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Revealing urban traffic emission patterns: A complex network perspective#

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ABSTRACT

Urban traffic emissions from vehicle fuel pose significant challenges to urban sustainability. Revealing urban traffic emission patterns is crucial for effective urban planning. Current research often overlooks the spatial interaction links facilitated by traffic flows. This oversight limits our ability to map the attribution of emissions from vehicular travels between different locations. To this end, our study introduces a novel perspective and corresponding methodologies to reveal emission patterns of urban traffic. Utilizing extensive, all-day activity data from individual vehicles across multiple types, this research quantifies CO_2 and NO_X emissions from vehicular travels within the urban center of the case city. This quantification of emissions defines the link weights in the construction of the Urban Traffic Flows Emission Network (UTFEN). Applying complex network theory, this study uncovers emission patterns within UTFEN, ranging from the micro to the macro level. Our findings demonstrate that private car emissions exhibit a bimodal fluctuation throughout the day, whereas truck emissions peak at noon. Micro-level network analysis shows that nodes linked to high-emission links are predominantly situated at the city's ingress and egress points, with these high-emission links displaying a certain degree of directional consistency. At the macro level, statistical measures expose significant structural differences in networks composed of different vehicle types. Additionally, statistical analysis indicates that the link emission distribution within UTFEN follows a power law distribution, revealing the heterogeneity of emissions of spatial interaction traffic flows. This study offers a network perspective on urban traffic emission patterns, offering data-driven insights critical for formulating sustainable urban traffic strategies.

Keywords: climate change, air pollution, origin-destination, spatial interaction, sustainable city, power law

NONMENCLATURE

Abbreviations	
OD	Origin-Destination
UTFEN	Urban traffic flows emission network
ALPR	Automatic license plate recognition
IVE	International vehicle emission model
CBD	Central business districts

1. INTRODUCTION

Urban traffic system serves as a vital link between urban spaces. However, the resultant emissions present a threat to climate security and public health [1]. Revealing urban traffic emission patterns is crucial to urban sustainability.

Existing studies often rely on partitioning urban areas into discrete analysis units, such as 1 × 1 km grid cells [2] or road segments [3], to reveal the emission patterns. In this approach, when a vehicle completes a travel from the origin to the destination (OD), the emissions produced during the travel are split and classified into the various analysis units it passes through. This method compromises the integrity of travel and overlooks the spatial interactions between origin and destination points. Such oversight limits the ability of this research to address specific traffic management challenges. For instance, it presents difficulties in mapping vehicular emission flows between different locations, and it is challenging to identify which locations contribute to high emission events by generating (or attracting) significant volume of travels. Therefore, studying the emissions of urban point-to-point interaction traffic flows is crucial, which can provide key information for urban planners to formulate targeted traffic emission reduction strategies. However, travel volumes and emissions on the spatial interaction links present a dynamic and interconnected pattern, which has additional complexity. It is challenging

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to effectively extract descriptive and macroscopic information from such a complex system [4] .

To overcome these limitations, this study proposes a novel perspective to reveal urban traffic emission patterns: treating urban traffic flow and its emissions as a directed weighted network, namely the Urban Traffic Flows Emission Network (UTFEN). Within UTFEN, the weight of each link reflects the emissions or travel volume between OD pairs. This study explores the microscopic pattern of UTFEN based on the basic elements of the network (nodes and links) and their attributes (weighted degree and weight). Microscopic pattern quantitatively analyzes the ability to generate traffic emissions of different locations, and the emission intensity of spatial interaction traffic flows between different locations. Additionally, the study examines the macroscopic statistical measures of UTFEN, unveiling the network's global topological features and the emission distribution law across links.

Furthermore, accurate quantification of urban traffic emissions is a necessary prerequisite for revealing emission patterns. Diverging from traditional sampling-based approaches, this study employs an automatic license plate recognition system (ALPR) to collect comprehensive activity data from individual vehicles. This data is then integrated with the International Vehicle Emission (IVE) model, thereby enhancing the quantification of traffic emissions across various vehicle types. Such a method provides a richer and more accurate data foundation for UTFEN Establishment [5].

