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The Effects of Weather on Passenger Flow of Urban Rail Transit

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Abstract

Predicting passenger flow on urban rail transit is important for the planning, design and decision-making of rail transit. Weather is an important factor that affects the passenger flow of rail transit by changing the travel mode choice of urban residents. This study aims to explore the influence of weather on urban rail transit ridership, taking four cities in China as examples, Beijing, Shanghai, Guangzhou and Chengdu. To determine the weather effect on daily ridership rate, the three models were proposed with different combinations of the factors of temperature and weather type, using linear regression method. The large quantities of data were applied to validate the developed models. The results show that in Guangzhou, the daily ridership rate of rail transit increases with increasing temperature. In Chengdu, the ridership rate increases in rainy days compared to sunny days. While, in Beijing and Shanghai, the ridership rate increases in light rainfall and heavy rainfall (except moderate rainfall) compared to sunny days. The research findings are important to understand the impact of weather on passenger flow of urban rail transit. The findings can provide effective strategies to rail transit operators to deal with the fluctuation in daily passenger flow.

Keywords: Urban Rail Transit; Weather Effect; Passenger Flow; Estimation Model.

1. Introduction

The passenger flow estimation of urban rail transit is commonly used as the basis for the planning, design, and daily operations of rail transit. Weather can influence people's travel mode choice, and then have an impact on passenger flow of rail transit. But, weather factors are not usually presented in the existing models for estimating rail transit ridership, which results in an insufficient or excessive estimation in the design stage, and unexpected large fluctuations in operation stage. With the rapid development of urban rail transit, one challenge is to figure out the impacts of weather factors on passenger flow of rail transit. The relevant research mainly includes three aspects: data pre-processing of passenger flow [1, 2], quantitative analysis of impact factors [3-7] and the development of estimation models [8, 9].

Several studies have established the effects of rain and snow on public transit ridership. Inclement weather has an impact on people's travel modes and travel routes, and further affects on passenger flow in public transport [10, 11]. Changnon [12] found that summer rain days have a reduced number of passengers using public bus compared to summer sunny days. Cravo et al. [13] found that rain and snow have negative impacts on passenger flow of bus and subway.

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Guo et al. [14] investigated the impact of weather elements, and revealed that rain has a negative impact on bus and rail ridership. Zhou et al. [15] found that the negative impact of rain on bus ridership appears obvious during off-peak time, and no significant effect shows during peak hours. Wei et al. [16] examined the influences of weather conditions on transit ridership, and found that the transit ridership decreased on rainy days.

The findings of the impact of temperature on passenger flow are inconsistent. Arana et al. [17] showed increasing temperature leads to an increase in bus ridership on weekends. But, Kashfi et al. [18] exhibited no obvious relationship between temperature and bus ridership. Stover et al. [19] found that snow temperature has no obvious impact on bus passengers. Liu et al. [20] showed that extreme temperatures have diverse effects such as decreasing travel demand.

When referring to the estimation models for daily passenger flow, Cravo et al. [13] used a cross-sectional regression model to determine the impact of weather on New York City Transit's daily ridership. Stover et al. [19] used the least square methods to analyze the impact of weather on bus ridership. Zhao et al. [20] identified the impact of weather factors on passenger flow rate using multiple linear regression. Qu et al. [21] used fully connected deep neural networks to capture the relationship between the weather and traffic flow.

Most existing research has focused on the effects of weather (e.g. rain, snow, and temperature) on public transport ridership, but the effects on rail transit remain largely unexplored. On the other hand, little evidence is available to examine the weather-transit ridership in urban rail transit. Hence, there is a need for transport scholars to begin to determine the effects of weather on rail transit ridership in multiple locations. This study will identify the impacts of weather on rail transit ridership, in the four cities in China. One year of data will be used to model the relationship between weather and ridership with linear regression method.

2. Research Method

2.1. Data Collection

Passenger flow data and weather data

The datasets used in this study consist of two types: passenger flow data and weather data. The passenger flow data covering a one-year period from Jan 01, 2017 to Dec 31, 2017 was obtained from China Railway Corporation official website (e.g. https://weibo.com/bjsubway?from=myfollow_all&is_hot=1). The average daily passenger flow was calculated by weekday, weekend and holiday, shown in Table 1. The data were from the four big cities - Beijing, Shanghai, Guangzhou and Chengdu (see Figure 1). It should be noted that Chengdu opened a new rail transit line on Sep 06, 2017, which led to a significant change of passenger flow. Therefore, the 2017 data after Sep 06 was excluded. It was observed that the daily average passenger flow is higher on weekday than on weekend, and weekend is higher than holiday in the four cities.

