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Traffic Congestion Analysis and Probability Estimation Based on Stochastic Characteristics of Traffic Arrival

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ABSTRACT

Urban traffic congestion has emerged as a global challenge constraining sustainable development. Estimating the traffic congestion probability is crucial since it presents valuable information for formulating congestion mitigation strategies and improving traffic management. The existing studies employ deterministic models to predict congestion; however, they do not consider the dynamic coupling between intrinsic traffic flow randomness (e.g. spatiotemporal heterogeneity in vehicle arrivals) and congestion formation mechanisms, causing prediction biases under high-uncertainty scenarios. In this study, we propose a probability-based congestion estimation framework that employs the stochastic traffic flow theory. The traffic arrival process is described using discrete probability distributions owing to the stochastic nature of traffic flows. To prevent the misclassification of transient traffic surges as congestion, we adopt a spatiotemporal persistence criterion with dual thresholds (vehicle accumulation exceeding a critical level and duration surpassing a minimum time) for congestion identification. Additionally, we perform empirical validation using traffic datasets from Portland, USA, which demonstrates that there is no statistically significant deviation from the measured data at the 95% confidence level in the calculated congestion probabilities. The proposed method facilitates the development of targeted congestion mitigation countermeasures and presents novel insights for future transportation planning.

KEYWORDS

congestion probability; traffic arrival; randomicity; traffic breakdown.

1. INTRODUCTION

Traffic congestion increases fuel consumption and greenhouse gas emissions, which exacerbates urban air pollution and presents significant socioeconomic burdens [1, 2]. Road network expansion can provide short-term congestion mitigation. However, it fails to resolve the systemic issues of nonlinear interaction between stochastic traffic flow fluctuations and the network's capacity constraints. Therefore, it is crucial to identify the key factors that cause traffic congestion and estimate congestion probability for traffic management.

The congestion probability indicates the likelihood of congestion formation based on a range of traffic-flow values [3,4]. Previous studies have primarily employed descriptive statistics to identify the traffic states and determine congestion probabilities. Ju, Sun, and Jin [5] obtained the congestion probability through parameter estimation of the travel time index distribution based on floating car data, and proposed a method for the online prediction of urban-congestion probability based on historical traffic data from the Berlin traffic management centre. Similarly, Xu and Chen [6] identified the congested cells and tracked the sources of congestion using the massive vehicle trajectory data. Laval [7] classified the traffic state into voids, capacity and jams, and demonstrated that within the critical region, the traffic dynamics exhibit chaotic behaviour and become particularly sensitive to infinitesimal variations in the initial conditions. Various other studies have been conducted focusing on the global perspectives to calculate the congestion probability of an entire road network rather than a road section. Laval [7] and Yuangyai, Nilsang and Cheng [8] analysed the traffic-congestion probability of an area per period based on the ratio of the congested conditions to the entire traffic network, and calculated the congestion based on the total delay and traffic speed. Subsequently, Tran Quang and Bae [9] proposed a hybrid deep convolutional neural network method to predict the short-term traffic congestion index in urban networks based on probe vehicles by using gradient descent optimisation algorithms. System dynamics are typically adopted to depict and predict the traffic congestion probability owing to its intricate and dynamic nature. Andreotti et al. [10] analysed the statistical properties of traffic fluctuations within a road network and related the fluctuation amplitude to the congestion probability, which was evaluated using Kramer's transition rate theory. They compared the probability density computed using the Monte Carlo method with the stochastic dynamics and demonstrated that the congestion probability of a road network could thus be estimated. Wang, Chen and Jim [11] employed discrete-time Markov chains and online traffic-monitoring data to predict the congestion probability and facilitate optimal vehicle routing. Yuangyai, Nilsang and Cheng [8] used the historical traffic-speed data, images obtained from the Google Maps API and social-media data (e.g. Twitter) to estimate the traffic speed and congestion probability in various areas using Markov-chain traffic speed assignment for allocating the ambulance bases.

In summary, considerable advancements have been achieved in both congestion-probability calculations and predictions. However, these studies present various limitations, particularly in the use of macroscopic traffic parameters to describe the traffic conditions, thereby ignoring the randomness of traffic. Furthermore, standard parameters reflect the past road conditions, whereas the congestion probability must reflect the future conditions. Essentially, in the models that directly employ traffic-state parameters to estimate the congestion probability, the past traffic states cannot be used to calculate the future congestion probability. Additionally, most studies have used the state threshold of traffic breakdown to determine the traffic congestion, but disregarded the differences between the two states. Traffic breakdown indicates the transition from freely flowing traffic to a congested state; however, not all traffic breakdowns evolve into congestion [12]. Limited research has been conducted on estimating the congestion probability by considering the distinction between breakdown and congestion.

