Research on the Application and Management of Shared Bikes in Smart Cities

Weiqing Liu
EDP School of Intelligent Engineering, Hubei Enshi College, Enshi, Hubei, 45000, China

Keywords: Shared Bike Management, Smart Cities, Urban Air Quality, Sustainable Transportation.

Abstract: As a typical means of shared transportation, the application and management of shared bikes face some challenges. Therefore, the application and management of shared bikes in smart cities have been studied indepth in this paper. This study founds that an effective management system and policies are needed to ensure the healthy development of the bike-sharing industry. In addition, the relationship between bike-sharing and urban air quality. The use of a large number of motor vehicles has led to increasingly serious air pollution problems, and shared bikes, as a low-carbon and environmentally friendly mode of transportation, can reduce vehicle exhaust emissions and improve air quality. In summary, Shared cycling in the wisdom of city application and management is facing some problems, but through the optimization measures, intelligent control methods and air quality improvement strategy related research, can effectively solve these problems, the government, Shared cycling enterprises and related departments of cooperation and regulation is a key factor in the management of Shared bicycle therefore, Shared cycling managers and policy makers need to pay attention to these research results, formulate corresponding policies and measures to promote the sustainable development of Shared cycling industry.

1 INTRODUCTION

With the rapid growth of the urban population and the aggravation of traffic congestion problems, sharing traffic and emerging transportation modes have become one of the important means to reduce the traffic pressure. The development of shared transportation and emerging transportation modes in smart cities is becoming a focus of research. As a low-carbon, environmentally friendly and convenient way of transportation, shared bikes have gradually attracted people's attention. However, the chaos caused by the excessive number of shared bikes or mismanagement has brought considerable problems to city managers. Therefore, it is necessary for the application and management of shared bikes in smart cities.

In recent years, many studies have deeply explored the application and management of shared bikes. By analyzing the use data of shared bikes, Zhang et al. proposed some optimization measures, such as reasonably adjusting the distribution of vehicles and setting up parking spots, to reduce traffic congestion and improve user experience (Lei et al 2017). Zhang discusses the intelligent control method to realize the shared bikes in the smart city environment class human beings (Wang et al 2018). Burda Studying the strategy of implementing public bike sharing in Dhaka City, Bangladesh (Zhang and Zhou 2019). Shaheen et al. studied early operator understanding and trends of public bike sharing in North America (Burda and Hakim 2017). Sun studied the relationship between shared bikes and urban air quality by analyzing the use of shared bikes and urban air quality data and proposed some strategies to improve air quality, such as encouraging the use of shared bikes instead of motor vehicles (Shaheen et al 2015). To sum up, sharing transportation and emerging transportation modes are of great significance in smart cities. As one of its representatives, shared bikes have management problems, but reasonable management and technical means can give full play to their advantages and bring convenience and environmental benefits to urban transportation. Therefore, it is of great practical significance to strengthen the research and management of shared transportation and emerging transportation modes.

This paper aims to make a comprehensive analysis of the application and management of shared

Liu, W.
Research on the Application and Management of Shared Bikes in Smart Cities.
DOI: 10.5220/0012815600004547

In *Proceedings of the 1st International Conference on Data Science and Engineering (ICDSE 2024)*, pages 234-241
ISBN: 978-989-758-690-3

bikes in smart cities. This paper adopts the scientific data collection method, collects a large number of data, including user data, vehicle data and traffic data, and uses the statistical principle to make a comprehensive analysis and processing of the data. Finally, this paper makes an in-depth analysis of the cases of shared bike management in different cities and different enterprises and summarizes the problems and solutions existing in the management of shared bikes. The results of this paper can provide valuable reference and suggestions for bike-sharing managers and policy makers, and promote the healthy development of the bike-sharing industry.

2 METHODS AND DATA

2.1 Data Source

The data source of this article is the Washington, D. C. Bike sharing system is a way of renting bikes, the process of automatic membership, renting and returning bikes through the network of kiosks locations throughout the city. Using these systems, people can rent a bike from one place and return it elsewhere as needed. Currently, there are more than 500 bike-sharing programs worldwide. The data generated by these systems make them attractive to researchers by explicitly recording the duration of travel, departure location, arrival location, and elapsed time. Thus, bicycle-sharing systems serve as sensor networks that can be used to study urban mobility. Combine historical usage patterns with weather data to predict bike rental demand in the Capital Bike Sharing program in Washington, DC.

