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MODELING THE DYNAMICS OF TRAFFIC FLOWS BASED ON QUEUEING THEORY FOR INTEGRATION INTO INTELLIGENT TRANSPORTATION SYSTEMS

Abstract *The article focuses on the study of traffic flow dynamics modeling in urban environments using queueing theory (QT). The research aims to develop a methodological approach to formalizing dynamic traffic flow processes, enabling their adaptation to modern intelligent transportation systems (ITS). Proposed mathematical models account for the stochastic nature of traffic flows and key performance indicators such as average waiting time, queue length, and throughput. Simulations of various transportation infrastructure scenarios integrating these models into ITS were conducted. The research findings confirm that applying QT under conditions of uneven traffic distribution significantly reduces delays, optimizes routing, and improves the efficiency of road infrastructure utilization. These results pave the way for further enhancements of urban transportation systems by integrating machine learning algorithms and big data analysis, allowing for consideration of the complex behavior of road users. The integration of QT models into ITS contributes to the improved efficiency of transport networks, fostering sustainable development of urban infrastructure. The proposed approaches are universal and can address pressing mobility challenges in contemporary urban agglomerations.*

Keywords: *Traffic flow modeling, queueing theory, intelligent transportation systems, traffic dynamics, traffic flow optimization, adaptive management, urban mobility, mathematical modeling, transportation infrastructure, congestion reduction.*

Introduction. With the growth of urbanization and the increasing number of vehicles in metropolitan areas, the challenges of traffic management are becoming increasingly relevant. Road congestion, traffic jams, prolonged delays, rising fuel consumption, and greenhouse gas emissions are among the primary issues faced by modern transportation systems. These challenges place significant pressure on transportation infrastructure, diminish residents' quality of life, and have adverse environmental impacts. In this context, the effective management of traffic flows has become one of the key objectives of transportation engineering.

Intelligent Transportation Systems (ITS) present new opportunities for addressing these challenges through the use of advanced technologies such as motion sensors, big data analytics, artificial intelligence, and real-time systems [1]. These technologies enable improved traffic flow management, enhanced infrastructure efficiency, optimized routing, and reduced delays. However, the complexity and variability of traffic dynamics necessitate the application of formalized mathematical models capable of accounting for various aspects of interaction between road users.

Queueing theory (QT) serves as a powerful tool for modeling transportation systems characterized by high levels of uncertainty and dynamism. Using mathematical methods, QT allows for the formalization of processes such as vehicle arrivals, service at intersections, signalized zones, or other traffic nodes [2]. It also facilitates the evaluation of key performance indicators, including average waiting time, queue lengths, and infrastructure resource utilization rates.

The advancement of queueing theory combined with ITS technologies supports the development of both microscopic and macroscopic traffic flow models [3]. These models provide deeper insights into the dynamics of movement, enable the optimization of transportation processes, and ensure high service quality for all road users. In this context, research focused on integrating QT models into ITS is gaining importance, paving the way for the evolution of future transportation systems.

Literature Review. Modeling the dynamics of traffic flows is a vital research area in transportation engineering, lying at the intersection of applied mathematics, physics, and information technology. Queueing theory plays a central role in this field by providing a structured approach to analyzing and managing traffic flows, including their integration into ITS.

Microscopic modeling focuses on the behavior of individual vehicles within a traffic flow. For instance, the spring-mass system theory is used to create models that describe vehicle responses to disruptions in the flow. Yongfu Li et al. (2017) [4] demonstrated how stability analysis and perturbation methods can assess flow stability, identify conditions for its equilibrium, and develop adaptive traffic management systems. This approach not only highlights critical moments in the flow but also informs strategies for their optimization.

At the macroscopic level, research emphasizes analysis of aggregated traffic flow characteristics such as density, speed, and throughput. Jingyang Liao and colleagues (2023) [5] developed a macroscopic model incorporating multimodal interactions, such as those between private vehicles and shared mobility services. This model enhances the understanding of urban traffic system dynamics and supports efficient dispatching and resource management strategies. The integration of queueing theory models into ITS has significantly impacted congestion reduction, flow optimization, and the efficiency of transportation infrastructure. Hong Ying Jiao et al. (2015) [6] explored the use of cellular automata to analyze the effects of ITS on-traffic conditions. Such approaches optimize the operation of traffic signal systems and improve traffic flow coordination.