2. DATA AND METHODOLOGY

2.1 Research Area and Data

In this study, the core urban area of Xuancheng city was selected as a research case, depicted in Fig. 1. As one of the 27 central cities in the Yangtze River Delta, Xuancheng represents a typical example of China's rapidly developing small and medium-sized cities. Light passenger cars account for over 85% of total vehicular mileage, with trucks comprising approximately 10%. This fleet composition mirrors that of similar cities, thus providing a representative basis for analysis [6]. Densely distributed across the study area, ALPR detectors capture comprehensive vehicle activity data, thus facilitating precise emission quantification. ALPR detectors are strategically placed at each intersection within the urban road network. Each time a vehicle passes through an ALPR detector, a node record will be generated. Table 1 presents an example of the node record of ALPR data. The ALPR system collected approximately 1 million records on May 30, 2018, providing a substantial dataset for this analysis.

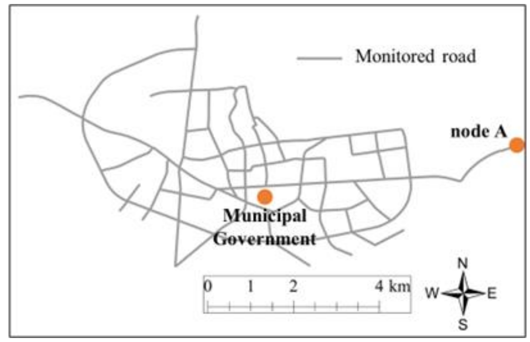


Fig. 1 Core urban area of Xuancheng

Table 1. Examples of ALPR data.

Index	Detector Location ID	License Plate Number (Anonymized)	Detection Time
1	HK-84	964352155	2018/05/30/07:00:05

2.2 Travel data extraction and emission quantification

This study employs data from ALPR systems to extract travel data. The urban road network can be conceptualized as a graph, consisting of nodes (intersections) and road links (road segments). Each ALPR detector's location is treated as a network node. A vehicle's movement between two adjacent detectors is defined as a trip. Given the dense deployment of ALPR system, with an average monitoring section length is approximately 600 meters, it is reasonable to assume that the origin and destination of vehicle trips are proximate to these nodes. Consecutive trips by a single vehicle form a complete travel, with the origin node(O) defined as the start of the first trip and the destination node (D) as the end of the last trip.

Emission quantification for urban traffic utilizes the International Vehicle Emission (IVE) model, which calculates the emissions of gases such as CO_2, NO_X, HC, and NH_3 during vehicle operation. The emissions for a single trip are calculated as follows:

$$E_{v,u} = \sum_k E_{v,u,k} \tag{1}$$

$$E_{v,u,k} = ln\, L_{v,u,k} \times Q_{v,u,k} \tag{2}$$

Where $E_{v,u}$ represents the emissions from travel u by vehicle v. $E_{v,u,k}$ represents the emissions from trip k within the travel u. $L_{v,u,k}$ indicates the distance in trip k. $Q_{v,u,k}$ denotes the corresponding emission factor determined by the IVE model. The emission factor Q is expressed by:

$$Q = B \times \prod K_w \tag{3}$$

Where B is the baseline emission factor, and K_w is the correction factor indexed by w. These factors are determined based on the methodology proposed by Yu et al. [5]. Consequently, the emission quantification for traffic flows between OD links is described as:

$$E_{ij} = \sum_v \sum_{u \in S_{ij}} E_{v,u} \tag{4}$$

Where E_{ij} is the total emissions for the OD link from node i to node j, summed over all travels from node i to j. Meanwhile, S_{ij} represents the set of all travels originating at and terminating at node j.

