Detecting the Critical Thresholds of an Urban Traffic System Using Percolation Theory

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Abstract

We employ high-resolution speed data to develop a percolation theory-based network analysis framework by integrating two identified critical thresholds. This framework effectively captures the dynamic behaviors of traffic networks before, during, and after the critical phase transition point. Our study reveals characteristic congestion thresholds around this critical phase transition for each studied network. Critical thresholds mark **tipping points where small disruptions may trigger widespread congestion in traffic systems. Near these thresholds, traffic behavior akin to a first-order phase transition occurs during rush periods, while a second-order phase transition is observed during non-rush periods. These insights facilitate the establishment of critical thresholds for urban areas. Additionally, our framework identifies essential links, termed bottlenecks, which are crucial for maintaining the functional connectivity of urban transport networks and ensuring the required level of service in cities. Our findings indicate that these traffic bottlenecks consistently appear at the same times on different days. Notably, links with high betweenness centralities often act as persistent seeds of congestion at the onset and throughout rush periods. Finally, the results indicate that disturbances in links with low**

congestion index and low betweenness centrality are unlikely to cause catastrophic fragmentation or the decomposition of the giant component.

1. Introduction

Maintaining the stability and connectivity of urban transportation networks amidst various disturbances—such as prolonged congestion due to a sharp increase in travel demand or a drop in supply—remains a significant challenge for city planners and managers.

Urban traffic congestion is a pervasive and multifaceted challenge that continues to plague modern cities. Despite significant advancements in transportation infrastructure and technology, the propagation of traffic jams remains a complex phenomenon that demands further exploration. Over the past decades, numerous studies have endeavored to unravel the complexities of traffic congestion and propose effective mitigation strategies. These studies employ a wide spectrum of theories and methodologies, such as percolation theory, macroscopic fundamental diagrams (MFD), fragmental models, deep learning, and machine learning techniques, to offer an efficient analysis of urban traffic dynamics and congestion propagation. Percolation theory has emerged as a powerful framework for understanding the spread of congestion in heterogeneous traffic flows [1]. By combining percolation theory with the MFD, researchers have revealed how traffic jams propagate through urban networks, uncovering the underlying bottlenecks that exacerbate congestion [2]. Moreover, the identification of critical percolation modes and the impact of moderate flooding on road network collapse have highlighted the vulnerabilities within urban infrastructure [3–5].

Further investigation into the reaction-diffusion-like dynamics of urban congestion has provided new insights into how traffic spreads through large-scale road networks [6]. These dynamics resemble contagion processes, with traffic jams behaving like infectious diseases that propagate and recede across the network [7]. Such analogies have been extended to model airport congestion and traffic congestion in urban networks using epidemic spreading frameworks [8,9]. Moran et al. (2024) also recently explores the concept of timeliness in various socio-technical and economic systems where timing is crucial. They introduce a model of delay propagation on temporal networks, using the magnitude of delay-mitigating buffers as a control parameter. This model reveals a novel form of critical behavior called "timeliness criticality", characterized by fluctuations near criticality, often referred to as "avalanches". The study identifies the corresponding critical exponents and demonstrates that timeliness criticality is also present in real-world systems like production networks.

Recent advancements in artificial intelligence, particularly deep learning and graph convolutional networks, have revolutionized traffic prediction and congestion propagation inference [11]. Techniques such as dynamic Bayesian graph convolution networks and fusion-based graph convolutional networks have demonstrated remarkable accuracy in predicting congestion levels and estimating traffic states across two-dimensional networks [12–14]. Additionally, the application of self-attention based approaches and Bayesian clustering ensemble models has further enhanced the explanatory power and prediction accuracy of traffic congestion models [15,16].

In urban traffic networks, the imbalance between capacity supply and travel demand can induce phase transitions. This study utilizes percolation theory to identify the critical phase transition point, based on the largest giant component (GC) decomposition point and the topological failures (TF) jump point. TF refers to links that, while structurally and functionally intact, have become segregated from the GC. At this critical phase transition point, we introduce critical thresholds and demonstrate that network dynamics exhibit distinct behaviors for values below, at, and above these thresholds. The critical thresholds are detailed in subsequent sections of this paper. An essential question arises: does the percolation phase transition of traffic networks occur similarly during different traffic periods, such as rush and non-rush hours? This query motivates the use of our combined method to investigate the dynamic behaviors of complex traffic systems near the critical phase transition point. By addressing this question, we aim to provide deeper insights into the management and optimization of urban traffic networks under varying conditions.

Most existing studies focus on either the physical topology of road networks during disturbances [17–19] or the transportation functionality under normal conditions [1,3]. However, the impact of various disturbances on maintaining functional connectivity within traffic networks remains insufficiently understood. This study aims to identify links whose disruption significantly reduces the quality of the network's functional connection, which we refer to as bottlenecks. Bottlenecks present significant challenges to the efficiency and functionality of transportation networks. Addressing these bottlenecks is crucial for enhancing urban mobility and mitigating traffic-related issues.

The latest breakthroughs in data-driven techniques have provided powerful tools for identifying road network bottlenecks. By leveraging vast amounts of traffic data, critical congestion points can be uncovered with precision [20]. Additionally, methodologies incorporating speed transition matrices and real-time traffic data offer robust frameworks for bottleneck detection [21]. Dynamic traffic control methods, particularly variable speed limit control (VSLC) and reinforcement learning, have shown significant promise in managing bottlenecks [22]. Studies have highlighted the effectiveness of adaptive speed control in stabilizing traffic flow and reducing congestion, further supported by real-world implementations [23]. These approaches demonstrate the benefits of speed matching strategies in maintaining optimal traffic conditions [24].

Understanding the spatiotemporal dynamics of traffic bottlenecks provides early signals of heavy congestion. Analyzing traffic patterns over time can predict and alleviate congestion before it becomes severe, highlighting the importance of proactive management [25]. This proactive approach is essential for effective traffic management and urban planning. Integrating percolation theory into traffic analysis offers unique insights into network connectivity and bottleneck identification [26,27]. By understanding critical thresholds, urban planners can develop more resilient transportation networks. Studies demonstrate the efficacy of this approach in identifying critical congestion points.

Typically, bottlenecks are determined based on traffic status, often neglecting their role in maintaining the functional connectivity of the traffic network. In this study, we present a theoretical framework grounded in percolation theory and critical thresholds to identify traffic bottlenecks with the greatest impact on connectivity loss. Specifically, we seek to identify links whose failure could trigger a first-order phase transition in the network. Furthermore, one of the notable contributions of this research is the examination of the evolution and appearance of bottlenecks across different time periods on consecutive days. The results section provides a detailed discussion of these findings, offering a comprehensive understanding of the dynamic behaviors of complex traffic systems and their implications for enhancing network resilience.

Based on percolation theory, we have developed a method that uses the combination of two critical thresholds ρ_c and η_c, to identify traffic bottlenecks. While ρ_c is a crucial measure for evaluating the robustness of traffic networks, it is not sufficient on its own to identify bottlenecks. In our study, the percolation process in the network is considered a function of two thresholds ρ and η, where $\rho, \eta \in [0,1]$. Our framework operates as follows: First, we identify ρ_c by removing links with a congestion index lower than predetermined thresholds. The congestion index is the ratio of a link's speed to its maximum speed. ρ_c is the critical percolation threshold at which the largest giant component (GC) suddenly decomposes into smaller components, and topological failures (TF) significantly increase. Then, the network links are ranked in ascending order, subject to the condition that their congestion index does not exceed ρ_c. This ranking is established based on two key attributes: (**I**) the congestion index and (**II**) betweenness centrality. In the final step, by removing η percent of the selected links, we seek to identify the links whose removal causes the GC to break down and leads to significant structural failures. Since our method is based on real traffic network data, a more precise dataset allows our methodology to better identify links that play a critical role in network connectivity. Additionally, we find that the traffic bottlenecks identified by our framework frequently appear at the same times on different days, highlighting the need for efficient real-time bottleneck identification.