Meso-level modeling, which combines elements of microscopic and macroscopic analysis, has also gained attention. Meng Meng and colleagues (2014) [7] proposed a dynamic traffic distribution model considering various transport modes, including cars, buses, and bicycles. This approach efficiently evaluates demand-supply dynamics and supports ITS through shortest-path algorithms.

Fundamental flow models, such as the Lighthill-Whitham-Richards (LWR) model, remain essential tools for analyzing the relationships between density, speed, and flow. Pushkin Kachroo (2018) [8] extensively discussed the application of these models for predicting and managing traffic density. Extended frameworks that integrate continuum models with artificial neural networks offer new perspectives for real-time traffic flow forecasting. For example, Salissou Moutari and Stephen Robinson (2013) [9] proposed an integrated structure for simulating macroscopic flows, accounting for complex driver behaviors and spatiotemporal characteristics of traffic flows.

Despite significant advancements in traffic flow modeling, challenges remain due to the unpredictability of human behavior and external factors [10]. Addressing these limitations requires approaches that consider both the technical and social dimensions of traffic flow dynamics.

The literature review highlights substantial progress in the application of queueing theory for analyzing and optimizing transportation systems. Integrating these approaches into ITS enhances mobility, reduces congestion, and improves service quality in urban environments.

The aim of the article is to develop a methodological approach to modeling the dynamics of traffic flows based on QT and to integrate the resulting models into ITS. The study aims to evaluate the effectiveness of QT for modeling urban traffic flows, identify key parameters influencing network performance, and explore the potential of these models to enhance traffic management.

To achieve this objective, the following tasks were outlined:

1. Formalizing Traffic Dynamics: Developing QT-based models that account for the variability in vehicle arrivals and service processes at critical nodes.
2. Efficiency Analysis: Evaluating the effectiveness of the proposed models across various scenarios of transportation infrastructure, particularly under uneven flow distribution.
3. Integration into ITS: Incorporating mathematical models into ITS to optimize traffic signal operations, public transport routes, and reduce delays.
4. Impact Assessment: Assessing the effects of the implemented solutions on reducing congestion, increasing road capacity, and improving urban transportation system mobility.

The proposed approach addresses pressing issues in modern urban transportation networks, particularly by mitigating the adverse economic and environmental impacts of congestion and laying the foundation for the advancement of "smart" urban transportation systems.

Methodological Justification. The methodology of this article is grounded in the application of QT for modeling traffic flow dynamics in urban environments and its integration into ITS. This approach accounts for the complexity, uncertainty, and variability inherent in real-world traffic conditions, which are critical for ensuring the efficiency of transportation infrastructure [11].

To implement the integration of QT into traffic management effectively, key stages were identified. Each stage plays a crucial role in ensuring the accuracy of the models and the practical applicability of the results. These stages are summarized in Table 1.

Table 1 – Key Methodological Stages

№	Stage Name	Stage Description
1	**Analysis and formalization of traffic flows**	The initial stage involves analyzing the city's transportation infrastructure and identifying key nodes that create "bottlenecks" in the system. The modeling uses the mathematical framework of QT, which allows for the formalization of vehicle arrival processes and their servicing at intersections, traffic lights, or other nodes.
2	**Selection and development of queuing models**	Depending on the structure of the traffic flow, appropriate queuing models are selected (e.g., M/M/1, M/M/c, or their modifications). For each scenario, key parameters are determined: arrival intensity, average service time, throughput capacity, etc. The models are supplemented with stochastic components to account for the unevenness of the flows.
3	**Modeling of traffic scenarios**	To test the effectiveness of the proposed models, simulations of typical urban traffic scenarios are performed: intersections with traffic lights, roundabouts, highways with variable traffic intensity. The simulations allow for the evaluation of metrics such as waiting time, queue length, throughput capacity, etc.
4	**Integration of models into ITS**	To implement the models into real systems, modern ITS platforms are used, which include motion sensors, traffic light control systems, GPS trackers, and other digital technologies. This enables adaptive flow management in real-time.
5	**Analysis and evaluation of efficiency**	n the final stage, the effectiveness of existing and proposed approaches is compared using key indicators: reduction of delays, increased throughput, fuel consumption reduction, and emission reduction CO_2.