Therefore, in this study, we developed a congestion-probability estimation method by considering both the advantages and disadvantages of the previous methods. We implemented the concept of stochasticity to traffic arrivals to obtain a probability density function that assesses the congestion-probability for a given traffic flow. The method is structured as a mathematical description of the congested conditions by combining the breakdown and congestion thresholds. The proposed method presents a mathematical tool for handling uncertainty and complexity when estimating the congestion probability. This study contributes significantly to the literature on congestion probability estimation in the following aspects:

1) Based on the intrinsic correlation between traffic flow and stochastic fluctuations, we analysed the formation mechanisms of traffic congestion. The proposed model explicitly accounts for the essential relationships among complex traffic states across the road segments, thereby establishing a theoretical foundation for congestion probability estimation.
2) The proposed method employs a rigorous probabilistic model that calculates the probability of complex traffic conditions. The proposed framework integrates the stochastic modelling of traffic arrival patterns to enable the quantification of the joint probability that a road segment will simultaneously satisfy the critical conditions of congestion.
3) The proposed model supports an arbitrary congestion definition that can be used to calculate the congestion probability for any type of traffic flow. No statistical analyses have been conducted using this methodology or the exact combination of predictors, to the best of our knowledge.

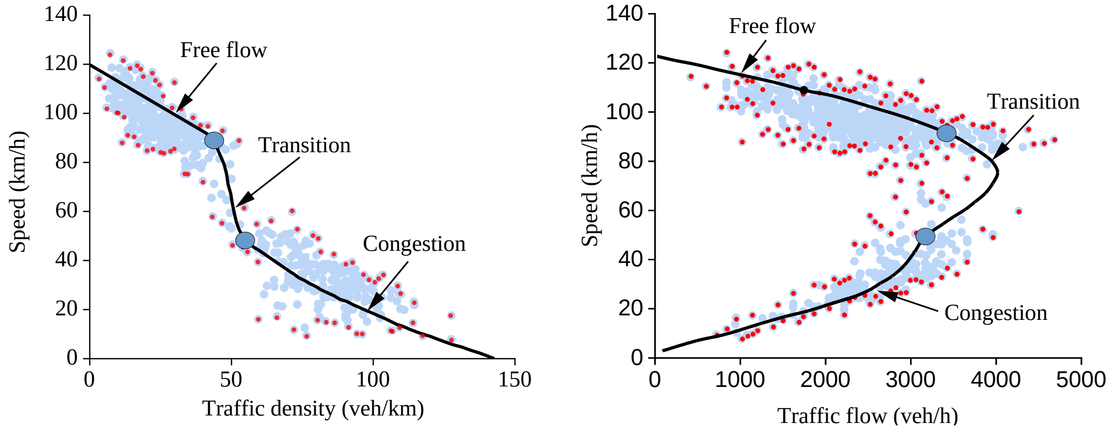
The remainder of this paper is organised as follows. Section 2 presents the probabilistic inference of congestion based on the randomness of traffic flow, describes the proposed approach, establishes the calculation model for congestion probability and summarises the data processing steps. Section 3 presents the results and discusses them. Finally, Section 4 concludes the paper and presents direction for future research.

2. MATERIALS AND METHODS

2.1 Probabilistic inference of congestion

Stochastic analysis of traffic congestion

The generally accepted metrics of traffic congestion include traffic flow, density, speed and their variants or combinations. These indicators provide a relatively comprehensive description of traffic-flow states from a macro perspective but fail to explore their microscopic conditions. For example, the relationship between traffic flow, density and speed based on data obtained from the German freeway A43 is shown in *Figure 1* [13]. A critical behaviour occurs during the transition from free-flow to congestion [7]. Such transitions are probabilistic because breakdown and congestion are not always observed under the same conditions. The three-phase traffic theory describes critical behaviour as a breakdown, which is the phenomenon of phase transition from an initial free-flow to congestion at a bottleneck [14].



(a) Relationship between speed and density *(b) Relationship between speed and flow*

Figure 1 – Traffic statuses in speed–density and speed–flow relationships

As shown in *Figure 1*, traffic-state descriptions based on traffic speed typically focus on its overall change trend, neglecting the variability of the random parts (distribution of scatter points). Therefore, statistical indices comprise reference values for traffic-state descriptions; however, they can introduce significant estimation errors when analysing the formation mechanism or probability of traffic congestion as they conceal the characteristics of random variation [15]. The description differences between statistical data and random arrivals are illustrated in *Figure 2* from a micro-perspective. From traffic density, we can obtain the number of vehicles per unit length but not the vehicle distribution in the road section. This implies that the traffic flow described by density can be considered as the state shown Scene 1 by default. However, all three scenes are possible because the traffic flow arrives randomly in real networks. Therefore, the traffic speed fluctuates significantly, even under the same density, which is consistent with the data presented in *Figure 1* [16].

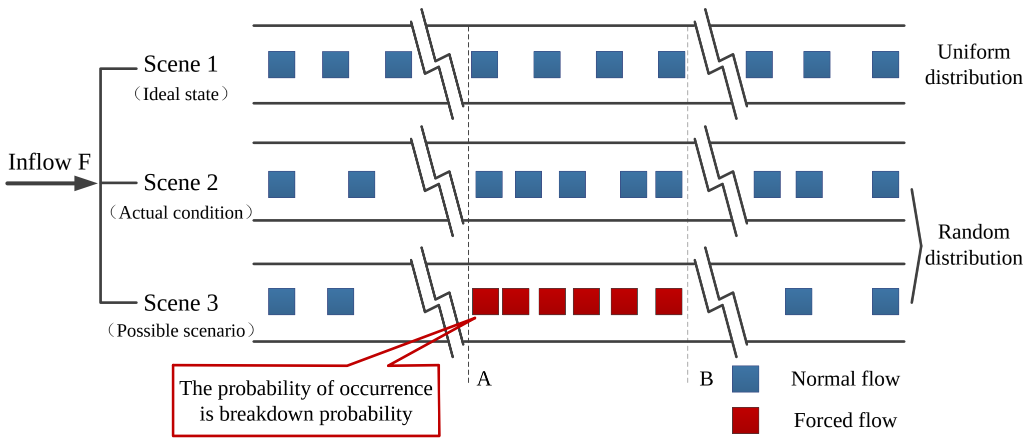


Figure 2 – Schematic of vehicle-arrival distribution and traffic-operation states