We implemented our proposed framework on the Shenzhen and Chengdu networks as examples of real traffic networks. Our innovative approach provides a novel strategy to address the challenges of identifying traffic bottlenecks. Additionally, this study offers a comprehensive method to better understand the vulnerability and resilience of urban transportation networks under both anticipated and unanticipated disturbances. This has significant implications for infrastructure planning in various cities.

2. Methodology

2.1. Determining the congestion index of the links

We applied our method of identifying critical percolation thresholds and traffic bottlenecks to two datasets, representing time-dependent travel speeds on each link in the urban areas of Shenzhen and Chengdu, during the morning and evening rush periods. In these urban networks, links and nodes correspond to the roads and their intersections, respectively. The ratio of a link's speed to its maximum speed serves as an effective indicator for assessing congestion levels. Due to potential overstatement of maximum speeds for technical reasons or the presence of very fast vehicles during light traffic, we used the ninety-fifth percentile of speed as a more accurate measure. Thus, the congestion index for each link i at time step t was calculated by dividing its speed at time step ($V_i(t)$) by the ninety-fifth percentile of the speeds of that link throughout the data period (V_i^{95th}). We use this percentile value only to remove the occasional high speeds that may happen during very low-traffic hours [3–5,28]. A threshold value was then established to classify the traffic state of the network links: a link is considered congested if and only if its congestion index is below the threshold value.

In Fig. 1, the 2D heatmap illustrates the probability matrix ρ during the morning and evening rush periods over three consecutive days for the Shenzhen and Chengdu networks. Darker cells indicate a higher probability of congestion for network links in that interval. Furthermore, the heatmaps reveal that the probability matrices ρ exhibit very similar patterns over the same time intervals on consecutive days, while such similarity is not observed across different time intervals on the same day.

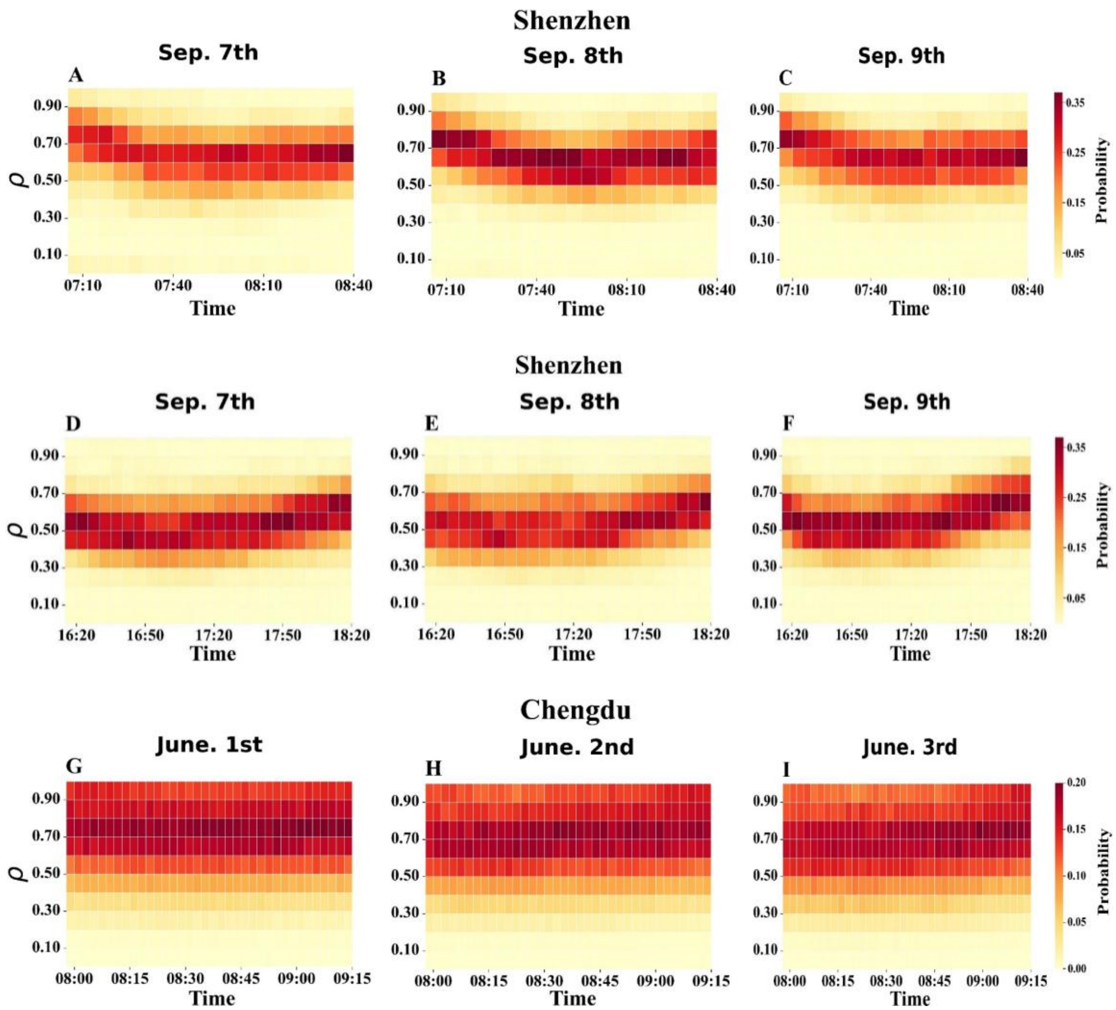


Fig. 1. The 2D heatmap of the probability matrix ρ during the morning and evening rush periods for three consecutive days in both networks

3. Dataset

We use real-time data, including time-dependent travel speeds and link lengths, from the road networks of two major metropolitan cities, Shenzhen and Chengdu in China. These speeds are derived from a map-matching algorithm applied to approximately 20,000 taxis' GPS points integrated with the road map. The dataset consists of over 40 million spatiotemporal GPS coordinates, each recorded at roughly 30-second intervals for every taxi and trip, covering an area of about 140 km² in the city center. Specifically, our analysis is based on speed estimates recorded over three full days—from September 7th to 9th, 2011 (https://doi.org/10.6084/m9.figshare.7212230). Shenzhen network comprises 2,013 links and 1,858 nodes.

The Chengdu dataset contains 3.01 billion GPS trajectory samples collected from over 12,000 taxis during 45 days (June 1, 2015, to July 15, 2015). Data were gathered for each road link during distinct time windows—specifically 3:00–5:00, 8:00–10:00, 12:00–14:00, 17:00–19:00 and 21:00–23:00—capturing the gamut of traffic conditions from rush hour to off-peak and nighttime periods, with each recording segment spanning two minutes. Each trajectory record consists of precise geographic coordinates (latitude and longitude), the taxi's operational status, its real-time travel speed, and the corresponding sampling time. To ensure uniform precision across all data, every taxi is equipped with the same type of GPS-enabled device, and the sampling rate remains constant at one record every 10 seconds. The Chengdu network consists of 5,943 links and 1,902 nodes [29].