Table 1. Passenger flow of rail transit in the four cities

City	Average daily passenger flow (thousand)			Time
	Weekdays	Weekends	Holidays *	
Beijing	9601	6332	5178	2017.01.01～2017.12.31
Shanghai	10793	7614	6763	2017.01.01～2017.12.31
Guangzhou	7860	7506	6680	2017.01.01～2017.12.31
Chengdu	2207	1779	1487	2017.01.01～2017.09.05

* Include seven national holidays in China, see Table 2 for details.

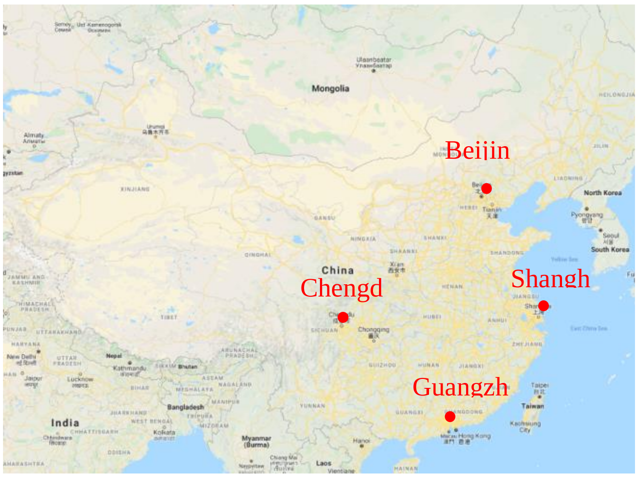


Figure 1. The four selected cities in China

The meteorological data for the entire year of 2017 were gained from the World Weather Online (https://www.worldweatheronline.com/map/), including daily temperatures (°C) (the lowest and highest), weather conditions (sunny, cloudy, rainy and snowy), wind speed (m/s), cloud fraction (%), precipitation (mm), air pressure (bar) and humidity (%). The flowchart of this research method is available in Figure 2.

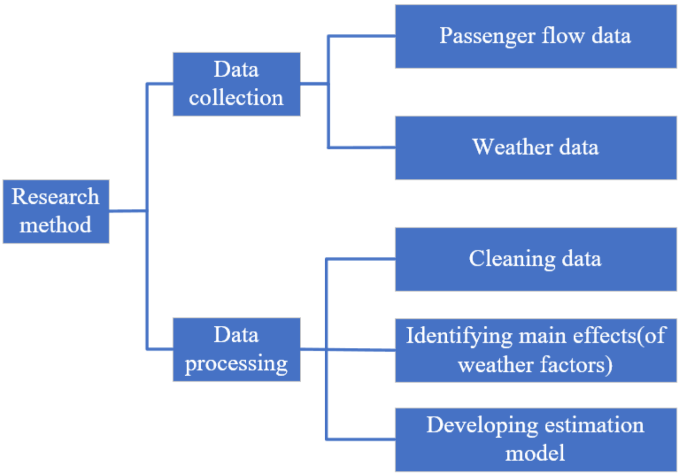


Figure 2. The flowchart of the research method

2.2. Data Processing

Rail transit passenger flow

Before analyzing the relationship between passenger flow and weather, it is necessary to clean raw data. Daily passenger flow of rail transit is affected by many factors such as holidays, large-scale events, and emergencies. The purpose of data cleaning is not only to detect and correct incomplete or inaccurate records, but also to reduce or eliminate the effects of other factors except weather.

First, it is important to identify the outliers of passenger flow data. Figure 3 shows Beijing's daily passenger flow for the entire year. It was observed that several obvious outliers are presented at the end of January and the beginning of February. This time period is exactly in the longest national holiday in China (Lunar New Year). China has seven national holidays (shown in Table 2), in which the passenger flow varies significantly. Therefore, the holiday effect needs to be removed from passenger flow data.

