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Review Article

Evolution Regularity Mining and Gating Control Method of Urban Recurrent Traffic Congestion: A Literature Review

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To understand the status quo of urban recurrent traffic congestion, the current results of recurrent traffic congestion, and gating control are reviewed from three aspects: traffic congestion identification, evolution trend prediction, and urban road network gating control. Three aspects of current research are highlighted: (a) The majority of current studies are based on statistical analyses of historical data, while congestion identification is performed by acquiring small-scale traffic parameters. Thus, congestion studies on the urban global roadway network are lacking. Situation identification and the failure to effectively warn or even avoid traffic congestion before congestion forms are not addressed; (b) correlation studies on urban roadway network congestion are inadequate, especially regarding deep learning, and considering the space-time correlation for congestion evolution trend prediction; and (c) quantitative research methods, dynamic determination of gating control areas, and effective countermeasures to eliminate traffic congestion are lacking. Regarding the shortcomings of current studies, six research directions that can be further explored in the future are presented.

1. Introduction

In recent years, with the rapid development of the social economy, the contradiction between the limited carrying capacity of urban roadway networks, and the rapidly growing traffic demand has become increasingly acute. With the significant increase in motor vehicles, traffic congestion is increasing due to limited roadway resources, which has reduced the comfort, and convenience of travel for numerous residents. The problem of traffic congestion has aroused widespread concern in society and has become an important constraint factor that affects the development of the national economy [1–3]. Based on previous studies, visualization of traffic congestion can be achieved by collaboration network analysis with a total of 248 keywords from 1975 to 2019, as shown in Figure 1. Each node represents a keyword, and the node sizes indicate the number of published papers. The links between two nodes represent collaborations, and the greater width of a link represents a closer collaboration.

As shown in Figure 1, traffic congestion in urban areas primarily includes two types: occasional and recurrent. Occasional congestion is usually caused by sudden incidents, such as special events, traffic accidents, and temporary traffic control, while recurrent congestion is usually generated by periodic traffic flow. Compared with occasional congestion, the proportion of recurrent congestion is greater but the processes of its formation, propagation, and dissipation have certain rules. In the time dimension, the formation, and dispersion times of congestion often have the same time window, while in the spatial dimension, the location of congestion, direction of propagation, and range of dissipation have a high degree of similarity [4–7]. The temporal and spatial evolution of recurrent congestion should be continually evaluated, and this rule should be applied to actively control the traffic flow in a congested area.

Additional alternatives can be employed to investigate traffic congestion with the introduction of advanced technology and methods. The arrival of the big data era and the application of vehicle GPS and wireless communication technology

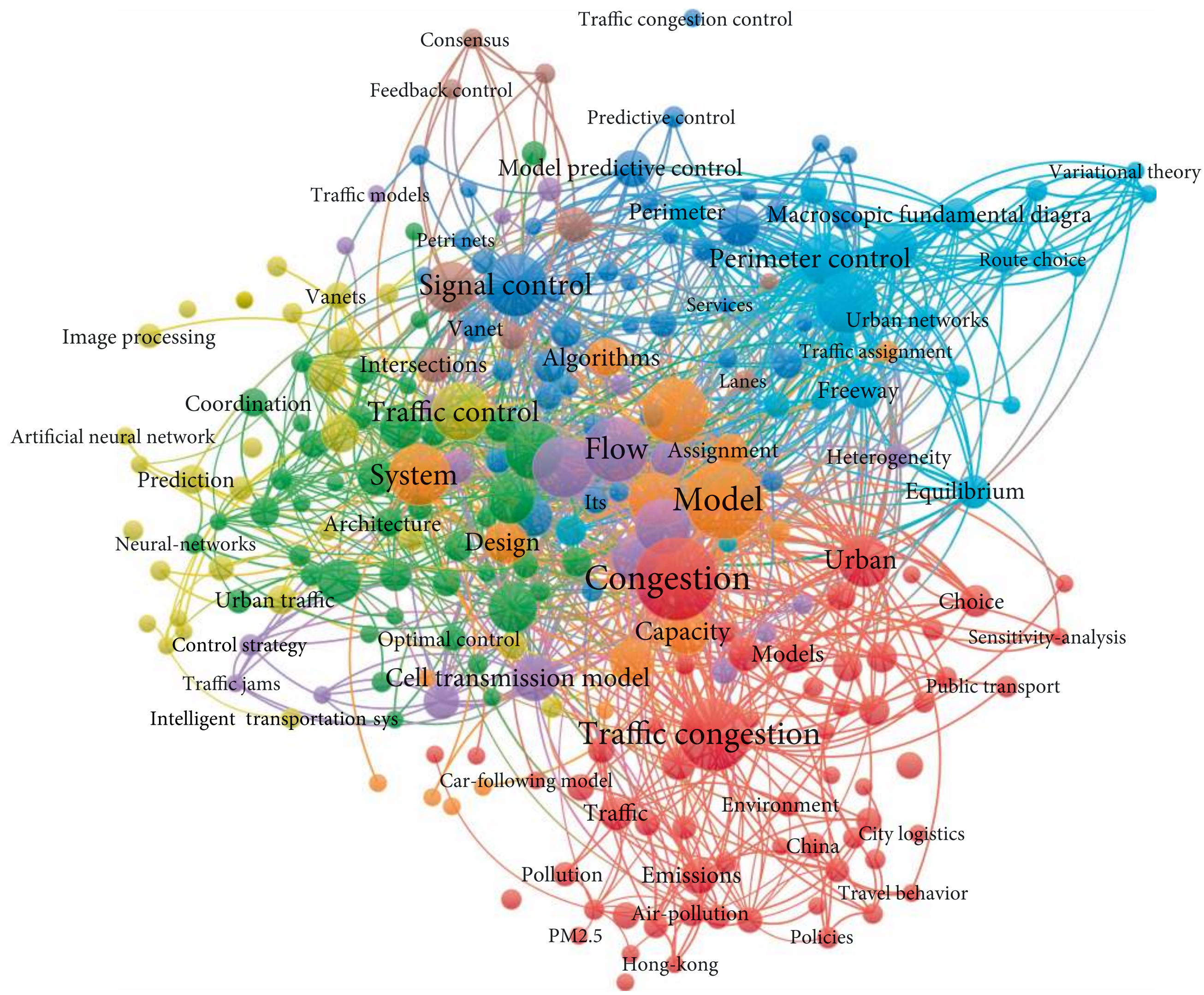


Figure 1: Keyword co-occurrence network of traffic congestion studies.

provides massive order data and travel trajectory data for urban traffic congestion analysis. These data can be integrated with traditional traffic flow detection data, and the relevant time and space features can be extracted by data mining technology to perform an in-depth analysis of the traffic flow characteristics. This process can be utilized to efficiently identify congestion and reveal the temporal and spatial correlation and evolution of the congestion state, which has an important role in the formulation of traffic control schemes and the control of traffic congestion.