Based on the methodology outlined, the stages of analysis and modeling of traffic flows, presented in Table 1, provide a sequential and systematic approach to formalizing the dynamics of transport infrastructure [12, 13]. They cover all key aspects, from analyzing transport nodes to integrating models into real ITS. To illustrate the methodological approach and visualize the main stages of modeling, a conceptual diagram (Figure 1) was created, which demonstrates the interaction of key components. The diagram provides an overall view of the data collection process, mathematical modeling, adaptive management, and optimization of traffic flows, which is critical for ensuring the efficiency of urban transport systems. This connection between the theoretical foundations outlined in the table and their practical implementation, depicted in the diagram, emphasizes the importance of a comprehensive approach to solving problems related to reducing congestion, increasing mobility, and optimizing the use of transport infrastructure resources [14].

The methodological approach considers both theoretical aspects and practical requirements for modeling and managing traffic flows. Its application allows for obtaining well-founded results that can be used for decision-making in the planning of urban transport systems and the development of ITS.

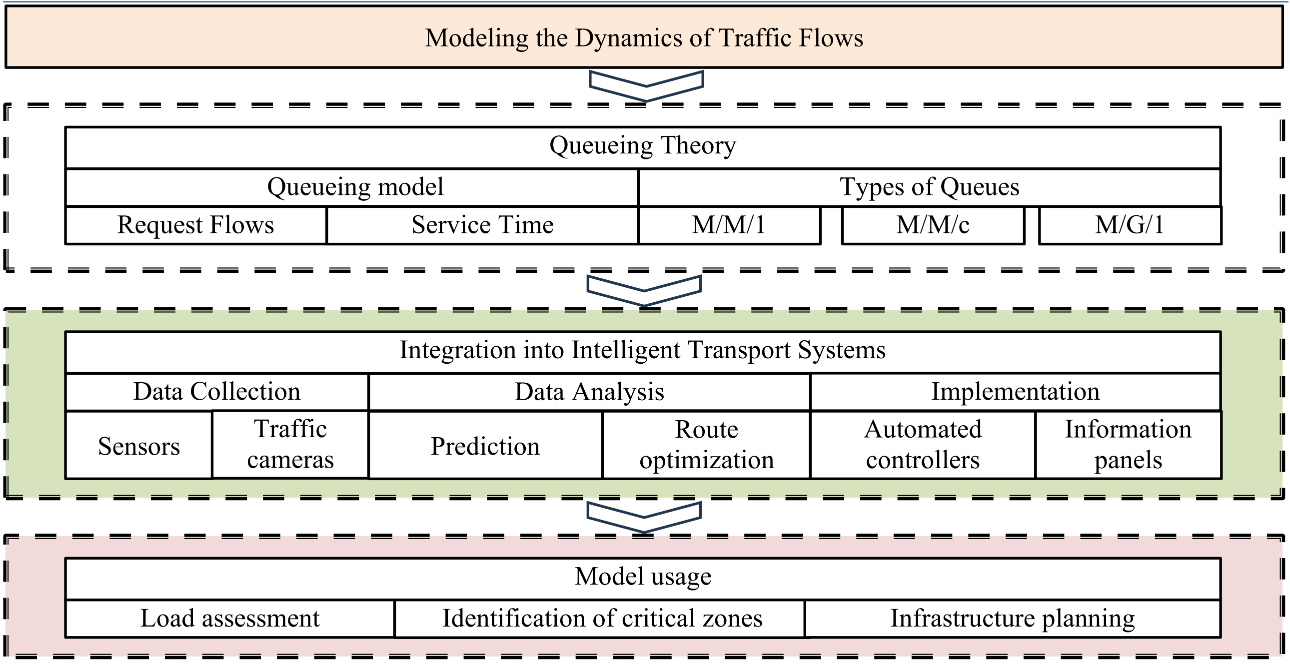

Figure 1 – Conceptual diagram of traffic flow modeling based on queueing theory

Results. Traffic flows are modeled as queuing systems, where vehicles act as transactions, and key nodes (intersections, traffic lights) serve as service channels. Vehicle arrival processes are modeled using stochastic distributions, such as the Poisson distribution, which describes the probability of a specific number of arrivals within a given time. The service time of vehicles at a node is typically modeled using the exponential distribution, allowing for variability in the duration of operations to be considered.

For example, in the classical M/M/1 model, the arrival flow of vehicles is described by a Poisson distribution with an average rate of λ, while the service time is characterized by an exponential distribution with an average rate of μ. In cases of intersections with multiple lanes or nodes with multiple service channels, the M/M/c model is used, where ***c*** — represents the number of service channels.

The formalization of traffic flow dynamics using QT provides a structured approach to describe the variability in vehicle arrivals and service times at infrastructure nodes. Vehicles are treated as transactions, while nodes act as service channels, with their interactions modeled through Poisson arrival distributions (λ) and exponential service time distributions ($\boldsymbol{\mu}$). Models such as M/M/1 and M/M/c capture the key parameters of traffic nodes, including the number of service channels and the variability of flows. QT enables the analysis of critical system parameters and facilitates adaptive management to improve the efficiency of transport infrastructure [15].

