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Review

Spatio-Temporal Graphs in Transportation: Challenges, Optimization, and Prospects

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Abstract: Intelligent and information systems in transportation record and accumulate large volumes of raw data on dynamic transportation processes. However, these data are not fully utilized for forecasting, real-time planning, and transportation management. Spatio-temporal graphs allow describing simultaneously both the structure of transportation systems of different modes of transportation and the dynamics of transportation flows. Optimization of such graphs makes it possible to justify management decisions in real time, as well as to forecast the parameters of traffic flows and transportation processes. The purpose of the study is to identify trends in the use of spatio-temporal graphs for solving various problems in transportation, as well as the most common methods of optimization of such graphs. The sample papers studied include 114 publications from the Scopus database over 25 years, from 1999 to 2024. First, a bibliometric analysis was conducted to establish the increase in the number of publications, journals, countries, institutions, subject areas, articles, authors, and keyword matches, to understand the amount of literature generated. Secondly, a literature review was conducted based on content analysis to predict future research directions in the field. We have found that the development of deep learning methods and approaches for designing graph neural networks based on spatio-temporal graphs is a promising direction. Such methods are mostly used to solve the tasks of real-time control of urban transportation systems. There are fewer publications in areas that require in-depth knowledge of transportation technology, such as air, sea, and rail transportation. This study contributes to the expansion of scientific knowledge about methods of spatio-temporal optimization of transport systems based on bibliometric analysis.

Keywords: spatio-temporal graphs; optimization methods; transportation systems; bibliometric analysis; Scopus database

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1. Introduction

The tasks of transportation systems management are the most complex in science and have become especially relevant under conditions of increasing uncertainty in the external environment and increasing complexity of transportation systems themselves [1]. Improvements in information technologies [2], the intensive spread of Industry 4.0 [3], and Internet of Things concepts [4] have formed prerequisites for obtaining large amounts of dynamic, reliable data on the parameters of transportation systems [5], as well as for employing these data to facilitate management decision-making in real time. The dimensionality of operational management tasks within the transport sector is expanding in response to the necessity for the analysis of substantial volumes of detailed current data [6]. An examination of scientific literature has facilitated the categorization of five distinct groups of methods for addressing these challenges: mathematical programming methods, simulation modeling, heuristic methods, analytical models, and combined (hybrid) methods.

In the domain of mathematical programming, numerous single-objective and multi-objective methodologies exist for addressing optimization problems. These methodologies have been extensively utilized in the optimization of traffic flow parameters [7]. Various approaches are employed to account for spatial and temporal dependencies within these methodologies. A distinct category encompasses methods derived from control theory and dynamic programming [8]. Methods based on dynamic programming effectively consider intricate spatial and temporal dependencies. The dynamic optimization of traffic flow parameters, facilitated by the utilization of substantial volumes of spatio-temporal data collected in real time, results in an escalation in the dimensionality of the optimization problem.

The insufficient development of mathematical programming methods and analytical models based on large volumes of real-time data limits the accuracy of their results and reduces management efficiency. Analytical models [9] are employed to address large-scale management problems that incorporate multiple criteria. A promising avenue for the advancement of these models involves multicriteria analysis methods for decision-making in management. The primary factor constraining the application of these methods in the operational management of transport systems is their limited accuracy in accounting for frequent interactions and fluctuations in the state of control objects.

Heuristic methods and artificial intelligence methodologies facilitate the resolution of large-scale problems within constrained timeframes and with requisite accuracy [10]. The primary focus of development for these methods, in the context of transport systems, is the advancement of novel adaptive algorithms and techniques for the formation of neural networks, with the objective of enhancing the precision of monitoring the positions of individual components within traffic flow, followed by the optimization of transport system parameters in real time.

The simulation modeling method is an alternative approach for forecasting transportation flows and developing plans for the structural development of transportation systems [11]. This method is primarily used for justifying infrastructure projects or making decisions at the strategic management level. The main limitations of this method include the complexity of accurately describing real-world systems and the significant time required to build and validate the simulation model [7]. Nevertheless, the combination of different simulation modeling paradigms with optimization models in modern software tools enables the use of this method for constructing synchronized simulation models of transportation systems [12].

Metaheuristic strategies are also used to select optimal solutions based on predictive scenarios [13]. However, the computational efficiency of metaheuristic algorithms decreases as the structure of the optimized system becomes more complex or as the topology of the solution space for possible decision sequences becomes more intricate [14].

A key research trend in recent years in the field of forecasting and optimal management of transportation systems has been the combination of the above methods. The results of such studies include, for example, combined simulation-analytical models, hybrid multi-criteria models, hybrid neural networks, and deep learning structures [15]. A promising development in this area, in our view, is the use of graph theory methods to describe the structure, topology, and temporal changes of transportation systems, as well as management decision options, followed by the application of the discussed optimization and forecasting methods [15].

In transportation systems, the structure of space topology dynamically depends both on the parameters of transportation flows [16] and the individual elements of these flows. A promising way to overcome these limitations is to combine graph theory and optimization methods. Currently, there is an intensive improvement of graph theory in the direction of creating new methods of optimization for solving a wide range of applied problems [17]. However, the use of traditional methods of describing the space of complex topology using graphs has limitations. These relate to two main factors—peculiarities of the topology of transport systems, especially railway transport systems, and variability of parameters of transport flows in a broad sense. The complex and specific topology of transportation systems, especially in railway transport, requires the use of additional constraints in the process of solving optimization problems on spatial graphs. An alternative solution is the creation of specialized spatial graphs through various transformations of the original graphs. The factor of traffic flow dynamics affects the dimensionality of temporal graphs, complicating the use of such graphs for solving optimization and forecasting issues with most known methods.

The problem of improving the accuracy of system state prediction based on the development of graph structure optimization methods has only been considered in a discrete formulation until recently. The result of this approach is the multivariate structure of graphs used to describe complex transportation systems. Most of the known algorithms for predicting the state of transportation systems are based on heuristic and meta-heuristic methods [18]. These algorithms are characterized by insufficient accuracy in predicting the state of complex transport systems [19].

The use of combined spatio-temporal graphs potentially enables the creation of more accurate and computationally efficient methods of describing and predicting the state of complex transportation systems [20]. The need to expand the understanding of the state of research in the use of spatio-temporal graph optimization methods in transportation, and the prospects for the development of these methods as applied to complex control problems, necessitated a systematic literature review.

We searched for review articles in the Scopus database to identify previous similar studies. The keywords "Spatio-Temporal graph" AND "Review" were used for the query. As a result, 36 review articles were found. Most existing literature reviews focused on a specific scientific field, especially in areas related to the use of the "Spatio-Temporal graph" in neuroscience, medicine, biochemistry, genetics and molecular biology, and computer science. The results of the review article analysis show that spatio-temporal graphs are actively used to solve a wide range of applied problems related to optimizing parameters and forecasting the state of complex dynamic systems. Out of 36 articles, only one article is related to the topic of this study, and it is a review of machine learning-based traffic prediction methods [21]. The value of this study lies in summarizing research on the use of spatio-temporal graphs in transportation systems to address relevant and widespread problems of forecasting their state and optimizing transportation flow parameters in real time. Therefore, this study uses a systematic literature review methodology to synthesize graph theory research as applied to transportation systems of different modes and varying complexity.

This paper aims to fill the gap in the analysis of scientific papers on the use of spatio-temporal optimization methods for transportation systems by conducting a systematic literature review of a 25-year period from 1999 to 2024. The main scientific contributions of this paper are as follows:

1. The formulation of a comprehensive view of the research environment that links spatio-temporal graphs, optimization methods, and transport systems of different modes of transport.

2. The identification of the main tasks and methods of spatio-temporal optimization of transport systems based on bibliometric and content analysis of scientific publications.

3. The identification of future research directions in spatio-temporal optimization of transport systems to fill the research gap.

To comprehensively evaluate and analyze the existing research, identify the tasks and areas of application of the “Spatio-Temporal graph” in transportation, as well as to identify promising directions for the development of the “Spatio-Temporal graph” in the future, we formulated the following questions.

1. What quantitative and qualitative changes have been observed in publications on the application of the “Spatio-Temporal graph” in transportation systems?

2. Which authors and organizations, and from which countries, contributed to the development of scientific knowledge in the field of “Spatio-Temporal graph” application to transport systems?

3. What are the most cited publications, and which scientific journals publish research on the use of the “Spatio-Temporal graph” in transportation systems most frequently?

4. What problems and methods of spatio-temporal optimization of transport systems are relevant and promising?

This article consists of four sections. After the “Introduction” section, the “Research Method” section presents a description of the research methodology. The “Analysis Results” section contains the results of bibliometric analysis and content analysis of publications from the Scopus database, as well as the systematization of spatio-temporal optimization problems and methods as applied to transport systems. Finally, the “Conclusion” section summarizes the results of the study and points out its limitations.

2. Research Method

A systematic literature review aims to identify, evaluate, interpret, and categorize research papers addressing one or more research questions and topics. The main steps of the systematic review methodology in this study are as follows [22]:

1. Defining the research questions: formulating the research questions that need to be answered.

2. Literature search and selection: developing a strategy for finding documents using different combinations of keywords to get the most comprehensive overview of the research area, and setting up filters to obtain the most relevant sample of articles.

3. Bibliometric analysis: presenting quantitative analysis and data visualization of the selected sample of articles to understand the key characteristics of the study area, including publication, journal, and citation trends, collaboration, and keyword focus.

4. Content analysis: analyzing the content of the articles selected in the second step to understand the content of current and prospective research.

In this study, the Scopus database was used to analyze research trends in the literature on the application of spatio-temporal optimization methods for solving relevant problems in the operation of various transportation systems. The Scopus database covers a large volume of scientific publications, which provides a rich and diverse dataset for a systematic literature review and reliable analysis results.

