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Research Article

Weighted Complex Network Analysis of the Different Patterns of Metro Traffic Flows on Weekday and Weekend

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We present a multilayer model to characterize the weekday and weekend patterns in terms of the spatiotemporal flow size distributions in subway networks, based on trip data and operation timetables obtained from the Beijing Subway System. We also investigate the disparity of incoming and outgoing flows at a given station to describe the different spatial structure performance between transfer and nontransfer stations. In addition, we describe the essential interactions between PFN and TFN by defining an indicator, real load. By comparing with the two patterns on weekday and weekend, we found that the substantial trends have roughly the same form, with noticeable lower sizes of flows on weekend ascribed to the essential characteristics of travel demand.

1. Introduction

In recent years, complex network theory has become an important approach to the study of the structure and dynamics of traffic networks. Mining spatiotemporal statistical regularities of the human behavior is a common focus of statistical physics and complexity sciences. The human behavior spatiotemporal regularities are the bases of reasonable traffic infrastructure planning, improvement of level of service, and traffic jam control. The patterns on weekday and weekend have been paid more attentions because they affect common lives. Because subway is an important subsystem of urban commuting transportation system, the travel demands on weekdays are quite different from that on weekends.

Transportation engineers studied the differences of human travel behaviors between weekdays and weekends by collecting databases with the survey data [1–7]. However, some problems are still observed in the survey data approach. For example, survey data is disadvantaged by high cost, low frequency, and small sample size [7]. Moreover, it still lacks a precise method to analyze the statistical regularities of a single mean of transportation.

Nowadays, with the development of electronic technique, more and more approaches (such as mobile phone data, GPS, and smart card) can be used for recording the data of human individual spatiotemporal movements. The data provide a possibility to analyze human travel behavior statistically [8–13]. Complex network theory is a research field that is concerned with the connections and interactions among components in a system, and it has offered an important approach to study the structure of subway systems [14–20]. Recently, studies of metro traffic flow distributions underlying the physical topology with a weighted network-based approach have proved that complex network is a useful method for human travel behavior statistical analysis [21–27]. Kurant and Thiran [21, 22] were the first researchers to analyze train flow networks using timetables from Warsaw's mass transportation system; they found the edge weight and node strength distributions to be heavily right-skewed and heterogeneous, although they did not focus on the differences between weekdays train flow patterns and those on weekends. Soh et al. [24] applied a complex weighted network to the passenger flows of the Singapore Rapid Transit System (RTS) and concluded that weighted eigenvector centralities elucidated significant differences in the passenger flows on weekdays and weekends, although they use an average weight to describe passenger moving between the different nodes on weekdays and weekend. But they have focused only on passenger flow networks.

Table 1: Parameters used in studies of different travel behaviors on weekdays and weekends.

Study	Data type	Period	Scope	Time
Seoul metropolitan area [1]	Survey data	Weekend	3,700 households	June 2002
Montreal and Quebec [2]	Survey data	81 weekdays and 32 weekend days	1,400,000 households	From August 24 to December 13, 1998
Calgary [3]	Survey data	Weekdays and weekends	13,000 records	Late 2001 and early 2002
The greater Phoenix metropolitan area in Arizona [4]	Survey data	Weekend	4,400 households	2008-2009
Paris region [5]	Survey data	Weekdays and weekends	23,656 persons in 2001 and 23,601 in 1983	1983 and 2001
San Francisco bay area [6]	Survey data	2-day period (Friday and Saturday or on Sunday and Monday)	15,000 households	2000
Chicago metropolitan region [7]	Survey data	1-day or 2-day survey	10,552 households (32,366 individuals)	Between January 2007 and February 2008
Singapore [8]	Smart card data	One complete week	Over 36 million individual trip records	From March 19, 2012, (Monday) till March 25, 2012 (Sunday)
Rennes Métropole [9]	Smart card data	The month of April 2014	—	2014
Our study (Beijing Subway System)	Smart card data	Weekday and weekend	Over 27 million individual trip records	April 15, 2014, and April 19, 2014

However, because traffic data is difficult to collect, previous studies have usually focused on the physical topology of subway systems, whereas few studies have considered the differences between traffic flow characteristics on weekdays and weekends.

First, this paper aims to obtain statistical properties, such as weights and strengths distributions, that characterize the structure and behavior of both passenger flow network (PFN) and train flow network (TFN) on weekday (WDPFN, WDTFN) and weekend (WEPFN, WETFN). Second, we suggest appropriate ways to measure the essential interactions between patterns in PFN and TFN and to explain the meaning of these results moreover. Third, we give helpful suggestion to improve the organizations of metro systems.

A comparison between our work and the existing literature considering travel behaviors on weekdays and weekends is given by Table 1.

This paper is organized as follows. In Section 2 we present a multilayer model to analyze traffic flow patterns in subway networks based on trip data and operation timetables obtained from the Beijing Subway System. Section 3 presents the weekday and weekend patterns and the differences between these two patterns. Section 4 summarizes the results.

2. Data Preparation

2.1. Graph Dataset. In this study, we define a graph of a subway network with N stations connected by E bi-directional edges. Our data contains the stations with their physical coordinates in Beijing Subway System (BSS). As of May, 2015, the BSS network has 18 lines; $N = 319$ unique stations and $E = 612$ sections between stations in operation, which can be seen in Figure 1.