2.3 Network Construction and Measures

In this study, urban traffic flows and emissions are conceptualized as a weighted directed network, termed the UTFEN. This approach aims to delineate emission patterns across various levels of urban traffic. Within UTFEN, nodes correspond to specific geographic locations acting as origins and destinations, and directed links between these nodes represent the traffic flows between OD pairs. The weight w_{ij} on a link from node i to j indicates either the emissions (E_{ij}) or travel volume.

At the micro level, this study examines emission patterns by analyzing the weights of links and weighted out-degrees of nodes, as outlined in Table 2. When considering travel volume as the weight, d_i^{out} and d_i^{in} denote the frequency of travels originating from and terminating at node i, respectively. Incorporating ecological principles, Liu et al. [7] applied the "source-sink" concept to travel volumes to uncover dynamic traffic patterns. Adopting this framework, emissions are used as weights to compute the weighted degree of nodes, where d_i^{out} represents the total emissions from travels starting at node i, and d_i^{in} encompasses the emissions for travels ending at the node. This method not only highlights the emissions linked with traffic attraction or generation by nodes but also facilitates an assessment of the environmental impact and management significance of each node within the urban transport network.

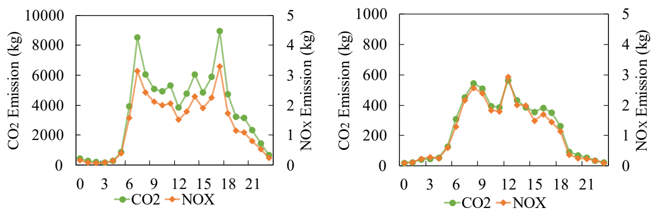
At the macro level, the study employs various statistical measures to describe the global attributes of UTFEN. These measures offer insights into the network's structural and operational properties, and furnish benchmarks for comparative analysis of different networks. As detailed in Table 1, the network density δ can reflect the connectivity of UTFEN. The average clustering coefficient C reflects the tightness of the network structure connection, and the average shortest path L reflects the accessibility between nodes. Furthermore, statistical analysis of link weight distributions plays a crucial role for revealing the underlying patterns and regularities in emission distribution across the UTFEN.

Table 2 Measure of network

Measure	Symbol or equation	General implication
Weighted-in-degree	$d_i^{in} = \sum_j w_{ji}$	The sum of the weights of the links pointing to node i.
Weighted-out-degree	$d_i^{out} = \sum_j w_{ij}$	The sum of the weights of the links from node i to other nodes.
Weighted degree	$d_i^{tot} = d_i^{in} + d_i^{out}$	The sum of the weights of the links connected to node i.
Interaction strength	$d_i^{\leftrightarrow} = \sum_j w_{ij} w_{ji}$	The sum of the weights of the links between node i and node j.
Network density	$\delta = \frac{m}{n^2}$	The interconnectivity density among nodes within a network, m represents the total number of links, and n denotes the total number of nodes in the network.
Clustering coefficient	$C_i = \frac{[W^{[1/3]} + (W^T)^{[1/3]}]_{ii}^3}{2[d_i^{tot}(d_i^{tot} - 1) - 2d_i^{\leftrightarrow}]}$	The degree of cohesiveness among a node's neighbors. W is the weight matrix, $[W]_{ii}$ represents the value at the diagonal position corresponding to node i.
Average clustering coefficient	$C = \frac{1}{\mathrm{n}} \sum_i C_i$	The mean value of C_i of all nodes in the network[8].
Average shortest path	$L = \frac{1}{\mathrm{n}(\mathrm{n}-1)} \sum_{i \neq j} d_{ij}$	The mean number of edges among the shortest paths between all pairs of nodes, reflecting the network's accessibility and compactness. d_{ij} is the shortest path between i and j。

3. MAPPING EMISSIONS OF UTFEN

This study has effectively quantified traffic emissions within the study area through the methodologies outlined. We focus on CO_2 and NO_X emissions, due to their roles as a prevalent greenhouse gas and potential health risks, respectively. ALPR system collects activity data across all vehicle types. This analysis considers two main mobility, car, reflecting human mobility, and truck, reflecting freight movement. As shown in Fig. 2, private cars and trucks exhibit distinct diurnal emission fluctuation for CO_2 and NO_X. Private cars emit 85,803 kg of CO_2 and 33 kg of NO_X in a single day, with notable bimodal peaks in emissions during the typical urban commuting peaks in the morning and evening. In contrast, the peak daily emissions for trucks occur at noon, trucks emit 5,932 kg of CO_2 and 27 kg of NO_X in one day. Between 1AM and 5AM emissions from both types of vehicles were low, reflecting the reduction in nighttime traffic activity.