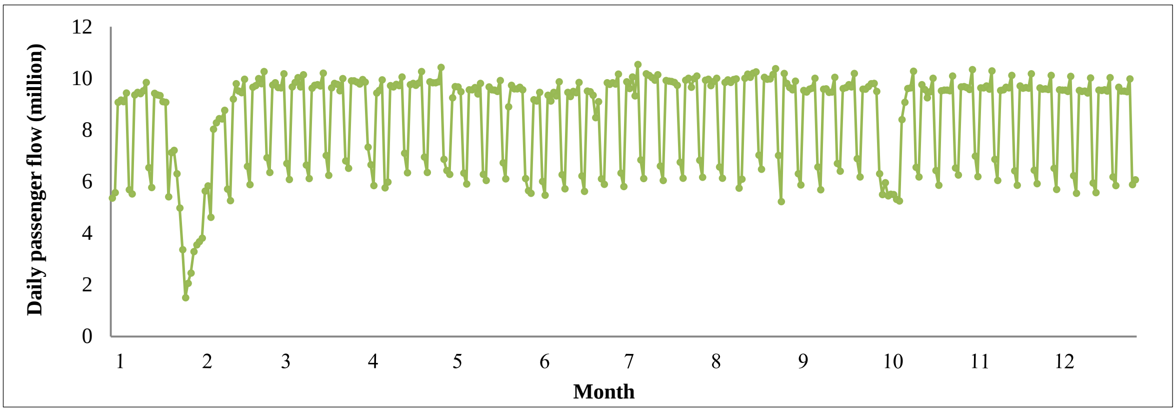


Figure 3. Beijing's daily passenger flow in 2017

Table 2. Holiday schedule in 2017

Holidays in China	Date	Total days
New Year's Day	2016.12.31～2017.01.02	3
Lunar New Year	2017.01.27～2017.02.02	7
Qingming Festival	2017.04.02～2017.04.04	3
May Day	2017.04.29～2017.05.01	3
Dragon Boat Festival	2017.05.28～2017.05.30	3
Mid-autumn Festival and National Day	2017.10.01～2017.10.08	8

It was also noticed that significant changes in passenger flow usually present in several days before or after a holiday. To determine the days, the standard deviations of data sequences were compared. Standard deviation is the measure of dispersion of a set of data from its mean. The smaller the standard deviation, the lower the dispersion. Results show that the standard deviation of the dataset decreases, excluding the first day before holiday and the first day back after, compared to the original dataset. When two or more days before and after holiday are removed, the standard deviations do not change much. Therefore, to keep the original data as much as possible, only data of the first day before holiday were selected to eliminate.

Table 3. Standard deviations of data sequences removing days before or after holiday

Days eliminated	0	1	2	3	4
	SD	SD	SD	SD	SD
Before holiday	163.37	161.52	161.15	161.54	162.79
After holiday	163.37	163.86	164.39	163.96	163.75
Before and after holiday	163.37	162.00	162.15	162.14	162.78

Note: SD- Standard Deviation

Weather data. In this study, weather data was cleaned in the following three aspects:

(1) Eliminate the data whose corresponding passenger flow data were removed.

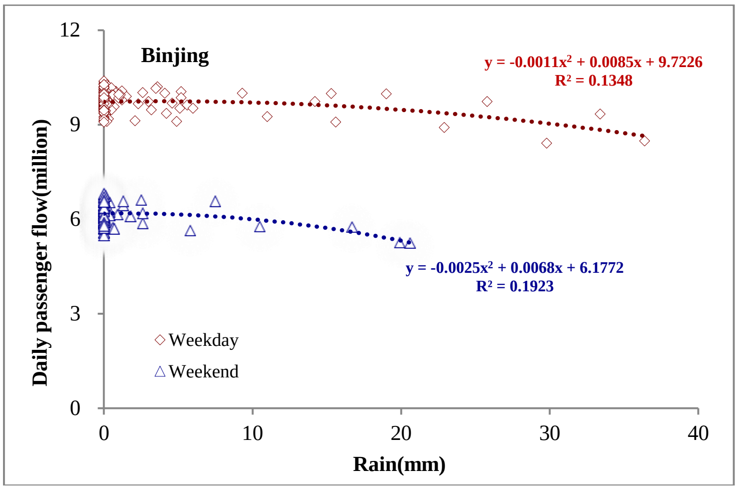
(2) Eliminate the data with missing values.