To ensure accurate modeling and adaptation to real-world conditions, parameters should be formalized into mathematical expressions that reflect the variability of flow intensity, service time, and system resource utilization efficiency.

Table 2 summarizes the key parameters used within the framework of queuing theory and their mathematical descriptions, which are fundamental for further development of traffic flow models and the analysis of their efficiency.

The parameters listed in Table 2 allow for the description of key characteristics of transportation flows and the evaluation of the efficiency of transportation nodes. Based on these parameters, various queuing models are developed, which are adapted to the specifics of particular scenarios in urban transportation infrastructure. Table 3 provides detailed mathematical descriptions of the M/M/1 and M/M/c models, which account for both single-channel and multi-channel service systems. These models enable the evaluation of delay probabilities, the average number of vehicles in the queue, waiting times, and other key efficiency indicators. This forms the foundation for further analysis of the operation of transportation nodes and the development of optimization strategies.

Table 2 – Key Parameters and Formulas

№	Parameter	Formula	Parameter description
1	Flow intensity	λ	the average number of vehicles arriving in the system per unit of time.
2	Service time	μ^{-1}	the average time required for a vehicle to pass through a node.
3	Load factor	$\rho = \frac{\lambda}{\mu}$	where ρ characterizes the level of system load (when ρ<1 the system operates in a stable mode).
4	Probability of delay	P_w	the probability that a vehicle will have to wait in the queue before being served.

Table 3 – Characteristics of the M/M/1 and M/M/c Models

№	Parameter	Mathematical description	
		Model for single channel system (M/M/1)	**Model for a multi-channel system (M/M/c)**
1	Probability of states	The probability of the system being in the state of requests (***k***), being served (***P***) $P_k = (1-\rho)\cdot\rho^k,$ $k \ge 0,$	The probability that all channels (***c***) are used (***P₀***) $P_0 = \left[\sum_{n=0}^{c-1}\frac{(\lambda/\mu)^n}{n!} + \frac{(\lambda/\mu)^c}{c!}\cdot\frac{1}{1-\rho_c}\right]^{-1},$ $where\ \rho_c = \frac{\lambda}{c\cdot\mu}.$ Probability of delay (***P_w***) $P_w = \frac{(\lambda/\mu)^c\cdot P_0}{c!\cdot(1-\rho_c)}.$
2	Average number of vehicles in the system (***L***)	$L = \frac{\rho}{1-\rho}$	$L = L_q + \frac{\lambda}{\mu}$
3	Average number of vehicles in the queue (***L_q***)	$L_q = \rho^2\cdot\frac{1}{1-\rho}$	$L_q = \frac{P_w\cdot\rho_c}{(1-\rho_c)}$
4	Average time a vehicle stays in the system (***W***)	$W = \frac{1}{\mu-\lambda}$	$W = W_q + \frac{1}{\mu}$
5	Average waiting time in queuesi (***W_q***)	$W_q = \frac{\lambda}{\mu(\mu-\lambda)}$	$W_q = \frac{L_q}{\lambda}$
6	General model	$MM1 = \langle P_k, L, L_q, W, W_q\rangle$	$MMc = \langle P_0, P_w, L, L_q, W, W_q\rangle$