(a)Car (b)Truck

Fig. 2 Emissions of car and truck

Mapping emissions of the UTFEN visually delineates the micro-level emission patterns. In the UTFEN, N_{car} and N_{truck} represent network of private cars and trucks, respectively. Fig. 3 illustrates the spatiotemporal distribution of travel source emissions (d_i^{out}) and OD link emissions (w_{ij}). Emissions are categorized into five levels using the natural breakpoint method, chosen for its ability to optimally separate data into distinct classes, with darker colors representing higher emissions. From the node perspective, there is no clear spatial pattern in the N_{car} emission hotspots, as depicted in Fig. 3(a-h). The most intense emission event occurs at node A, which serves as the entry point of the study area when discussing out-degrees, generating 1,006 kg of CO2 and 0.4 kg of NOx between 17-18 hours. In contrast, as shown in Fig. 3(i-p), the emission hotspots for trucks are concentrated at the entry points of the study area, with the highest emissions also recorded at node A, where 123 kg of CO_2 and 0.4 kg of NO_X were emitted between 12-13 hours. This indicates that travels entering the study area from outside significantly contribute to urban traffic emissions. Unlike major cities such as Shanghai [9], significant travel originate from the city boundaries rather than central business districts (CBD), reflecting differences in urban development levels and city planning.