4. Results and discussion

4.1. Determining the critical percolation thresholds

Traffic congestion not only causes functional failures and reduces travel speed, but it also exacerbates connectivity loss within the transportation network, leading to topological failures (TF) and the fragmentation of the giant component (GC) into smaller components. In topological failures, the structure and function of a link remain intact, but the link becomes isolated from the GC. This raises a fundamental question that has rarely been addressed: how can we determine the critical threshold in urban transportation networks? We have obtained evidence indicating that the characteristics of urban networks are dependent on this threshold (see Fig. 2).

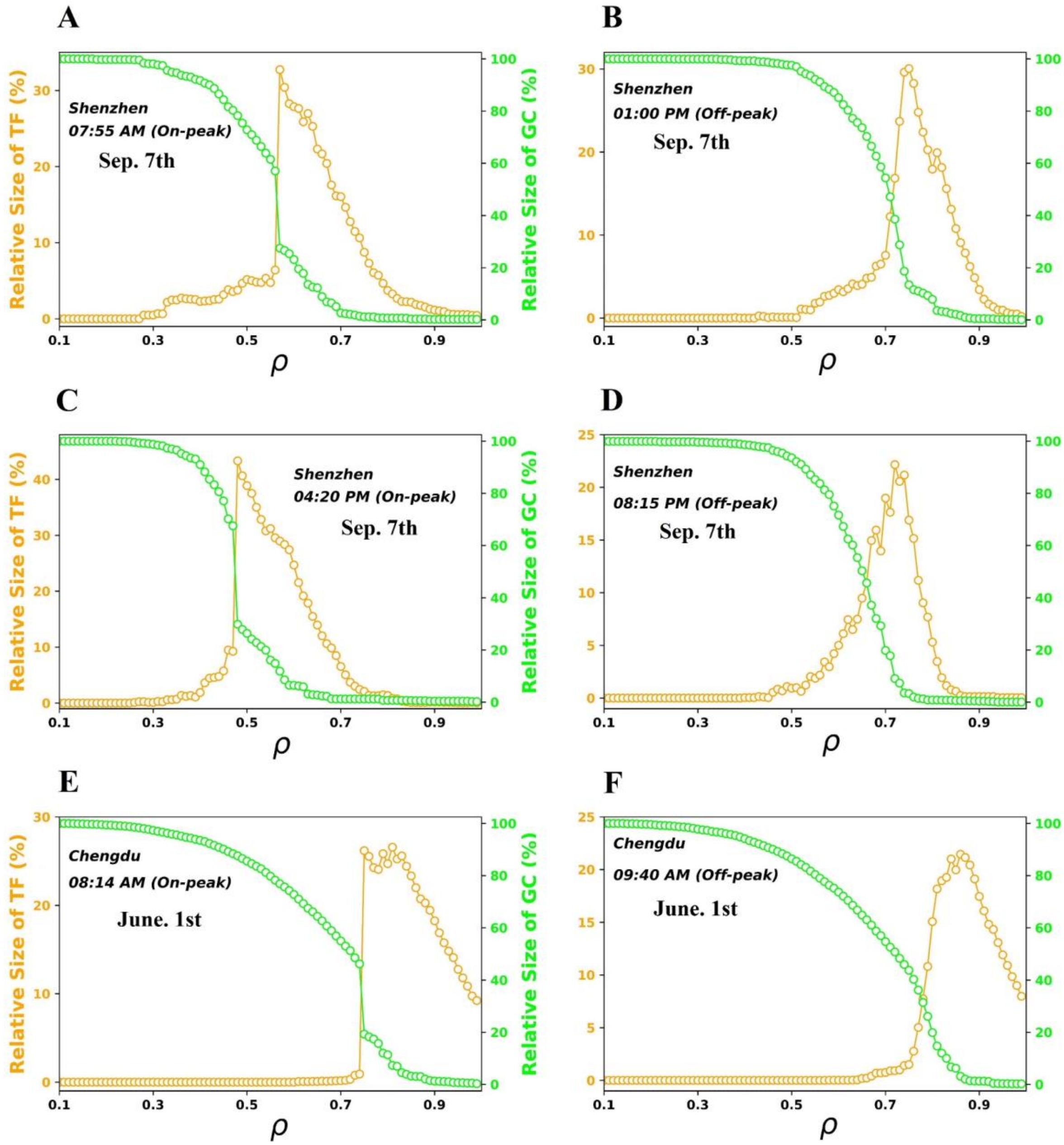


Fig. 2. Relative size of TF and GC for different values of ρ at different instants during rush periods and non-rush periods in Shenzhen and Chengdu networks

As ρ increases, the connectivity of the network decreases, and the GC decomposes into smaller components. Figure 2A, C, E illustrates that with an increase in ρ during rush periods, reaching the critical percolation threshold (ρ_c), a behavior akin to a first-order phase transition occurs, significantly increasing the relative size of TF. For example, during rush periods in the Shenzhen network, when ρ_c =0.48, the relative size of TF experienced a jump of more than 35% (see Fig. 2C). Conversely, with increasing ρ during non-rush periods, a second-order phase transition behavior in the relative size of TF is observed (see Fig. 2B, D, F).

In reality, ρ_c reflects the percolation critical point of global dynamic traffic. Due to traffic network dynamics, ρ_c changes with time throughout the day (see Fig. 3A, B, C). At the beginning of the loading process, ρ_c decreases during rush periods and reaches its lowest value at the end of the loading process. However, with the onset of the unloading process, ρ_c shows an increasing trend. Figures 3A and 3B reveal that the value of ρ_c during the evening rush period is smaller than that of the morning rush period in Shenzhen, indicating heavier traffic congestion in the evening. Additionally, the critical percolation threshold is depicted in both dynamic traffic networks over three consecutive days (see Fig. 3D, E, F). On each day, ρ_c was examined during the morning and evening rush periods, and similar patterns were observed across different days during the same time span.