2.2 Application of Time Series Analysis in Bike-Sharing Research

Time series analysis is an important statistical method that can dig deep into patterns and trends over time from data points. In the field of bike-sharing research, time series analysis plays a key role, helping us to fully understand the dynamic trends and patterns of the use of shared bikes.

Through sophisticated time series analysis, this paper can predict the amount of shared bikes used in different periods (for example, different time periods of the day, different days of the week, etc.). This predictive ability is crucial to the effective management and scheduling of bike-sharing companies. It can help companies better plan vehicle distributions and optimize scheduling algorithms to meet user needs and improve operational efficiency.

Furthermore, time series analysis can also reveal seasonal and cyclical changes in bike-sharing use. These findings help companies better understand user needs and develop targeted operational strategies. Moreover, time series analysis can also detect abnormal usage behavior, such as a sudden increase in usage in a short period or a prolonged sustained trough. These abnormalities may mean the occurrence of certain special events, such as bad weather, holidays, large events, etc. With this information, companies can adjust their operational strategies promptly to address possible challenges.

2.3 Selection and Suitability of the ARIMA Model

ARIMA model was used for time series prediction. The model is particularly suitable for non-stationary time series data and enables efficient analysis of the changes in shared bike usage over time. By studying past data trends and patterns, the ARIMA model predicts the use trend in the future and provides a scientific basis for the effective management of shared bikes.

To be more accurate, this study also involves the analysis of autocorrelation and partial autocorrelations. These analyses help to determine the parameters in the ARIMA model, such as lag order (lag) and differential order. By analyzing the autocorrelation and partial autocorrelation of shared bike use data, this paper can have a deeper understanding of the change law of bike use over time, to predict the future use trend more accurately.

3 TIME SERIES ANALYSIS OF SHARED BIKE USAGE DATA

3.1 Analysis of Autocorrelation and Bias Toward Autocorrelation

In this paper, SPSS 25 and ARIMA models were used for time series analysis and prediction in hours. The analysis of autocorrelation and partial autocorrelation revealed sequences with significant and partial autocorrelation, especially in a 1 to 6 h delay (Figure 1). This suggests that the past values of these sequences have significant effects on the future values and that this effect diminishes over time. This analysis is important for understanding changes in time series data and for predicting future trends.

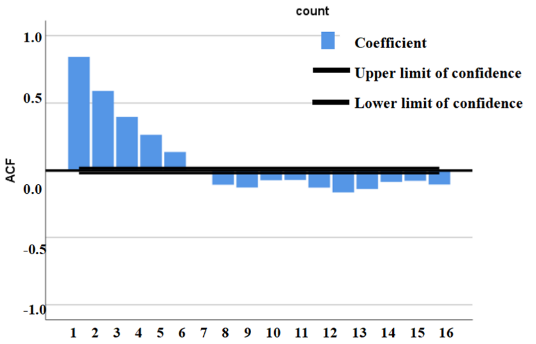

Figure 1: Time series analysis (Picture credit: Original).

Autocorrelation (ACF) and partial autocorrelation (PACF) are commonly used in time series analysis. A sequence autocorrelation diagram is a (linear) diagram between a sequence and its lag. Figure 2 shows the hysteresis weights as a function of hysteresis. How the correlation between individual time steps decrease or disappear with increasing time steps. Sequence autocorrelation graph is a method to test the presence of sequences.

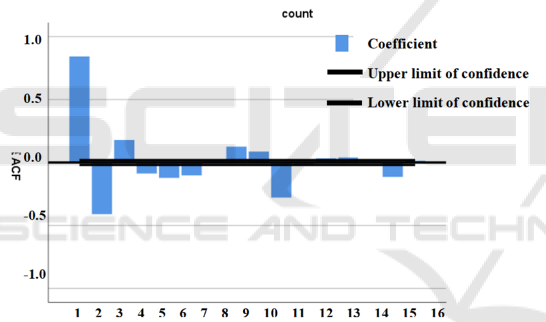

Figure 2: The hysteresis weights (Picture credit: Original).