2. Research Status of Traffic Congestion Identification

Traffic congestion identification can effectively alleviate traffic congestion by timely and accurate estimation of the traffic state for the entire roadway network, identify congested road sections based on the estimation results, and release relevant information to guide vehicular travel. In recent years, many scholars have devoted their research to traffic congestion identification. One traditional method was to use coil data and video monitoring data to identify the congestion mode [8]. With the development of wireless communication and positioning technology, traffic congestion recognition algorithms based on GPS data were extensively adopted [9]. Tao et al. [10] estimated the traffic congestion of road sections by collecting real-time GPS data of mobile phones. Carli et al. [11] and Xu et al. [12] employed GPS bus data to identify traffic congestion in urban road networks. Liu et al. [13] analyzed the traffic congestion area and its spatial and temporal distribution characteristics using taxi trajectory data. Anbaroglu et al. [14] proposed an NRC detection methodology to support the accurate detection of NRCs on large urban road networks. Wang et al. [15] presented real data testing of a real-time freeway traffic state estimator, with a particular focus on its adaptive capabilities. Hossein and Abdelghany [16] proposed a real-time traffic network state estimation and prediction system with built-in decision support capabilities for traffic network management. The system provided traffic network managers with the capability of estimating current network conditions, predicting congestion dynamics, and generating efficient traffic management schemes for recurrent, and nonrecurrent congestion situations. The traffic network manager adopted a meta-heuristic search mechanism to construct schemes by integrating an extensive variety of control strategies. Although these methods are simple in principle, achieving seamless coverage by the majority of current detection devices is difficult. Thus, determining the traffic state without detection is not directly available. When the distribution of moving detection devices (e.g., buses and taxis) is too small or uneven, the traffic flow density of a road section cannot be accurately estimated; thus, the congestion situation cannot be effectively recognized.

In recent years, with the development of communication technology and storage technology, various positioning data have been collected and saved, which provides new ideas for research in the transportation field. Numerous scholars have performed a variety of studies on traditional traffic problems based on these massive trajectory data, which have become controversial. Sarvi et al. [17] obtained and analyzed five levels of road network operation statuses by tracking the travel trajectory of a floating car in time and space. Hu et al. [18] obtained taxi activity distribution characteristics from GPS data. Time distribution characteristics, such as inclusion of working days, weekends, geographical distribution, bicycle passenger time, and passenger frequency, and spatial distribution characteristics, such as empty search range, passenger mileage, and upper and lower passenger locations, are adopted. These characteristics provide guidance for the identification and prediction of taxi demand in the city. Yu et al. [19] proposed the use of the Markov model and BP neural network method to detect the campus traffic congestion state. The experimental results showed that both methods can detect campus traffic congestion, and the BP neural network-based method can achieve higher precision and more stable performance. Ngo [20] suggested that the emergence of Uber has an impact on the taxi industry, the environment, the transportation methods, and the driving behavior. Uber replaces some taxi itineraries and reduces its market share by 10–40% while reducing car ownership and improving travel efficiency but may decrease average speeds and increase carbon dioxide emissions. Li et al. [21] collected data on fuel costs, urban socio-economic characteristics, characteristics of road transportation systems, number of road lanes, number of passengers, and congestion status in 87 regions of the United States for 11 years and analyzed the differences in time when Uber entered different regions. After Uber entered the market, the traffic congestion problem in the area was significantly improved. Goves et al. [22] presented the results after applying artificial intelligence, especially artificial neural networks, to estimate traffic conditions 15 minutes after current/historic traffic information was provided. Duret et al. [23] proposed a model-based framework for estimating the traffic states using Eulerian and Lagrangian data. The Lagrangian-Space formulation that was adopted as the underlying traffic model provides suitable properties for receiving Eulerian and Lagrangian external information. Three independent methods are proposed to address the Eulerian data, Lagrangian data, and the combination of both types of data.