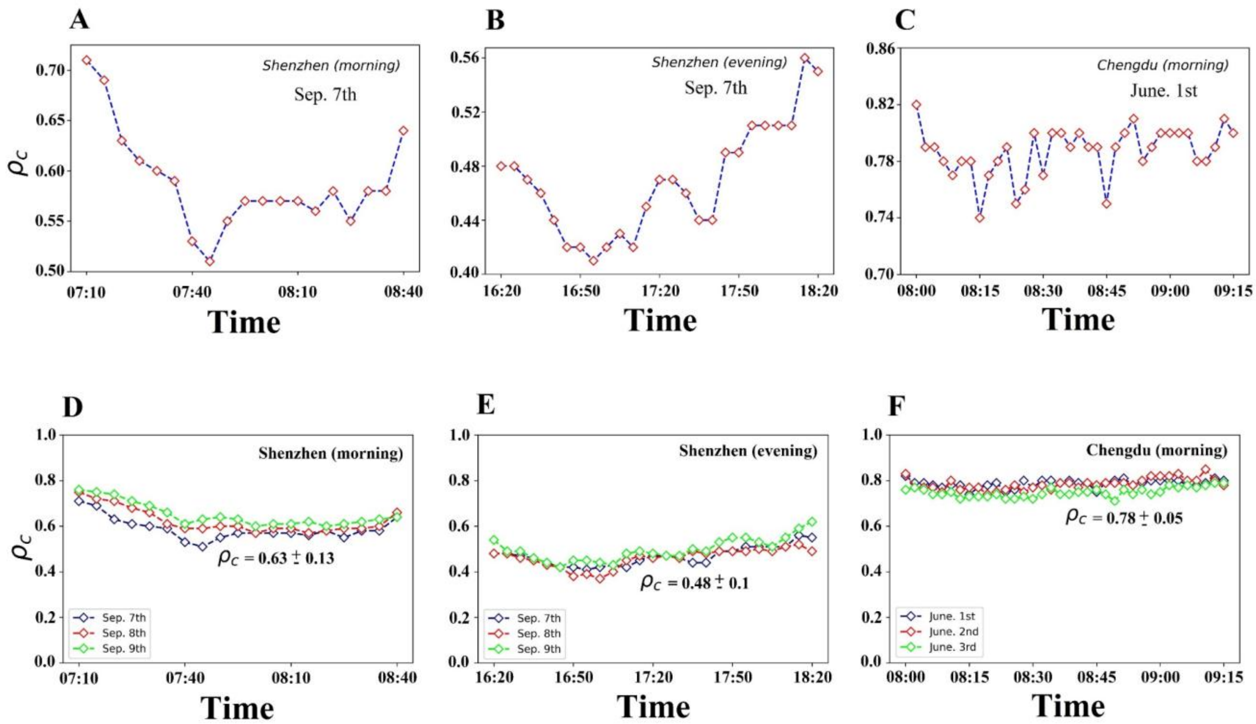
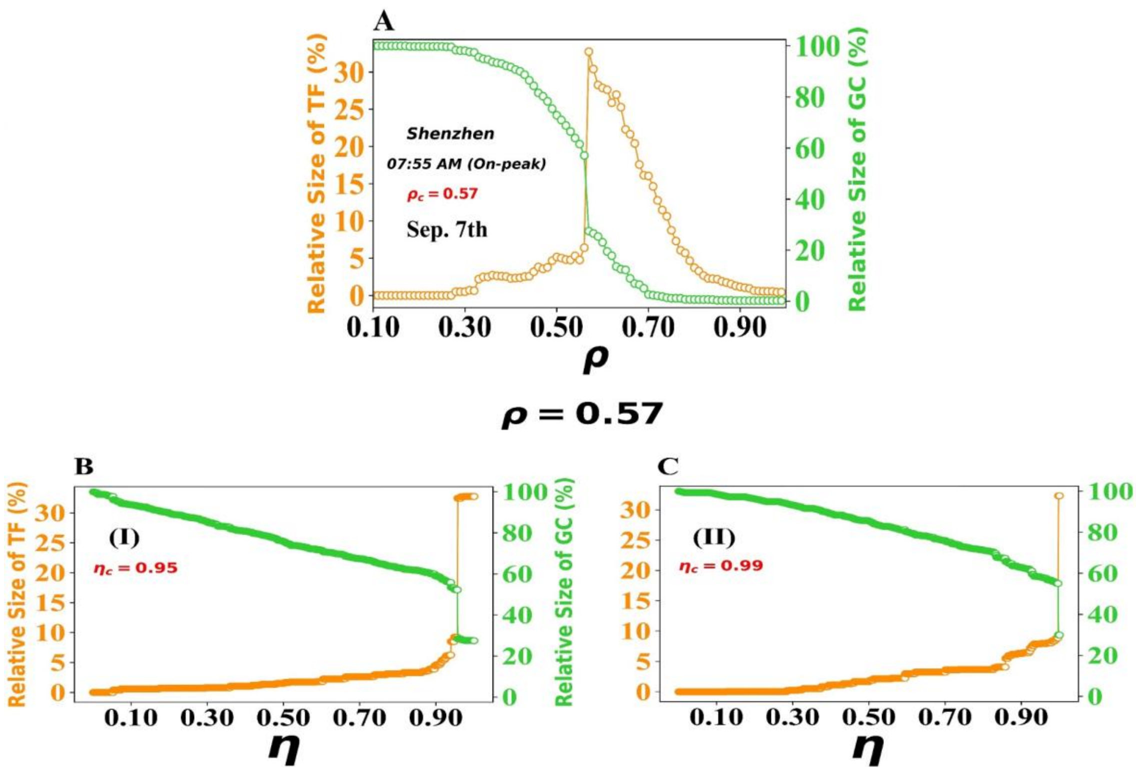


Fig. 3. Critical percolation threshold (ρ_c) as a function of time during rush periods in Shenzhen and Chengdu networks

Identifying the critical percolation threshold (ρ_c) at which traffic networks experience fundamental structural changes alone is insufficient to measure robustness. This is because networks exhibit completely different robustness behaviors based on the same values of ρ during rush periods and non-rush periods. To address this, we have used a combination of two thresholds, ρ and η, to measure the robustness of traffic networks. Let η represent the fraction of roads in the network with the condition $\frac{V_i(t)}{V_i^{95th}} \leq \rho_c$, ranked from smallest to largest based on either of two characteristics: **I** (congestion index) and **II** (betweenness centrality). Since traffic is a dynamic system that evolves over time, these two features are updated at each time step t.

Figure 4 illustrates the percolation process as a function of ρ and η. In each step, we measure the relative size of the GC and TF by removing roads with a congestion index lower than the threshold

ρ. Based on percolation theory, with an increase in ρ, we can identify ρ_c at the step when the network experiences substantial structural changes. The value of ρ_c at specific instants during the morning and evening rush periods in both networks is indicated in Fig. 4A, D and G. At the critical percolation threshold point (ρ_c), we examined the variations in the size of GC and TF as a function of η, unveiling key structural changes (see Fig. 4B, C, E, F, H, and I). This enhanced analysis provides a more comprehensive understanding of the robustness of traffic networks under varying conditions.