The partial autocorrelation coefficient plot shows the partial autocorrelation coefficient as a function of hysteresis. The partial autocorrelation coefficient can be seen as the remaining effect after removing some of the effects that have been explained by the previous lag value. Thus, the partial autocorrelation coefficient plot can be used to determine the number of periods p in the autoregressive AR model. The p-value of this model is 1.

This indicates that there is a time series association of shared bike usage, that is, there is a mutual correlation between the previous period and the latter period.

3.2 Non-Simulated Sequence and the ARIMA Model

The instability of the time series means that the statistical characteristics of the data such as the mean and variance will change significantly at different time points. Therefore, the overall characteristics of the time series cannot be described by a fixed model, but the model needs to be adjusted according to the time change. The effective analytical method for non-stationary sequences is the ARIMA (1,0,1) model. This model captures the dynamic changes of the time series by combining the differential and moving average terms and can fit the non-stationary time series data relatively well. Where "1" indicates the order of the difference, "0" indicates the order of the autoregressive part, and "1" indicates the order of the moving average part. By tuning these parameters, the ARIMA model can adapt to different time-series data features (Table 1). The purpose of this study is to use the ARIMA (1,0,1) model to conduct an in-depth analysis of non-stationary time series data, to better understand the internal laws and trends of time series data and provide strong support for subsequent data analysis and prediction.

As shown in Table 2, the parameter display, autoregressive (AR), and moving average (MA) terms of the ARIMA model all have significant effects on the model, which reveals the complexity and dynamics of the usage patterns of shared bikes.

Table 1: Model description.

			types of models
model ID	count	model _1	ARIMA(1,0,1)(0,0,0)

Table 2: Model fit.

Fitting statistics	average value	standard error	least value	crest value	centile						
					5	10	25	50	75	90	95
Stable R square	.764	.	.764	.764	.764	.764	.764	.764	.764	.764	.764
R square	.764	.	.764	.764	.764	.764	.764	.764	.764	.764	.764

3.3 Model Size and Prediction Accuracy

After the statistics of the output degree of the model, a series of indicators, such as stationary R square, RMSE and MAPE, are obtained(Table 3). They provide an important basis for us to evaluate the accuracy and stability of the selected model in the actual data prediction. From these statistics, this paper can see the validity of the model in predicting the use of shared bikes.

Specifically, the stationary R square value is 0.764, which is quite high, meaning that the model can explain 76.4% of the variation in the real data. This result fully demonstrates the powerful ability and accuracy of the model in capturing and predicting the usage of shared bikes, indicating that the model can effectively apply the patterns and trends in historical data to predict the future usage of shared bikes.

In addition, other indicators such as RMSE (root mean squared error) and MAPE (average absolute percentage error) also further confirm the superiority of the selected model in the output of actual data. These statistics provide us with a more comprehensive perspective, allowing us to more accurately evaluate the predictive performance of the model.

In conclusion, based on the output degree statistics of the model, this paper can conclude that the selected model is valid and reliable in predicting the usage of shared bikes. This conclusion provides strong support for decision-makers to enable them to make rational decision making and planning based on these prediction data.RMSE and MAPE values were 87.928 and 164.601, and these statistical measures further verified the accuracy of the model predictions.

Figure 3 shows the fitting and measured results, which show that the effect is better.

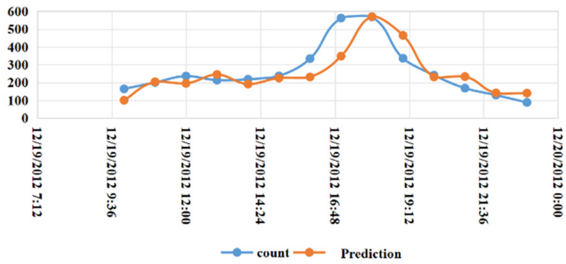

Figure 3: The fitting results (Picture credit: Original).

