounded approach to analyzing historical data. For instance, studies by Janicka, L., and Christofa, E. [12] have demonstrated that these methods achieve satisfactory performance for medium-term forecasting in relatively stable transport networks, although they exhibit limitations under conditions of fluctuating passenger behavior or unstable traffic conditions [13].

The Kalman filter, widely used in modeling both deterministic and stochastic processes, is also extensively applied in transport modeling tasks. This method enables real-time estimation of the transport system state based on data streams obtained from sensors and GPS devices. Studies indicate that adapting the classical Kalman filter for the analysis of large-scale transport data and the integration of multiple data sources can significantly improve the accuracy of traffic parameter forecasting [14–15].

Machine learning and deep learning methods have become the foundation of many innovations in transport forecasting over the past decade. Studies [16] have demonstrated that the use of recurrent neural networks (RNN) and variational autoencoders enables not only the prediction of transport movement but also the optimization of route schedules depending on the time of day and other influencing factors.

In turn, ***hybrid approaches*** that combine multiple methodologies (e.g., the integration of ARIMA models with neural networks) have attracted particular interest among researchers, especially in Europe. As argued in [17-19], such combined models achieve superior performance under highly dynamic traffic conditions, allowing them to adapt to sudden changes in transport system behavior.

Based on the literature review, it can be concluded that the most promising directions of development at the current stage involve the integration of big data with artificial intelligence systems and the advancement of adaptive models capable of learning under changing real-world conditions. However, the complexity of such models requires substantial computational resources and careful parameter tuning to ensure sufficient forecasting accuracy.

At the same time, the use of mathematical approaches, including regression analysis, time-series methods, and machine learning techniques, continues to demonstrate high effectiveness in solving forecasting problems, provided that high-quality data preprocessing is ensured [8, 19].

An important challenge remains the availability, systematization, and updating of data for transport movement forecasting, as well as the consideration of external factors such as changes in weather conditions (rain, snow, ice), road maintenance, and other unforeseen events. Improving transport forecasting requires the integration of diverse data sources, including GPS systems (vehicle coordinates, speed, and direction), Automatic Vehicle Location (AVL) systems, Automatic Passenger Counters (APC), Automated Fare Collection (AFC) systems, IC card data, data from mobile network operators, and traffic sensors [11, 20, 21].

Thus, the analysis of existing methods for forecasting urban public transport movement indicates the necessity of developing universal platforms capable of adapting to dynamic changes in the system. This creates opportunities for the implementation of smart transportation systems that can optimize passenger travel time and the operational resources of transport operators.

RESEARCH QUESTIONS

- RQ1. To analyze modern methods for forecasting urban public transport movement, including statistical time-series models, filtering techniques, machine learning and deep learning algorithms, neural networks, hybrid methods, and spatio-temporal models.
- RQ2. To evaluate the advantages and disadvantages of each method in order to determine their effectiveness under diverse urban transport infrastructure conditions.
- RQ3. To identify promising directions for improving forecasting systems with a focus on speed, scalability, and adaptability to dynamic conditions.

RESEARCH RESULT

Modern urban public transport forecasting systems are based on the integration of heterogeneous data sources, their preprocessing, and the application of advanced analytical methods. The primary sources of information include GPS monitoring data, passenger flow indicators, road conditions, and weather factors, which form the basis for developing predictive models of transport processes [18, 22].

At the preprocessing stage, data filtering, aggregation, and synchronization are performed, which are critically important for improving forecasting accuracy under conditions of large-scale and heterogeneous data [23]. Further analysis is carried out using various approaches, including statistical time-series models, filtering techniques, and machine learning and deep learning algorithms, each of which offers specific advantages depending on the nature of the data and the forecasting task [18, 24].

Recent studies indicate that hybrid approaches, which combine multiple methods and account for both temporal and spatial dependencies in transport systems, are the most effective, providing high forecasting accuracy in real-time applications [22, 25].

Thus, the structural scheme of the transport movement forecasting system (Fig. 1) reflects the sequence of data processing stages – from data acquisition to the generation of predictive information – used within intelligent transportation systems to support decision-making and improve the efficiency of urban transport operations.

Statistical forecasting methods based on historical data and time series

Among the methods used for forecasting public transport travel time, time-series-based approaches occupy a leading position. Comi, A., Nuzzolo, A., Brinchi, S., and Verghini, R. [8] analyzed the variability of bus travel time on routes in the city of Rome (Italy) using data from Automatic Vehicle Location (AVL) systems and Automatic Vehicle Counters (AVC). The results of the study revealed a significant influence of temporal factors (time of day and day of the week) on travel time variability and confirmed the similarity between bus travel time patterns and overall traffic flow dynamics. In particular, it was found that the variance of travel time is higher during the evening peak period compared to the morning peak.