We used the following rules to collect relevant literature:

- The papers should contain the keywords “Spatio-Temporal graph” and “Transport systems”. The filter [*Article title, Abstract, Keywords*] was used as a criterion for selecting publications.
- Papers should be indexed in the Scopus database and should include articles in peer-reviewed English language journals, conference proceedings, and book chapters on the field under study.

Spreadsheets were used to perform statistical analysis of publication search results, and VOSviewer [23] was used to visually represent and analyze the keyword network.

Figure 1 presents the scheme of the research methodology. The PRISMA flow diagram [24] approach was used to determine the number of papers selected for analysis, accounting for the exclusion of duplicates and papers not relevant to the field of study. At the "Identification" stage, we selected 184 papers according to the given query combinations: "spatiotemporal" AND "transport systems" (98 papers); "spatio-temporal" AND "transport systems" (86 papers). In the "Screening" stage, we excluded 37 publications that were duplicated from the analysis. An additional 26 papers were excluded based on the results of the abstract analysis as not relevant to the field of study. Thus, the total number of selected papers for bibliometric analysis and content analysis was 114.

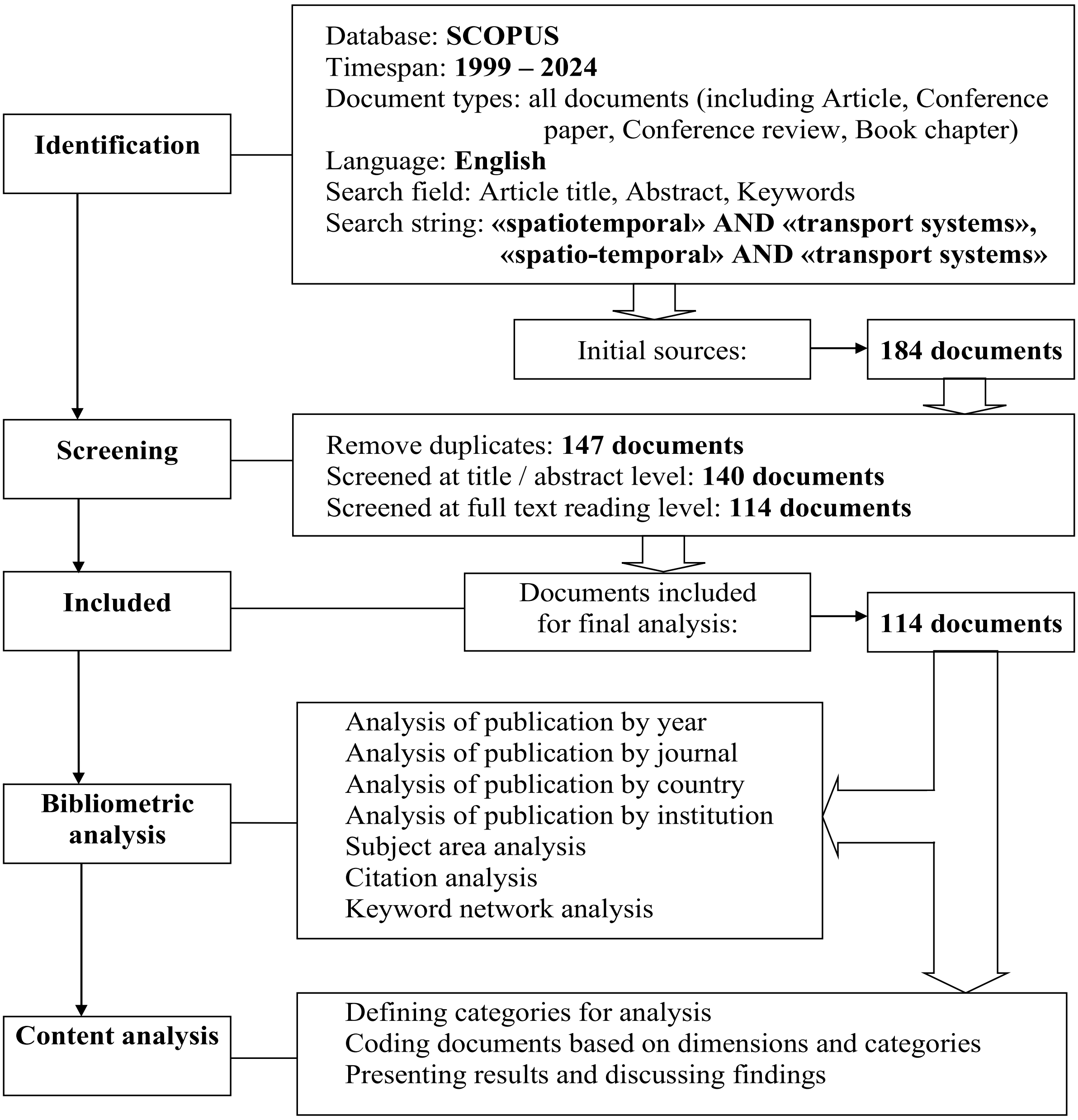

Figure 1. The PRISMA flow diagram.

3. Results

Studies on the use of spatio-temporal graphs for transportation systems of various complexities appeared in the late 1990s and became most prominent in the past five years—this period accounts for about 89% of indexed papers. Figure 2 shows the trend in the number of scientific papers indexed in the Scopus database from 1999 to 2024. Since

2019, there has been a significant increase in the number of publications, which shows the increasing interest of researchers in the use of spatio-temporal graphs to describe and model the operation of various transportation systems.

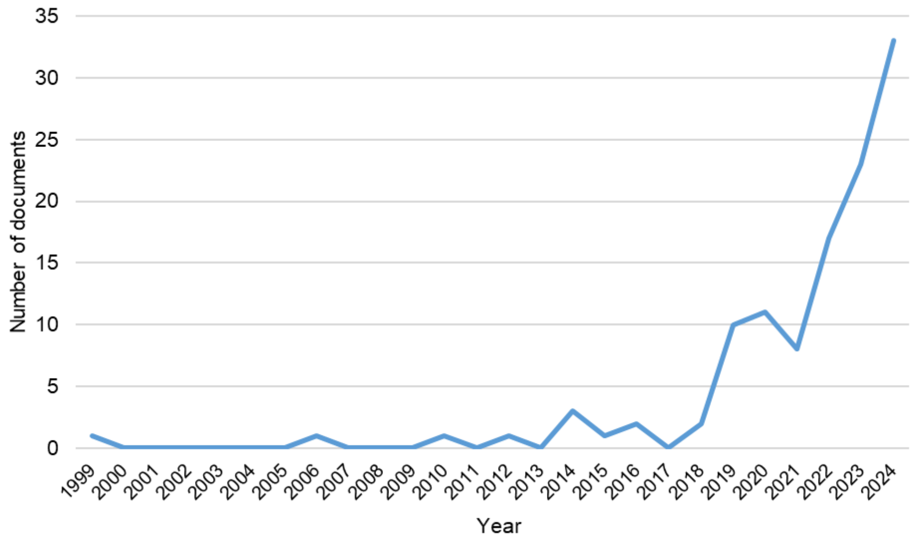

Figure 2. Distribution of papers on the researched subject in the Scopus database from 1999 to 2024 by year.

Most papers (about 93%) were published in English, and up to 80% of papers were published articles in scientific journals (Figure 3).

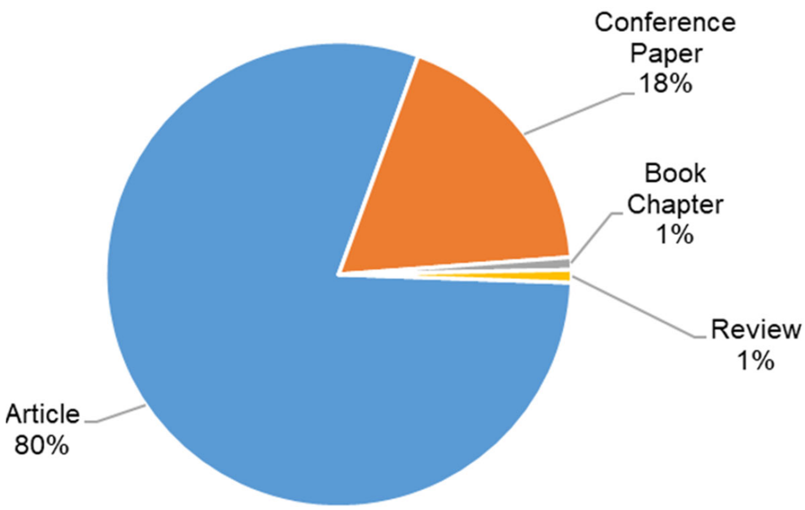

Figure 3. Distribution of papers by type.

Analysis of the distribution of papers across scientific journals shows broad coverage of various resources indexed in the Scopus database. The list of journals includes 63 titles. The top five journals by number of publications were *Transportation Research Part C: Emerging Technologies* (11 papers), *IEEE Transactions on Intelligent Transportation Systems* (7 papers), *IEEE Access* (5 papers), *Sustainability* (Switzerland) (4 papers), and *Computers Environment and Urban Systems* (3 papers). No more than three articles were published in 15 journals. We found only one paper in 43 journals. The number of these journals is shown in the “Other sources” column in Figure 4. The other columns of the diagram in this figure correspond to journals with more than two publications.