A decrease in the speed of traffic flow can result in a traffic breakdown owing to the excessive accumulation of vehicles, as illustrated in Scene 3 (*Figure 2*). Other studies have shown that breakdowns occur with some probability at the same flow rate; however, breakdowns are stochastic in nature [14, 16]. Additionally, *Figure 1* illustrates the stochastic nature of congestion and those high flows typically, but not necessarily, lead to congestion [17]. Therefore, we can analyse the probability of Scenario 3 based on the law of vehicle arrival at a road section, which adds a probabilistic characteristic to the formation of congestion.

Probability inference of congestion based on randomness of traffic flow

Although the aforementioned analysis verifies the stochastic nature of traffic congestion, its mechanism or trigger requires further discussion [17, 18]. According to the three-phase traffic theory, the traffic state is categorised into three states based on breakdown and congestion thresholds: free flow, synchronised flow and wide moving jam [12, 19]. Therefore, the congestion trigger satisfies the following critical conditions: (1) the system moves from free to synchronised flow (breakdown threshold) and (2) then from synchronised to congested flow (congestion threshold). Therefore, the probability of traffic congestion is determined based on the probability of traffic breakdown and that of the breakdown turning into congestion [20].

Empirical studies on vehicular traffic have shown that the average speed of vehicles decreases when the number of vehicles travelling on the road increases [5, 21]. According to the general traffic-flow model, a traffic breakdown occurs when the number of vehicles exceeds a critical condition [22]. This study formulated traffic breakdown as a binary decision problem of whether the number of vehicles exceeded a predefined threshold [23]. High and sustained flows in real traffic data are likely to result in congestion [14, 17]. Thus, we determined the congestion probability based on two criteria: (1) the probability that the number of arriving vehicles exceeds the critical value, and (2) the probability that the duration of criteria (1) exceeds the critical period. The criteria proposed in this study ensure that disturbances caused by transient peak flows are not misclassified as congestions. The stochastic nature of traffic critically influences the probability of random transitions between states [14]. Applying the concept of stochasticity to vehicle arrivals results in a probability density function that provides the congestion probability for a given traffic flow [24].

It must be noted that we do not provide a concrete decision regarding whether congestion would occur but only the probability of its occurrence. Additionally, the scope of this study included congestion caused by heavy traffic, regardless of incidents, accidents, roadwork and weather conditions.

2.2 Research approach

Uncertain traffic-arrival rates

Understanding the traffic-arrival process and its patterns is vital for traffic-flow analysis, which is the foundation for determining the congestion probability [25]. Following classical traffic-congestion-estimation models, we made the following assumptions regarding computational tractability [26]. Let $\Lambda = \{\lambda_1, \lambda_2, \cdots, \lambda_n\}$ represent the pattern of traffic-arrival-rate vector. The arrival rate at i^{th} time t is denoted as λ_i. The variable t is a suitable time interval for traffic investigation and analysis to meet the traffic-planning accuracy requirements and avoid resource wastage. Instead of deterministic values, actual arrival rates of traffic flows are often uncertain in practical applications. We describe fluctuations in uncertain traffic flows from the following three aspects.

First, traffic-arrival rates may vary, which can make it difficult to predict the actual variations. The upper bounds of the traffic flow can be obtained based on the limitation of road capacity, which is expressed as follows:

$$\lambda_i \le C_t \tag{1}$$

where C_t denotes a given parameter representing the road capacity within the time interval t.

Second, the traffic-arrival process is generally considered a renewable process, which means that vehicles on the road are independent random variables. Therefore, the arrival of each vehicle was regarded as a probabilistic process:

$$\Lambda \sim F\left(\lambda_i\right) \tag{2}$$

Third, it is possible to estimate vehicle arrival rates based on the observations of vehicle arrivals in each approaching lane [25]. The average arrival rate in time interval t is calculated as follows:

$$\lambda_i = \frac{1}{m}\sum_{j=1}^{m} N_j \tag{3}$$

where m represents the number of units in t, j =1,2,…m, and N_j denotes the number of vehicles that arrive on the road during the j[th] unit of time.