2.2. Smart Card Data. The smart card system used in BSS is called Yikatong electronic ticketing. The Yikatong electronic ticketing dataset contains precise timing and location information for both boarding and alighting.

This present study is conducted based on smart card records on Tuesday, April 15, 2014, and Saturday, April 19, 2014.

2.3. Timetables. BSS operation timetable describes the arrival and departure times for each station at which the trains stop, the length of time that each train stays at each station, and the running times for each track section.

Our train flow analysis uses BSS operation timetable from the same dates. It is important to note there are two different timetables on weekdays and weekends.

2.4. Case Study. Because the data is difficulty to collect, our study focuses on a subsystem network that consists of 5 lines; $N = 100$ unique stations, and $E = 192$ sections.

Moreover, the weekday datasets encompassed a total of 44,424 trains and 27,197,333 individual passengers moving through the network on Tuesday, April 15, 2014. And the weekend datasets encompassed a total of 42,965 trains and 7,060,927 individual passengers.

A train flow matrix A and a passenger flow matrix B were constructed to analyze the BSS train and passenger trip data. The elements of A and B, respectively, represented the numbers of trains and passengers taking trips between a pair of adjacent stations over a given period time. All of the data was divided into half-hour segments, so that the given period $\Delta t = 30$ min was the time interval over which the numbers of passenger movements were aggregated. The analysis of these flow matrices over several time intervals at different

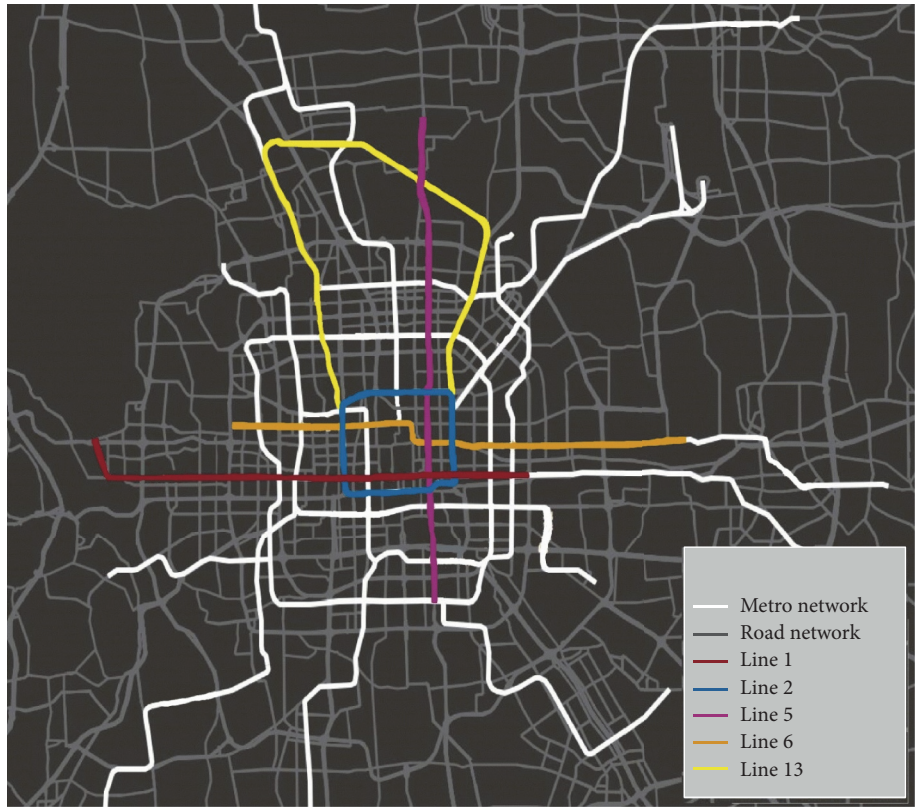


Figure 1: The subway real physical network of the BSS. The metro network and the road network are presented by white and gray lines, respectively. Moreover, the five lines we studied in this paper are shown by color.

operational times of day will explicitly define the traffic flow patterns within the network.

3. Model

We constructed two directed weighted networks TFN and PFN of a subway system by incorporating the trip data and the timetables. Figure 2 presents a simplified example of how the passenger transport demand through an operation service network (train flow network) and finally forms a passenger flow network on a physical network of $N = 8$ nodes and $E = 14$ directed edges. Sometimes the passenger demand cannot be satisfied by the train capacity; bottleneck occurs in the subway system. Thus, the passenger flow network is not mapped directly by the passenger transport demand network when the bottleneck occurs.

As shown in Figure 2, there are a passenger demand network and two traffic flow networks PFN and TFN, which are represented as three directed weighted graph G_d, G_p, and G_t.

3.1. Weight and Strength. In order to have a preliminary grasp on the data, we firstly analyze the weight and strength of traffic flow. An associated weighted adjacency matrix $W_t = \{w_t(ij)\}$ representing the train flow from station i to station j and an associated weighted adjacency matrix $W_p = \{w_p(ij)\}$ representing the passenger flow from station i to station j as follows

$$\begin{aligned} w_t(ij) &= \text{train flow from } i \text{ to } j, \\ w_p(ij) &= \text{passenger flow from } i \text{ to } j. \end{aligned} \tag{1}$$

The above subscripts i and j appear as destination-source station; for example, $f_t(ij)$ denotes the train flow of departure (outflow) of station i, moving in the $i \to j$ direction, while $f_t(ij)$ denotes the train flow of arrival (inflow) of station i, moving in the $j \to i$ direction. It is noted that in our content the subscripts particularly refer to a pair of two adjacent stations unless otherwise mentioned.