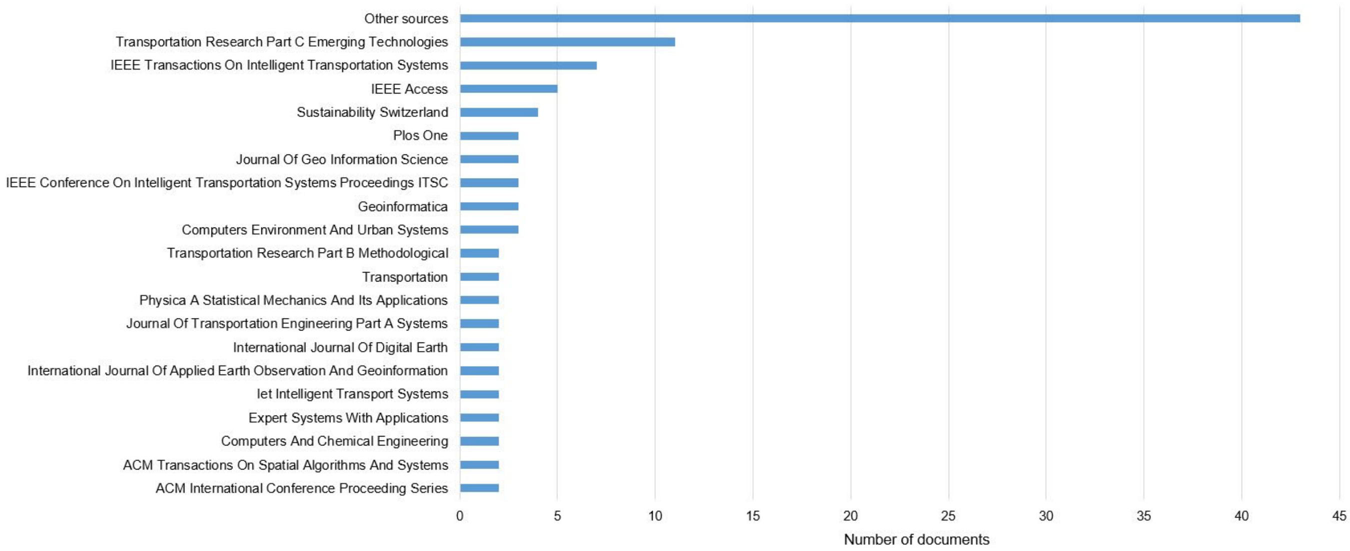

Figure 4. Distribution of papers by journals.

Figure 5 shows the distribution of publications by different branches of knowledge or subject areas. The topics of the articles are related to many subject areas, ranging from computer science, engineering, and social sciences to mining sciences. The diversity of subject areas indicates not only the importance of the topic under study but also the interdisciplinary nature of the issues related to the use of spatio-temporal graph methods for the optimization of transport systems.

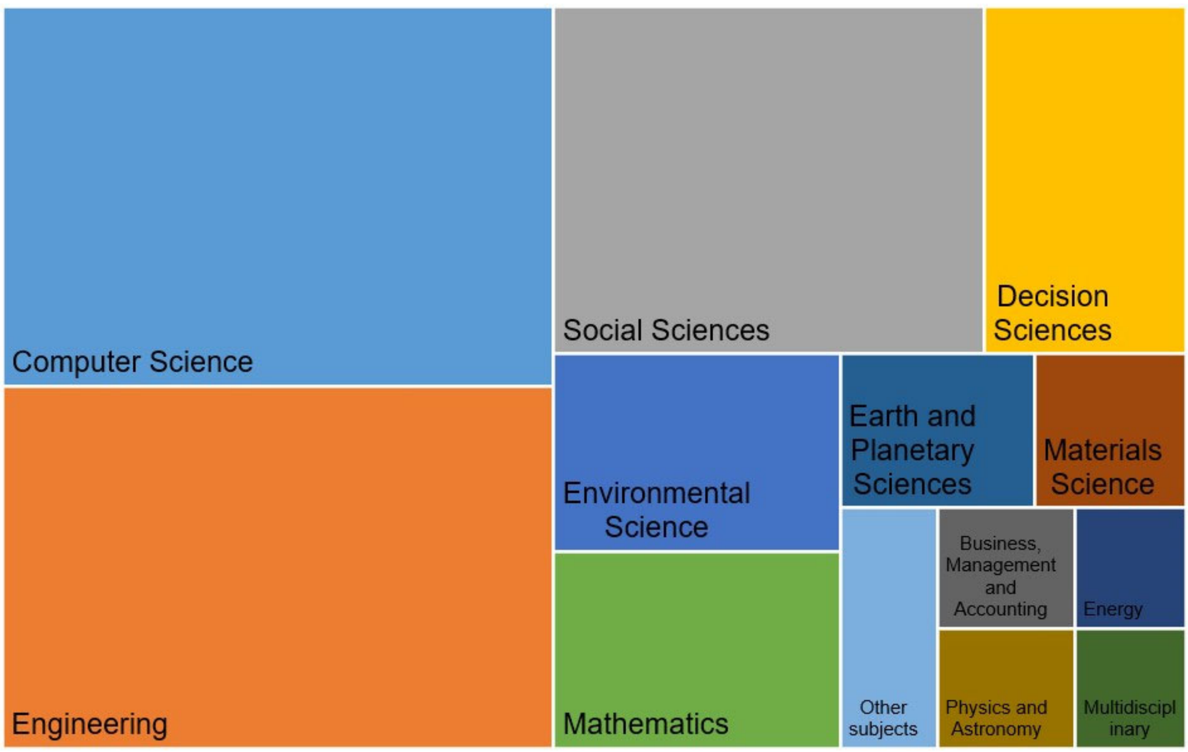

Figure 5. Distribution of papers by fields of knowledge.

Figure 6 shows the distribution of the analyzed publications across the countries to which the authors were affiliated. The leader in the number of publications is China (66 papers). In addition to China, the top five countries by publications are the USA (17 papers), Hong Kong (12 papers), the United Kingdom (8 papers), and South Korea

(6 papers). One publication per country was found in 17 countries, including Austria, Brazil, Canada, Egypt, Indonesia, Netherlands, Norway, Poland, Portugal, Qatar, the Russian Federation, Saudi Arabia, Slovakia, Spain, Sweden, Switzerland, and Taiwan. The Scopus database did not identify publications on the subject of the study from the countries of Central, Eastern, and Southern Africa, Central Asia, or South America, with the exception of Brazil.

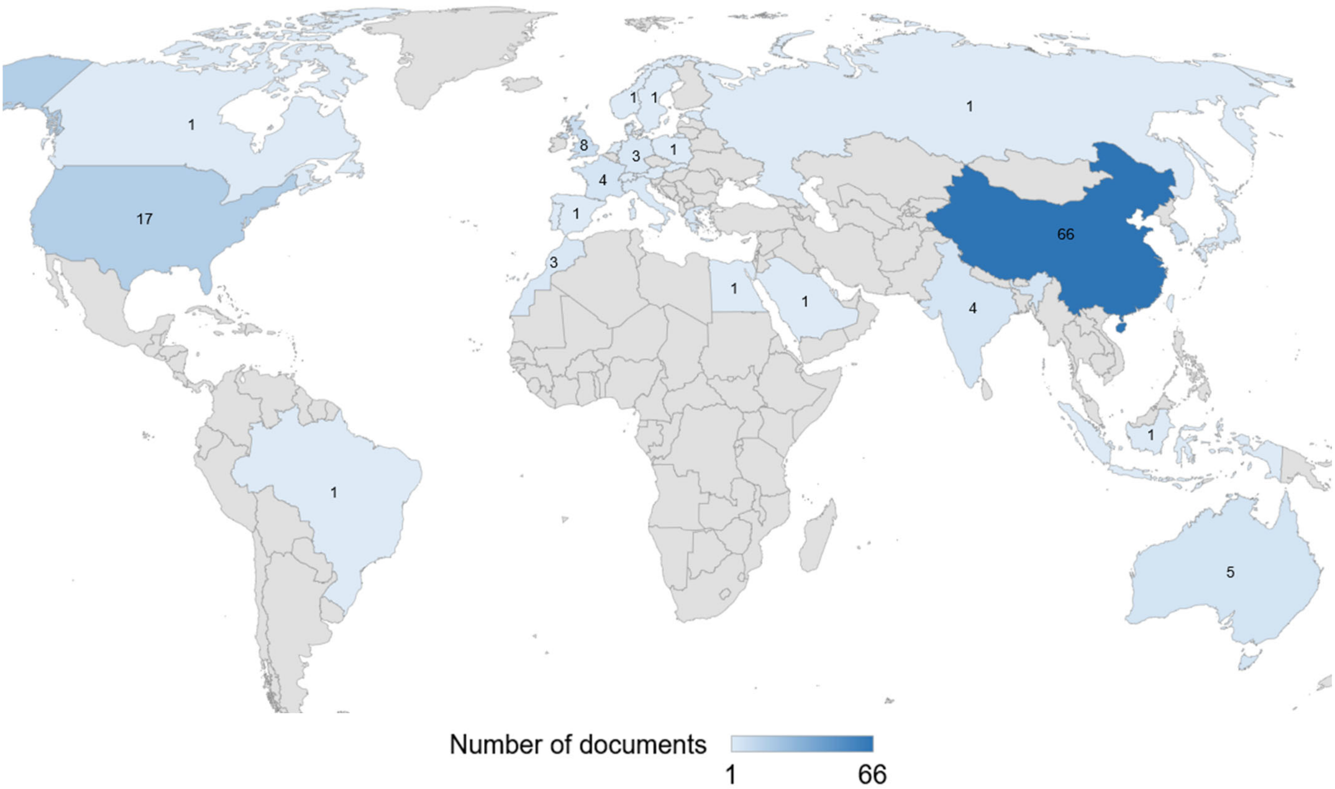

Figure 6. Distribution of papers by country.