Based on the floating car data, with 5 minutes as the time granularity, Zhang et al. [24] established a three-level discriminant index of constant congestion, namely, congestion gating index, time-barrier duration ratio index, and frequent frequency index, and screening of recurrently congested road sections in GIS. Based on a taxi's floating car data and by the conversion of the section travel time, section speed, and average speed, Lyu [25] built the road traffic operation index in Shenzhen and then evaluated the urban road network traffic operation status. Gao et al. [26] presented a road congestion assessment model based on a fuzzy analytic hierarchy process that is based on three parameters of speed, density, and flow, determined the road traffic congestion level, and proposed an early warning mechanism for road traffic congestion peaks. Zhu [27] used the fusion data of current traffic flow data and traffic flow prediction data as traffic state recognition input data and constructed a traffic state recognition method that is based on fuzzy C-means and an FCM integrated classifier, and traffic state recognition. The outputs are expressed in three states: "low saturation", "medium saturation", and "quasi-saturation". Yao and Zhang [28] proposed a traffic congestion state recognition algorithm based on fuzzy logic that is based on a fuzzy comprehensive evaluation algorithm. The algorithm combined the three basic traffic flow parameters of occupancy rate, density, and travel time to obtain three new characteristic variables: service level, relative density, and relative travel time. The algorithm uses a trapezoidal function to calculate the membership degree and assesses the traffic congestion state according to the membership degree. Ju et al. [29] employed taxi GPS movement trajectory data to construct an evaluation method of urban road mobility based on the road traffic speed and travel time index and conducted a detailed analysis in Shenzhen. Ji [30] established a quantitative evaluation system for urban road traffic congestion based on the combination of the traffic state index in space (road section, area, and road network) and time (real time, time zone, day, and other) in Shanghai from the three aspects of congestion level, congestion distribution, congestion trend. Jiang et al. [31] applied the main road as the research object and divided the urban road congestion state into five levels: blocked, congested, more congested, relatively smooth, and unblocked. Regarding the intersection and road section, factors such as saturation, average speed ratio of intersection, density, and average parking delay were selected as evaluation indicators. A data envelopment analysis model was established to evaluate the traffic status of urban main roads. Based on the tracking data of the traffic index from 2007 to 2014 in Beijing, Zhang [32] compared the road network traffic index of the year-end working day of the tail-limited year. Observing the growth in traffic congestion for the condition of a limited policy is unchanged. Ren et al. [33] selected the parameters of average maximum queue length, saturation, average vehicle delay, and speed ratio, which were the most sensitive and easily obtained for the traffic state change at intersections in the city as the evaluation index. The Relief algorithm was selected for the selected evaluation index, a weight determination was performed, and

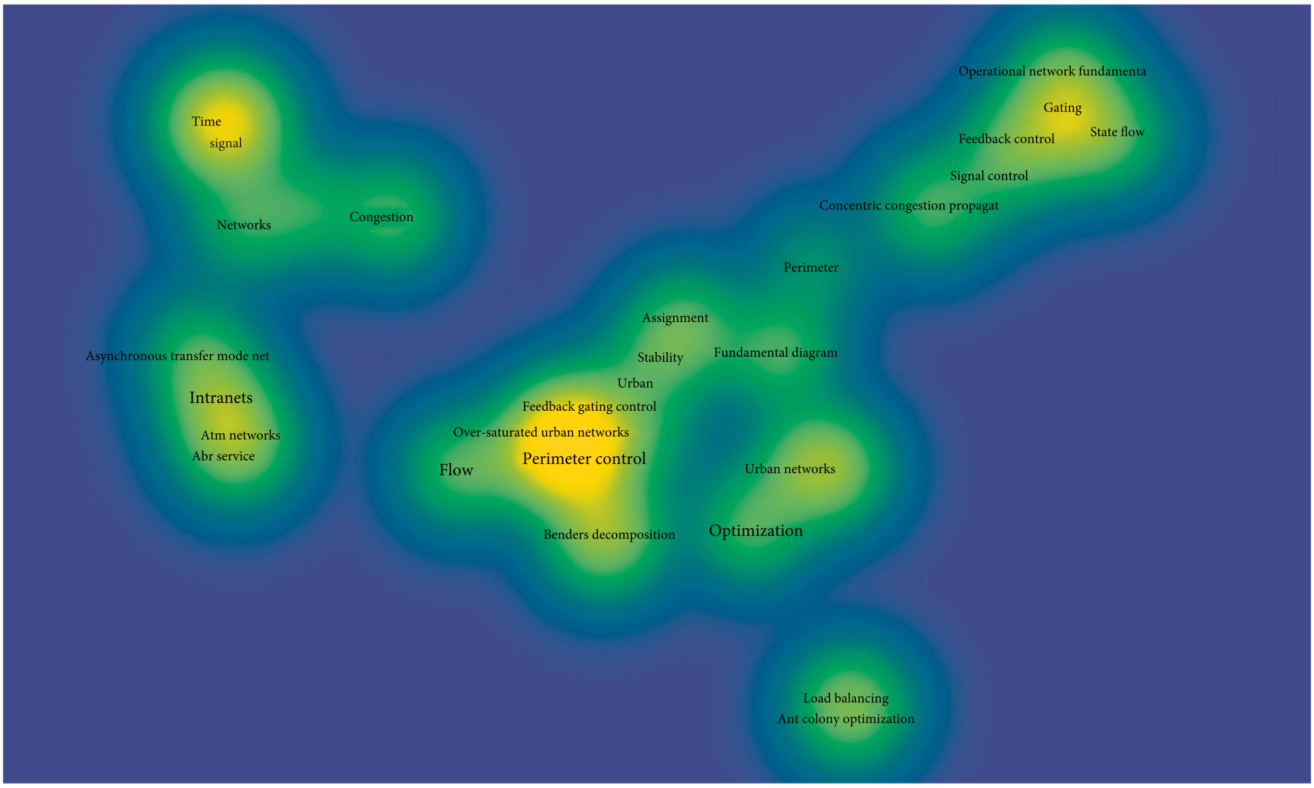


Figure 2: Visualization of gating control in traffic congestion studies.

a comprehensive discriminant model based on fuzzy FCM clustering was designed. An example was provided to demonstrate that the model can objectively and effectively evaluate the traffic state of urban intersections. Zheng and Yang [34] comparatively analyzed the advantages and disadvantages of various traffic congestion evaluation indicators, including the road traffic index that was first proposed by Shanghai in 2002. Weighted scoring modeling considers additional comprehensive factors; however, the calculation process is more complicated. Jiang et al. [35] proposed two improved average speed estimation models based on taxi GPS data for the problem for which the existing average speed estimation model of a road segment and satisfying the requirements of low cost and high precision were difficult. The example verification showed that the accuracy of the two improved models is 1.5% and 19.7% higher than the traditional model without an increase in cost. Huang and Xu [36] analyzed taxi GPS data to evaluate the real-time traffic flow of a road network, selected multiple fuzzy inference algorithms to predict traffic congestion, travel time, and the probability of congestion, and proposed an analysis framework for dynamically predicting road congestion. Zhang et al. [37] estimated the average travel time of a road segment in the case of both large samples of GPS data and small samples, and calculated the confidence interval and confidence. The small difference between the analysis results and the estimated values of the measured data shows the applicability of the research method for estimating the average travel time of a road segment. Lu et al. [38] integrated urban traffic network intersection traffic and taxi GPS data by adopting macroscopic basic maps and generalized macroscopic basic maps in urban road networks. Yu et al. [39] proposed a *K*-nearest neighbor model based on the time dimension, upstream segment-time dimension, downstream segment-time dimension, and a space-time parameter model to predict short-term traffic flow using taxi GPS data. By using mass taxi GPS data as the data source, Guo et al. [40] identified roads and extracted vehicle speed information with the boundary rectangle method, established the congestion subordinate discriminant model based on the average travel speed, and successfully determined the congested road section in a certain area of Shenzhen. Wu et al. [41] clustered vehicle GPS track points based on a density clustering algorithm and determined the distance interval gating, time interval gating, and speed gating between the first GPS data point and last GPS data point to define congested road segments. Nagy and Simon [42] provided a detailed presentation of traffic prediction methods for intelligent cities and provided an overview of the existing data sources and prediction models.