Subsequently, in TFN, a node's strength of station i noted as $s_t(i)$ is simply denoted as the sum of the weights on the edge incident upon it and shall be defined as

$$\begin{aligned} s_t(i) &= \sum_j w_t(ji) + \sum_j w_t(ij) \\ &= \text{node strength of station } i \text{ in TFN.} \end{aligned} \tag{2}$$

In PFN, the node strength of station i noted as $s_p(i)$ shall be defined as

$$\begin{aligned} s_p(i) &= \sum_j w_p(ji) + \sum_j w_p(ij) \\ &= \text{node strength of station } i \text{ in PFN.} \end{aligned} \tag{3}$$

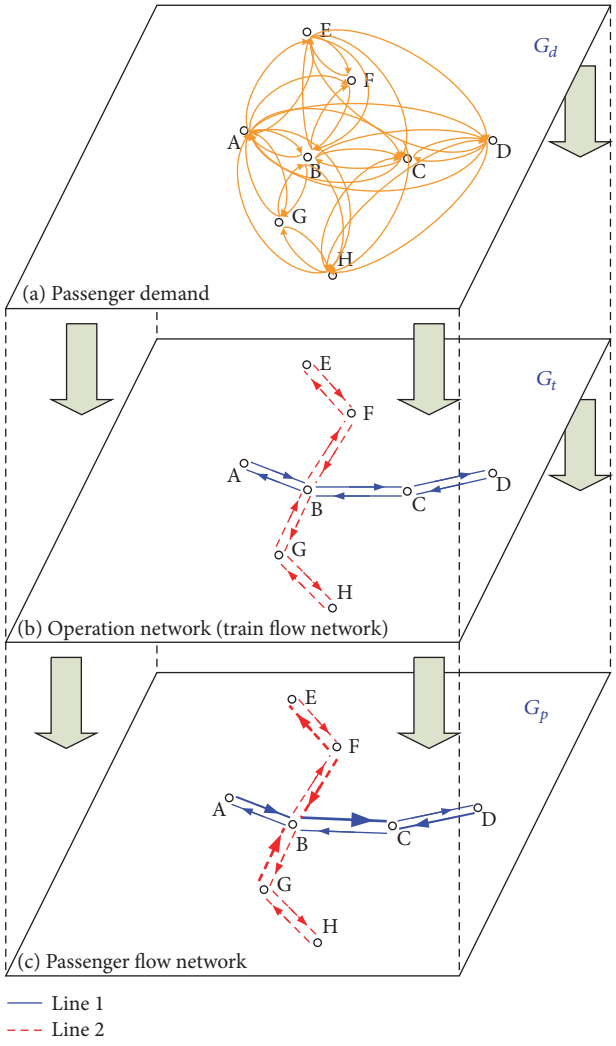


FIGURE 2: Schematic representation of an example of (a) the passenger transport demand of the subway infrastructure network with N nodes and $N(N-1)$ edges, (b) the train flow network with N nodes and E edges, and (c) the corresponding passenger flow network with N nodes and E edges.

Thus, we define the traffic flows on weekday and weekend, respectively, as ${w_p}^{\mathrm{wd}}(ij)$ and ${w_p}^{\mathrm{we}}(ij)$ and ${w_t}^{\mathrm{wd}}(ij)$ and ${w_t}^{\mathrm{we}}(ij)$ and the strength as ${s_p}^{\mathrm{wd}}(i)$ and ${s_p}^{\mathrm{we}}(i)$ and ${s_t}^{\mathrm{wd}}(i)$ and ${s_t}^{\mathrm{we}}(i)$.

Furthermore, in PFN, there are considerable passenger flows moving into station i from outside the network and moving out of the network for the same station, which can be denoted by $\delta_p(oi)$ and $\varphi_p(io)$ as follows

$$\begin{aligned} &\delta_p(oi) = \text{passenger flow from outside to } i, \\ &\varphi_p(io) = \text{passenger flow from } i \text{ to outside.} \end{aligned} \tag{4}$$

We define the incoming flow $U_p(i)$ and outgoing flow $V_p(i)$ at a given station i in order to explore the average crowdedness and utilization rate of a station.

$$\begin{aligned} &U_p(i) \\ &= \sum_j w_p(ji) \\ &\quad + \delta_p(oi) \ \text{ passenger flow incoming station } i, \\ &V_p(i) \\ &= \sum_j w_p(ij) \\ &\quad + \varphi_p(io) \ \text{ passenger flow outgoing form station } i. \end{aligned} \tag{5}$$

3.2. Disparity. We now define the time averaged incoming passenger flow and outgoing flow at a given station:

$$\begin{aligned} &U_{\mathrm{in}}(i) = \sum_j \overline{U}_p(i) \text{ average passenger flow incoming station } i, \\ &V_{\mathrm{out}}(i) = \sum_j \overline{V}_p(i) \text{ average passenger flow outgoing station } i. \end{aligned} \tag{6}$$