Based on the above, the uncertainty set of traffic-arrival rates is defined as follows:

$$U = \left\{\Lambda \middle| (1),(2),(3)\right\} \tag{4}$$

Probability of traffic congestion based on traffic-arrival rates

Roads with a reasonable arrival rate and favourable network performance can effectively help clear the traffic. Otherwise, the number of vehicles on these roads will increase rapidly. However, traffic breakdowns can occur under any traffic-flow level [20, 27]. Andreotti et al. [10] found that the densities of some roads are higher than the critical value, even if the average density is below the critical value. The occurrence of breakdowns in various traffic flows can be described using the probability theory [28, 29]. The traffic flow breaks down when the actual number of arriving vehicles exceeds the capacity of the road section. Therefore, the breakdown probability P_{B,t_i} is equal to the probability that the number of vehicles is higher than the threshold. According to the characteristics of random arrival, the breakdown probability during analysis period *t* when the number of arriving vehicles exceeds the number of vehicles (N_{BT}) can be obtained directly as follows:

$$P_{\mathrm{B},t_i} = 1 - \sum_{k=0}^{N_{BT}-1} p(F(\lambda_i), t_i, k) \tag{5}$$

where N_{BT} is the threshold representing the number of vehicles corresponding to the traffic breakdown, which occurs if the number of arriving vehicles exceeds a predefined threshold N_{BT}. Different countries adopt different indicators that to determine the traffic status, such as average speed, flow and density [30]. Any index can be transformed into threshold N_{BT} and combined using the proposed method. Because the methods employed by various countries are not the focus of this study, this will not be further elaborated upon. $p(F(\lambda_i), t_i, k)$ is the probability that the number of vehicles arriving at a road section is equal to *k* under a traffic-arrival rate λ_i, which conforms to Definition (4). $F(\lambda_i)$ is a probability function determined using a traffic-flow arrival distribution rule.

The slow traffic owing to a breakdown in the road section may be restored to free-flow after a small disturbance and may also be affected by subsequent vehicles in the congested state [12, 17]. The occurrence of congestion depends not only on the number of arrivals causing the traffic breakdown but also on the duration of the speed drop. To avoid recording short-term speed fluctuations as congestion, traffic congestion was assumed to occur when the number of arriving vehicles over the congestion threshold was sustained for at least a time period T based on the occurrence of a traffic breakdown [28, 31]. *T* is a suitable analysis period for traffic investigation and analysis. Considering the above, the congestion probability is defined as follows:

$$P_{\mathrm{C},\mathrm{t}_{i+e-1}} = 1 - \sum_{k=0}^{N_{CT-1}} p\left(F\left(\lambda_{i+e-1}\right), t_{i+e-1}, k\right) \tag{6}$$

$$P_{\mathrm{C}} = P_{B,t_i} \prod_{s=2}^{S} P_{C,t_{i+e-1}} \tag{7}$$

where $P_{C,t_{i+e-1}}$ denotes the probability that more than N_{CT} vehicles arrive at the section within the period t_{i+e-1}, e=1,2,…E. E denotes the number of analysis periods t required during the congestion state, $T = t \cdot E$, whereas N_{CT} denotes the number of vehicles corresponding to the congestion threshold that makes the speed drop caused by the breakdown sustainable. P_C denotes the congestion probability during the analysis period and is expressed as follows:

$$P_C = \left(1 - \sum_{k=0}^{N_{BT}-1} p(F(\lambda_i), t_i, k)\right) \prod_{e=2}^{E} \left(1 - \sum_{k=0}^{N_{CT-1}} p\left(F\left(\lambda_{i+e-1}\right), t_{i+e-1}, k\right)\right) \tag{8}$$

2.3 Data collection and pre-processing

In our experiments, we used actual publicly available historical traffic data collected from 1 October 2011 to 31 October 2011 by dual-loop detectors deployed on the mainline and ramps of a freeway in Portland, wherein the traffic information for sections I-205 NB and I-205 SB were recorded. Each record comprised the time, detector ID, road section ID, flow, occupancy and speed.

To use the dataset with our model, we converted the data from the given format to a custom format. The pre-processing phase comprised the following phases:

1) Data filtering: Let I_i represent the i^{th} record in the dataset in a chronological order, and Si and Fi represent the mean speed and traffic flow of traffic item I_i, respectively, denoted as $I_i\left(F_i, S_i\right)$. We verified the data and observed no traffic flow at some temporal points. To ensure the reliability of the results, we deleted entries with missing information. If $S_i = 0$ or $F_i = 0$, then the data from I_i was removed without further processing and denoted as $I_i\left(F_i, S_i\right) = I_i\left(0,0\right)$.
2) Data reconstitution: The proposed method involves determining the breakdown-analysis period and congestion duration. Based on the characteristics of the raw data, we can determine that the breakdown duration is 10 min (i.e. t). The raw data were converted to grouped sets with a period of $t \cdot E$ (i.e. T) based on the analysis accuracy. Therefore, the raw data were reorganised as $G_k = \left\{\left(F_k, S_k\right); \left(F_{k+1}, S_{k+1}\right); \ldots; \left(F_{k+E-1}, S_{k+E-1}\right)\right\}$, $k = ROUNDUP\left(i/E, 0\right)$. Note that G_k was deleted if any observed value of mean speed and traffic flow was 0 in the group G_k.
3) Data grouping and sequencing: Let F_j and S_j represent the flow rate and average speed of group G_j, respectively, and let $G_j\left(F_j, S_j\right) = G_j\left(\sum_{k}^{k+E-1} F_k, \frac{1}{E}\sum_{k}^{k+E-1} S_k\right), j = k$. The reorganised data were grouped using F_j, which encodes categorical features, and sorted in order.
4) Traffic-condition binarisation: The thresholding of numerical features to obtain Boolean values is called condition binarisation. Therefore, a binary variable was used to define the traffic state: if a section was congested during an interval, the traffic state was denoted as 1; otherwise, it was denoted as 0.
5) Threshold setting: Researchers often assign a response variable, such as travel time, speed and road occupancy, as a threshold to distinguish between congested and free-flowing traffic [32]. We set a critical threshold to represent the traffic conditions by referring to previous studies.
6) Probability calculation: The congestion probability was calculated as the ratio of the number of times traffic-congestion occurred in a certain flow range to the total number of times the flow was observed within the same range during the same period.