However, the majority of existing studies address the improvement in models and algorithms with single-source traffic data and focus on traffic state analysis and prediction within congested sections or regions. Studies on multi-source traffic big data for urban road network congestion are lacking.

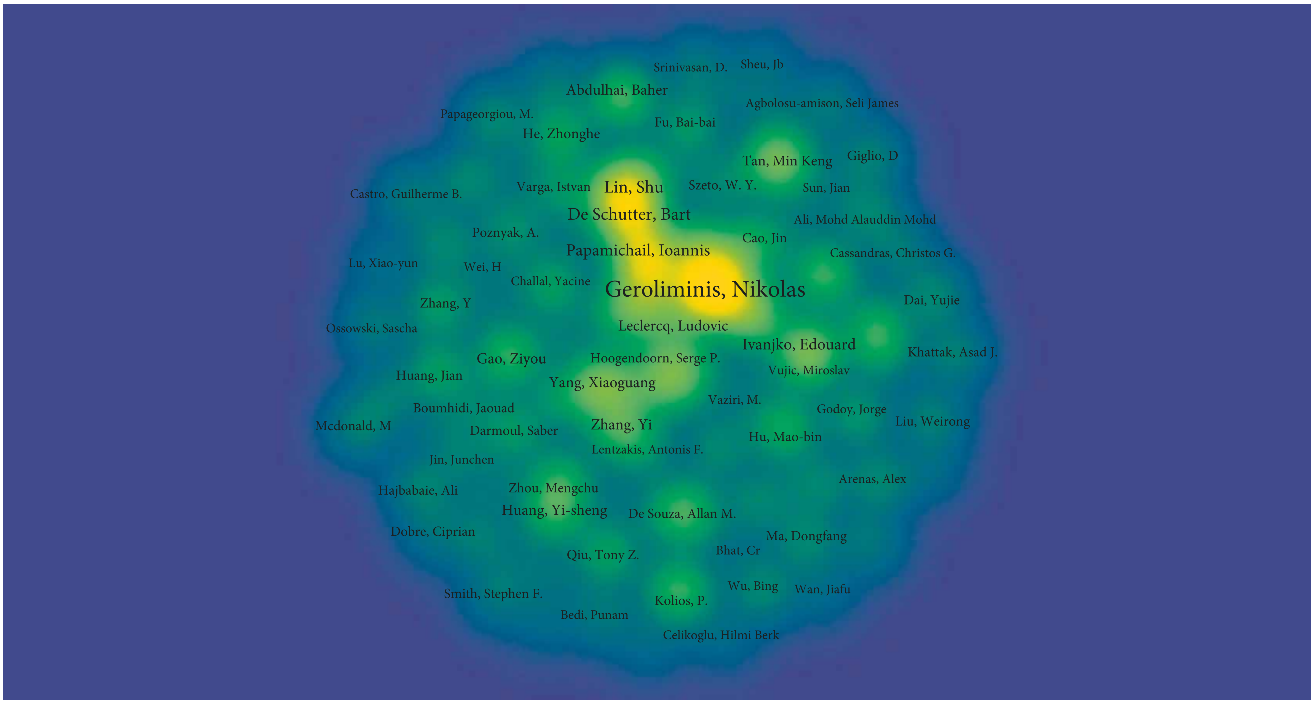
3. Research Status of Traffic Congestion Evolution Regularity Mining

Traffic congestion evolution regularity mining is referred to as the possible roadway traffic conditions within a period of time after obtaining the traffic information and the prediction algorithm. The algorithm is divided into two categories, namely, the conventional algorithm and big data-based prediction algorithm. Regarding the prediction algorithm of the congestion evolution trend, since the 1960s, many scholars have applied conventional prediction models to the congestion trend prediction algorithm, and numerous studies, which are not described here, have been produced. During past years, with the development of big data technology, many scholars have applied big data-related theories and methods to the prediction of congestion evolution trends and continuously improved and innovated methods to promote the prediction accuracy. Recent results include self-organizing fuzzy neural networks [43], spectrum analysis [44], support vector regression [45], GA-BP algorithm [46], stochastic adaptive Kalman filtering [47], chaotic time series analysis [48], support vector machine and spatio-temporal data fusion model [49], improved time series model [50], model based on BP neural network and fuzzy inference system [51], and combined models [52]. In terms of deep learning, Kuremoto et al. [53] applied time-series prediction based on a deep confidence network model that limits the Boltzmann machine. Huang et al. [54] integrated multitasking learning into a deep confidence network framework for future traffic forecasting. Lyv et al. [55] proposed a congestion prediction model based on deep learning, using a stacked self-encoder to learn the general characteristics of traffic flow, and training the model according to the greedy layering method. Ma et al. [56] combined the depth-restricted Boltzmann machine with the recurrent neural network model to predict the evolution of congestion in large-scale traffic networks. Cats et al. [57] developed a method to capture the benefits of increased capacity by using a dynamic and stochastic transit assignment model. The model was embedded in a comprehensive framework for project appraisal. Existing studies focus on obtaining the external characteristics of the road network traffic state but lack in-depth discussion about the formation mechanism and internal causes of the traffic macroscopic state for the roadway network, which is not adequate for formulating traffic management, and control measures to solve congestion problems on the roadway network level.