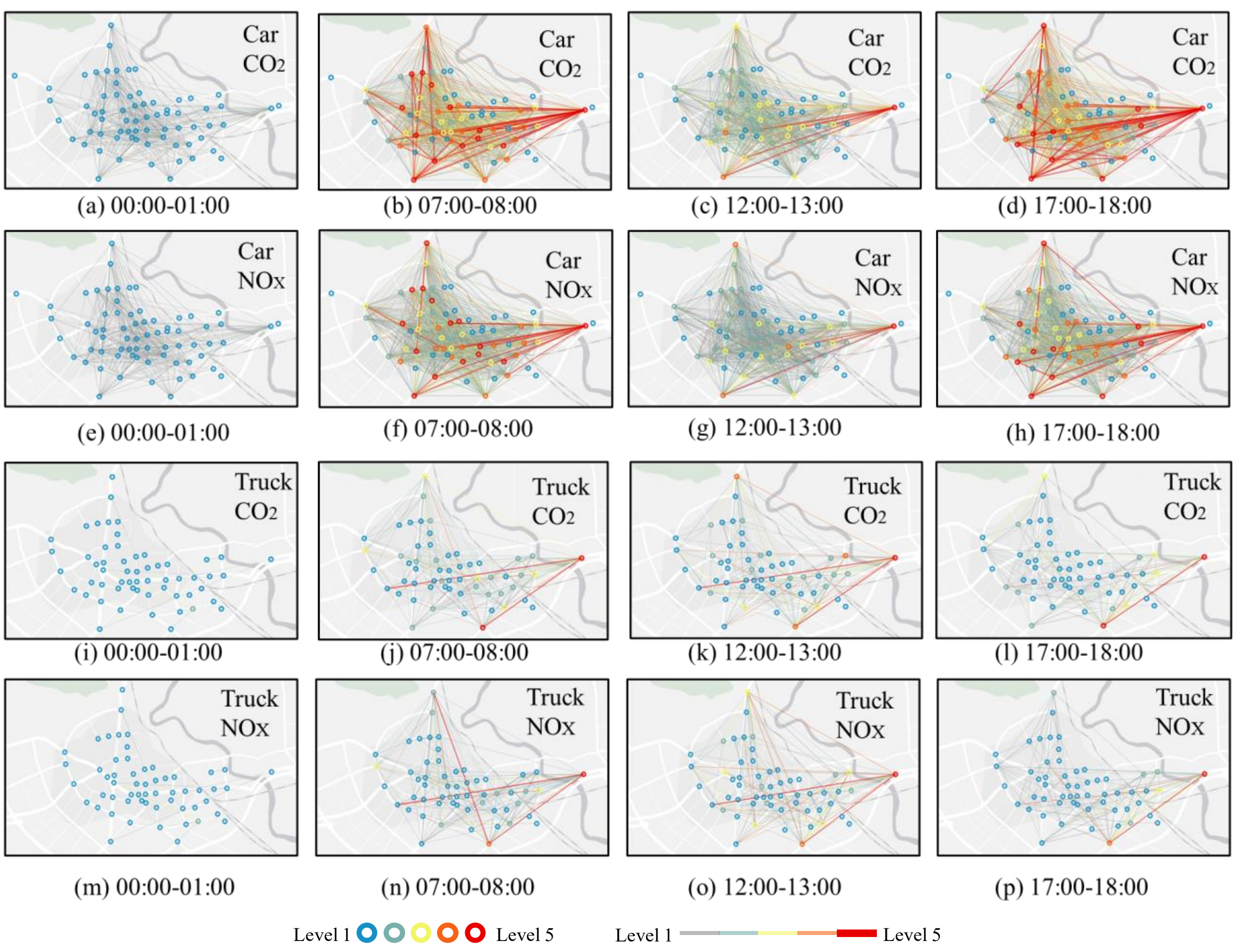


Fig. 3 Travel source emissions levels and link emissions levels of UTFEN

Moreover, traffic emissions on spatial interaction links exhibit pronounced spatiotemporal heterogeneity. Overall, compared to north-south links, high-emission flows predominantly move in an east-west direction. For N_{car}, it is evident that high-emission links often have one end at the study boundary. Although links within the inter-city in N_{car} are not ranked high in emissions, they are very dense. In contrast, N_{truck} has fewer links, with high-emission links typically found between boundary nodes. Possibly related to trucks' transit function, the origin and destination of the trucks' travels are typically outside the study area, with the area merely serving as a pass-through city. This phenomenon indicates that the environmental impact of through-traveling trucks is more significant compared to the local freight demand within the study area.

4. STATISTICAL ANALYSIS OF UTFEN

In this section, we thoroughly investigate the macroscopic network parameters of UTFEN through statistical Measure. The detailed results of N_{car} and N_{truck} are shown in Table 3. Notably, the number of nodes n for both N_{car} and N_{truck} are comparable. However, the number of links m for N_{car} is nearly double that of N_{truck}. This discrepancy leads to significant differences in network density, echoing the visual data in Section 3, confirms that private vehicle travel has high randomness and diversity in cities, while the travel OD of trucks is relatively fixed. The average shortest path length L for both networks is less than 2, suggesting high node reachability within UTFEN, typically with no more than two travels required to connect any two nodes. When analyzing the average clustering coefficient, with traffic volume as the weight, the N_{car} network exhibits tighter structural connections than N_{truck}. These network macro topological indicators demonstrate the non-randomness and centralization of UTFEN.

Further, to elucidate the distribution law of UTFEN, we examine the complementary cumulative distribution functions (CCDF) of link emissions for N_{car} and N_{truck}. The CCDF of many real networks' link weights often exhibit a heavy tail, such as power law distribution: $p(x) \propto x^{-\alpha}$. A heavy-tailed distribution means that there is a probability of observing very large values in the tail of the distribution. This study employs exponential and power law distributions as hypothetical models. Utilizing the log-likelihood ratio test [10], the power law provides a better fit for the CCDFs of N_{car} and N_{truck} than the exponential, with p-values < 0.1, aligning with the traits of heavy-tailed distributions. Employing the standard power-law fitting technique [11], we determine the optimal power-law fit for the link emissions' CCDFs of both N_{car} and N_{truck}.