Comi and Polimeni [9] proposed a time-series-based approach for forecasting travel time using Automatic Vehicle Monitoring (AVM) data from bus routes in Rome (Italy) and Lviv (Ukraine). The comparison of these two cities, which differ significantly in size and economic structure, revealed that travel time patterns are primarily determined by the intensity of traffic congestion associated with lifestyle characteristics and working hours, rather than by city size. In both cities, buses operated within mixed traffic conditions alongside other vehicles, which had a significant impact on their travel speed.

Comi, Zhuk, Kovalyshyn and Hilevych [10] demonstrated the effectiveness of time-series-based approaches for forecasting bus travel time in Lviv (Ukraine). The authors showed that, among the numerous factors influencing public transport operations, the majority follow specific temporal patterns. This enables the effective application of time-series methods for forecasting and reducing the gap between actual and scheduled travel times.

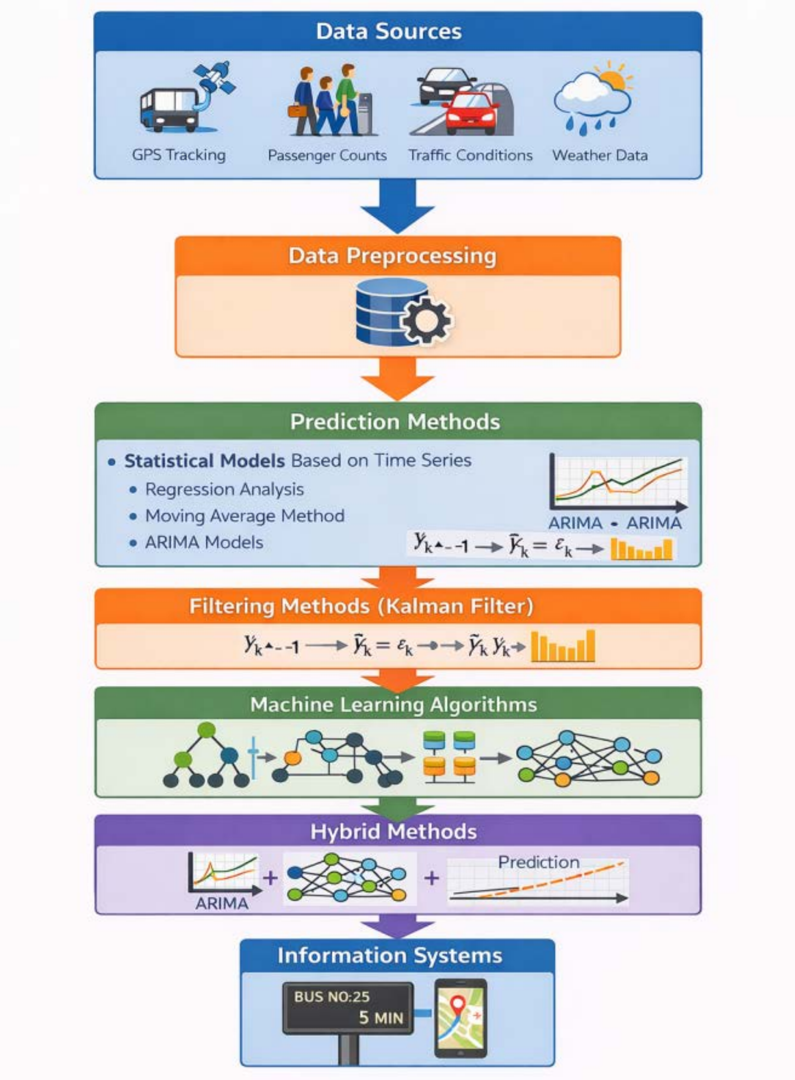

Fig. 1. **Structural scheme of an urban transport movement forecasting system based on multi-source data integration and advanced predictive methods**

Nuzzolo and Comi [11] examined methodological issues related to the development of short-term forecasting tools for intelligent transportation systems (ITS). The authors emphasized that the collection and processing of large-scale transit data (big data), as well as passenger interaction with system control centers for forecasting optimization, create new opportunities for improving forecasting methods.

ARIMA (Autoregressive Integrated Moving Average) models and their seasonal variant, SARIMA, are widely used for forecasting bus travel time [26]. These models combine autoregressive components, differencing, and moving average terms.