And we define that the disparity [28, 29] in the weights of a given station i can be evaluated by the quantities $Y_{2\text{-in}}(i)$ and $Y_{2\text{-out}}(i)$ defined as [30, 31]

$$\begin{aligned} &Y_{2\text{-in}}(i) \\ &= \sum_j \left[\frac{w_{ji}}{U_{\mathrm{in}}(i)}\right]^2 \text{ disparity of passenger incoming flow at station } i, \\ &Y_{2\text{-out}}(i) \\ &= \sum_j \left[\frac{w_{ij}}{U_{\mathrm{out}}(i)}\right]^2 \text{ disparity of passenger outgoing flow at station } i. \end{aligned} \tag{7}$$

3.3. Real Load. The real load [21, 22] of a node $l(i)$ is the sum of the weights of all logical edges whose paths traverse this node. In a subway system, there are three kinds of real load: $l_t(i)$, $l_p(i)$, and $l_{p\text{-}t}(i)$. The first two are the train flows and passenger flows loading on the physical topology of subway system network, which can be presented by node strength. However, the third one is to measure the passenger flows average crowdedness underlying the TFN, which fully reveals the essential interactions between PFN and TFN.

An associated weighted adjacency matrix $L_{p\text{-}t} = \{l_{p\text{-}t}(i)\}$ representing the passenger flow underlying the train flow network from station i to station j:

$$l_{p\text{-}t}(i) = \sum_j \frac{w_p(ij)}{w_t(ij)} \text{the real load moving from } i \text{ to } j. \tag{8}$$

4. Results and Discussions

4.1. Weight and Strength Distributions. In order to get a preliminary grasp on the data, we first obtain statistical properties of the train flow and passenger flow networks for the

Table 2: Statistical properties of the PFN and TFN on weekday and weekend.

Property	WDPFN	WEPFN	WDTFN	WETFN
Weight range	(0, 22220)	(0, 9437)	(0, 14)	(0, 10)
Average weight, $\langle w \rangle$	2951.10	2261.26	4.81	4.07
Strength range	(0, 116123)	(0, 48805)	(0, 125)	(0, 66)
Average strength, $\langle s \rangle$	12689.78	7905.14	21.16	17.50
Weight fitted distribution	Power law	Power law	Weibull	Weibull
Strength fitted distribution	Power law	Power law	Weibull	Weibull

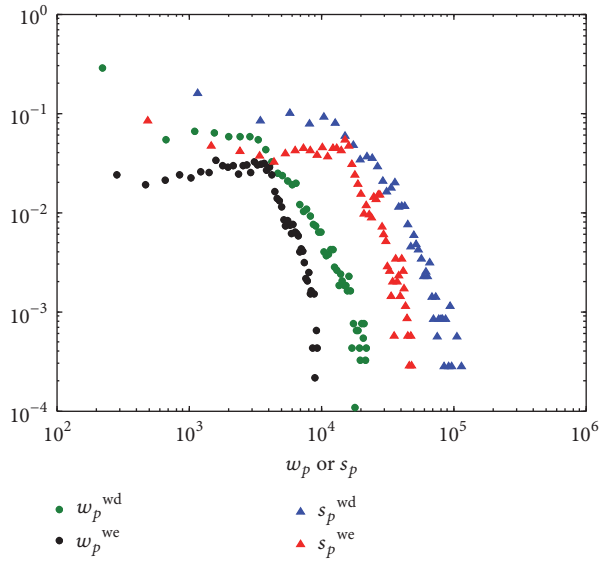


Figure 3: In PFN, flow weight and node strength distributions. The weights of passenger flow w_p^{wd} and w_p^{we} can be fitted by power law distributions with exponents $\gamma = 0.96$ and $\gamma = 0.90$, respectively. The goodness-of-fit (R^2) are all 0.99. And the strengths s_p^{wd} and s_p^{we} can be fitted by power law distributions with exponents $\gamma = 0.73$ and $\gamma = 0.50$, respectively. The goodness-of-fit (R^2) are 0.99 and 0.56.

BSS. The basic statistical properties of weight and strength distributions are listed in Table 2. According to Table 2, the sizes and fitted distributions of PFN and TFN are obviously different. In order to get a deeper insight of these two networks, we carried out a weighted analysis and plotted the results, respectively, in Figures 3 and 4. Figure 3 shows the distributions of the number of passenger trips between two adjacent stations and the distributions of the number of passengers one station handles, respectively, on weekday and weekend.

There are three aspects that have to be addressed and can be seen in Figure 3. Firstly, it is observed that all of the passenger flow weight and strength distributions $P(w_p)$ and $P(s_p)$ are significant right-skilled on log-log scale which can be fitted by power law distributions. This indicates that the passenger flow patterns vary in intensity, and there exist travel