In the first part of Section 3.1, we evaluate whether the traffic-congestion probability provided by the proposed method is effective under different breakdown and congestion thresholds based on data from a traffic dataset of Portland, Oregon. In the second part, we examine the statistical significance between the congestion probability based on the measured dataset and that returned by the proposed model using a quantitative description based on a paired-sample t-test. Subsequently, in Section 3.2, we explore the effects of different breakdown and congestion thresholds on congestion probability by visualising their variation tendencies.

3. RESULTS AND DISCUSSION

In this section, we evaluate the effectiveness of the proposed method for estimating the traffic-congestion probability through a case study. During the evaluations, we focused on the accuracy of the congestion probability calculated using the mathematical estimation and that of the real traffic data. Specifically, we examined the extent to which the results estimated by the proposed method correctly characterised the traffic congestion. Finally, we present quantitative discussions by analysing the effects of the breakdown and congestion threshold parameters on the model performance.

3.1 Comparing the calculated values with actual traffic data

This study was performed as a function of the breakdown and congestion threshold values as they affect the output. In this section, we empirically examine the outputs to analyse the effectiveness of the proposed congestion-probability-estimation method under several threshold settings based on historical traffic data. The breakdown thresholds were set to 15, 25 or 35 mph/h based on the traffic conditions in Oregon [33]. Subsequently, to examine the effect of the breakdown threshold on model performance, we fixed the congestion threshold to 20 min, i.e. S=2. Finally, the arrival-rate was assumed to be a Poisson arrival distribution, which conforms to the findings of mainstream studies [33, 35]. We used the absolute error (AE) as the evaluation metric to determine the absolute difference between the congestion probability measured from the dataset and those returned by the proposed model [4]. *Figure 3* shows the estimated congestion probabilities and ground truths under various breakdown thresholds. *Table 1* presents the match ratio of different probability thresholds.

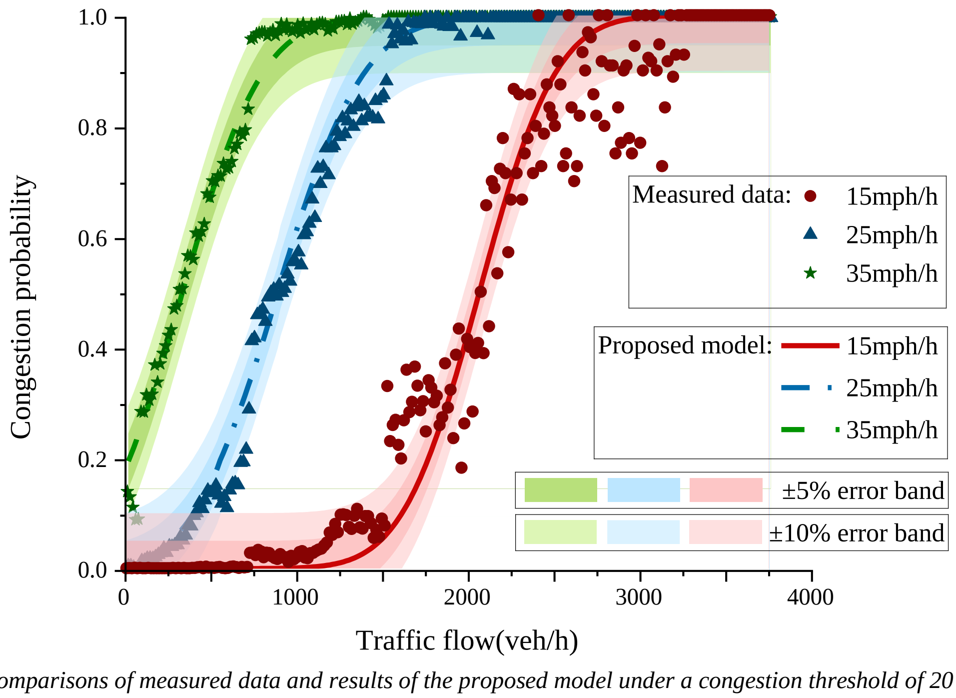


Figure 3 – Comparisons of measured data and results of the proposed model under a congestion threshold of 20 minutes and breakdown thresholds of 15 mph/h, 25 mph/h and 30 mph/h

Table 1 – Match ratio of different breakdown thresholds

Items	**15 mph/h**	**25 mph/h**	**35 mph/h**
±5% error	60.43%	87.66%	93.19%
±10% error	80.00%	97.87%	98.72%

Each point in *Figure 3* represents the ratio of the number of traffic-congestion occurrences in a certain flow range to the total number of occurrences, indicating the reliability of the model predictions with the AEs under different thresholds. The curves in the figure (including solid, dashed and dash-dotted lines) represent the ideal reference outcomes. The closer the measured data points are to these curves, the smaller the discrepancy between the observed values and model predictions. Furthermore, the dark and light shaded regions correspond to the 5% and 10% error bands, respectively. Across all threshold configurations, at least 60.43% of the data points lies within the 5% error band, while 80.00% reside within the 10% error band. This demonstrates that a significant portion of the predicted probabilities conform to the allowable tolerance margins. For these cases, the best result of 98.72% was obtained under a breakdown threshold of 35 mph, confirming that the predictions of our empirical model are close to reality and thus, validating its effectiveness.