4 DESCRIPTIVE STATISTICS AND REGRESSION ANALYSIS

4.1 Descriptive Statistical Analysis

In this analysis, this paper used the correlation coefficient to quantify the relationship between the analyzed terms (Table 4). First, by calculating the correlation coefficient, this paper assessed whether these relationships were present. Then, by positive and negative symbols, this paper determined the direction of these relationships. Moreover, the magnitude of the correlation coefficient also reflects the strength of the linear relationship between the variables.

The Pearson correlation coefficient (PCC)and the Spearman correlation coefficient are two commonly used correlation coefficients, both of which can be used to describe the degree of correlation. The basic criteria for these two coefficients are consistent. Generally, when the absolute value of the correlation coefficient is greater than 0.7, this paper can that a strong correlation is greater than 0.4, and when the absolute value is less than 0.2.

In the previous section, this paper performed a descriptive statistical analysis of the sample data and found that the data used had a certain degree of rigor and rationality. Next, this paper will initially judge the degree of correlation between the variables through the correlation analysis.

Table 3: Model statistics.

model	Number of predictive variables	Model fit degree statistics			Young-Box Q (18)			The number of outliers
		Stable R square	R square	normalization BIC	statistics	DF	conspicuousness	
count-model _1	0	.764	.764	8.956	2287.039	16	.000	0

Table 4: Descriptive statistics.

	N	least value	crest value	mean	standard deviations
season	10886	1	4	2.51	1.116
holiday	10886	0	1	.03	.167
workingday	10886	0	1	.68	.466
weather	10886	1	4	1.42	.634
temp	10886	.82	41.00	20.2309	7.79159
atemp	10886	.760	45.455	23.65508	8.474601
humidity	10886	0	100	61.89	19.245
windspeed	10886	.0000	56.9969	12.799395	8.1645373
casual	10886	0	367	36.02	49.960
registered	10886	0	886	155.55	151.039
count	10886	1	977	191.57	181.144
Number of valid cases (in a column)	10886				

Table 5: Relativity.

		season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
season	PCC	1	.029*	-.008	.009	.259*	.265*	.191*	-.147*	.097*	.164*	.163*
holiday	PCC	.029*	1	-.250*	-.007	.000	-.005	.002	.008	.044*	-.021*	-.005
workingday	PCC	-.008	-.250*	1	.034*	.030*	.025*	-.011	.013	-.319*	.119*	.012
weather	PCC	.009	-.007	.034*	1	-.055*	-.055*	.406*	.007	-.136*	-.109*	-.129*
temp	PCC	.259*	.000	.030*	-.055*	1	.985*	-.065*	-.018	.467*	.319*	.394*
atemp	PCC	.265*	-.005	.025*	-.055*	.985*	1	-.044*	-.057*	.462*	.315*	.390*
humidity	PCC	.191*	.002	-.011	.406*	-.065*	-.044*	1	-.319*	-.348*	-.265*	-.317*
windspeed	PCC	-.147*	.008	.013	.007	-.018	-.057*	-.319*	1	.092*	.091*	.101*
casual	PCC	.097*	.044*	-.319*	-.136*	.467*	.462*	-.348*	.092*	1	.497*	.690*
registered	PCC	.164*	-.021*	.119*	-.109*	.319*	.315*	-.265*	.091*	.497*	1	.971*
count	PCC	.163*	-.005	.012	-.129*	.394*	.390*	-.317*	.101*	.690*	.971*	1
*. At the 0.01 level (two-tailed), the correlation was significant.												
*. At the 0.05 level (two-tailed), the correlation was significant.												

Table 6: Model summary.

model	R	R square	Adjusted R square	Error in the standard estimation
1	.743[a]	.552	.551	121.325

a. Predictor variables: (constants), casual, holiday, windspeed, weather, season, workingday, attemp, humidity, temp

In this section, the Pearson coefficient and Spearman coefficient were used for correlation. Among them, the Pearson coefficient was used in this analysis. After testing, the results are shown in the Table 5.