The main advantages of ARIMA models include:

- effective performance in modeling time-series data;
- clear mathematical interpretation.

However, their limitations include the complexity of parameter selection and a limited ability to incorporate multiple influencing factors.

The general ARIMA(p, d, q) model is defined by the following equation [26]:

$$Y'_t = c + \varphi_1 Y'_{t-1} + \ldots + \varphi_p Y'_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}, \quad (1)$$

where Y'_t – is the differenced time series of order d; c – constant; $\varphi_1, \ldots, \varphi_p$ – autoregressive parameters of order p; $\theta_1, \ldots, \theta_q$ – moving average parameters of order q; ε_t – error term (white noise).

The advantages of statistical time series forecasting methods include simplicity of formulation, high computational efficiency, and a relatively small number of operational variables. However, their main limitation lies in the restricted ability to model complex nonlinear traffic dynamics and high variability caused by external factors.

Filtering Methods (Kalman Filter)

The Kalman filter is widely used for predicting bus arrival times, demonstrating high accuracy in short-term forecasting. Zhang, Lauber, Liu et al. [20] proposed a bus travel time prediction model based on the Kalman filter using multi-source data (AVL and IC card data) applied to the transport network of Madison, Wisconsin (USA). The results showed that, given the availability of multi-source data, the model is capable of meeting forecasting accuracy requirements, with route-level predictions being more accurate than predictions for individual segments between stops.

Jairam, Kumar, Arkatkar and Vanajakshi [27] conducted a comparative analysis of bus travel time prediction models in several Indian cities (Surat, Mysuru, and Chennai), using k-NN, the Kalman filter, and ARIMA methods. The study confirmed that the Kalman filter provides high accuracy for one-step-ahead forecasting and is capable of processing large volumes of data.

The Kalman filter algorithm consists of two main stages: prediction and update.

Prediction stage:

$$\hat{x}t|t-1 = F \bullet \hat{x}t-1|t-1 + B \bullet ut, \tag{2}$$

$$Pt|t-1 = F \bullet Pt-1|t-1 \bullet F^{T} + Q, \tag{3}$$

Update stage:

$$Kt = Pt|t-1 \bullet H^{T} \bullet (H \bullet Pt|t-1 \bullet H^{T} + R)^{-1}, \tag{4}$$

$$\hat{x}t|t = \hat{x}t|t-1 + Kt \bullet (zt - H \bullet \hat{x}t|t-1), \tag{5}$$

$$Pt|t = (I - Kt \bullet H) \bullet Pt|t-1, \tag{6}$$

where $\hat{x}t$ – status assessment (estimated travel time); F – state transition matrix; P – error covariance matrix; K – Kalman coefficient; H – observation matrix; Q and R – covariances of process and measurement noise; zt – actual observation.

The advantages of this method include high accuracy in one-step-ahead forecasting and the ability to process large volumes of data in real time. However, its main limitation is reduced effectiveness under conditions of complex nonlinear traffic dynamics and high variability of external factors.

Machine learning and deep learning methods

Machine learning methods, particularly artificial neural networks, have attracted significant attention due to their ability to model complex nonlinear relationships and integrate diverse types of data. A typical neural network architecture for travel time prediction (Fig. 2) consists of an input layer that receives data from multiple sources (AVL/GPS data, time of day, day of the week, weather conditions, passenger flow, and historical data), one or more hidden layers with activation functions (such as sigmoid, ReLU, and tanh), and an output layer that generates travel time predictions (ETA – Estimated Time of Arrival).

Depending on the problem type and data characteristics, various neural network architectures are applied, including fully connected networks, recurrent neural networks (particularly LSTM), graph neural networks (GNN), convolutional neural networks (CNN), and transformer-based architectures [28].