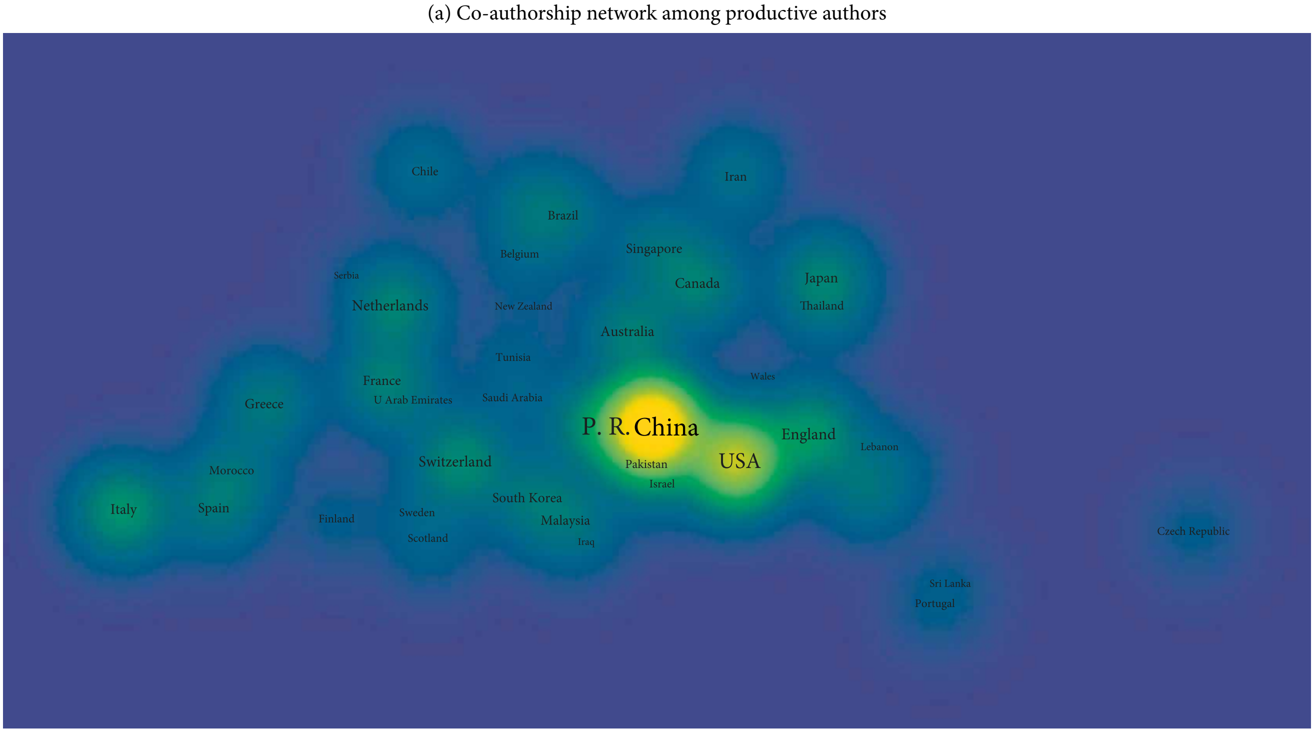
4. Research Status of Urban Road Network Gating Control

Gating control is a practical method of traffic control for a roadway network, as shown in Figure 2. This method is often employed in over-saturated traffic conditions or roadway sections or roadway networks that are prone to traffic congestion. The principle is to limit current control at the main intersection in the core area for the controlled roadway network, and then the road network gating is converted to intersection gating to balance traffic distribution and alleviate traffic congestion. Currently, gating control has become an emerging control technology for roadway network control. Many researchers have begun to investigate gating control as the collaboration network of gating control among productive authors; the research countries are shown in Figure 3. Wood et al. [58] first applied the gating control method to the traffic field and experimented with the gating control logic in SCOOT. According to the results, when all critical intersections are gating-controlled, only one critical intersection gating exists. When the limit is exceeded, 20% of the capacity is provided to the gating traffic flow.

However, when the traffic congestion of the road network reveals complex distribution characteristics, the effects of the methods may not be optimized. In a roadway network with complex traffic conditions, single regional boundary control may not be effectively implemented, and measures that can control multiple regions need to be considered. Aboudolas and Geroliminis [59] proposed a multi-layer control method for feedback adjustment in a complex region using a separate basic network diagram of a road network. The disadvantage of this method is that the boundary of a multi-layered area is fixed. As the dynamic evolution of traffic congestion spreads, the traffic flow may invade the uniform area, which render it ineffective. Keyvan-Ekbatani et al. [60] proposed a two-layer gating control strategy that consists of two feedback controllers. This study considered the area that includes the initial traffic congestion core as the first layer and must prevent network congestion via gating control. As traffic congestion expands, the boundary of the extended network portion is the second boundary of the gating control. However, these methods are explored after the congestion occurs; thus, only passive traffic management is realized. The passive nature of this control is not conducive to the actual control of the gating control method. To overcome the weakness, Gal-Tzur et al. [61] proposed a pre-urban urban road network control method. By controlling the incoming flow of the control area within the capacity of the key intersection, this method can effectively prevent the formation of congestion. However, the applicability is only for urban congestion networks with only one critical intersection. Zhang et al. [62] proposed a control method that can effectively solve the deadlock of a road network. The cumulative traffic number of a roadway network was applied as the state variable, and the state equation of the macro traffic flow of a congestion road network was constructed to congest the road network. The cumulative number of vehicles attains the optimal value, and Bang-Bang control is the optimal control method to maximize the road network capacity. Li [63] proposed a boundary control method to keep the roadway network traffic near saturation by limiting the traffic volume that enters the road network. This method can effectively improve the operational efficiency of road network traffic. Combined with the measured and simulated traffic flow data of Kunshan City, Liao [64] investigated the traffic congestion characteristics of an urban road network based on a macroscopic basic map, constructed a gating control model, and performed a performance evaluation based on a MATLAB programming environment. Yang et al. [65] attempted to determine the supersaturated road section, quantified the correlation degree between two intersections, and established a correlation degree calculation model. The division of the blocking zone, the transition zone, the normal zone, and the dissipative zone were performed, and a dynamic partitioning method for traffic control sub-areas in a supersaturated state was proposed. Saeedmanesh and Geroliminis [66] investigated the spatio-temporal relation among congested links by observing congestion propagation from a macroscopic