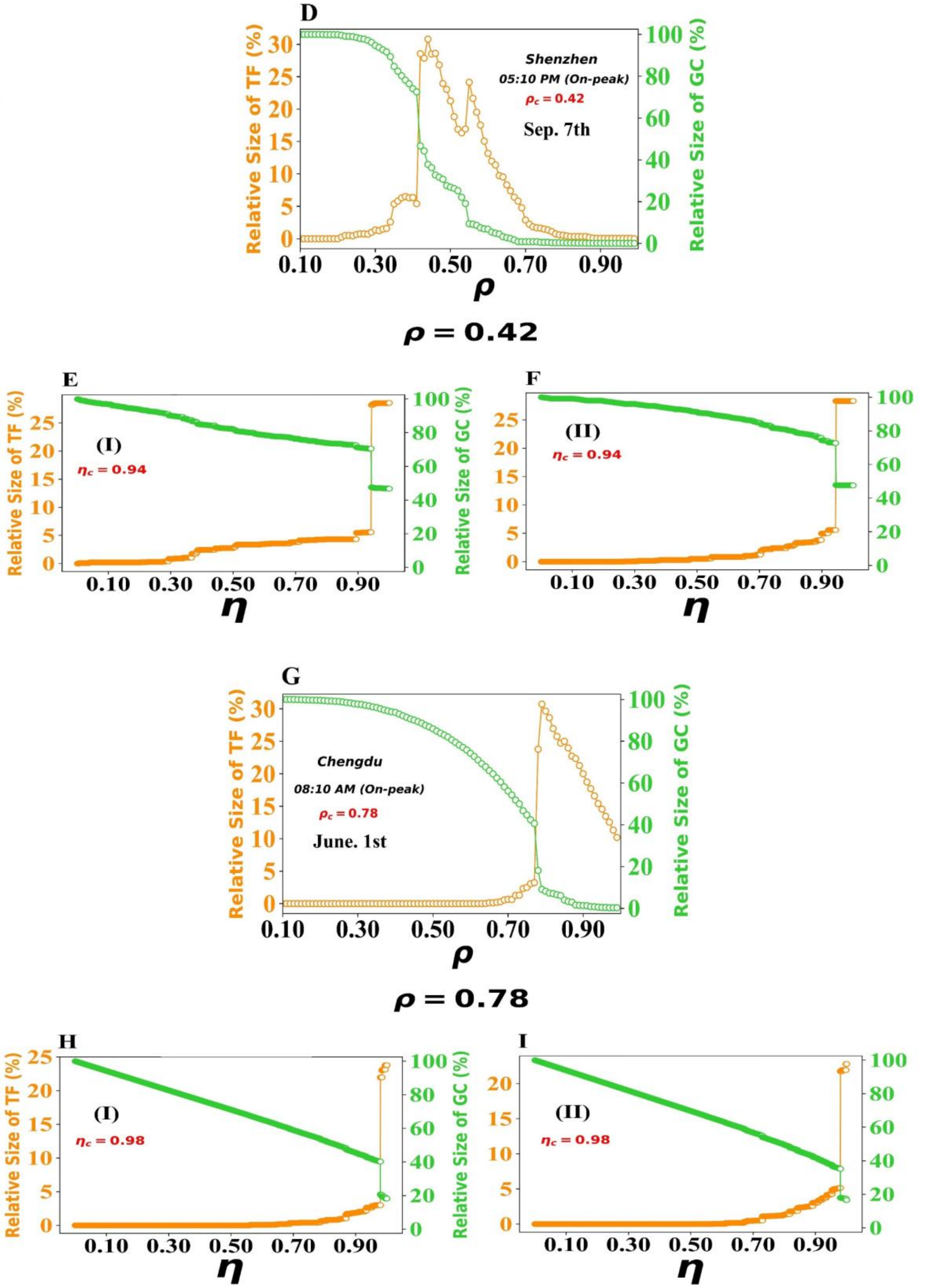


Fig. 4. Percolation processes as a function of ρ and η based on two characteristics **I** (congestion index) and **II** (betweenness centrality) at different instants during morning and evening rush periods in Shenzhen and Chengdu networks

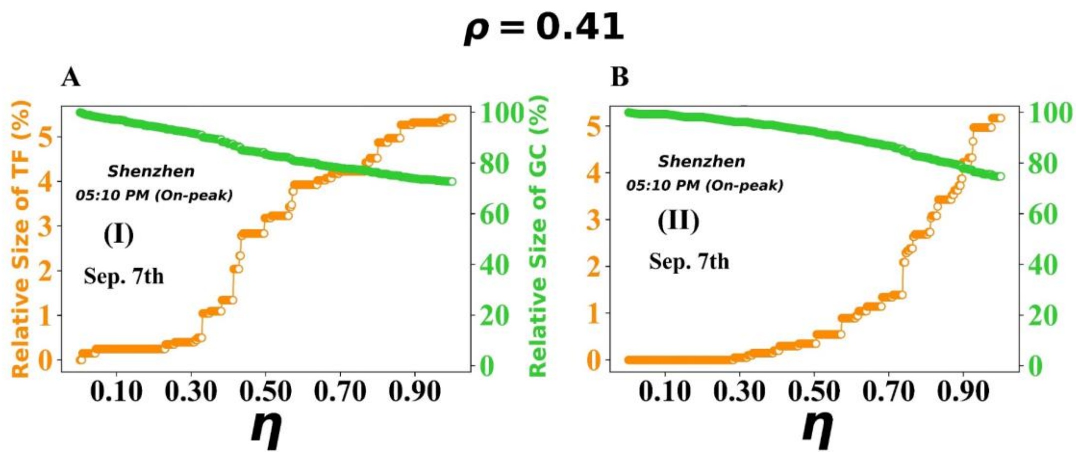


Fig. 5. Relative size of TF and GC as a function of ρ and η based on two characteristics **I** and **II**

By simulating disturbances such as floods, storms, and earthquakes through the removal of road network links, we can gain valuable insights into the robustness and resilience of traffic networks. Examining the dynamic behavior of these networks near the critical phase transition point provides a comprehensive understanding of their structural integrity. At each time step t, we evaluate the robustness of the network by removing η percent of the ranked links (from lowest to highest) based on two characteristics **I** and **II**. As shown in Fig. 4B, E, and H, more than 90% of the most congested network links (i.e., those with lower congestion index) need to be removed to identify the critical percolation threshold (η_c). This threshold is the point at which the removal of a specific link causes the GC to break down into smaller components, accompanied by a dramatic increase in TF and a first-order phase transition.

Similarly, η_c based on feature **II** follows a process akin to feature **I** (see Fig. 4C, F, and I), meaning that more than 90% of the network links with the lowest betweenness centrality must be removed for the network to experience substantial connectivity loss. However, it's important to note that if $\rho < \rho_c$, the phase transition does not occur in the networks. For instance, Fig. 5A, B illustrate that at 05:10 PM during the evening rush period in the Shenzhen network, with $\rho = 0.41$ (just 0.01 below ρ_c), no sudden connectivity loss occurs, indicating that crucial links have not yet been disrupted. The temporal evolution of η_c during the morning and evening rush periods over three consecutive days has been calculated for both networks (see Fig. 6). Based on both characteristics **I** and **II**, where η_c ranges from 0.91 to 0.99, similar temporal patterns are observed across different rush periods on different days and in different traffic networks. Ultimately, the results indicate that disturbances in links with low congestion index and low betweenness centrality are unlikely to cause catastrophic fragmentation or the decomposition of the GC into smaller components.