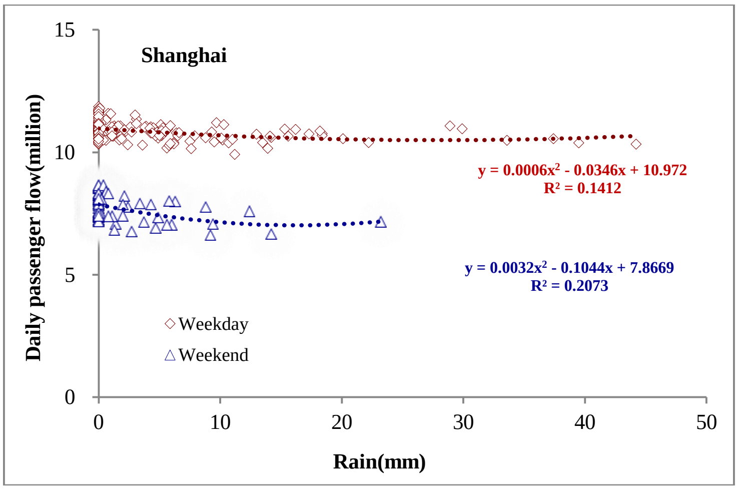
(3) Eliminate the data of extreme weather events, such as hailstorm.

2.3. The Estimation Model For Daily Passenger Flow

Correlation analysis between weather and passenger flow

Because the passenger flow distribution presents a significant difference on weekend and on weekday, the flow data of weekend and weekday were separated. Scatterplots were used to analyze if there are relationships between weather factors and rail transit passenger flow. In Figure 4, it was found that rainfall has an influence on passenger flow of rail transit in Beijing, Shanghai and Chengdu, as well as temperature (the average of the highest and lowest temperature) has an effect on passenger flow of Guangzhou rail transit. It was also observed that the weekend flow is more likely to be affected by weather than the weekday flow.





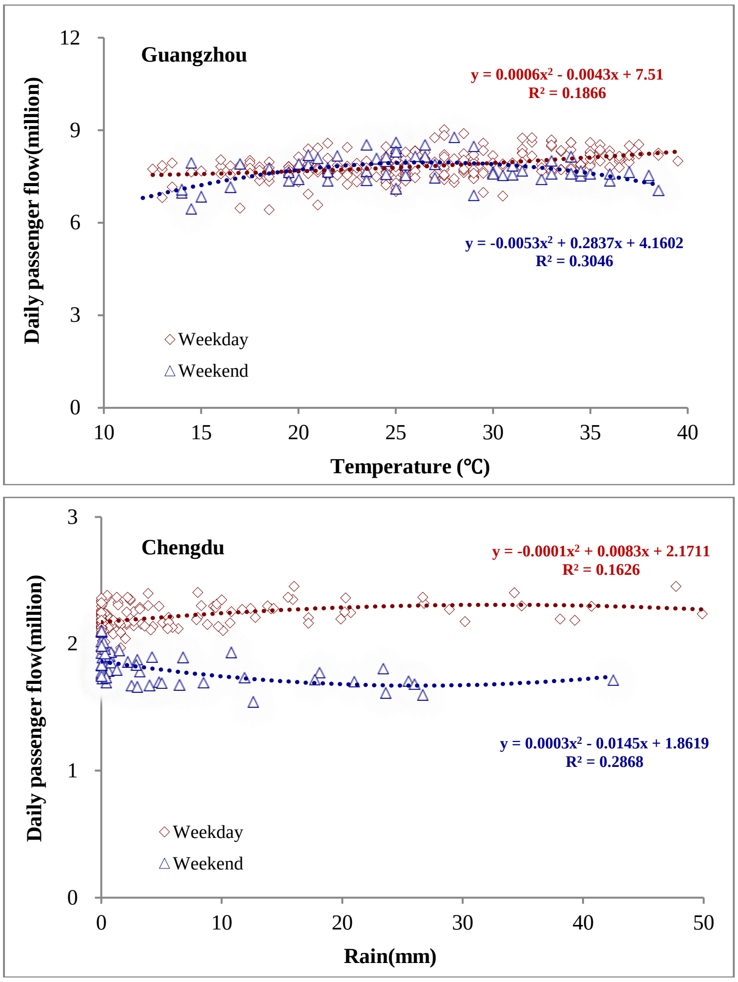


Figure 4. Effects of rainfall and temperature on passenger flow of urban rail transit