(a) Co-authorship network among productive authors



(b) Collaboration network among research countries

Figure 3: Collaboration network of gating control among authors and countries.

perspective and identifying critical pockets of congestion that can aid in the design of peripheral control strategies. Ahmed and Hawas [67] presented a traffic control system that can work standalone to handle various boundary conditions of recurrent and nonrecurrent congestion, transit signal priority, and downstream blockage conditions to improve the total traffic network vehicular productivity, and efficiency. Sheu and Yang [68] investigated an integrated freeway traffic management system that coordinates both dynamic toll pricing and ramp control strategies for the purpose of dynamic freeway congestion management. The proposed integrated dynamic toll–ramp control methodology is built mainly on the principles of stochastic optimal control approaches. Logi and Ritchie [69] described a real-time knowledge-based system (KBS) for decision support to traffic operation center personnel in the selection of integrated traffic control plans after the occurrence of nonrecurring congestion on freeway and arterial networks. The uniqueness of the system, which is referred to as TCM, is the ability to cooperate with the operator by handling different sources of input data and inferred knowledge and providing an explanation of its reasoning process. An efficient algorithm for the selection of control plans determines alternative traffic control responses. Lo [70] developed a novel traffic signal control formulation using a mixed integer programming technique. The formulation considered dynamic traffic, used dynamic traffic demand as input, and took advantage of a convergent numerical approximation to the hydrodynamic model of traffic flow. The formulation "automatically" adjusts to different traffic conditions. Lo et al. [71] developed a dynamic traffic control formulation that is designated dynamic intersection signal control optimization (DISCO). The formulation considered the entire fundamental diagram and captured traffic phenomena, such as shockwaves and queue dynamics. As a dynamic approach, the formulation derived dynamic timing plans for time-variant traffic patterns. Boillot et al. [72] presented the real-time urban traffic control algorithm CRONOS and evaluated an intersection by comparing two reference control strategies: a local strategy and a centralized strategy. The results showed high benefits of CRONOS for the total delay compared with the two reference control strategies, and the benefits for the total number of stops and percentage of stops were also obtained, especially compared with the local strategy. Keyvan-Ekbatani et al. [73] presented the recently developed notion of a network fundamental diagram for urban networks to improve the mobility in saturated traffic conditions via application of gating measures based on an appropriate feedback control structure. Keyvan-Ekbatani et al. [74] explored urban congestion gating control based on reduced operational network fundamental diagrams. The urban network of Chania, Greece was used as a test-bed for the investigations within a realistic microscopic simulation environment. Dahal et al. [75] proposed an Intelligent Traffic Control System (ITCS) based on a coordinated-agent approach to assist the human operator of a road traffic control center to manage the current traffic state. Castro et al. [76] proposed an adaptive biologically inspired neural network that received the system state and was able to change the behavior of the control scheme and the order of semaphore phases instead of prefixed cycle-based phases. The analyses conducted showed that the model was robust to different initial conditions and had fast adaptation among system equilibrium states. However, the idea of these studies is how to quickly evacuate traffic flow after traffic congestion. Thus, the time lag of traffic signal control is often generated.

5. Current Problems

An analysis of existing literature indicates at least three problems with respect to the evolution regularity mining and gating control method of urban recurrent traffic congestion, as discussed here.

(1) With the rapid development of traffic big data, various multi-source data, such as floating car data, unstructured video data, and Internet data, have become available for traffic state identification. However, most current studies are only based on historical traffic big data. Based on statistical analysis, congestion identification is obtained by acquiring parameters, speed, density, traffic volume, and vehicle delay in a small range. This approach lacks identification of congestion conditions within the global roadway network of a city and fails to effectively warn or even avoid traffic congestion before it is formed. In addition, existing studies disregard the formation law of traffic congestion, only quantify the congestion state based on traffic state evaluation indicators or traffic flow parameters, and rarely employ multi-source traffic data to study congestion evolution law and gating control methods.

(2) Most studies on congestion evolution trend prediction focus on traffic state analysis and prediction within congested road sections or areas, and correlation studies on urban roadway network congestion are lacking. In terms of the time and space of congestion, some scholars have adopted the method of space-time autocorrelation but the results of data analysis are deviated from the actual traffic state. The methods are concentrated on the improvement in classical models or shallow learning, such as neural networks and support vector regression. With the successful application of deep learning in language recognition, image recognition, video recognition, and multi-task learning, the related results of using deep learning and considering spatiotemporal correlation for congestion evolution trend prediction have not been expanded.

(3) Existing studies on traffic control in congested areas are aimed at evacuation after traffic congestion occurs, which are only applicable to effective grooming. Some scholars have adopted the gating control method for active control but the control boundary is determined by qualitative analysis. Thus, quantitative methods are necessary to dynamically determine the gating control area, adopt the gating control theory to actively control, and unblock the traffic flow that has not yet arrived to promptly eliminate the traffic congestion.