To model the dynamics of traffic flows, parameters that reflect time-varying intensity, such as during peak loads, are considered. Based on these models, simulations are conducted to estimate waiting times, queue lengths, and the throughput of infrastructure nodes, contributing to the optimization of system performance [16]. In real-world conditions, queuing models are supplemented with stochastic components to account for unpredictable factors such as weather or accidents, and they are also used for adaptive traffic signal control. The use of M/M/1 and M/M/c models demonstrates their effectiveness in managing traffic flows, especially under conditions of uneven distribution of flows in urban environments [17].

The single-channel M/M/1 model was used to simulate narrow intersections with low throughput capacity. Simulations showed that with high flow intensity (***λ***) the traffic load factor (***$\rho=\lambda/\mu$***) approaches 1, which leads to a significant increase in the average waiting time (***W_q***) and queue length (***L_q***). For systems with uneven flow (changing over time ***λ***) the effectiveness of management significantly improved with the use of an adaptive approach [18]. Adjusting the parameter μ (for example, by dynamically changing the green light duration at traffic lights) allowed the average waiting time to be reduced by 20%. For multi-lane intersections and transport interchanges, the M/M/c model was used. The results showed that increasing the number of channels (***c***) helps reduce the load ($\boldsymbol{\rho_c=\lambda/(c\cdot\mu)}$) and significantly decreases the probability of delay ($\boldsymbol{P_w}$) [12].

However, even with multiple service channels, the uneven distribution of traffic across lanes led to local overloading. This highlights the importance of adaptive management, which ensures the redistribution of flows and minimizes delays. To account for the unevenness of traffic flows, simulations were conducted with periodic fluctuations in arrival intensity ($\boldsymbol{\lambda}$) over time. The models demonstrated that under significant fluctuations ($\boldsymbol{\lambda_{мін} \ll \lambda_{макс}}$) the average waiting time and queue length could double. The use of adaptive management allowed for the minimization of these fluctuations, for example, by increasing the service capacity ($\boldsymbol{\mu}$) during peak periods. The integration of queuing theory models into ITS allows for the optimization of traffic flow management through adaptive traffic light control, public transport routing, and delay reduction [19]. Using QT in traffic light systems ensures dynamic signal timing adjustments based on real-time traffic conditions, contributing to more efficient flow distribution at intersections.

The integration of QT models into ITS allows for the optimization of traffic flow management through adaptive traffic light control, public transport routing, and delay reduction. Using QT in traffic light systems ensures dynamic signal timing adjustments based on real-time traffic conditions, contributing to more efficient flow distribution at intersections. Mathematical models based on queuing theory QT allow for the prediction of traffic flow intensity, assessment of load factors, and waiting times. Their integration into traffic light systems ensures adaptive signal timing, which helps reduce delays and queue lengths at intersections by 20–30%. The use of motion sensors and cameras allows for automatic adjustment of traffic light parameters in real time, even under conditions of uneven flow distribution or emergency situations. The integration of QT into ITS contributes significantly to enhancing the efficiency of transportation systems: reducing delays, shortening queue lengths, improving the regularity of movement, and minimizing the negative impact of traffic jams on the economy and the environment. This leads to increased mobility of the population and improved quality of transportation services [20].