Basic model for estimating daily passenger flow

The daily passenger flow shown in Figure3, presents a periodic fluctuation between weekday and weekend, and obvious changes in holidays. Thus, as developing the daily passenger flow estimation model, the day factor (DF, weekday and weekend) and holiday factor (HF) should be included. Based on Kashfi's study [21], we developed the ridership estimation model, comprising the two factors, shown in Equation 1.

$$\text{Model 1}: DR = \alpha_{c,1} + \beta_{c,1}(DF_{c,b} * HF_{c,d}) \quad (1)$$

Where, DR = estimated daily passenger flow of urban rail transit; $\alpha_{c,1}$= model constant; $\beta_{c,1}$= coefficient for estimation; $DF_{c,b}$=day factor for city $c \in \{Beijing, Shanghai, Guangzhou, Chengdu\}$ for day type $b \in \{Mon, Tues, Wed, Thu, Fri, Sat, Sun\}$; $HF_{c,d}$ = holiday factor for city c during holiday d.

Table 4. Calculated values of day factor ($DF_{c,b}$) and holiday factor ($HF_{c,d}$) for four cities

City	Weekday					Weekend		Holiday					
	Mon	Tues	Wed	Thu	Fri	Sat	Sun	New Year's	Spring	Qingming	May	Dragon Boat	Mid-autumn Festival and National
Beijing	1.13	1.13	1.13	1.16	1.17	0.77	0.71	0.68	0.35	0.79	0.77	0.69	0.67
Shanghai	1.10	1.11	1.11	1.11	1.16	0.81	0.74	0.79	0.47	0.83	0.86	0.76	0.72
Guangzhou	1.07	1.06	1.05	1.07	1.14	1.06	1.01	1.13	0.50	1.02	1.16	1.00	0.97
Chengdu	1.05	1.04	1.04	1.05	1.11	0.89	0.82	0.87	0.43	0.94	0.99	0.87	—

Day factor ($DF_{c,b}$) and holiday factor ($HF_{c,d}$) for the four cities were calculated by Equations 2 and 3 respectively, and the calculated values are shown in Table 4.

$$DF_{c,b} = \frac{\sum_{i=1}^{N_b} DR_{c,b,i}}{N_b DR_{c,av}} \quad (2)$$

Where, $DR_{c,b,i}$ = original daily passenger flow of city c on day i of day type b; N_b = the number of relevant days of day type b; $DR_{c,av}$ = original annual average daily passenger flow of city c.

$$HF_{c,d} = \frac{\sum_{i=1}^{N_d} DR_{c,d,i}}{N_d DR_{c,av}} \tag{3}$$

Where, $DR_{c,d,i}$ = original daily passenger flow of city c on day i of holiday d; N_d is the number of relevant days of holiday d.

Newly –developed models for estimating daily passenger flow

Maybe because the weather factors are not included in Model 1, it gives biased estimates of passenger flow. In this study, new daily ridership estimation models were proposed by adding weather factors to the basic model, to improve the accuracy of the prediction.

Temperature factor ($TF_{c,t}$) and weather type factor ($TWF_{c,tw}$) for the four cities were calculated by Equation 4 and Equation 5 respectively, and the calculated values are demonstrated in Table 5.

$$TF_{c,t} = \frac{\sum_{i=1}^{N_t} DR_{c,t,i}}{N_t DR_{c,av}} \tag{4}$$

Where $DR_{c,t,i}$ = original daily passenger flow of city c on day i for a given temperature interval $t \in [-10, 0) \cup [0, 10) \cup [10, 20) \cup [20, 30) \cup [30, 40)$; N_t= the number of relevant days occurring in a temperature interval t.

$$TWF_{c,tw} = \frac{\sum_{i=1}^{N_{tw}} DR_{c,tw,i}}{N_{tw} DR_{c,av}} \tag{5}$$

Where $DR_{c,tw,i}$ = original daily passenger flow of city c on day i for a given weather type $tw \in \{\text{sunny, cloudy, light rain, moderate rain, heavy rain, snow}\}$; N_{tw} = the number of relevant days for a given weather type.