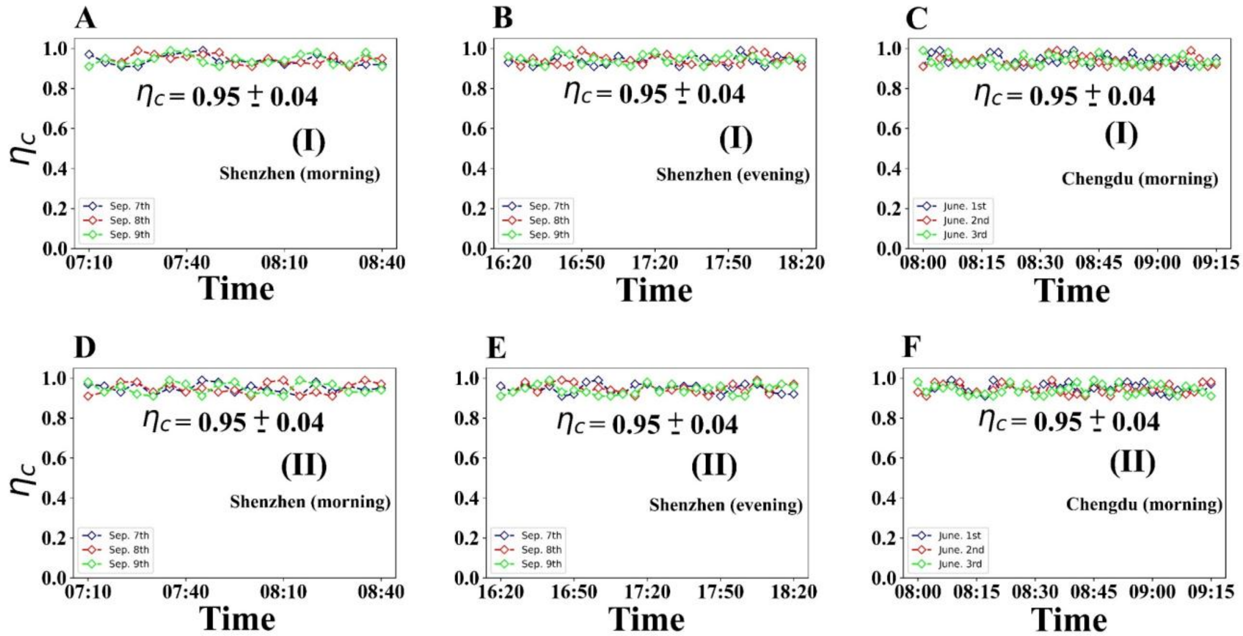


Fig. 6. Critical percolation threshold (η_c) based on two characteristics **I** and **II** as a function of time during rush periods for three consecutive days in Shenzhen and Chengdu networks

4.2. Bottleneck identification based on the critical percolation thresholds and the effect of them on network functional connectivity

We aim to identify the links whose removal causes η_c in networks. These links are crucial for connecting smaller components, and their removal can lead to major structural failures, significantly challenging the robustness, efficiency, and performance of traffic networks. In simpler terms, disruptions in these links cause the collapse of the largest network cluster, leading to drivers being trapped in smaller clusters. Therefore, these links can be considered as bottlenecks. It is important to note that the bottlenecks identified through our method are distinct from static bottlenecks, which are identified solely based on topological and structural characteristics. Figure 7 shows an example of identified bottlenecks at the same instant during the evening rush period on three consecutive days in the Shenzhen network. The red link, located along a freeway, when removed, decomposes the GC into two smaller components. The differences in travel patterns during the morning and evening rush periods result in different identified bottlenecks during these times. However, these bottlenecks repeatedly appear at the same hours on different days (see more examples in Figs. 8,9 and 10). This enhanced understanding provides valuable insights into the dynamic nature of traffic bottlenecks and their impact on network robustness and resilience.

Shenzhen

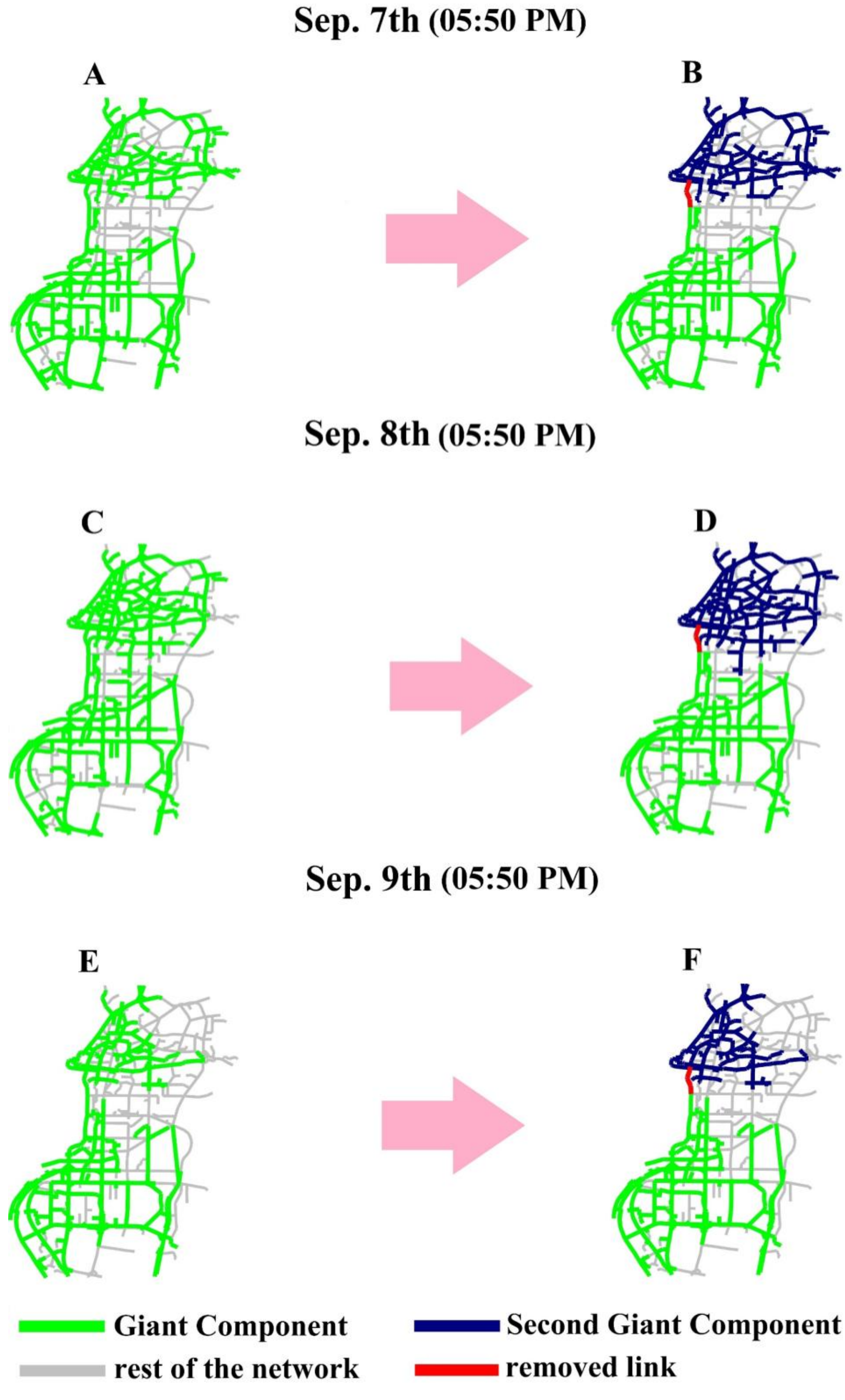


Fig. 7. A typical example of the identified bottleneck before and after its removal in the Shenzhen network at a given time t = 05:50 PM during evening rush period for three consecutive days that led to GC decomposition