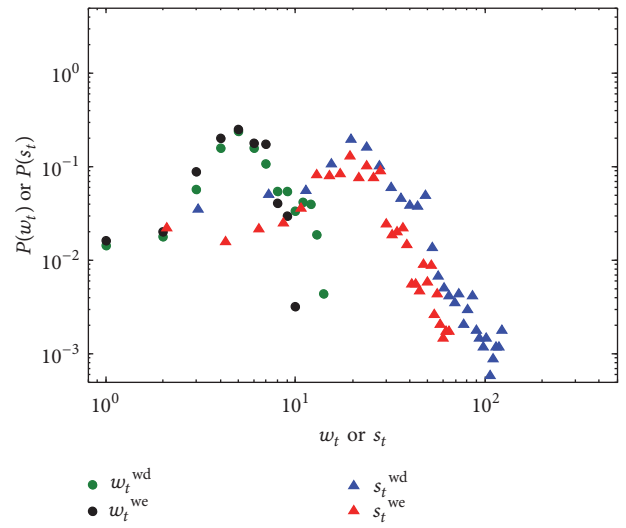


Figure 4: In TFN, flow weight and node strength distributions. The weights of train flow w_t^{wd} and w_t^{we} can be fitted by Weibull distributions with parameters $\beta = 3.13$ and $\eta = 274.73$ and $\beta = 3.69$ and $\eta = 654.45$, respectively. The goodness-of-fit (R^2) are 0.77 and 0.93. And the strengths s_t^{wd} and s_t^{we} can be fitted by Weibull distributions with parameters $\beta = 1.65$ and $\eta = 219.64$ and $\beta = 0.82$ and $\eta = 16.64$, respectively. The goodness-of-fit (R^2) are 0.90 and 0.90.

routes and hub nodes with very high traffic. This kind of heterogeneous passenger flow organization is corroborated by previous studies [23, 24, 27]. However, compared to previous studies, our case networks are more significant than the Metropolitan Seoul Subway system ($\gamma = 0.56$) [23] and more noticeable than the Singapore Rapid Transit system ($\gamma = 1.664$ on weekday and $\gamma = 1.637$ on weekend) [24] but are similar to the total system of BSS ($\gamma = 1.02$) [27]. This can be attributed to the heterogeneous flow intensities caused by an urban spatial mismatch. Secondly, the sizes of passenger flows on weekend are considerably lower than those on weekday, especially at the travel routes and hub nodes handling high traffic. This indicates that the travel demand on weekend is lower than that on weekday. This discrepancy in magnitude shown here implies different travel patterns between weekdays and weekends, as people would have to choose different way to fulfill their goals (such as shopping, socializing, entertainment, and leisure) on weekend, which has been reported in human travel activities survey studies [3, 5, 6]. For example, the average number of daily person trips for every traveler is 3.40 for weekdays and 3.14 and 2.85 for Saturdays and Sundays [6]. Thirdly, the weight and strength distribution lines on weekend both have a significant turning point in the plots, which are not as smooth as those on weekday.

As shown in Figure 4, the train flow weight distributions have significantly unimodal trend with a skewness leaned to the front and a smoothly light tail on log-log scales, which can be fitted by Weibull distributions. The strength distributions present a clear right-skewed asymmetry trend and a heavy-tailed characteristic on log-log scales, which also can be fitted by Weibull distributions. It is clear that the sizes of train flow

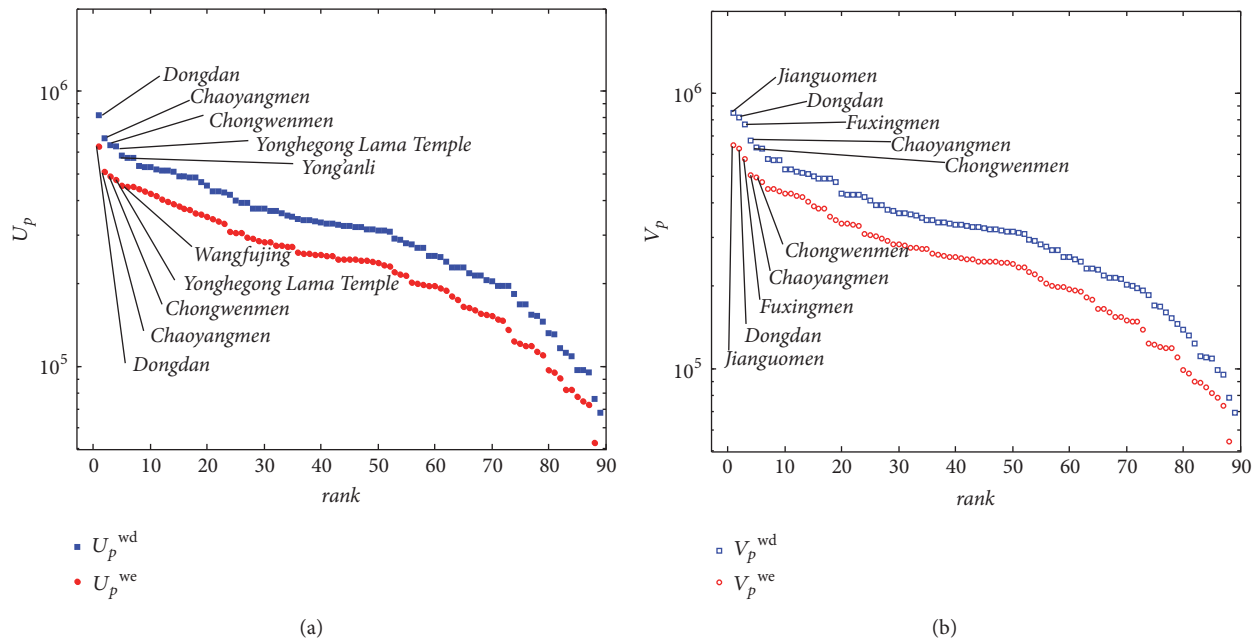


FIGURE 5: Incoming and outgoing passenger flows distributions. The weight of incoming flow on weekday and weekend U_p^{wd} and U_p^{we} can be fitted by exponential distributions with exponents $\theta = 0.0167$ and $\theta = 0.0184$, respectively. The goodness-of-fit (R^2) are 0.97 and 0.96. The weight of outgoing flows V_p^{wd} and V_p^{we} can be fitted by exponential distributions with exponents $\theta = 0.0173$ and $\theta = 0.0183$, respectively. The goodness-of-fit (R^2) are both 0.97.