Table 5. Calculated values of temperature factor ($TF_{c,t}$) and factor of weather type ($TWF_{c,tw}$) for four cities

City	Temperature（℃）					Weather Type					
	-10～0	0～10	10～20	20～30	30～40	Clear	Overcast	Small Rain	Moderate Rain	Heavy Rain	Snow
Beijing	0.98	0.99	1.07	1.03	1.06	1.03	1.06	1.04	0.98	1.04	1.02
Shanghai	—	1.00	1.03	1.04	1.02	1.02	1.04	1.04	0.94	1.05	0.76
Guangzhou	—	—	1.04	1.06	1.09	1.09	1.06	1.06	1.07	1.06	—
Chengdu	—	0.91	0.98	1.02	1.04	1.00	0.94	1.02	1.02	1.02	—

To determine the weather effect on daily ridership rate, the three models were proposed with different combinations of the factors of temperature and weather type. Using Model 1 as the base model, three combinations of the factors were introduced into candidate models, which are as follows:

$$\text{Model 2: } DR = \alpha_{c,2} + \beta_{c,2}\left(DF_{c,b} \times HF_{c,d} \times TF_{c,t}\right) \tag{6}$$

$$\text{Model 3: } DR = \alpha_{c,3} + \beta_{c,3}\left(DF_{c,b} \times HF_{c,d} \times TF_{c,t} \times TWF_{c,tw}\right) \tag{7}$$

$$\text{Model 4: } DR = \alpha_{c,4} + \beta_{c,4}\left(DF_{c,b} \times HF_{c,d} \times TWF_{c,tw}\right) \tag{8}$$

3. Results

Table 6 shows the parameter estimates for the four models, including the coefficient (β), constant (α), t-statistics and R^2 value. R^2 is a goodness-of-fit measure for models: the higher the R^2 value, the better the estimation model fits the passenger flow data. R^2 increases when a weather variable is added to the model, which indicates that the weather factor is related to passenger flow of rail transit.

Table 6. Parameter estimates of the four models

City	Model 1			Model 2			Model 3			Model 4		
	$\beta_{c,1}$	$\alpha_{c,1}$	R^2	$\beta_{c,2}$	$\alpha_{c,2}$	R^2	$\beta_{c,3}$	$\alpha_{c,3}$	R^2	$\beta_{c,4}$	$\alpha_{c,4}$	R^2
Beijing	8.75 (58.70)	-0.14 (-0.91)	0.906	8.19 (50.54)	0.39 (2.40)	0.877	8.23 (51.93)	0.35 (2.19)	0.883	8.73 (58.88)	-0.11 (-0.75)	0.908
Shanghai	8.79 (35.14)	0.88 (3.46)	0.776	7.65 (33.53)	1.61 (6.59)	0.759	8.14 (33.61)	1.31 (5.18)	0.760	8.25 (35.73)	1.21 (5.02)	0.781
Guangzhou	6.49 (22.22)	0.82 (2.64)	0.580	5.81 (22.40)	1.15 (3.93)	0.584	4.78 (21.04)	1.97 (7.21)	0.553	5.27 (20.83)	1.75 (6.11)	0.549
Chengdu	1.83 (26.43)	0.20 (2.86)	0.743	1.54 (22.91)	0.46 (6.53)	0.684	1.53 (24.11)	0.44 (6.43)	0.706	1.79 (27.21)	0.21 (3.08)	0.754

Note: Numbers in parentheses are t-statistics.

First, an analysis was performed for Beijing, Shanghai and Chengdu. Compared to Model 1, Model 2 has a lower R^2, which demonstrates unfavorable results for explaining variability in passenger flow rate. Model 3 performed slightly better than Model 2, but it's R^2 still reflects unfavorable results for explaining variability in passenger flow rate. It is evident that the temperature factor decreases the predictive capability of the model, and thus it was excluded in the next model. Model 4, which includes the day factor, holiday factor and weather type factor, performed better than Model 1 in predication. It reveals that the weather type has an impact on passenger flow of rail transit.

For Guangzhou, compared to Model 1, the R^2 value of Model 2 increases with an addition of temperature factor. Models 3 and 4, including the weather type factor, performed worse than Model 1 with lower R^2 value. The results indicate that temperature has an impact on passenger flow of Guangzhou rail transit.

Next, Beijing and Guangzhou were selected as examples to compare the estimates using the newly-developed models with the original ridership rate. The estimated daily passenger flow, calculated using Model 4 for Beijing and Model 2 for Guangzhou respectively, were compared with the original daily passenger flow (shown in Figures. 5and 6). It was observed that in general, the estimates for the two cities are in close proximity to the actual values.