To better understand the probability curves, we prepared *Figure 4*, wherein the measured and estimated probabilities are compared for different congestion thresholds. As the curve for the breakdown threshold of 25 mph in *Figure 3* provides a relatively complete probability curve and better prediction results, the same breakdown threshold was used to obtain the results shown in *Figure 4*. *Table 2* presents the match ratio of different probability thresholds.

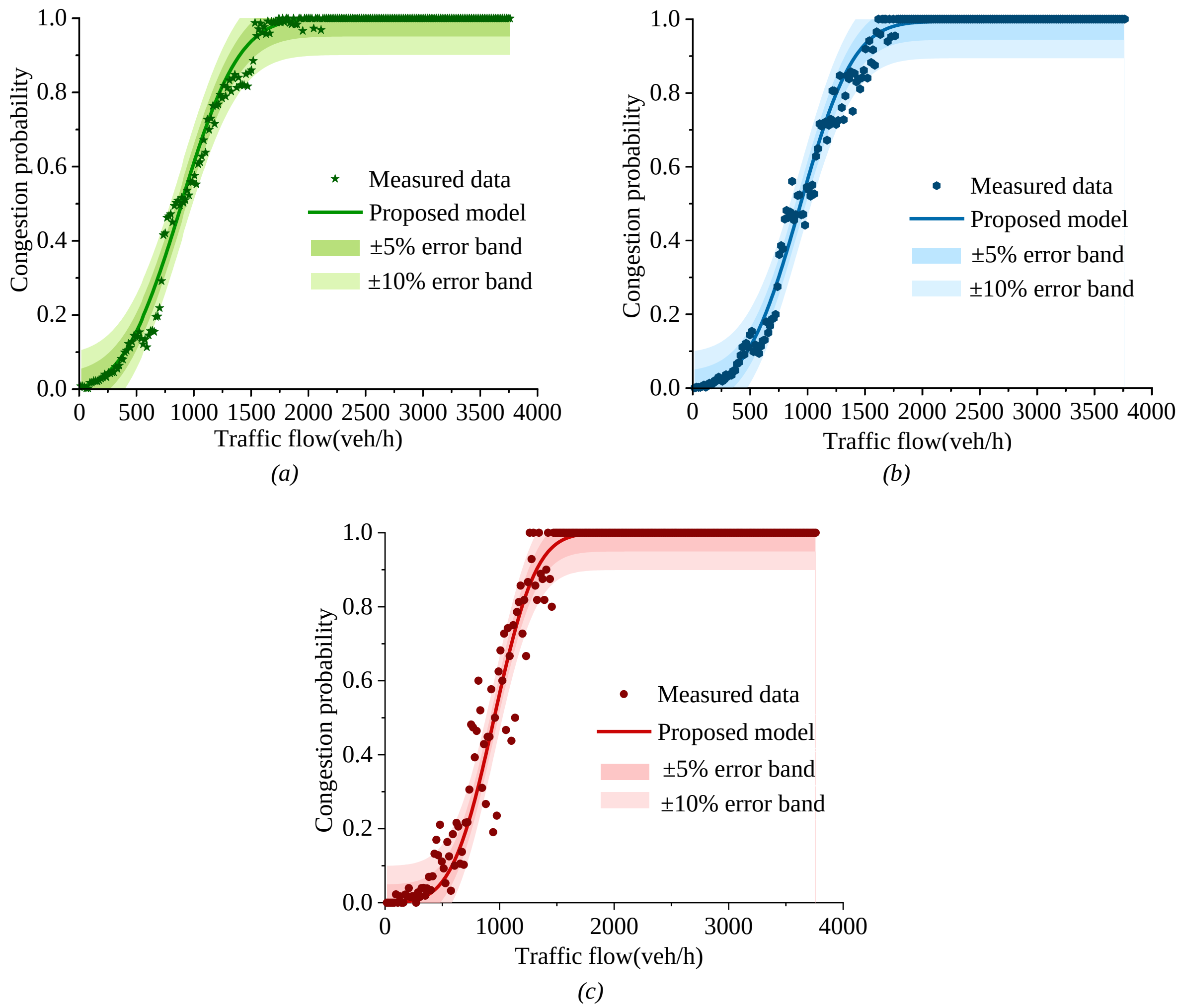


Figure 4 – Comparisons of measured data and results of the proposed model under a breakdown threshold of 25 mph and congestion thresholds of: (a) 20 minutes, (b) 30 minutes, and (c) 60 minutes

Table 2 – Match ratio of different congestion thresholds

Items	**20 min**	**30 min**	**60 min**
±5% error	87.66%	84.68%	82.13%
±10% error	97.87%	97.45%	90.64%

Figure 4 shows the specific probability of the traffic flow for different congestion thresholds. Evidently, the prediction performance was relatively unsatisfactory under the congestion threshold of 60 minutes. Compared with the other subpanels in *Figure 4*, larger errors are typically evident for cases wherein the corresponding dataset contains fewer samples. This is because all estimations were based on the same raw data, whereas different congestion thresholds correspond to different data. As more traffic data are available for smaller congestion thresholds (e.g. 20 minutes), the results are more reliable. By contrast, the performance deteriorates under larger congestion thresholds owing to data sparsity. In general, the higher the amount of data, the more accurate the congestion-probability predictions.