The leading organizations with which authors with the largest number of scientific articles on the research topic are the Chinese Academy of Sciences (seven papers), Hong Kong University of Science and Technology (six papers), The Hong Kong Polytechnic University (six papers), Beijing Jiaotong University (five papers), and The University of Hong Kong (four papers). In total, the analysis identified 160 organizations from 34 countries.

Analysis of publication citations indicated that the first citation appeared in 1999, and the total number of citations reached 1728 at the time of the study. A total of 87 papers out of 114 were cited in the Scopus database at least once, which is 76% (Figure 7).

The most cited papers at the time of the study are presented in Table 1. Researchers have focused primarily on areas related to modeling and control of traffic in urban networks [25], bike sharing systems [26,27], traffic speed prediction in Intelligent Transportation Systems [28], and forecasting the demand for urban taxi rides within an online car-hailing system [29].

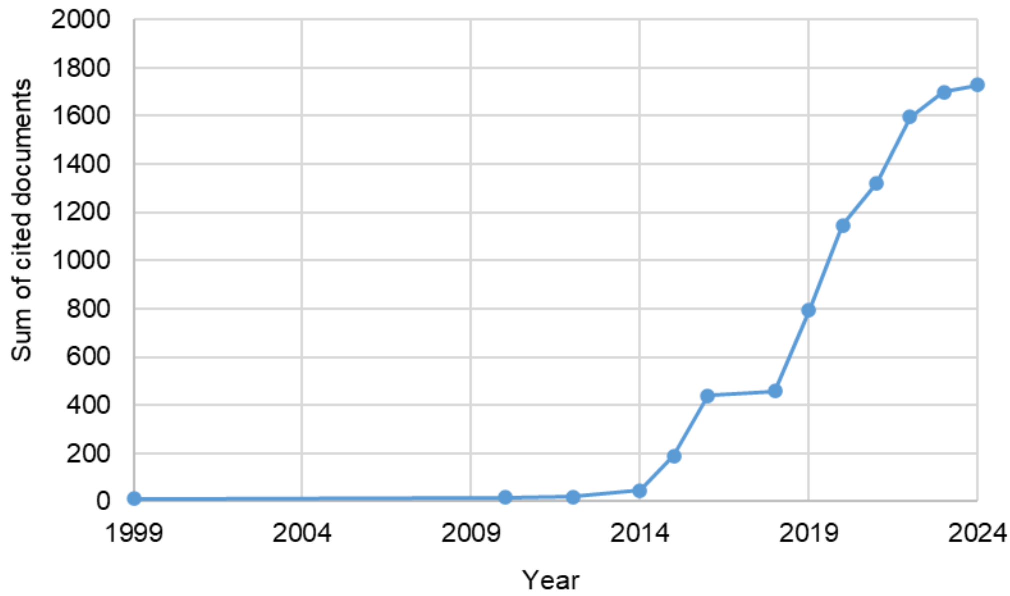

Figure 7. Number of citations cumulatively by year.

Table 1. Top 5 most cited papers.

№	Title	Author(s)	Year	Number of Citations	References
1	Clustering of heterogeneous networks with directional flows based on «Snake» similarities	Saeedmanesh, M., Geroliminis, N.	2016	195	[25]
2	Understanding spatio-temporal patterns of biking behavior by analyzing massive bike sharing data in Chicago	Zhou, X.	2015	143	[26]
3	A spatio-temporal and graph-based analysis of dockless bike sharing patterns to understand urban flows over the last mile	Yang, Y., Heppenstall, A., Turner, A., Comber, A.	2019	119	[27]
4	Spatial-temporal graph attention networks: A deep learning approach for traffic forecasting	Zhang, C., Yu, J.J.Q., Liu, Y.	2019	114	[28]
5	Urban ride-hailing demand prediction with multiple spatio-temporal information fusion network	Jin, G., Cui, Y., Zeng, L., (. . .), Feng, Y., Huang, J.	2020	92	[29]

Keyword analysis was performed by dividing the papers by year of publication into two periods—from 1999 to 2018 and from 2019 to 2024. This division is justified by the sharp increase in the number of publications starting from 2019. In the papers from the first period, 194 keywords were identified. The keywords are grouped into three clusters: red, blue, and green (Figure 8), each represented by four main areas with high linkage strength.

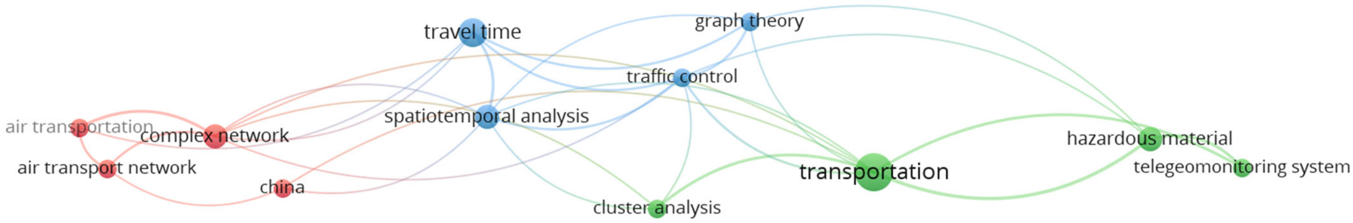

Figure 8. Most frequently used keywords in papers published between 1999 and 2018.

The red cluster reflects the relevance of issues related to “complex network” formation. Research topics are devoted to the assessment of air network development in China, and to modeling and traffic management in urban networks. The blue cluster covers problems related to "travel time". The subject matter of these works includes the estimation of vehicle travel time, passenger departure time, modeling of road users' behavior, and estimation of probable spatial and temporal travel paths. These studies cover both air and urban modes of transport. The green cluster, "transportation", reflects the solution of problems related to the transportation of dangerous goods, route selection in multimodal transport systems, and modeling the location of transport hubs.

In papers published during the second analysis period, from 2019 to 2024, 1318 keywords were identified. In the subsequent analysis, all keywords were grouped into four clusters comprising 29 main areas (Figure 9). The red cluster includes nine domains—graph, data, approach, algorithm, graphic method, public transportation, demand prediction, bicycle, and COVID-19. The green cluster includes nine areas—street, road, motor transportation, road network, traffic prediction, travel time, and spatio-temporal data. The blue cluster includes eight areas—graph convolutional network, spatio, convolutional network, traffic flow prediction, traffic forecasting, intelligent transportation systems, and intelligent vehicle highway system. The yellow cluster includes three areas—transportation systems, traffic management, and China.

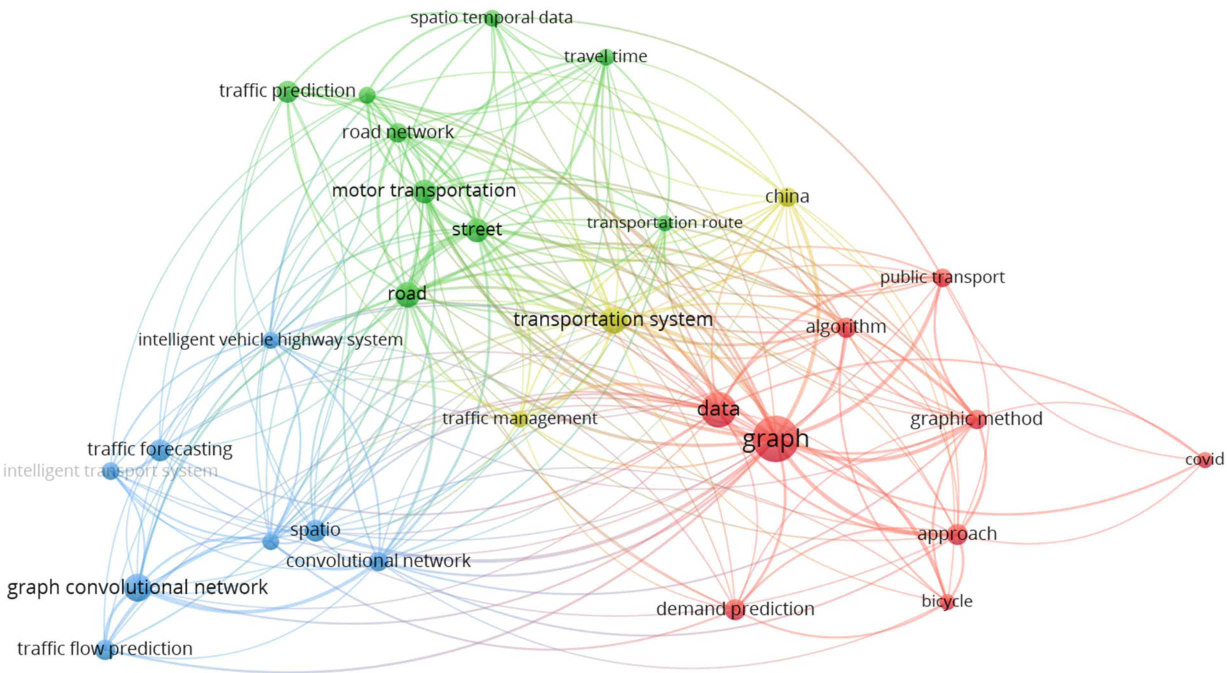

Figure 9. Most frequently used keywords in papers published between 2019 and 2024.

The results of keyword analysis in the 114 selected papers revealed 506 words (Figure 10).

The keywords "spatio-temporal graph", "neural networks", "machine learning", "deep learning", "forecasting", "analysis", "traffic flow", "spatio-temporal data", and "transportation system" are the most frequently used. Thus, a formal analysis of keyword frequency shows a clear interest among scientists in using neural networks and machine learning methods combined with spatio-temporal graphs to address various problems in transportation systems. A set of key terms including "optimization", "dynamic optimization", "hybrid methods", "spatio-temporal graph neural networks", "combined model" or "hybrid model", "deep learning", and "hybrid neural network" holds promise for further detailing research publications on the use of spatio-temporal graphs in transportation.