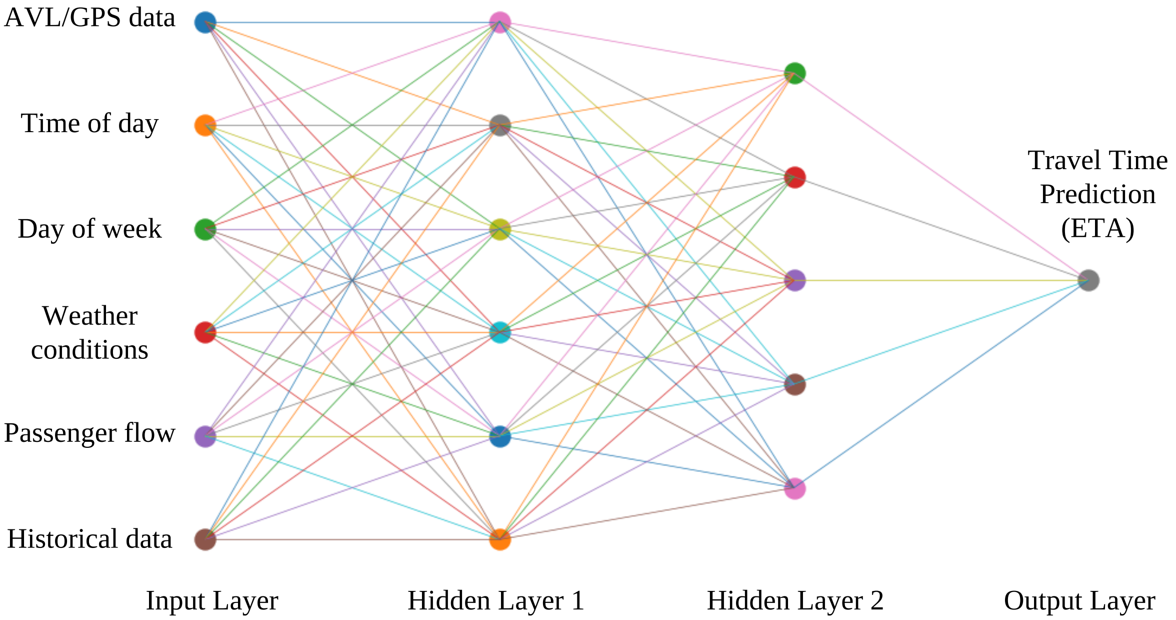

Fig. 2. **Neural Network Architecture for Travel Time Prediction**

Rashvand [28] proposed a methodology based on a fully connected neural network for predicting bus arrival times in New York City. The study identified an average delay of approximately eight minutes between scheduled and actual arrival times, highlighting the need for accurate predictive models. The model incorporated factors such as day type (weekday/weekend), peak hour status, and the distance to the next stop.

Approaches based on graph neural networks (GNN) are rapidly evolving, as they enable the incorporation of transport network topology into forecasting models. Baghbani, Bouguila and Patterson [29] proposed a graph convolutional network with recurrent layers for short-term passenger flow prediction across 929 bus stops in Laval (Canada). This approach effectively captures spatio-temporal correlations between different stops and routes, representing a significant advantage over models that treat each stop independently.

Neural network methods are characterized by their ability to model complex nonlinear relationships, integrate heterogeneous data sources, and adapt to dynamically changing conditions. However, their limitations include the requirement for large volumes of high-quality training data and substantial computational resources, as well as sensitivity to noisy data (e.g., GPS signal loss and human-related factors), which may reduce forecasting accuracy.

Hybrid and combined approaches

A promising direction involves the integration of different methods within hybrid models. Nuzzolo and Comi [21] developed an approach for identifying dynamic optimal routing strategies in intelligent stochastic transit networks, which includes a system for forecasting bus travel time and arrival time at stops. Such an approach enables the provision of optimal route predictions to passengers in real time, taking into account the stochastic nature of the transport network, where actual bus arrival times may significantly differ from scheduled or predicted values.

The advantages of hybrid approaches lie in their ability to compensate for the limitations of individual methods and to achieve higher forecasting accuracy. However, their main drawbacks include implementation complexity, the need for tuning a large number of parameters, and scalability challenges for large transport networks with hundreds of routes.

Comparative analysis of methods

Urban public transport forecasting has been extensively studied in recent years, with researchers increasingly employing advanced analytical and data-driven approaches depending on data availability, computational resources, and the complexity of transport systems. Contemporary studies still acknowledge the relevance of statistical time-series models, such as regression analysis and ARIMA-based approaches, which remain effective for short-term forecasting and baseline modelling of traffic flow and passenger demand [24, 30].

At the same time, traditional methods have been enhanced and extended through hybridization and integration with real-time data sources. In particular, filtering techniques, including the Kalman filter and its modifications, are widely used for real-time estimation and prediction of dynamic traffic states, especially in applications involving connected vehicles and sensor-based monitoring systems [31-32].

With the rapid growth of intelligent transportation systems and big data technologies, machine learning methods have become a dominant approach in transport forecasting. These methods enable efficient processing of large-scale heterogeneous data and identification of nonlinear relationships in traffic patterns [17, 23]. Countries such as China, the United States, and Singapore actively implement these techniques in smart mobility systems and urban traffic management.