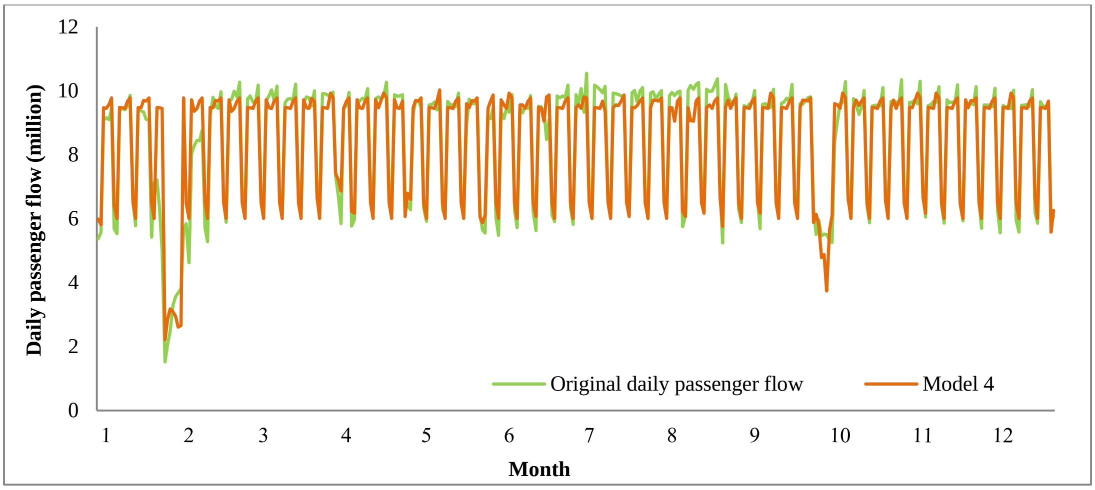


Figure 5. Time series graph of actual daily passenger flow trend & fitting of Model 4 using Beijing as sample

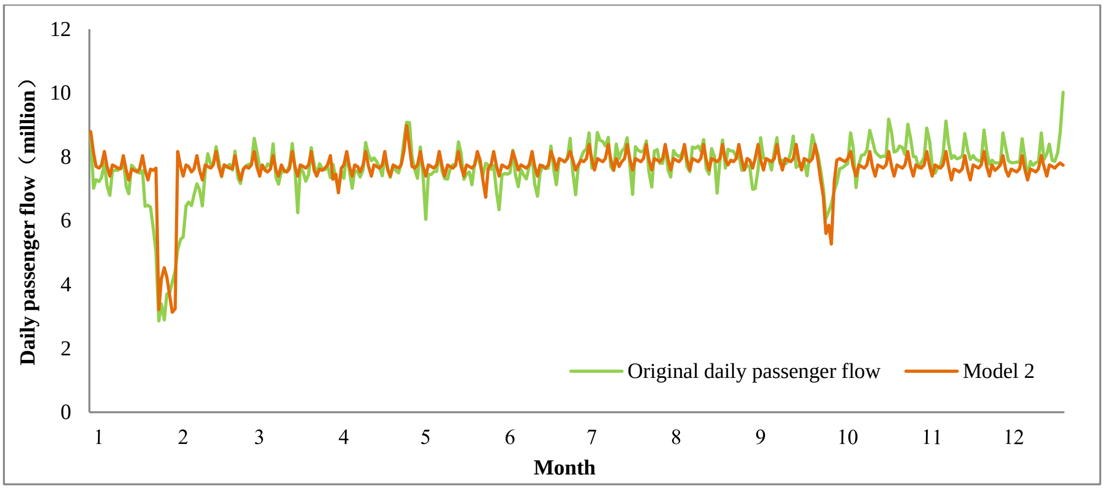


Figure 6. Time series graph of actual daily passenger flow trend & fitting of Model 2 using Guangzhou as sample

As mentioned above, of the three developed models, Model 4 with the day factor, holiday factor and weather type factor, produced a better result for Beijing, Shanghai and Chengdu. Model 2 with the day factor, holiday factor and temperature factor, produced a better result for Guangzhou. It was noticed that in Models 2 and 4, three explanation variables (e.g. $\mathrm{DF_{c,b}} * \mathrm{HF_{c,d}} * \mathrm{TF_{c,t}}$) were considered as a whole for analysis. As a result, it was difficult to identify the influence of each variable. To overcome this weakness, Models 2 and 4 were transformed to a multiple linear regression by taking the logarithm, shown in Equations 9 to 10.