Figure 10. Frequency of keywords in the selected research papers.

In addition to the keyword analysis, all papers were grouped by areas of application of the spatio-temporal graph as applied to different modes of transportation or transportation systems (Table 2). Despite the interdisciplinary nature of most publications on each mode of transportation, specific areas of application can be attributed to individual elements of transportation systems—transport communications and infrastructure, vehicles, road users, control systems, information-telecommunication systems, etc.

Table 2. Distribution of papers by mode of transport and subject areas.

№	Mode of Transportation (Transport System)/ Number of Papers	Subject Areas	References
1	Road transport/22	Smart transportation	[30]
		Urban built environment and traffic congestion	[31]
		Traffic forecasting congestion	[32]
		Control of traffic in urban networks	[25,33]
		Pick-up and drop-off locations in taxi services	[34]
		Taxicab traffic control	[35,36]
		Taxi demand prediction	[29,37]
		Bus routes	[38]
		Bus systems	[39]
		Bus stations	[40]
		Bus operation	[41]
		Prediction of urban traffic	[42]
		Automatic license plate recognition	[43–45]
		Predicting occupancy of urban parking	[46]
		Designing mobile priority parking lots	[47]
		Transportation networks with heterogeneous vehicular flow	[48]
		Carriage of dangerous goods	[49]

Table 2. *Cont.*

№	Mode of Transportation (Transport System)/ Number of Papers	Subject Areas	References
2	Rail transport/9	Shaping the railroad network Digital twin railway Inter-urban container traffic flow Mobility of urban rail transport passengers Prediction of cascading delays in the railroad network Prediction of transit flow in urban transportation systems Passenger flow forecast Predicting the delay time of trains	[50] [51,52] [53] [54] [55] [56] [57] [58]
3	Maritime transport/4	Cargo transportation on the maritime transportation network Traffic density prediction Traffic flow prediction for busy waterway segments Autonomous ships	[59] [60] [61] [62]
4	Air transport/4	Air transport network Forecasting framework for en route airspace emissions Passenger travels Predicting airport delays	[63] [64] [65] [66]
5	Urban land transport systems/13	Bike sharing systems	[26,27,67–77]
6	Underground transport/2	Metro systems	[78,79]
7	Multimodal transport systems/14	Mobility on public transport Clean air routing Route in urban multimodal transport networks Multimodal transport demand forecasting Supply chain design The reliability of transport systems Transportation of products in supply chains	[80] [81] [82–84] [85,86] [87] [88] [89]
8	Intelligent transportation systems (ITC)/48	Urban traffic prediction Road traffic/road network data Vehicle trajectory Traffic speed prediction Urban traffic demand forecasting Regional-scale traffic framework Routing Modeling of road segments and intersections Traffic flow forecasting Forecasting passenger flows Mobile conveying units Autonomous vehicles Resilient urban transport network Traffic signal control Monitoring system for the transportation of hazardous goods Order dispatching Traffic monitoring system Vehicle type classification Interaction of vehicles with intelligent systems for transport automation Multi-traffic modes system Multioperation transport processes	[90–102] [103] [104–107] [28,108] [109,110] [111] [112] [113–120] [121–123] [124] [125,126] [127] [128] [129,130] [131] [132] [133] [134] [135] [136]

In recent years, there has been increased interest among researchers in using various spatio-temporal optimization methods in real-time transportation applications. Such methods are applied to traffic forecasting (34 papers) and passenger flow forecasting (5 papers), route and trip planning (13 papers), vehicle allocation (demand forecasting), vehicle sharing forecasting (29 papers), and monitoring the use of transport infrastructure by different modes of transport (33 papers).

Based on the results of the content analysis of publications, we arranged the methods of spatio-temporal optimization into groups and subgroups (Table 3). The most frequently used methods for spatio-temporal graph optimization are mathematical programming methods (linear programming, multi-criteria analysis, dynamic programming), graph theory (simple graph, dynamic graphs and methods for generalizing their structure, spatio-temporal graphs and methods for their formation, biological graphs), and heuristic methods (heuristic strategies, feedforward neural networks, convolutional neural networks (CNNs), graph convolutional neural networks (GCNs), graph neural networks (GNNs), and other methods).

Table 3. Distribution of studies by method of transport systems spatio-temporal optimization.

№	Method Group	Method Subgroup/ Number of Papers	Study Objective	References
1	Mathematical programming	Linear Programming (LP)/4	Forecasting transportation flows	[87,123]
			Forecasting demand and resource allocation	[131]
			Route optimization	[82]
		Multi-criteria Analysis/3	Routing with arrival window constraints	[137]
			Collision avoidance for autonomous vehicles	[62]
			Optimizing bike sharing systems in urban areas	[74]
		Dynamic Programming/3	Optimization of urban land use system structure based on time-distance accessibility criteria	[39]
			Predicting railroad infrastructure development	[50]
			Predicting train delay times	[58]
2	Graph theory	Simple Graphs/6	Forecasting transportation flows	[30,102]
			Hybrid parking allocation	[47]
			Bike sharing	[27]
			Optimal route for health (clean route)	[81]
			Optimization of parameters of intra-city container railway hubs	[53]
		Dynamic Graphs/5	Identification of bus routes and urban hotspot	[34,38]
			Clustering of traffic of different vehicles	[25]
			Clustering of demand-responsive bicycle stations	[76]
			Identification of urban traffic flow patterns	[107]
		Spatio-temporal Graph/2	The shortest possible routes for mobile conveyors	[124]
			Optimized product distribution	[89]
		Biological Graphs/1	Transportation control to prevent spoilage of perishable goods	[136]
3	Heuristic methods	Heuristic Strategies/4	Analysis of cyclists' behavior	[26]
			Analysis of changes in cyclist behavior during COVID-19	[73]
			Adjusting the route in case of congestion	[138]
			Vehicle type classifications	[133]
		Feedforward Neural Networks (FFGN)/3	Traffic flow forecasting	[32]
			Travel time reduction	[125]
			Forecasting multimodal transportation demand	[86]
		Converged Neural Networks (CNN)/7	Automatically identify potential congestion points in cities	[31]
			Forecasting transit flows	[56]
			Recover missing traffic data	[103]
			Subway traffic forecasting	[79]
			Forecasting demand for cab services	[110]
			Traffic density forecasting	[60]
			Traffic flow forecasting	[119]

Table 3. *Cont.*

№	Method Group	Method Subgroup/ Number of Papers	Study Objective	References
3	Heuristic methods	Graph Convolutional Neural Networks (GCN)/6	Traffic flow forecasting	[96,98]
			Predicting the spatial distribution of free shared bicycles	[72]
			Travel time estimation	[105]
			Predicting delays	[66]
			Forecasting demand for cab services	[29]
		Graph Neural Networks (GNN)/16	Traffic flow forecasting	[42,61,92,93,95,99,113]
			Transportation risk assessment	[88]
			Cyclist flow forecasting	[68–70]
			Forecasting vehicle positioning	[104]
			Forecasting vehicle queues	[97]
			Predicting cascading delays in the rail network	[55]
			Identification of large-scale traffic congestion	[126]
			Multimodal route planning	[84]
		Hybrid Neural Networks/12	Traffic flow forecasting	[44,73,90,100,116]
			Air pollution forecasting	[64]
			Parking lot occupancy prediction	[46]
			Transportation resiliency analysis for extreme weather events	[127]
			Route optimization	[115]
			Transport demand forecasting	[71,85]
			Air pollution forecast for air transportation	[63]
		Complex Network Theory Methods/7	Traffic flow forecasting	[120]
			Passenger flow forecasting	[121]
			Standardization of flight times in Europe	[65]
			Transportation demand forecasting (cabs)	[37,109]
			Traffic management	[33]
			Identify bottlenecks in the metro system	[78]
		Machine Learning/19	Rail project management	[51]
			Real-time traffic monitoring	[35,132]
			Passenger flow forecasting	[40,122]
			Traffic flow forecasting	[111,135]
			Data representation method in digital twin in railway transportation	[52]
			Bus distribution planning	[41]
			Public transport passenger mobility forecasting	[54]
			Distributed spatio-temporal network of hazardous materials data repositories	[49]
			Multimodal route forecasting	[84]
			Vehicle and transportation demand forecasting	[36,75]
			Traffic flow identification	[45]
			Spatio-temporal patterns in maritime freight transportation networks	[59]
			Monitoring hazardous materials transportation.	[129,130]
			Resource allocation	[77]
		Deep Learning Methods/11	Trip planning	[80]
			Traffic flow forecasting	[48,91,101,118]
			Traffic trajectory data retrieval, real-time vehicle trajectory imputation	[43,106]
			Forecasting demand for multiple modes of transportation	[67]
			Travel time estimation	[112]
			Automating vehicle interaction	[134]
			Traffic speed prediction	[28]
		Genetic Algorithms/1	Traffic light control	[128]

The results of the extended analysis of the advantages and limitations of current methods for spatio-temporal optimization of transport systems are presented in Table 4.

Table 4. Advantages and limitations of spatio-temporal optimization methods for transport systems.