on weekend are slightly lower than those on weekday. It is important to note that there are two different timetables on weekday and weekend in order to match the working and nonworking day passenger flow patterns. For the total passenger trip data on weekend is an order of magnitude lower than the data on weekday and the operational train numbers have been reduced. Moreover, the form of fitted distributions in TFN is the Weibull distribution, which is different from that in PFN. The fundamental differences between these two coexisting flow networks may be attributed to the fact that the dynamic evolution rules of TFN are similar to a branching process and the dynamic patterns of PFN are self-organized. In other words, in TFN the size of newly train flow is determined by the redistribution of the size of preexisting flow intensities; thus the Weibull distribution is expected to emerge [25, 32]. On the contrary, in PFN the size of newly passenger flow is determined by not only the size of preexisting flow but also the passenger flows moving between that station and outside of the network, which will be studied in Section 4.2

4.2. Disparity Distributions in PFN. Now we aim to find and highlight the patterns of passenger flows both taking trips between adjacent stations and using a station (i.e., entering into and leaving a station). The size distributions of total incoming flow and outgoing flow at a given station i are presented in Figure 5.

As detailed in Figure 5, the weight distribution patterns of incoming and outgoing passenger flows show mostly noticeable declined characteristics, smoothly in the middle and rapidly at the front and the tail. First, the incoming and outgoing flows on both weekday and weekend can be fitted by exponential distributions. This pattern displays the same trend as the cases observed in many works, such as metro passenger flows [27] and Internet traffic [31]. And this exponential trend means that the spatial structure of total incoming and outgoing flows in PFN display a bilevel performance [31]. Second, it is not a surprise to find that the weights on weekday are both larger than those on weekend, which is attributed to the travel demand. Roughly, the orders of most visited and passenger sending stations are stable on both weekday and weekend. To clearly characterize the fine structure of the incoming and outgoing flows at station i, we plot the disparity distribution in Figure 6.

There are three aspects that have to be noticed in Figure 6. The first question involves that the $P(Y_2)$ distributions all present a special bimodal structure. This is a further illustration of the bilevel performance presented in spatial patterns structure. The second problem relates to the differences between $Y_{2\text{-in}}$ and $Y_{2\text{-out}}$ that the $Y_{2\text{-out}}$ are larger in small value range and $Y_{2\text{-in}}$ are larger in large value range. In PFN, a small value of Y_2 means that the weights on each adjacent edge are similar, and a large value indicates the existence of dominative edge. Thus, the spatial patterns of incoming flows are scattered and those of outgoing flows seem to be more concentrated. The third aspect deals with the fact that the values of Y_2 are similar to $1/J$ (J is the number of adjective stations of station i) $\simeq 1/2 = 0.5$ (except for few transfer stations with more than 2 adjective stations and terminal stations with only 1 adjective station). This high homogeneity means that the

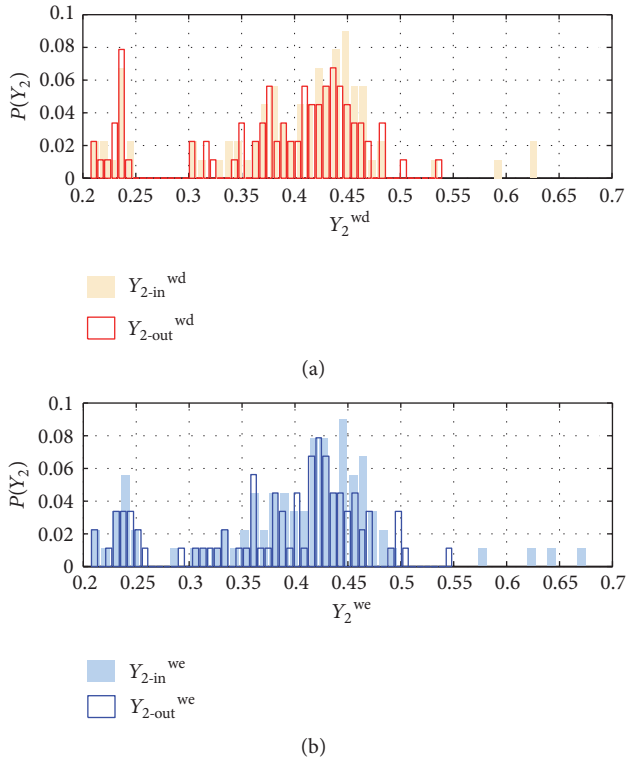


FIGURE 6: The probability distributions of Y_2 for both incoming and outgoing flows on (a) weekday and (b) weekend. The distributions on weekday are peaked for $Y_{2\text{-in}} \approx 0.45$ and $Y_{2\text{-out}} \approx 0.24$ and both concentrated in the range (0.20, 0.25) and (0.30, 0.48). The distributions on weekend are peaked for $Y_{2\text{-in}} \approx 0.45$ and $Y_{2\text{-out}} \approx 0.43$ and both concentrated in the range (0.20, 0.26) and (0.30, 0.50).

weights of incoming and outgoing flows in each level are relatively close.