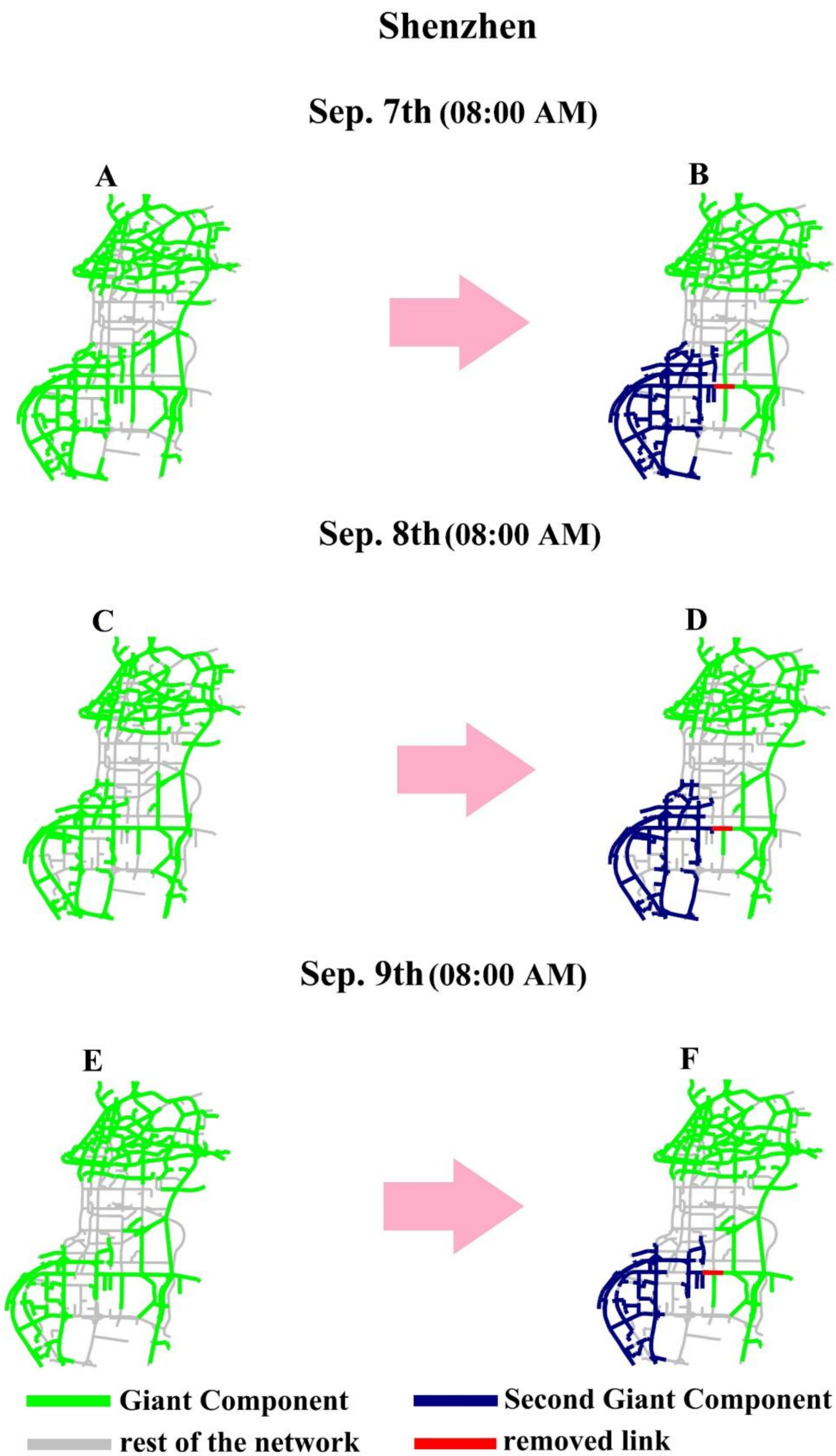


Fig. 8. A typical example of the identified bottleneck in the Shenzhen network at a given time t = 08:00 AM during morning rush period for three consecutive days

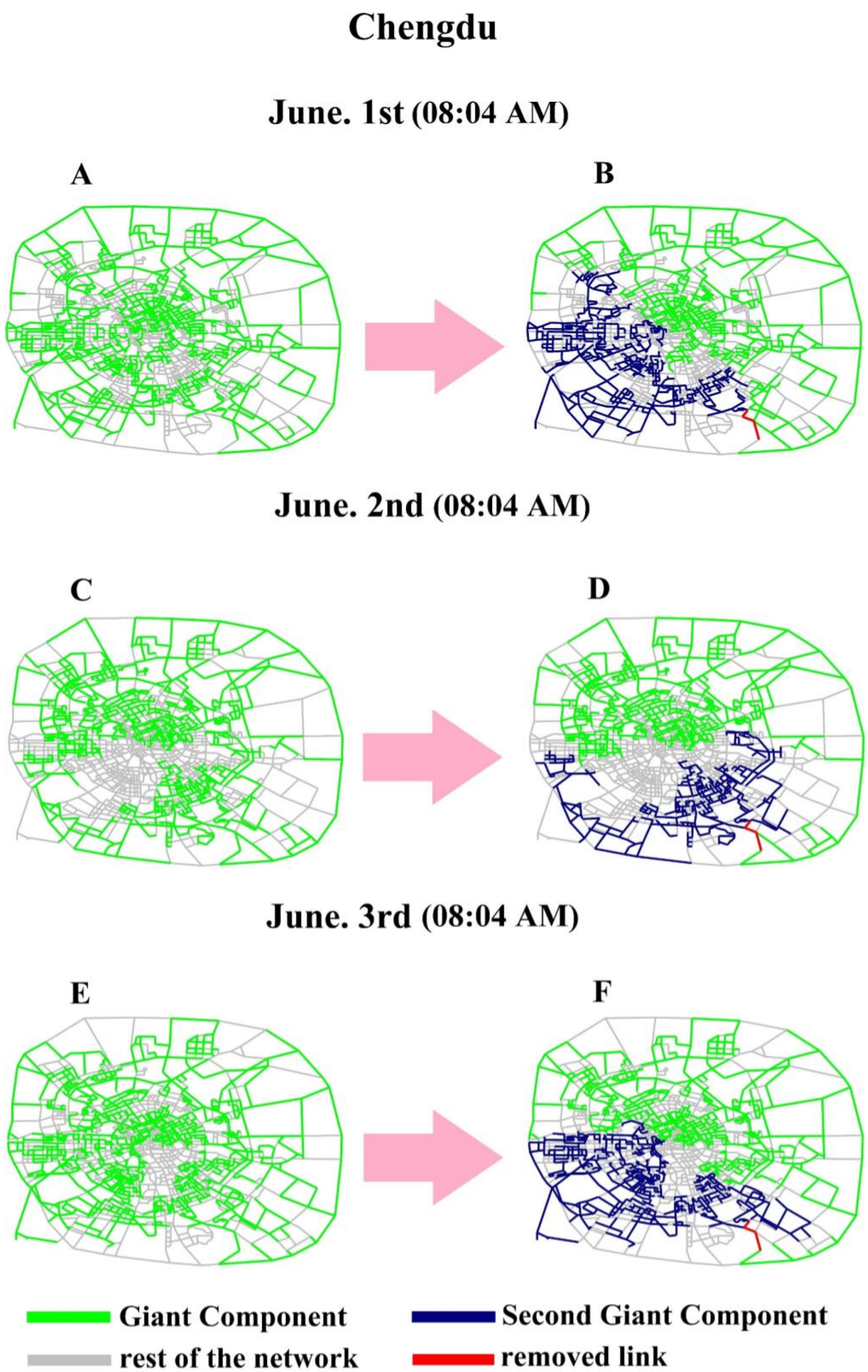


Fig. 9. A typical example of the identified bottleneck in the Chengdu network at a given time t = 08:04 AM during morning rush period for three consecutive days