Model 5: $\ln \mathrm{DR} = \alpha + \beta_1 \mathrm{DF_{c,b}} + \beta_2 \mathrm{HF_{c,d}} + \beta_3 \mathrm{TF_{c,t}}$ (9)

Model 6: $\ln \mathrm{DR} = \alpha + \beta_1' \mathrm{DF_{c,b}} + \beta_2' \mathrm{HF_{c,d}} + \beta_3' \mathrm{TWF_{c,tw}}$ (10)

Table 7 illustrates the estimates of the parameters and constants in the regression equations using SPSS software, including the correlation coefficient (B), standard error (S. E), t-statistics, P and R^2 value. It was seen that the day and holiday variables have low standard errors and high coefficients, which indicates that they play a dominant role in daily passenger flow ($P < 0.001$). The weather type has a significant impact on passenger flow for Beijing, Shanghai and Chengdu ($P < 0.05$), and the temperature has a significant impact on passenger flow for Guangzhou ($P < 0.05$). These results are consistent with the findings from Table 6.

Table 7. Fitting results of regression model

Beijing	**B**	**S. E**	**t**	**P**	**Shanghai**	**B**	**S. E**	**t**	**P**
Constant	-0.81	0.07	-11.72	0.000	Constant	-0.39	0.11	-3.40	0.001
$DF_{c,b}$	1.11	0.03	42.90	0.000	$DF_{c,b}$	0.92	0.03	27.53	0.000
$HF_{c,d}$	1.42	0.04	35.48	0.000	$HF_{c,d}$	1.17	0.06	20.03	0.000
$TWF_{c,tw}$	-0.99	0.37	-2.69	0.007	$TWF_{c,tw}$	0.54	0.11	4.85	0.000
	R^2=0.908					R^2=0.799			
	Adjusted R^2=0.907					Adjusted R^2=0.797			
	Model 6					*Model 6*			
Guangzhou	**B**	**S. E**	**t**	**P**	**Chengdu**	**B**	**S. E**	**t**	**P**
Constant	-0.22	0.16	-1.35	0.177	Constant	-1.50	0.07	-20.74	0.000
$DF_{c,b}$	0.57	0.08	7.56	0.000	$DF_{c,b}$	0.74	0.05	16.06	0.000
$HF_{c,d}$	1.28	0.07	19.07	0.000	$HF_{c,d}$	1.47	0.06	24.64	0.000
$TF_{c,t}$	0.35	0.16	2.18	0.030	$TWF_{c,tw}$	0.39	0.10	3.24	0.003
	R^2=0.670					R^2=0.795			
	Adjusted R^2=0.667					Adjusted R^2=0.793			
	Model 5					*Model 6*			

Note: Significant level $\alpha = 0.05$

4. Discussion

This study analyzed the effects of temperature and weather type on daily passenger flow of rail transit. It was found that the effects of the two weather factors on ridership rate vary in the four cities, probably because people perceive weather conditions differently in different urban environment. Temperature has a positive impact on passenger flow of Guangzhou rail transit, that is, the daily ridership rate increases with increasing temperature.

Adverse weather, such as rainfall, has been found to be negatively associated with passenger flow of rail transit [1, 13, 14, 24], but the opposite might be possible. Our results show that in Chengdu, the ridership rate increases in rainy days compared to sunny days. While, in Beijing and Shanghai, the ridership rate increases in light rainfall and heavy rainfall (except moderate rainfall) compared to sunny days. The results indicate that the rainfall pattern has an impact on passenger flow. The variances in the impact of adverse weather highlight the necessity to make further study on passenger's preference for mode choice in adverse weather conditions.

5. Conclusion

This study performed large-scale data analysis on the data of daily passenger flow and weather elements to explore the impacts of weather factors on usage of rail transit. The daily ridership estimation models were established under different weather conditions. The analytical results show that in China's megacities, in general, the increase in temperature and rainfall are associated with an increase ridership in rail transit. The degree and the statistical significant of the impact vary from one city to another. It was found that the different amount of rainfall has a varying impact on passenger flow of rail transit. These findings provide rail transit operators with valuable information to deal with daily passenger flow fluctuation related to varying weather conditions.

6. Funding

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7. Conflicts of Interest

The authors declare no conflict of interest.

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