More recently, deep learning models, including recurrent neural networks (RNN), long short-term memory (LSTM), and graph-based neural networks, have demonstrated superior performance in predicting traffic flow, travel time, and congestion levels [22, 25]. These approaches are particularly effective in data-rich environments and are widely applied in technologically advanced countries such as China, South Korea, and the United States.

The latest research trends focus on spatio-temporal and hybrid models, which integrate statistical methods, machine learning, and deep learning techniques to capture both temporal dynamics and spatial dependencies in transport networks. Such models have shown significant improvements in forecasting accuracy and robustness under highly dynamic urban conditions [20, 23].

Distribution of urban transport forecasting methods used in different countries according to the scientific literature (Fig. 3).

The evolution of methods for forecasting urban public transport movement reflects a gradual advancement of approaches in transportation system research. In the early stages, statistical models based on historical data – such as route characteristics and timetables – played a dominant role, enabling the development of baseline predictive frameworks. Early studies from the mid-20th century primarily relied on simplified empirical models that described traffic behavior using aggregated observations. With the advancement of computational technologies, these approaches were further refined through the integration of regression analysis and time-series techniques, allowing for more accurate estimation of travel time and operational parameters [1,4,13,29].

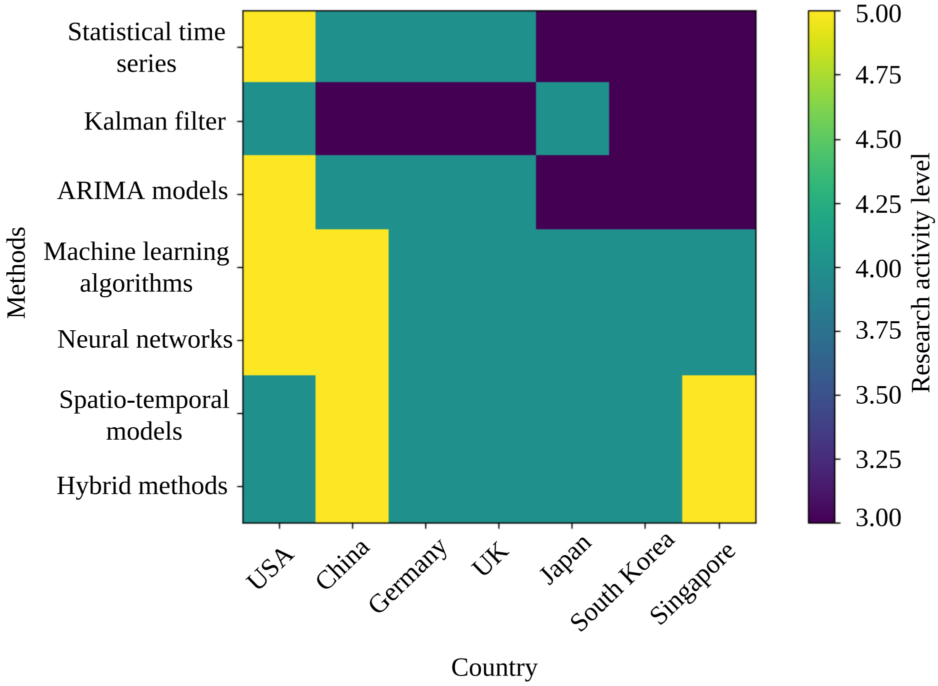

Fig. 3. **Distribution of urban transport forecasting methods by Country**

In recent decades, transport movement forecasting has increasingly relied on artificial intelligence and machine learning techniques. The application of deep learning models and big data analytics enables real-time processing of heterogeneous data sources and incorporation of complex influencing factors, such as weather conditions, traffic congestion, and dynamic passenger demand. As a result, modern forecasting systems demonstrate significantly improved accuracy and adaptability. Furthermore, the emergence of hybrid and spatio-temporal models has enhanced the ability to capture both temporal dynamics and spatial dependencies within urban transport networks [3,8,9,19]. These advancements contribute to more efficient transport planning and improve accessibility and reliability of urban mobility systems (Fig. 4). The given chronology illustrates the periods of application of forecasting methods in transportation research.