6. Research Prospect

6.1. Using Multi-Source Traffic Data to Study the Evolution Regularity of Urban Recurrent Traffic Congestion. With the development of the "Internet +" era and the construction of smart cities, sources of traffic data range from the original manual collection method to the initial method with coils and radar gauges, and then to the current floating vehicle, and portable equipment measurement method. The magnitude of the data obtained is increasing, and the information is becoming increasingly abundant, which provides an excellent data basis for the identification of congestion, and the prediction of congestion trends [77–81]. A large number of high-frequency, high-precision, spatial-temporal correlation vehicle trajectory data, and traffic flow detection data are obtained in real time. These data contain a wealth of information that can describe the running situation of complex traffic systems. These data provide an opportunity

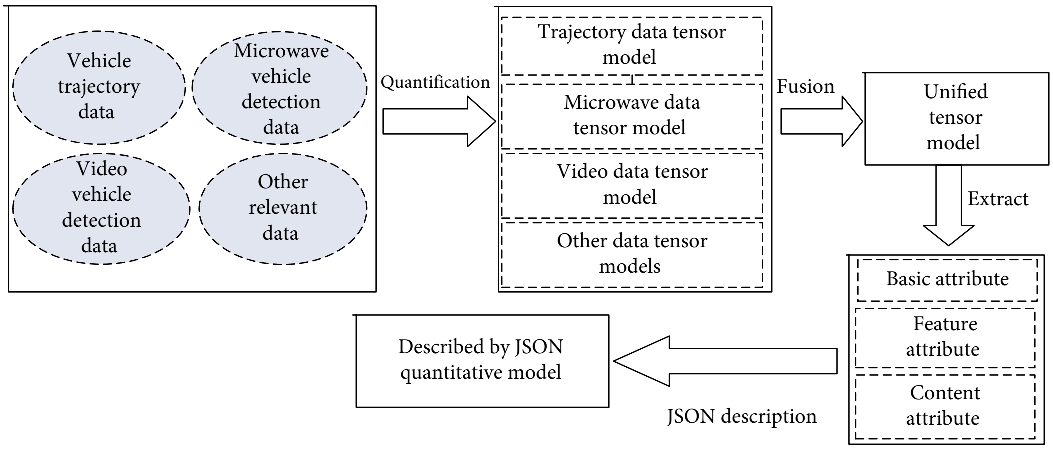


Figure 4: Traffic big data tensor model described by JSON.

for people to reveal the evolution law of traffic congestion and scientifically control traffic flow [82–91].

Unified preprocessing and data quality evaluation are performed on the data (collectively referred to as traffic flow detection data) collected by multi-source trajectory data sets (including bus, cruise taxi, net taxi, and express track big data), microwave vehicle detectors, and video number recognition equipment and are then combined with GIS to complete coordinate transformation and map matching.

Faced with the complex structure of an urban road network, the method of refining spatial grid partition is adopted to analyze the density and traffic state of the region, with an emphasis on grid generation technology and methods to determine the size of the grid. The tensor model is used to fuse multi-source trajectory data and traffic flow detection data. With a JavaScript Object Notation (JSON) description tensor model, the collected data can be transmitted to the data management platform via the data acquisition platform. JSON can be used to describe the basic attributes, feature attributes, and content attributes of the model.

Because the tensor model can represent the original characteristics of unstructured data, semi-structured data, and structured data, and realize the fusion, and representation of multi-source heterogeneous data in high-order, and high-dimensional space, JSON has the advantages of scalability, a fast index, and lightweight; thus, it is suitable for describing the tensor model. Therefore, this paper intends to employ the JSON description tensor model to transfer the collected data to the data management platform via the data acquisition platform and then describe the basic attributes, feature attributes, and content attributes of the model via JSON. The model is queried by a JAQL query statement to verify the feasibility of the model. The basic process is shown in Figure 4.

6.2. Using Macroscopic Fundamental Diagram (MFD) and Convolution Neural Network (CNN) to Identify the Recurrent Traffic Congestion. By constructing the discrimination model of traffic congestion within the grid, the recurrent congestion region can be defined as one or more recurrent congestion grid sets adjacent to each other in space. A recurrent congestion region identification model can be designed based on the clustering algorithm.

The traditional traffic flow three-parameter features are extracted in the grid, and the different parameters are classified and visually analyzed. The relationship between the grid cell speed and traffic flow is investigated by using an MFD, and the results are compared with the actual road network structure to investigate the changing characteristics of traffic flow and the generation, development, and dissipation process of traffic congestion.

By constructing the three-parameter characteristics of grid traffic flow and defining the traffic congestion index, the vehicle trajectory, and traffic flow detection data are divided, excavated, and collected to clearly describe the process of the generation, development, and dissipation of traffic congestion and calculate the three parameters of grid traffic flow and grid traffic congestion index. According to these data, graphs intend to be converted into images at intervals of 30 s or 60 s.

When addressing a large amount of graph data, traditional modeling methods cannot reasonably describe the spatial, and temporal characteristics of the data. For this reason, we can use the advantages of a convolution neural network in image recognition and time series problems by combining a residual neural network to improve the training efficiency and accuracy and establishing a spatial-temporal evolution model of congestion, as well as performing a deep analysis of the emergence, development, and dissipation of congestion to reveal the law of congestion evolution.

According to the three parameters of grid traffic flow and based on the structure mechanism of a convolution neural network, a spatio-temporal analysis model of recurrent traffic congestion in an urban roadway network can be established. Using the spatio-temporal residual network model, the evolution rules of grid traffic flow parameters and the grid traffic congestion index in the target area can be explored.

6.3. Using Deep Learning Theory to Predict the Development Trend of Recurrent Traffic Congestion in Road Network. The development trend prediction model of network recurrent traffic congestion can be constructed by using a deep

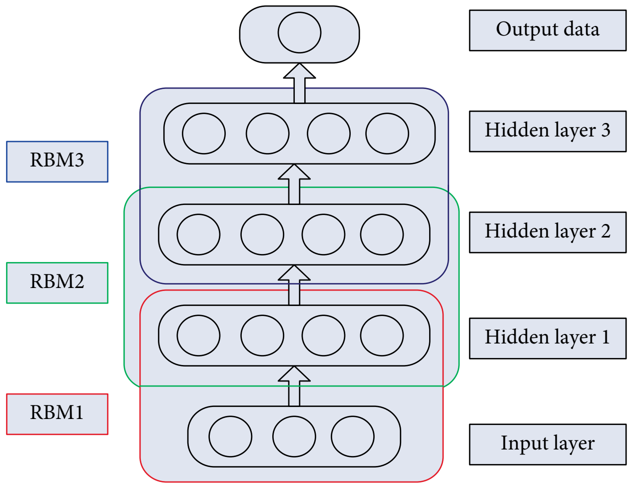


Figure 5: Structure of the deep confidence network based on the Boltzmann machine.

learning algorithm to predict the development trend of traffic congestion.