Additionally, we conducted a paired-sample t-test to determine whether the congestion probability differs significantly between the measured values and the model predictions. The results confirmed that the differences were not statistically significant at 5% significance level, as presented in *Table 3*.

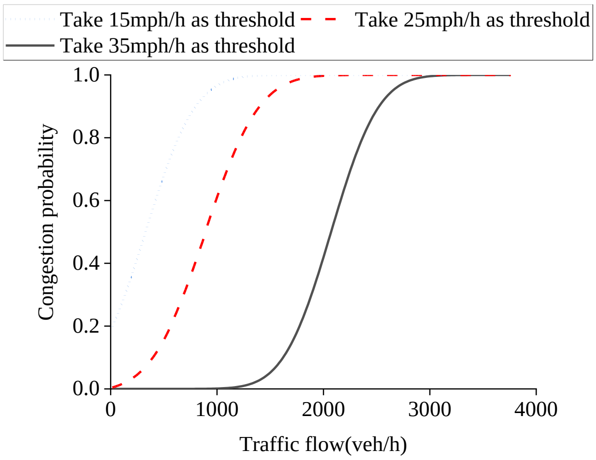
Table 3 – Results of the paired sample t-test

Items		Breakdown threshold (mph)			Congestion threshold (min)		
		15	25	35	20	30	60
Measured values	Mean	0.4495	0.7531	0.9040	0.7531	0.7447	0.7547
	Standard deviation	0.4093	0.3569	0.2103	0.3569	0.3656	0.3736
	Standard error	0.0267	0.0233	0.0137	0.0233	0.0238	0.0244
Results	Mean	0.4511	0.7522	0.9045	0.7522	0.7475	0.7485
	Standard deviation	0.4423	0.3472	0.2015	0.3472	0.3626	0.3814
	Standard error	0.0289	0.0226	0.0131	0.0226	0.0237	0.0249
Paired mean different	Mean	-0.0016	0.0008	-0.0005	0.0008	-0.0029	0.0063
	Standard deviation	0.0855	0.0330	0.0251	0.0330	0.0347	0.0628
	Standard error	0.0056	0.0022	0.0016	0.0022	0.0023	0.0041
Correlation		0.9828	0.9960	0.9935	0.9946	0.9960	0.9864
Significance level		5.3704E-173	3.8602E-231	6.2976E-222	3.1754E-231	3.8602E-231	1.4133E-184
95% Confidence Interval	Lower limit	-0.0126	-0.0034	-0.0037	-0.0034	-0.0073	-0.0018
	Upper limit	0.0094	0.0051	0.0027	0.0051	0.0016	0.0144
t-value		-0.2873	-0.3903	-0.3137	-0.3960	-0.3903	1.5328
Degrees of freedom		234	234	234	234	234	234
Sig. (two-tailed test)		0.7741	0.6966	0.7540	0.6925	0.6966	0.1267

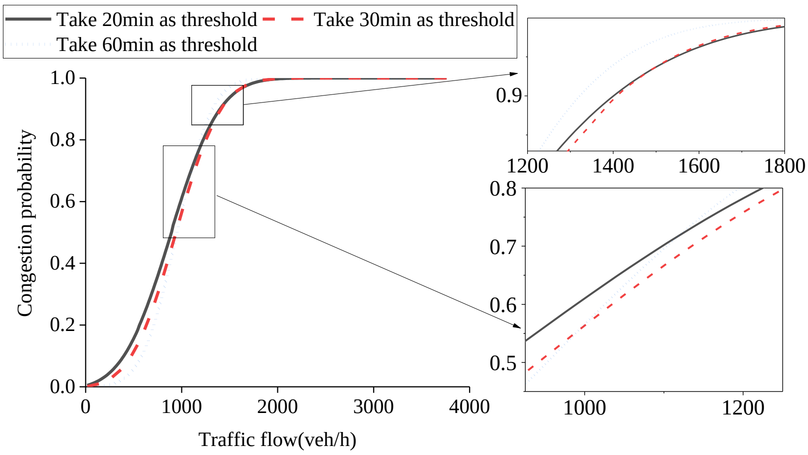
Based on these results, we can conclude that the proposed model can adequately estimate the congestion probability as it captures the randomness of traffic flow. From the perspective of a traffic administrator, the predictions of the proposed method can be practically employed owing to the low error margins. Traffic infrastructure that provides appropriate interventions (e.g. tuning traffic lights, variable message signs, congestion warnings or diversions) can be prepared for congestion-prone sections to alleviate congestion or prevent it from occurring [26]. Limiting the number of vehicles entering a road section is also an effective strategy for preventing recurrent congestion [17, 36].

3.2 Further analysis and discussion

We conducted a sensitivity analysis by adjusting the threshold values to evaluate the effects of the threshold values and analyse the characteristics of congestion probability. *Figure 5* shows the estimated congestion probabilities for various breakdown and congestion thresholds.