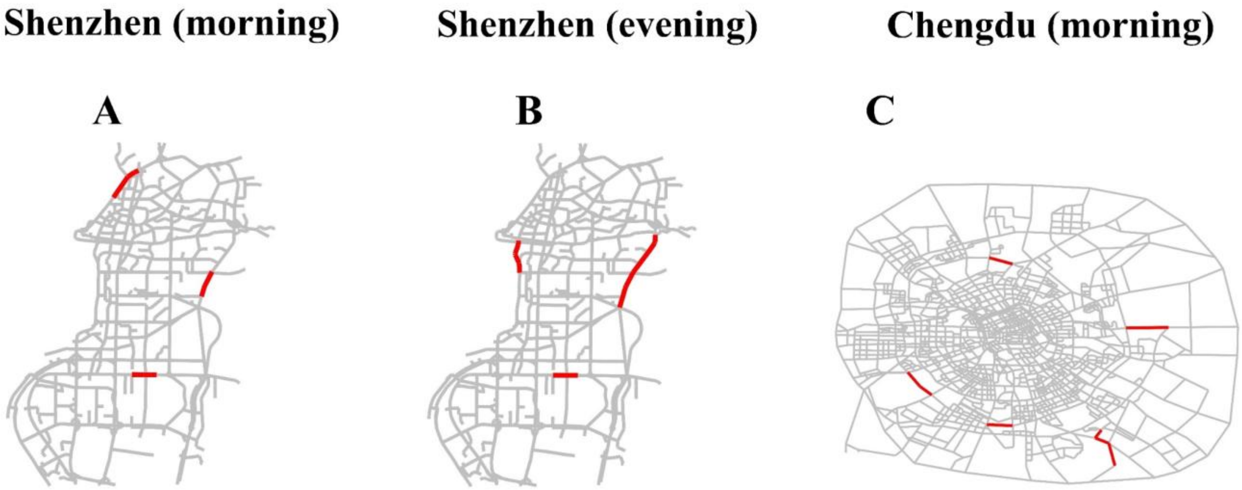


Fig. 10. Examples of the identified bottlenecks (red links) in Shenzhen and Chengdu networks during morning and evening rush periods

4.3. Average congested cluster betweenness centrality

We calculate the betweenness centrality of the Congested Giant Component (CGC) and all other network links and observe their evolution through the network congestion. A congested giant component is a connected component containing a significant fraction of the network's congested links. In other words, CGC is a set of interconnected links whose congestion index is smaller than a predetermined threshold. In this section, we probe the average of the largest congested cluster betweenness centrality in our studied networks.

Betweenness centrality (BC) of a node/link shows the portion of shortest paths connecting all pairs of network nodes passing through that node/link. The basic BC version considers the shortest paths based upon the number of nodes/links within the path regardless of link length. Hence, we used the weighted BC version by considering free flow travel of links as their weight [30]. The purpose of doing this to incorporate road length and network hierarchy in the analysis ahead. We calculated the BC of all network links, then grouped the links to two groups: "CGC" and "the rest of the network". Then we summed up the links of each group's BC values and divided it by the number of links in that group to get each group's average cluster BC. Fig. 11 shows the evolution of the average cluster betweenness for Shenzhen and Chengdu networks during the evening and morning peak period, respectively. These analyzes were performed for reasonable values of ρ, so that the loading and unloading processes of the congested clusters are well observed.

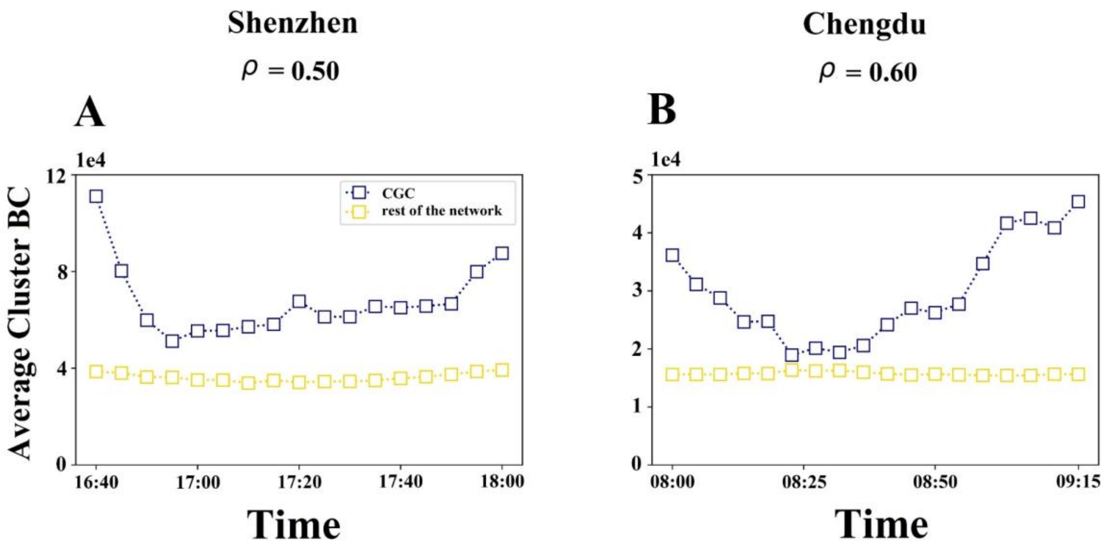


Fig. 11. Evolution of BC in CGC and the rest of the network in Shenzhen and Chengdu

The average betweenness of the cluster at the beginning of the loading process and the end of the unloading process is much larger (see Fig. 11) because this cluster's initial core consists of links with high values of BC. But gradually, the links with lower BC values become congested and join the CGC, causing the average BC of the CGC to decrease. As the unloading process begins and the clusters' size shrinks, the marginal links with low betweenness separate from clusters and as a result, the average betweenness of the clusters starts to increase. Thus, at the end of the unloading process, the initial clusters' cores consist of links with high betweenness.

5. Conclusion

Our research indicates the presence of characteristic congestion thresholds around the critical phase transition point for each studied network. Near these thresholds, a behavior similar to a first-order phase transition occurs during rush hours, while a second-order phase transition is observed during non-rush hours. Following the dynamics of demand in traffic networks, percolation thresholds also exhibit dynamic behavior and change over time throughout the day. This understanding can be used to establish critical congestion thresholds for cities. Additionally, our analysis reveals that traffic bottlenecks, as pinpointed by our framework, consistently emerge at identical time intervals across multiple days. This recurrence underscores the urgent necessity for a sophisticated and highly efficient real-time bottleneck detection system, ensuring proactive traffic management and optimal network performance.

Furthermore, our findings indicate that the core of the initial congested giant cluster (CGC) consists of links with very high betweenness. This observation is crucial as it identifies specific areas within the urban network that should be targeted for remedial actions. Since these actions often impact a portion of the commuter population, it is wise to limit the geographical area affected. This approach can reduce congestion in these areas before it spreads to other parts of the network. Our results suggest that the most effective strategy is to focus countermeasures, such as adjusting signal timings, in urban network areas containing links with the highest betweenness centrality values, thereby alleviating congestion in these areas before it extends to other network links.

It is necessary to identify critical road segments (e.g., bottlenecks) within traffic networks and use advanced strategies such as capacity increases, road widening, traffic signal control, and route changes to improve overall network traffic conditions [31–36]. With the growing availability of urban traffic network data, our approach has significant implications for city managers, transportation planners, and emergency managers to better assess network performance during disruptions. Additionally, our proposed framework can be extended to other spatiotemporal dynamic networks, such as power distribution networks. Consequently, this study can serve as a turning point for future research and the development of theoretical tools for network analysis, aiming to achieve a deeper understanding of these complex systems.

We implemented our proposed framework on the Shenzhen and Chengdu networks as examples of real traffic networks. Our approach provides a novel strategy to address the challenges of identifying traffic bottlenecks. Additionally, this study offers a comprehensive method to better understand the vulnerability and resilience of urban transportation networks under both anticipated and unanticipated disturbances. This has significant implications for infrastructure planning in various cities.

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Declarations

Competing interests

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