The traffic state of each roadway in the network has spatial correlation. Thus, the prediction model that only considers the characteristics of the target section cannot guarantee the prediction accuracy. To improve the prediction accuracy, a congestion trend prediction model that is based on multi-source data can be built by considering the spatio-temporal correlation. The time trend method, top-*k* correlation method and top-*k* neighbor method can be used to enhance the input characteristics of the prediction model. Fusing multi-source information with the help of deep belief networks theory based on a restricted Boltzmann machine is proposed. The structure is shown in Figure 5.

6.4. Study of Gating Control Method Based on Model Prediction Control. The goal of gating control is to reduce the traffic congestion degree of a roadway network by actively controlling the traffic demand at the boundary intersection of the road network to effectively reduce the duration of traffic congestion and decrease the probability of roadway network oversaturation. The specific content focuses on the gating control domain determination method according to the network traffic congestion evolution state. The mathematical model of the traffic congestion gating control problem can be constructed according to the model predictive control principle and network traffic state constraints, and the implementation strategy of gating control should be investigated.

Model Predictive Control (MPC) has the advantages of excellent effectiveness and robustness, which can effectively address the uncertainties and nonlinearity of the control process and address the constraints of various variables in the control process. Therefore, from a macroscopic perspective, the congestion problem of a roadway network can be converted to a mathematical model based on the congestion characteristics network, and the model predictive control principle [92–100].

6.5. Research on Gating Control Method of Intelligent Transportation System Based on Crowed Sourcing Data. With the popularity of the mobile Internet, in-vehicle devices, and smart phones, travelers can easily access and upload dynamic data of vehicles, which have a complete electronic system that collects data on the engine, chassis, speed, and tire pressure [101–106]. The vehicle driving data collected by the automobile electronic system is transmitted to the data center via the mobile internet, which completes the collection problem of vehicle-related data. In addition, travelers can voluntarily provide the starting and ending data of each trip, booking travel data, urgency, and time value. The data collected via this crowd sourcing model is referred to as crowd sourcing data. The use of this crowd sourcing model for data collection not only collects large amounts of data but also solves the problem of excessive data collection costs [107–111]. After the data collection is completed, the isolated data are linked, shared with each other, and socialized to establish true big data. The intelligent transportation system data center uses the collected big data for data analysis and mining to achieve intelligently dispatch, gating control, and demand management of the traffic control system, which is expected to help the identification and mitigation of frequent traffic congestion.

6.6. Research on the Gating Control Method in the Situation of Connected and Autonomous Vehicles. The Internet of Vehicles (IoV) is an important subsystem that integrates the Internet of Things (IoT) with an intelligent transportation system, which can realize the state perception and information collection of the vehicle exterior environment via various sensors, GPS, and other sensing devices. The use of advanced and reliable means of communication, in accordance with the corresponding communication protocol, can realize information exchange via the network of people-vehicle-infrastructure. With computer technology, complete specific application functions such as information release, real-time traffic control, and real-time travelling routes can realize intelligent monitoring, scheduling and management of people, vehicles, and roads. With improvement in artificial intelligence, sensor detection, and other technologies, autonomous vehicles have been rapidly developing. In the vehicle network environment, the self-driving vehicle can communicate with roadside facilities, and the regional center control system in real time, and obtain real-time information about the road network, traffic flow state, and status of the downstream traffic signals in advance. Speed adjustments are made in time to enable a vehicle to smoothly pass through signalized intersections.

With the described scenarios, the urban traffic system gating control method can be realized in the situation of connected and autonomous vehicles, and the forward-looking technical results can be employed to solve the limitations of traditional urban signal control. By estimating the traffic characteristic parameters in some connected and autonomous vehicle environments, online, and offline estimation algorithms should be constructed to restore the vehicle information of a road network and estimate the traffic parameters. The traffic system gating control algorithm in the situation of connected and autonomous vehicles can be constructed to satisfy the signal control requirements of different scenarios, and a set of signal control solutions can be obtained for future connected and autonomous vehicles.

7. Conclusions

Currently, traffic congestion has spread from large cities to medium- and small-sized cities. Although many scholars have performed numerous studies of this problem, determining the mechanism of congestion evolution is difficult since the urban transportation system is a complex and vast system. Therefore, the effect of blocking is not very optimistic. The contradiction between the limited carrying capacity of an urban roadway network and the rapidly growing traffic demand is becoming increasingly acute; thus, traffic congestions often occur.

Numerous studies have been performed on traffic congestion identification, traffic congestion evolution trend prediction, and urban roadway network gating control of urban recurrent traffic congestion, and fruitful results have been achieved. After reviewing the relevant literature, the authors discovered three shortcomings of existing studies, and identified a research direction that can be further explored in the future.

With the development of communication technology and smart cities, a large number of high-frequency, high-precision, space-time related vehicle trajectory data, and traffic flow detection data are acquired in real time. These data contain rich information that can describe the operation situation of complex transportation systems, while the information provides an opportunity for people to determine the evolution of traffic congestion and scientifically control traffic. High-precision trajectory data and traffic flow detection data are merged to construct a recurrent traffic congestion recognition algorithm for an urban road network. The convolutional neural network can be used to deeply depict the complete development process of roadway network congestion, and a deep learning algorithm can be employed to predict congestion and mine the evolutionary regularity of recurrent traffic congestion. The recurrent traffic congestion problem of the roadway network is transformed into an optimal control problem. Considering that the minimum total travel time of the roadway network is the goal, model predictive control theory can be utilized to construct the gating control optimization model, and a gating control scheme for the traffic congestion problem can be obtained. The results can provide strong support for urban roadway planning, dissemination of traffic guidance information and management of recurrent traffic congestion.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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