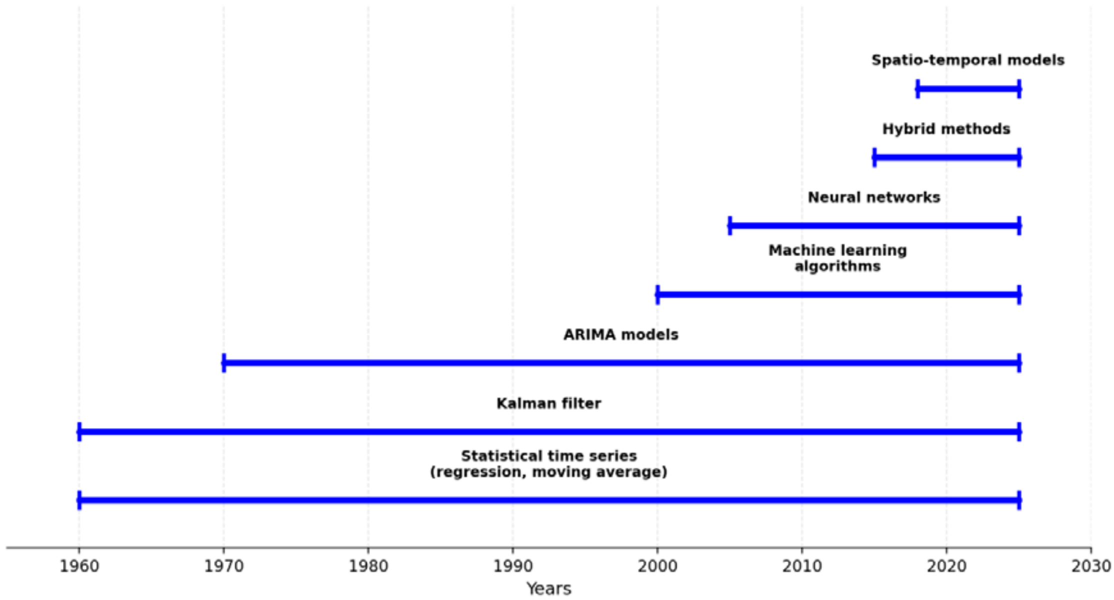

Fig. 4. **Timeline of the evolution of forecasting methods for urban public transport movement**

Table 1 presents a comparative analysis of the main forecasting methods used in urban public transport systems. It highlights their key characteristics, including accuracy, computational complexity, data requirements, as well as their advantages and limitations.

Table 1.

Comparative Analysis of Forecasting Methods for Urban Public Transport Movement

Forecasting Method	Model Type	Prediction Accuracy	Computational Complexity	Data Type	Main Advantages	Main Disadvantages
Time-Series Methods (ARIMA / SARIMA)	Statistical time-series model	Medium (high for stable data)	Low	Historical time series	Simple implementation, strong mathematical interpretability	Lower accuracy, limited ability to capture nonlinear relationships and external factors
Kalman Filter	Stochastic model	Medium – high	Medium	Streaming data, GPS, sensor data	Effective for real-time forecasting, robust to noise	Requires precise model parameter tuning
Machine learning algorithms, Neural networks	Machine learning / deep learning	High	High	Large datasets (GPS, passenger flow, weather, traffic)	Captures complex nonlinear relationships, high accuracy	Requires large datasets and significant computational resources
Hybrid Models (ARIMA + NN)	Combined model	Very high	High	Combined datasets	Combines strengths of statistical and ML methods	High implementation and tuning complexity

The analysis shows that traditional statistical methods remain useful due to their simplicity and interpretability but are limited in handling complex and nonlinear patterns. In contrast, machine learning and neural network approaches provide higher accuracy at the cost of increased computational requirements and data dependency. Hybrid models demonstrate the best overall performance by combining the strengths of different approaches, although they require more sophisticated implementation and tuning. Overall, the choice of method depends on the availability of data, computational resources, and the required level of prediction accuracy.

DISCUSSION OF THE RESULTS OF THE STUDY AND SUMMARY

The conducted analysis confirms that forecasting urban public transport movement is a multidimensional task that requires the integration of heterogeneous data sources and the application of methods with different levels of mathematical complexity. No single forecasting method can be considered universally optimal for all transport systems, since forecasting performance depends on network structure, service variability, data quality, and the influence of external factors such as weather, incidents, and fluctuations in passenger demand.

Traditional statistical time-series methods preserve their practical relevance because they are relatively simple to implement, computationally efficient, and mathematically interpretable. At the same time, their predictive capability is limited in highly nonlinear and unstable environments. Filtering methods, especially the Kalman filter, are effective for real-time estimation and short-horizon prediction, particularly when continuous streams of GPS, AVL, and sensor data are available. These methods are especially valuable for operational monitoring and control of transport systems.