(a)



(b)

Figure 5 – Congestion-probability predictions under different (a) breakdown and (b) congestion thresholds

Based on our proposed model, 'S' shaped curves were obtained to represent congestion probability for observed traffic flows, which aligned with the actual results for Portland data and those of widely cited studies [17, 20, 27]. In other words, the changes in congestion probability for a one-unit increase in flow vary. Moreover, although the congestion probabilities of relatively low traffic flows were less severe than those of high traffic flows, traffic congestion was still observed under all traffic flows.

From the results presented in *Figure 5(a)*, it is evident that the congestion-probability predictions are affected by threshold variations. The probability curves change significantly with changes in breakdown threshold. The number of congested items followed an upward trend as the congestion threshold increased. This trend was expected because an increasing number of traffic statuses are considered as congestion [7, 32]. Thus, the breakdown threshold setting is inconsistent with the actual traffic conditions, which presents a significant error in the congestion probability. In particular, heavy congestion is associated with low threshold values, whereas light congestion is associated with high threshold values. These patterns strongly concur with the results of a previous study [5, 16].

Compared with the breakdown threshold, the congestion threshold had considerably lower effect on the model performance. It is evident from *Figure 5(b)* that the probability curves are similar; however, as we have added more details to the diagram, the trends of the curves differ. Under low-flow conditions, it is easier to identify congestion by using a smaller congestion threshold. However, as the traffic flow increases, the curve for the higher threshold increases rapidly and exhibits the highest congestion probability, as shown in the two right-hand panels of *Figure 5(b)*. The total traffic flow with a long duration easily exceeded the preset threshold and exhibited instability as the flow increased. By contrast, congestion cannot be triggered if the flow is insufficient for a short duration. In these instances, an excessively large congestion threshold may render the model bulky and not allow it to capture congestion under low traffic. However, if an excessively low threshold is employed, the instantaneous traffic peak is erroneously considered to be a congestion state. Therefore, an appropriate congestion threshold can be beneficial estimating congestion probability under any traffic flow.

Thus, even though traffic flow is the primary predictor of congestion, our results indicate that breakdown and congestion thresholds are also vital factors. Specifically, the breakdown threshold affects the location of the probability curve and the congestion threshold affects its trend.

4. CONCLUSIONS

Handling frequent congestions in road networks is a significant challenge for traffic management authorities. In this study, we introduced a new method that can estimate the congestion probability under a certain traffic flow by applying the concept of stochasticity to traffic arrivals. In addition to introducing this novel method, we offered a new perspective on congestion triggers that, unlike previous solutions, does not rely on statistical parameters of traffic conditions and can instead estimate congestion probability based on breakdown and congestion thresholds. The proposed method was subjected to a detailed performance analysis using a dataset extracted from real road networks, wherein we examined the accuracy its congestion-probability predictions. Our experimental results were consistent with our assumptions and offered clear evidence that traffic congestion can occur at any traffic-flow level. Combined with the experimental results, we verified that there was no significant difference between the calculated congestion probability and the measured data at a confidence level of 95%. This is a good result that enables traffic management to prepare for appropriate interventions and mitigate potential congestion situation by ensuring that arriving vehicles always remain well below the threshold. Although congestion cannot be completely eradicated in the short-term, the proposed model can contribute to the development of strategic plans.

A significant advantage of the proposed method is that it is robust and can be applied to a broader range of scenarios as it considers the occurrence mechanism of traffic congestion. Thus, it can serve as a general model for estimating congestion probabilities at diverse locations. In the future, we aim to develop methods that incorporate multiple sources of weather conditions, road surface status, and accident reports through Bayesian spatiotemporal fusion frameworks to achieve high prediction accuracy. Furthermore, the existing models fail to capture behavioural heterogeneity across various traffic flow states, and future works must provide a deeper understanding of the heterogeneous driving strategies causing the emergence of macroscopic congestion.

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DECLARATION OF INTEREST STATEMENT

We declare that we have no financial and personal relationships with other people or organisations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

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基于交通到达随机特性的交通拥堵分析与拥堵概率估计

摘要

城市交通拥堵已成为制约可持续发展的全球性挑战。由于交通拥堵研究可为制定缓解拥堵策略和优化交通管理提供信息，因此，准确估计拥堵概率至关重要。现有研究多采用确定性模型分析拥堵，未考虑交通流内在随机性（如车辆到达的时空异质性）与拥堵形成机制间的动态耦合关系，导致在拥堵不确定性场景下的预测偏差。本研究运用随机交通流理论，深入剖析交通拥堵形成机理，提出基于概率的交通拥堵估计框架。针对交通流的随机特性，采用离散概率分布刻画车辆到达过程。为避免将短期交通激增误判为拥堵状态，构建一套具有双重阈值的时空持续性拥堵判别准则，即到达车辆的累积量需超过临界水平，且持续时间超过临界时间。通过美国波特兰市交通数据集进行实证验证，结果表明在 95%置信水平下，模型所得拥堵概率与实测数据无统计学显著偏差。该方法可为制定缓解拥堵对策提供支撑，并为未来交通规划提供新思路。

关键词

交通拥堵概率; 交通到达; 随机性; 交通中断.