4.3. Real Load Distribution. Next we investigate the real load distributions of the two network systems: WD and WE. It is important to note that the real load distribution here is an important indicator to analyze the correlation between PFN and TFN. This indicator can be seen as appropriate measure of the train capacity utilization rate in the metro system, which can be interpreted as the passenger density in a train. Figure 7 shows the distributions and the temporal patterns of the real load on weekday and weekend. In order to get a deeper insight into the structure of the two real load networks, we present the spatial patterns in Figure 8.

In Figure 7(a), we can clearly observe that the real load distributions $P(l_{p\text{-}t}^{wd})$ and $P(l_{p\text{-}t}^{we})$ are remarkable right-skilled on log-log scale which can be fitted by power law distributions and show markedly heavy-tailed characteristics. Moreover, the quantities of $l_{p\text{-}t}^{we}$ are lower than $l_{p\text{-}t}^{wd}$ in the tail part of distribution line, indicating that the real load on weekend is less than that on weekday. Figure 7(b) presents the temporal patterns of passenger traveling in TFN on weekday. It is clear that there are two distinct peaks—07:00~10:00 and 18:00~20:00 corresponding to the peak hours on working day. Moreover, the morning peak is more prominent than the evening peak in both the traffic density and the temporal duration. As apparent from Figure 7(c), there are two moderate morning and evening peaks, 07:00~09:00 and 19:00~22:00 with the morning peak more prominent in traffic density and the evening peak more prominent in the temporal duration. Comparing Figures 7(b) and 7(c), the peaks on weekend are much lower than those on weekday, which indicates a highly uneven utilization of the underlying train flow network on weekday and a highly level of service supplied by the metro system on weekend. It could be concluded that the temporal pattern on weekday and weekend networks presents a dissimilar match as expected.

As illustrated by Figure 8(a), the spatial clustering of a large number of heavy-burden nodes is distributed along Line 1's east-west route and Line 5's north-south route on weekday. On the other hand, the spatial pattern on weekend presents the clustering phenomenon around the transfer stations. In summary, the dense distribution areas in the spatiotemporal pattern indicate bottlenecks in the train capacity, which can aid in the effective operation of train services.

In this paper, we found and highlighted the statistical properties and spatiotemporal patterns including the size distributions in PFN that can be well approximated with a power law distribution which indicates that the passenger flow patterns vary in intensity with hub nodes and busy edges on both weekday and weekend; by contrast, the fitted form of the size distributions in TFN is Weibull, which may be attributed to the fact that the dynamic evolution in TFN is similar to a branching process for there are no train flows exchanged between TFN and outside. We also suggest using a quantity Y_2 to measure the disparity of each node in PFN, and the results show a significant two-level performance caused by the different dynamics flows evolution process between the transfer and nontransfer stations.

By comparing with the two patterns on weekday and weekend, we found that the substantial trends have the roughly same form, with noticeable lower sizes of flows on weekend ascribed to the essential characteristics of travel demand on weekends. As a result, the real load on weekend presents a loose and comfortable performance on spatiotemporal patterns.

5. Conclusions

Prior work has documented that complex network methods are useful for studying the underlying physical topology of traffic flows in metro systems. However, little research has been conducted on both passenger and train flow patterns or intrinsic differences between weekday and weekend.

In this paper, we found and highlighted the statistical properties and spatiotemporal patterns in PFN and TFN based on a contribution of two directed weighted networks using the trip dataset collected from smart card transactions and the train movement dataset processed from operation timetable. We characterized the flow weight and strength distributions and found that the heterogeneous feature of passenger flow shows a self-organized pattern in which spatial mismatch occurs as individual passengers commute through