Machine learning, deep learning, and spatio-temporal approaches currently represent the most promising class of methods for advanced forecasting tasks. Their main advantage lies in the ability to model nonlinear relationships, integrate multiple influencing variables, and capture both temporal dynamics and spatial interactions within transport networks. Hybrid approaches further enhance this potential by combining the interpretability of statistical methods with the flexibility and predictive power of neural and data-driven models. As a result, such models achieve the highest accuracy in complex urban conditions.

The practical use of the obtained results may involve the development of intelligent decision-support systems for public transport operators, real-time passenger information platforms, adaptive timetable optimization tools, and smart city mobility services. Further research should focus on the creation of scalable forecasting platforms based on big data integration, explainable artificial intelligence, and self-learning adaptive models capable of responding to structural changes in transport behavior. Special attention should also be paid to the transferability of forecasting models across cities with different infrastructural, demographic, and operational characteristics.

REFERENCES

1. Gkiotsalitis K., Cats O. (2021). Public transport planning adaption under the COVID-19 pandemic crisis: literature review of research needs and directions, Transport Reviews, 41:3, 374-392, https://doi.org/10.1080/01441647.2020.1857886
2. Van Lint, J. W. C., Hoogendoorn, S. P., & Van Zuylen, H. J. (2005). Accurate freeway travel time prediction with state-space neural networks under missing data. Transportation Research Part C: Emerging Technologies. Volume 13, Issues 5–6, October–December 2005, Pages 347-369, https://doi.org/10.1016/j.trc.2005.03.001
3. Nuzzolo, A., Crisalli, U., & Comi, A. (2015). An aggregate transport demand model for import and export flow simulation. Transport, 30(1), 43–54. https://doi.org/10.3846/16484142.2013.820215
4. Cats., O. (2019) Determinants of bus riding time deviations: Relationship between driving patterns and transit performance. Journal of Transportation Engineering Part A: Systems 145(1), https://doi.org/10.1061/JTEPBS.0000201
5. Eleni I. Vlahogianni, Matthew G. Karlaftis, John C. Golias (2014). Short-term traffic forecasting: Where we are and where we're going, Transportation Research Part C: Emerging Technologies, Volume 43, Part 1,Pages 3-19, https://doi.org/10.1016/j.trc.2014.01.005
6. Z. Liu, Z. Li, K. Wu and M. Li (2018) Urban Traffic Prediction from Mobility Data Using Deep Learning," in IEEE Network, vol. 32, no. 4, pp. 40-46, https://doi.org/10.1109/MNET.2018.1700411
7. Chen, Z., Lu, Z., Zhong, H., Zhang, Y., & Xue, J. (2022). A spatial-temporal short-term traffic flow prediction model based on graph convolution networks https://doi.org/10.48550/arXiv.2205.04762
8. Comi, A., Nuzzolo, A., Brinchi, S., Verghini, R. (2017) Bus travel time variability: some experimental evidences. Transportation Research Procedia, vol. 27, pp. 101–108 https://doi.org/10.1016/j.trpro.2017.12.072
9. Comi, A., Polimeni, A. (2020) Bus Travel Time: Experimental Evidence and Forecasting. Forecasting, vol. 2, no. 3, pp. 309–322 https://doi.org/10.3390/forecast2030017
10. Comi, A., Zhuk, M., Kovalyshyn, V., Hilevych, V. (2020) Investigating bus travel time and predictive models: a time series-based approach. Transportation Research Procedia, vol. 45, pp. 692–699 https://doi.org/10.1016/j.trpro.2020.02.109
11. Nuzzolo, A., Comi, A. (2016) Advanced Public Transport and Intelligent Transport Systems: New Modelling Challenges. Transportmetrica A: Transport Science, vol. 12, no. 8, pp. 674–699 https://doi.org/10.1080/23249935.2016.1166158
12. Janicka, L., & Christofa, E. (2019). A data-driven approach for short-term bus travel time prediction. Transportation Research Record: Journal of the Transportation Research Board, 2673(8), 574–585 https://doi.org/10.1109/SMC53654.2022.9945254
13. Williams, B. M., & Hoel, L. A. (2003). Modeling and Forecasting Vehicular Traffic Flow as a Seasonal ARIMA Process: Theoretical Basis and Empirical Results. Journal of Transportation Engineering, 129(6), 664–672 https://doi.org/10.1061/(ASCE)0733-947X(2003)129:6(664)
14. Seo, T., Kusakabe, T., & Asakura, Y. (2017). Estimation of flow and density using probe vehicles with spacing measurement equipment. Transportation Research Part C. https://doi.org/10.1016/j.trc.2015.01.033
15. Work, D. B., Tossavainen, O. P., Blandin, S., Bayen, A. M., Iwuchukwu, T., & Tracton, K. (2019). An ensemble Kalman filtering approach to highway traffic estimation. Transportation Research Part C. https://doi.org/10.1109/CDC.2008.4739016
16. Ma, X., Tao, Z., Wang, Y., Yu, H., & Wang, Y. (2015). Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. Transportation Research Part C, 54, 187–197. https://doi.org/10.1016/j.trc.2015.03.014
17. Polson, N. G., & Sokolov, V. O. (2017). Deep learning for short-term traffic flow prediction. Transportation Research Part C, 79, 1–17. https://doi.org/10.1016/j.trc.2017.02.024
18. Zhang, J., Zheng, Y., & Qi, D. (2017). Deep spatio-temporal residual networks for citywide crowd flows prediction. Proceedings of AAAI Conference on Artificial Intelligence. https://doi.org/10.1609/aaai.v31i1.10735
19. Zhang, G. P. (2018). Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing, 50, 159–175. https://doi.org/10.1016/S0925-2312(01)00702-0