№	Method Group	Method Subgroup	Method Essence	Advantages	Limitations
1	Mathematical programming	Linear Programming (LP)	Single-objective optimization	Accuracy of optimization results	Single criterion
		Multi-criteria Analysis	Establishing dependencies between conflicting criteria and ranking alternatives	Consideration of conflicting objectives	Impossibility of application in case of frequent changes of influencing factors
		Dynamic Programming	Partitioning a complex problem into subproblems of lower dimensionality	Consideration of dynamics of control object parameters and their mutual influences	Computational complexity when solving problems of high dimensionality
2	Graph theory	Simple Graphs	Formalization of the problem as a graph of static structure	Accuracy of optimization results	Changes to the graph structure are not allowed
		Dynamic Graphs	Formalization of the problem as a graph of dynamic structure	Possibility to change the graph structure depending on the dynamics of control object parameters	Consideration of spatial and temporal data separately
		Spatio-temporal Graph	Problem formalization in the form of a graph with spatio-temporal estimations	Simultaneous consideration of both spatial and temporal data	Computational complexity when solving problems of high dimensionality
		Biological Graphs	Formalization of the problem in the form of a graph with ecological or social assessments	Formation of estimates of graph edges based on multifactor analysis	Data changes in the process of calculation are not allowed
3	Heuristic methods	Heuristic Strategies	Generalization of problem-solving practices	Ability to solve problems of high computational complexity	Insufficient accuracy
		Feedforward Neural Networks (FFGN)	A neural network in which connections between layers do not form a loop	Reducing optimization space	Does not recognize elements of transport infrastructure (transport network) and mobile objects (vehicles)
		Converged Neural Networks (CNN)	A neural network that contains convolutional layers	Recognizes elements of transport infrastructure (transport network) and mobile objects (vehicles)	Does not consider the dynamics of transport infrastructure elements loading with mobile objects
		Graph Convolutional Neural Networks (GCN)	A neural network that transforms a graph into convolutional layers	Use of graphs in recognizing the workload of transport infrastructure elements (transport network)	Additional transformations of graph structure to matrix
		Graph Neural Networks (GNN)	Graph-based neural network	Using graph structure without additional transformations	Additional transformations of temporal data
		Hybrid Neural Networks	A combined neural network of several types of neural networks	Fusion of spatial and temporal dependencies	Additional graph transformations
		Complex Network Theory Methods	Large-scale graph	Clustering based graph size reduction	Low scalability
		Machine Learning	Using statistics and mathematical programming methods	Ability to analyze large amounts of data	Use of spatial and temporal data separately. Data changes during training are not allowed
		Deep Learning Methods	Combining machine learning methods	Comprehensive consideration of stochastic spatial and temporal data	Short-term recognition of complex spatial and temporal dependencies
		Genetic Algorithms	Algorithms for random selection of solutions based on principles of natural selection	Increasing the accuracy of neural networks weighting coefficient tuning	Insufficient accuracy

Content analysis has shown the greatest number of uses of heuristic methods of spatio-temporal optimization for solving real-time decision support problems (90 publications). Neural networks, along with machine and deep learning methods (73 publications), are used to account for spatio-temporal dependencies in complex transportation systems with a high degree of accuracy. A promising direction is the use of graph neural networks (16 publications) and methods for their training. A distinctive feature of graph neural networks is the possibility of using a spatio-temporal graph without additional transformations. Machine learning methods (19 publications) and methods of their combination (deep learning methods, 11 publications) are used for training such neural networks.

The results of the paper analysis show the interest of researchers in combining graphs with methods of mathematical statistics and analysis, optimization, numerical methods, probability theory, and multicriteria analysis for training neural networks. The basis of such deep learning methods is the transformation of data on transportation system parameters into spatio-temporal estimates of the graph, and their use in solving problems of spatio-temporal optimization. This optimization is based on the formalization of spatial and temporal data in the form of graphs. We identified 16 different methods of graph theory and 11 methods of mathematical programming for forming spatial and temporal estimates of a graph and for optimizing it (Figure 11).

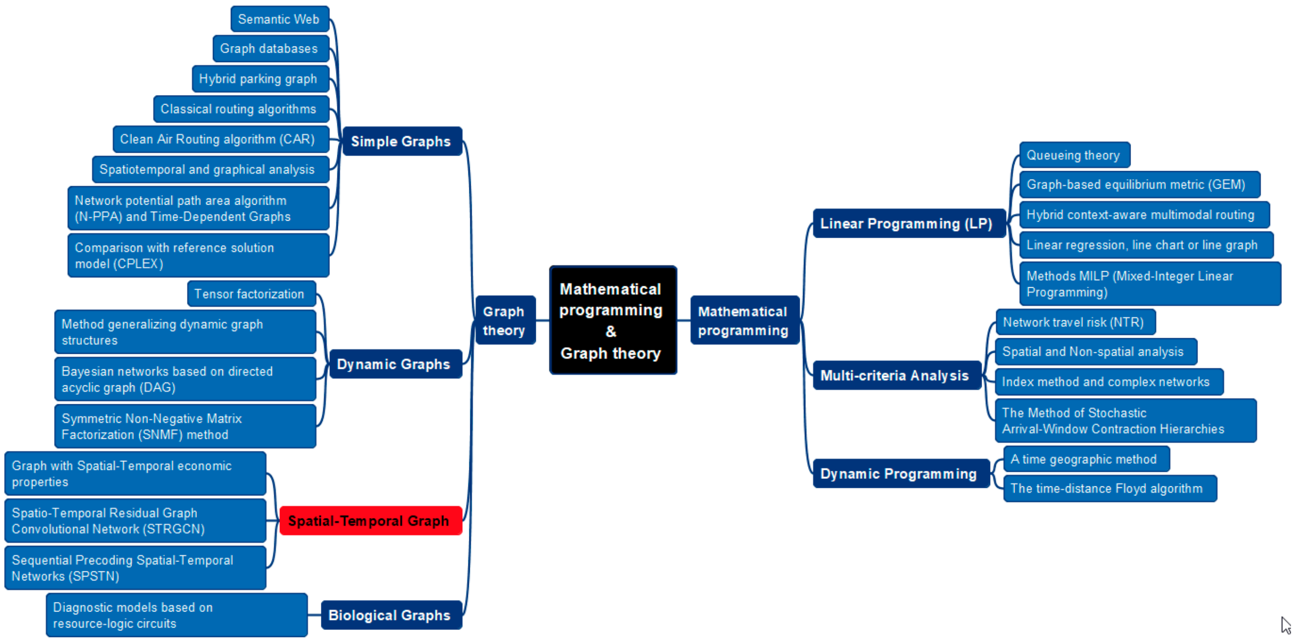

Figure 11. Methods of mathematical programming and graph theory for solving spatio-temporal optimization problems in transportation systems.

The operation of a complex transportation system is accompanied by a large volume of spatial and temporal data about its state. The need to improve the accuracy of describing such spatial and temporal dependencies leads to an increase in the dimensionality of optimization and forecasting problems for the state of the transportation system. Artificial neural networks are used to reduce the optimization space (Figure 12).

Graph theory and mathematical programming methods form the basis for creating and training feedforward neural networks (3 methods), convolutional neural networks (5 methods), graph neural networks (13 methods), graph convolutional neural networks (13 methods), and merged neural networks (hybrid neural networks, 7 methods) to recognize complex spatial and temporal dependencies. A total of 30 machine learning methods were been identified when using such neural networks. These methods account for spatial and temporal dependencies in different ways (Figure 13).

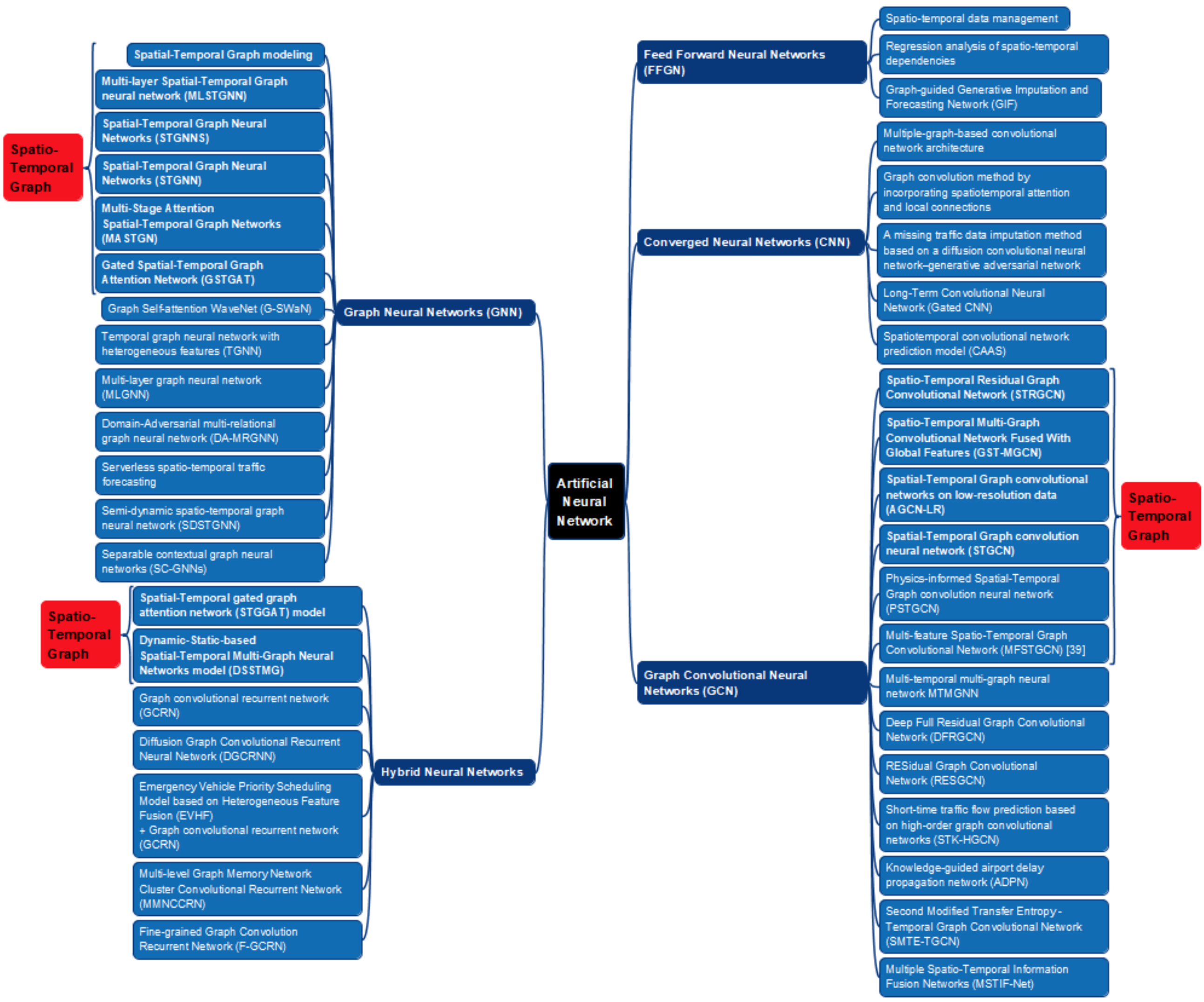

Figure 12. Artificial neural networks in spatio-temporal optimization problems of transportation systems.