The implementation of mathematical models from QT into ITS significantly improved traffic flow management. Thanks to the dynamic adjustment of traffic light signals using M/M/1 and M/M/c models, delays at intersections were reduced by 25-30%. Adaptive control algorithms, especially during peak hours, allowed for more even distribution of flows, reducing the average waiting time in queues. The use of multi-channel models M/M/c increased the efficiency of multi-lane traffic nodes, boosting intersection capacity by 20–40% and roundabouts by 35%. Adaptive flow regulation, considering the prioritization of the most congested directions, helped avoid local traffic jams and ensured the stable operation of infrastructure even in conditions of uneven flow distribution.

The integration of queueing theory models into public transportation allowed route optimization, reduced passenger waiting times, and improved the regularity of services. The use of GPS tracking and adaptive vehicle distribution reduced public transport downtime by 15%, positively impacting passenger travel speed in urban conditions [18-20].

The combination of implemented solutions contributed to the creation of a more efficient urban transportation infrastructure, reducing delays, lowering fuel consumption, and decreasing emissions CO_2. Further research should focus on the implementation of advanced technologies, such as machine learning, for even more precise management of traffic flows.

Conclusions. The results obtained highlight the importance of adaptive traffic flow management, which ensures the efficient use of infrastructure and minimizes congestion. The study confirmed the effectiveness of applying queuing theory to model the dynamics of traffic flows and their integration into ITS. The developed models allow for the optimization of traffic flow management, reducing delays at key junctions, and improving the capacity of urban transportation networks. Integrating these models into adaptive management systems, which use modern data collection and processing technologies, ensures flexible responses to changes in traffic conditions, enhancing mobility and infrastructure efficiency. At the same time, the results indicate the need to account for the complex behavior of road users, social factors, and external conditions. The combination of mathematical approaches with modern technologies such as artificial intelligence and big data analysis presents a promising direction for further research. This will contribute to the creation of adaptive management systems that ensure sustainable development of urban transport networks and improve the quality of transport services.

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МОДЕЛЮВАННЯ ДИНАМІКИ ТРАНСПОРТНИХ ПОТОКІВ НА ОСНОВІ ТЕОРІЇ МАСОВОГО ОБСЛУГОВУВАННЯ ДЛЯ ІНТЕГРАЦІЇ В ІНТЕЛЕКТУАЛЬНІ ТРАНСПОРТНІ СИСТЕМИ

***Анотація**. Стаття присвячена дослідженню моделювання динаміки транспортних потоків у міських умовах з використанням теорії масового обслуговування (ТМО). Метою дослідження є розробка методологічного підходу до формалізації динамічних процесів транспортних потоків, що дозволяє адаптувати їх до сучасних інтелектуальних транспортних систем (ІТС). Запропоновано математичні моделі, які враховують стохастичну природу транспортних потоків і ключові показники ефективності, такі як середній час очікування, довжина черг та пропускна здатність. Проведено симуляцію різних сценаріїв транспортної інфраструктури з інтеграцією моделей у інтелектуальні транспортні системи (ІТС). Результати досліджень підтверджують, що застосування ТМО в умовах нерівномірного розподілу транспортних потоків дозволяє суттєво зменшити затримки, оптимізувати маршрути та підвищити ефективність використання дорожньої інфраструктури. Отримані результати відкривають перспективи для подальшого вдосконалення міських транспортних систем шляхом інтеграції алгоритмів машинного навчання та аналізу великих даних, що дозволяє враховувати складну поведінку учасників дорожнього руху. Впровадження моделей ТМО в ІТС сприяє підвищенню ефективності транспортних мереж, забезпечуючи стійкий розвиток міської інфраструктури. Запропоновані підходи є універсальними та можуть бути застосовані для вирішення актуальних проблем мобільності в умовах сучасних міських агломерацій.*

***Ключові слова**: Моделювання транспортних потоків, теорія масового обслуговування, інтелектуальні транспортні системи, динаміка руху, оптимізація транспортних потоків, адаптивне управління, міська мобільність, математичне моделювання, транспортна інфраструктура, зниження заторів.*