20. Zhang, X., Lauber, L., Liu, H., Shi, J., Xie, M., Pan, Y. (2022) Travel time prediction of urban public transportation based on detection of single routes. PLoS ONE, vol. 17, no. 1, e0262535. https://doi.org/10.1371/journal.pone.0262535
21. Nuzzolo, A., Comi, A. (2021) Dynamic Optimal Travel Strategies in Intelligent Stochastic Transit Networks. Information, vol. 12, no. 7, 281. https://doi.org/10.3390/info12070281
22. Chen, C., Liu, Y., & Lv, Y. (2021). Deep learning approaches for traffic flow prediction: A survey. IEEE T-ITS. https://doi.org/10.21203/rs.3.rs-66048/v1
23. Y. Lv, Y. Duan, W. Kang, Z. Li and F. -Y. Wang (2015). Traffic Flow Prediction With Big Data: A Deep Learning Approach, in IEEE Transactions on Intelligent Transportation Systems, vol. 16, no. 2, pp. 865-873, https://doi.org/10.1109/TITS.2014.2345663 .
24. Wang, J., Deng, W., & Guo, Y. (2019). A Bayesian combination model for short-term traffic flow forecasting. Transportation Research Part C. https://doi.org/10.1016/j.omega.2022.102721
25. Z. Wang, J. Hu, G. Min, Z. Zhao, Z. Chang and Z. Wang (2023). Spatial-Temporal Cellular Traffic Prediction for 5G and Beyond: A Graph Neural Networks-Based Approach, in IEEE Transactions on Industrial Informatics, vol. 19, no. 4, pp. 5722-5731, https://doi.org/10.1109/TII.2022.3182768
26. Suwardo, Madzlan, N., Ibrahim, K. (2010) ARIMA models for bus travel time prediction. The Journal of the Institution of Engineers, Malaysia, vol. 71, no. 2, pp. 49–58.
27. Jairam, R., Kumar, B. A., Arkatkar, S. S., Vanajakshi, L. (2018). Performance Comparison of Bus Travel Time Prediction Models across Indian Cities. Transportation Research Record, 2018, vol. 2672, no. 31, pp. 87–98. https://doi.org/10.1177/0361198118770175
28. Rashvand, N., Ahn, C. R., Azar, E. R., Hasan, S. (2024). Real-Time Bus Arrival Prediction: A Deep Learning Approach for Enhanced Urban Mobility. arXiv preprint, 2024, arXiv:2303.15495v3. https://doi.org/10.48550/arXiv.2303.15495
29. Baghbani, A., Bouguila, N., Patterson, Z. (2023) Short-Term Passenger Flow Prediction Using a Bus Network Graph Convolutional Long Short-Term Memory Neural Network Model. Transportation Research Record, vol. 2677, no. 2, pp. 530–547. https://doi.org/10.1177/03611981221112673
30. Duan, Y., Lv, Y., & Wang, F. (2020). Travel time prediction with LSTM neural networks. IEEE Transactions on Intelligent Transportation Systems. https://doi.org/10.1109/ITSC.2016.7795686
31. Seo, T., Kusakabe, T., & Asakura, Y. (2017). Traffic state estimation using probe vehicles. Transportation Research Part C. https://doi.org/10.1016/j.trc.2017.02.012
32. Work, D. B., et al. (2019). Traffic estimation using Kalman filtering approaches. Transportation Research Part C. https://doi.org/10.1016/j.trc.2019.02.007