Most of the mentioned machine learning methods use either spatial or temporal data separately. We found only one machine learning method that allows for the integrated use of both spatial and temporal data to form a predictor for the objective function [132]. However, the high uncertainty of spatial and temporal data requires frequent adjustments of the predictor in the machine learning algorithm. This is the main limitation of using machine learning methods, as the predictor cannot be changed during the calculation process. Deep learning methods or deep (multilayer) neural networks are more effective for the integrated use of stochastic spatial and temporal data (Figure 14).

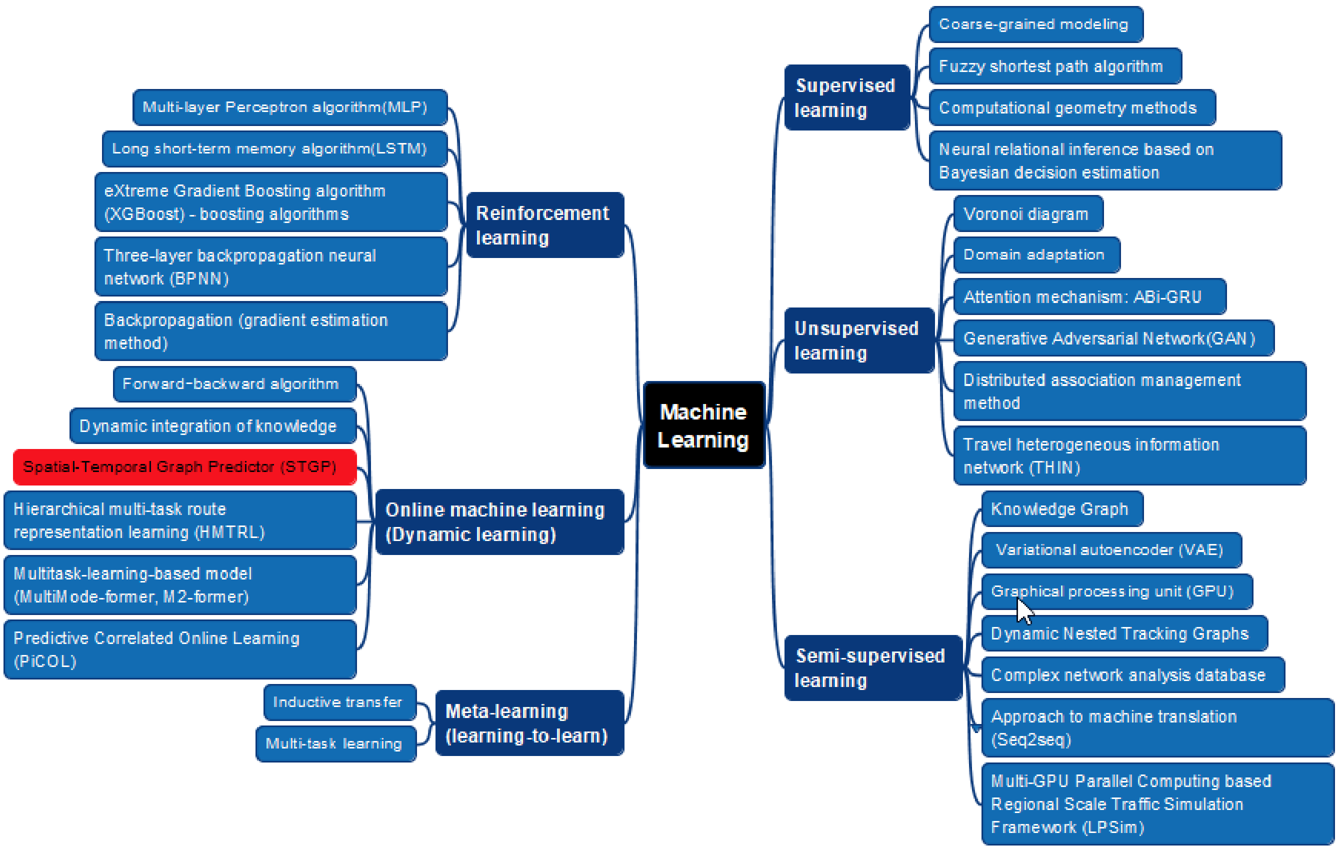

Figure 13. Machine learning methods in spatio-temporal optimization problems of transportation systems.

The creation and training of deep or multilayer neural networks for forecasting the state of transportation systems is an especially challenging task. The complexity is due to the frequent changes and large volume of spatial and temporal data collected and analyzed. The need to account for such data changes leads to an increase in the dimensionality of the problem. Four deep learning methods that use a spatio-temporal graph to reduce the problem's dimensionality have been identified [28,67,91,120].

Further analysis of research on the use of spatio-temporal graphs for forecasting and managing transportation systems revealed a promising direction for overcoming the identified challenges and limitations. This direction involves developing methods for constructing a spatio-temporal graph of the transportation system's state, in combination with methods for its optimization, as well as methods for creating and training artificial neural networks (Figure 15).

Such combinations are found in publications on graph theory (three publications) [58,89,124], graph neural networks (eight publications) [42,61,84,95,97,99,109,113], graph convolutional neural networks (six publications) [55,60,96,105,110,119], hybrid neural networks (two publications) [44,121], the dynamic machine learning method (one publication) [132], deep neural networks, and deep learning methods (four publications) [28,67,91,120].

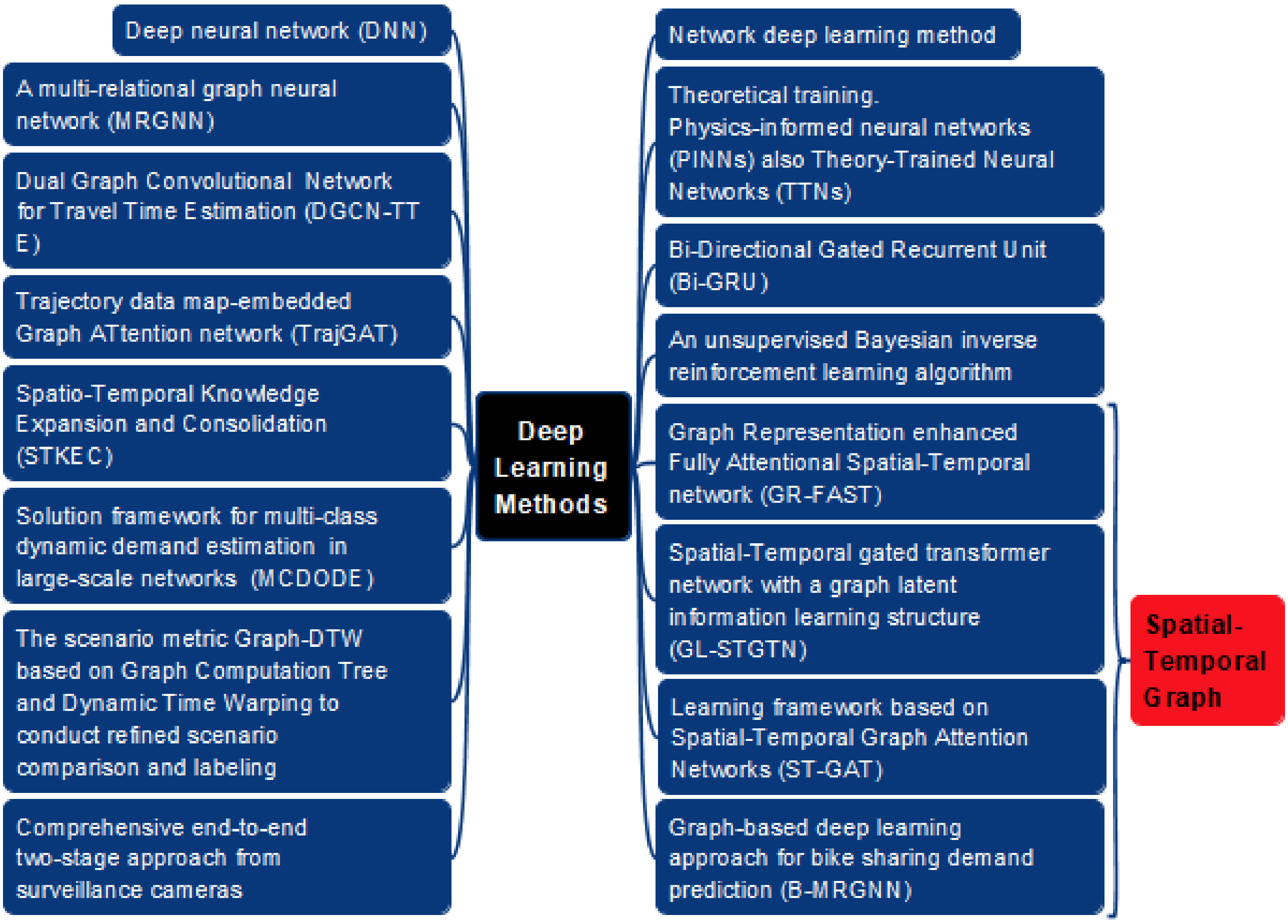

Figure 14. Deep learning methods in spatio-temporal optimization problems of transportation systems.