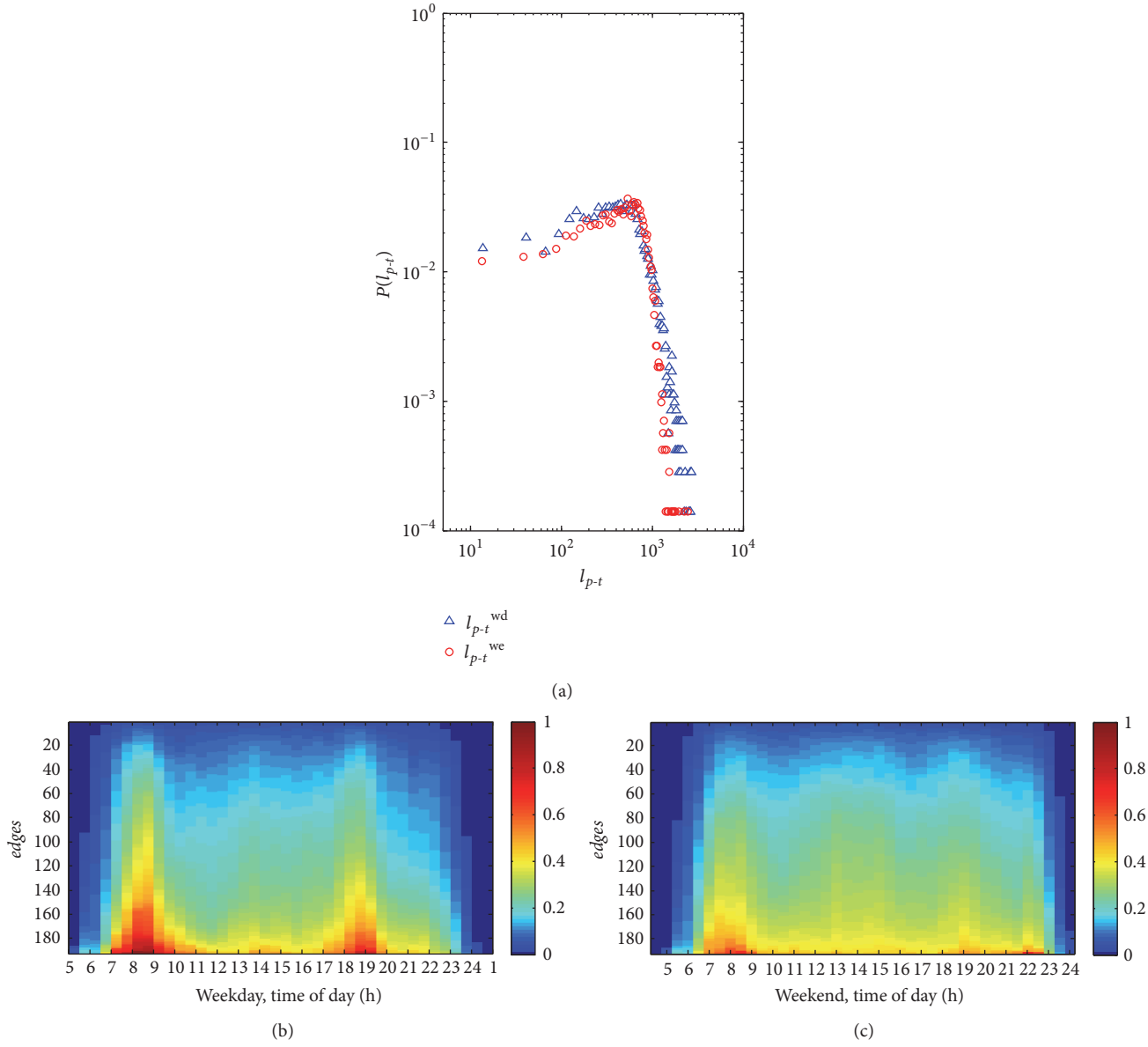
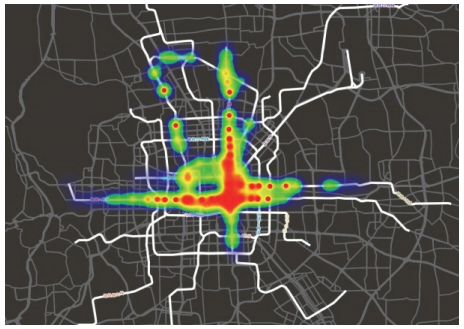


FIGURE 7: Real load (a) distributions on log-log scale and temporal patterns of (b) weekday and (c) weekend. In (a), the real loads $l_{p\text{-}t}^{wd}$ and $l_{p\text{-}t}^{we}$ can be fitted by power law fits with exponents 0.55 and 0.56, respectively. The R^2 are all 0.97.

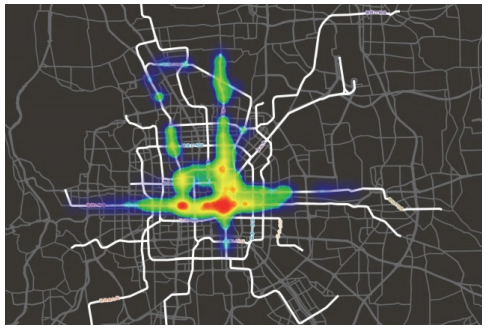
the city's center; on the other hand, the train flows evolution dynamics present a redistribution of preexisting flow intensities. We also investigated the disparity of incoming and outgoing flows at a given station to describe the bilevel performance (transfer and nontransfer stations) of the spatial structure. We further discussed the fundamental correlation between PFN and TFN by defining an indicator, real load, and characterizing the size distribution and spatiotemporal patterns on weekday and weekend, respectively. By comparing with the two different patterns, we found that the real load on weekend presents a loose and comfortable performance in whole temporal duration and that on weekday shows two obvious congested periods of time, which are the results of the sizes of flows on weekend that are noticeably lower than those on weekday ascribed to the essential characteristics of travel demand on weekends.

The empirical findings can give us some useful insights on patterns of urban human mobility within a large metro network on both weekday and weekend. As travel demand increases and infrastructure construction is constrained, traffic congestion takes place not only at morning and evening peak hours on weekdays but also in major shopping centers, sports arenas, and recreational areas in big cities over weekends. Adopting a complex network approach to study the passenger and train flow patterns can therefore be beneficial for effective operation of train services.

This study is limited in that only five subway lines were analyzed because of the difficulty associated with data



(a) Real load on weekday



(b) Real load on weekend

Figure 8: Real load spatial patterns on weekday and weekend.

collection, and research on the overall system with more lines should be conducted to further validate the above conclusions. Moreover, other traffic flow models of subway networks could be explored from a variety of layered perspectives.

Competing Interests

The authors declare that they have no competing interests.

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