As illustrated in Figure 4, the CCDFs of all link emissions demonstrate significant power-law traits in their tails. Despite most links exhibiting low emissions, a small number of links display exceptionally high emissions. For CO_2 emissions, the blue line predominates in the upper right, suggesting that private cars are more likely to generate higher emissions at the same OD pairs. For NO_X, trucks will most likely be the main contributor to NO_X emissions. For both CO_2 and NO_X, there is a phenomenon that the green line decreases slower than the blue line. This shows that the probability of high-emission events from trucks in interactive traffic flow in urban space is higher, and the heterogeneity of N_{truck} link emission distribution is more powerful.

Table 3 Statistical measures of N_{car} and N_{truck}

Type	n	m	δ	L	C
N_{car}	75	2470	0.44	1.46	0.78
N_{truck}	60	1046	0.29	1.7	0.51

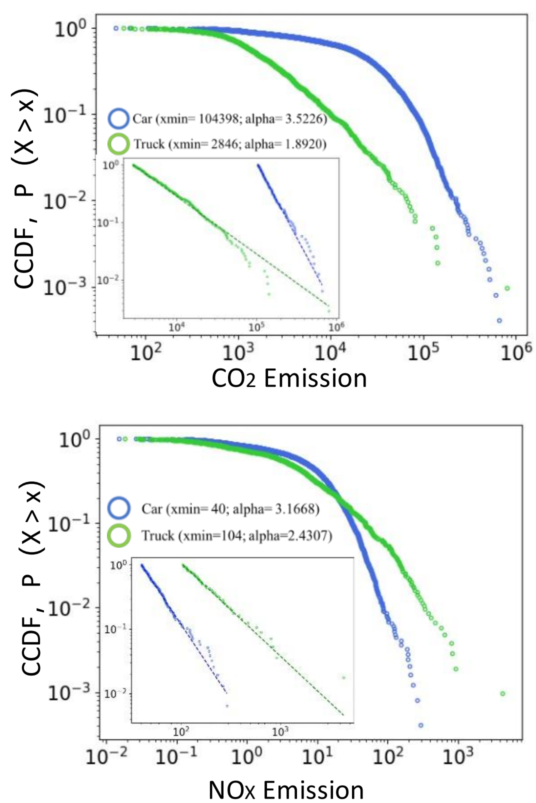


Fig. 4 The complementary cumulative *distribution function P(X ≥ x) and maximum likelihood power-law fit with parameters (xmin, α) of N_{car} and N_{truck}*

5. DISCUSSION AND CONCLUSIONS

This paper adopts a new perspective of complex networks to deeply reveal the internal structure of Xuancheng's traffic emission patterns. In contrast to traditional discrete analysis units, this approach emphasizes the spatial interactions that transcend conventional geographic limitations. By employing the network's weighted out-degree, we effectively pinpoint the locations of high-emission sources within the urban matrix. Targeted emission reduction strategies at these critical nodes, such as promoting targeted electric vehicle promotion or establishing low-emission zones, could mitigate emissions at their origin. Network link emissions reveal the high-emission OD in the city. The emissions corresponding to this type of OD can be reduced by optimizing urban configuration or improving public transportation substitution. In addition, the macro analysis of the urban emission network in this paper reveals the law of the distribution of spatial interaction vehicle flow emissions in Xuancheng, and the calculation results of network measure also provide new empirical data for network theory. Due to space constraints, we only discuss the out-degree, and it is necessary to continue the study of in-degree. Looking forward, the meso-level characteristics of the UTFEN model are also worth further exploration. At the same time, the impact of land use or POI on UTFEN can be further discussed. While this model is demonstrated within Xuancheng, its applicability extends to other urban contexts, offering a scalable tool for guiding sustainable urban development.

DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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