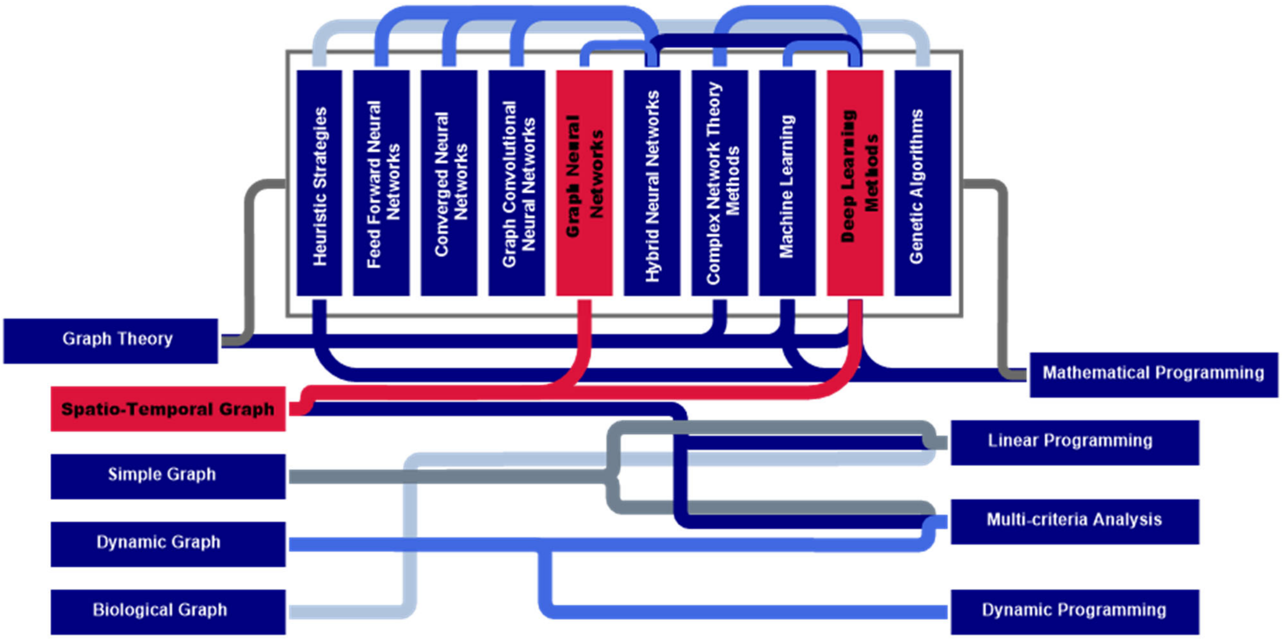

Figure 15. Possible combinations of identified methods for spatio-temporal optimization of transportation systems.

We identify a separate subgroup within graph theory that focuses on methods for constructing and optimizing spatio-temporal graphs, which serve as the foundation for developing and utilizing deep spatio-temporal graph neural networks [139]. Surprisingly, we could not find any publications on combining the popular simulation modeling methods either for training neural networks or for solving spatio-temporal optimization problems.

Most of the publications reflect the use and development of spatio-temporal optimization methods for solving problems of both real-time management of urban transport systems and planning tasks. The smallest number of publications was found in the areas of rail, sea, and air transportation. In our opinion, this is due to the need to consider the specific management and technology of the transportation process when using spatio-temporal optimization methods. When applying optimization methods to simple graphs, the formation of a vehicle route may include turning at points in the transport infrastructure where this is prohibited by traffic safety rules or infeasible according to the technology of operation. For such conditions, specialized graph structures like linear (edge) or two-vertex graphs are used. The result of using such graphs is the blocking of vehicle turns based on the introduction of additional rules and exceptions. For example, when using methods of spatio-temporal optimization of railway transport systems, it is necessary to consider the specifics of train shunting. The result of solving the problems of train shunting is significantly affected by changes in the direction of trains when following shunting routes, the structure of trains, timetables, and loading and unloading schedules of cars. These factors determine the method of spatio-temporal graph formation. On the one hand, the accuracy of data conversion into spatio-temporal graph estimates depends on the correct description of the transportation process technology. This requires the use of specialized graph structures: line graph (edge graph), two-vertex graph with connected bijective vertices, and two-vertex graph with separated bijective vertices and edges [140]. On the other hand, the management process in railway transportation is accompanied by many variations in managerial decisions related to train shunting. Depending on the choice of a certain variant of such a sequence, different changes in the spatio-temporal state of the railway transportation system are observed. Therefore, it is necessary to use technologically informed spatio-temporal graphs when making managerial decisions.

4. Conclusions

Recently, within the field of transport systems management, there has been growing interest in the use of various methods of spatio-temporal optimization in real time to solve problems such as forecasting traffic and passenger flows, planning routes and trips, distribution of vehicles, forecasting the joint use of vehicles, and monitoring the use of transport infrastructure by different types of transport. The main groups and subgroups of spatio-temporal optimization methods identified for solving such problems include the following: mathematical programming (linear programming (LP), multi-criteria analysis, dynamic programming); graph theory (simple graphs, dynamic graphs, spatio-temporal graph, biological graphs); heuristic methods (heuristic strategies, feedforward neural networks (FFGN), converged neural networks (CNN), graph convolutional neural networks (GCN), graph neural networks (GNN), hybrid neural networks, complex network theory methods, machine learning, deep learning methods, genetic algorithms). The main advantages and disadvantages of the identified methods regarding complex spatial and temporal dependencies are presented. A more detailed analysis of each spatio-temporal optimization method individually is part of future research.

The results of the conducted systematic literature review of publications show the intensive development of spatio-temporal optimization methods based on the use of spatio-temporal graphs for predicting changes in spatial topology structures depending on the parameters of transport flows.

The results of the analysis also highlight the interest of researchers in combining graphs with methods of mathematical statistics and analysis, optimization, numerical methods, probability theory, and multicriteria analysis for training neural networks. The basis of such deep learning methods is the transformation of transportation system parameter data into spatio-temporal estimates on a graph and their use in solving problems of spatio-temporal optimization.

Particular interest has been observed in the use of spatio-temporal graphs within heuristic methods. A promising direction is the development of deep learning methods and methods of forming graph neural networks based on the use of spatio-temporal graphs. These methods are most often used to solve problems related to the real-time control of urban transportation systems.

The fewest publications were found in fields requiring in-depth knowledge of transportation technology, such as air, sea, and railway transport. This is because the result of spatial and temporal optimization, and consequently, the forecast values of transport system parameters depend on the correctness and detail of the description of the specifics and technology of a particular transportation process. A multitude of specific constraints and requirements related to transportation safety and operating technology must be monitored in transportation management in these modes of transportation. On the other hand, the management process is accompanied by changes in the spatio-temporal state of the transportation system. These features of transportation systems require, in our opinion, the use of specific graphs such as, for example, line graphs (edge graphs), two-vertex graphs with connected bijective vertices, and two-vertex graphs with separated bijective vertices and edges.

The systematic review allowed us to identify both missing areas and prospects for research on the use of spatio-temporal optimization of transport systems. Such research should be focused on the development of deep learning algorithms of graph neural networks for predicting the parameters of transportation systems by determining the optimal sequences of changes in their state.

The improvement of deep learning methods for graph neural networks is a promising area of research. We highlight the high potential of methods for dynamic optimization of spatio-temporal graphs and the use of optimization results to train graph neural networks for predicting the state of transportation systems. The results of experiments on highly detailed simulation models can be used for training graph neural networks. These approaches, in our opinion, will expand the adaptability of the use of graph neural networks for transportation system state prediction. The most promising types of transport for the application of spatio-temporal optimization methods are railway, air, and sea transport systems.

The main limitations of our study are as follows:

- Only the Scopus database was used for analysis.
- The filter [Article title, Abstract, Keywords] was applied as a search criterion.
- Only specific keyword combinations ("spatiotemporal", "spatio-temporal", "transport systems") were used, which limited the depth of analysis and provided only an initial understanding of the use of spatio-temporal graphs in transportation.
- Open-source software with functional limitations was used for bibliometric analysis.

These limitations prevented a more detailed analysis and investigation of the specific problems associated with the use of spatio-temporal graphs in transportation systems. The authors intend to eliminate these limitations in future studies. The directions of our future research, considering the study's limitations, include the following:

- Utilizing additional databases for searching scientific publications, such as Web of Science.

- Enhancing the methodology for analyzing publications by incorporating more complex and statistically oriented text analysis methods (e.g., topic modeling, word embeddings, etc.).
- Applying additional search filters for articles and exploring alternative keywords and their combinations. The results of this study indicate that relevant keywords may include "optimization", "dynamic optimization", "hybrid methods", "spatio-temporal graph neural networks", "combined model" or "hybrid model", "deep learning", and "hybrid neural network".
- Implementing specialized software tools to support deeper analysis and provide a more reliable statistical foundation for research.

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