According to the descriptive statistical analysis, the use of shared bikes was significantly associated with factors such as season, holidays, weekdays, weather and temperature. Specifically, the season has a particularly significant impact on the shared usage of bikes, which reflects users' concern about the weather conditions in different seasons.

4.2 Regression Analysis

The R side, also known as the determination coefficient, is an indicator of quantifying the goodness of fit of the model (Sun et al 2018). Its explanatory ability is crucial because it can show the degree to which the model interprets the data. The closer the R square value is to 1, the higher the goodness of fit of the model is. In this case, the R square value is 0.551, indicating that the model is a good fit (Table 6).

Table 7: ANOVAa.

	model	quadratic sum	free degree	mean square	F	conspicuousness
1	regression	197079673.678	9	21897741.520	1487.632	.000b
	residual	160093239.998	10876	14719.864		
	amount to	357172913.676	10885			

a. Dependent variable: count
b. Predictor variables: (constants), casual, holiday, windspeed, weather, season, working day, attempt, humidity, temp

Table 8: Coefficient.

	model	Unstandardized coefficients		Standardization coefficient		
		B	Standard error	Beta	t	conspicuousness
1	(constant)	13.454	6.938		1.939	.053
	season	17.453	1.113	.108	15.683	.000
	holiday	23.985	7.230	.022	3.317	.001
	workingday	95.916	2.829	.247	33.909	.000
	weather	-2.765	2.042	-.010	-1.354	.176
	temp	-1.622	.890	-.070	-1.821	.069
	atemp	1.908	.819	.089	2.329	.020
	humidity	-.680	.077	-.072	-8.775	.000
	windspeed	.626	.156	.028	4.017	.000
	casual	2.611	.031	.720	84.010	.000

a. Dependent variable: count

As shown in Table 7, F (1487.632), significance p(0.00) is less than 0.05, indicating that the correlation coefficient of the regression equation is not 0, indicating that the regression equation is meaningful.

According to the regression coefficient in Table 8, the significance of all the variables except weather temp is less than 0.05, indicating that all the other variables have a significant impact on the count.

Regression analysis revealed the extent of different factors on the use of shared bikes. For example, there are significant differences in the effects of weekdays and holidays on usage, which may be related to the travel habits and daily activity patterns of urban residents.

4.3 Discussion and Management Suggestions Combined with Data Analysis

Data-driven management decision-making: The data analysis results of this paper highlight the importance of using data-driven decision-making methods when implementing bike-sharing management in smart cities. By analyzing the time series data of shared bike use, city managers can more effectively predict and respond to changes in the demand for shared bikes (Sun et al 2019 & Li et al 2020).

Scheduling strategy for weather forecast: regression analysis and correlation analysis reveal key factors affecting the use of shared bikes, such as weather, temperature, and urban activity. These findings could guide city managers to develop scheduling strategies for more weather forecasting, such as adjusting the allocation of shared bikes under specific weather conditions or holidays.

Standardized management system: Combined with the prediction results of the ARIMA model, a smart cities can develop a standardized bike-sharing management system, which can adjust the allocation of shared bikes in real time, optimize user experience, and alleviate traffic congestion.

5 CHALLENGES AND OPPORTUNITIES

Bike-sharing has played an important role in relieving urban traffic pressure, but it also brings new challenges. Due to the rapid growth of shared bikes, some cities have experienced problems such as excessive concentration and parking in disorder, affecting the urban landscape and traffic order.

In addition, the peak use period of bike-sharing often coincides with the commuting rush hour in the city, which strengthens the traffic congestion in the city to some extent.

In the context of smart cities, shared bikes provide an environmentally friendly and fast way to make short trips, which helps to reduce urban carbon emissions and improve residents' travel efficiency (Zhang et al 2020).

The popularity of bike-sharing also provides valuable data sources for data collection and analysis in cities, helping city managers to better understand urban traffic patterns and residents' travel needs.

In the future, the bike-sharing industry may be further developed through technological innovation, such as the use of more advanced positioning and navigation technologies, to improve the utilization rate and management efficiency of the bikes (Zhang and Qi 2018).

With the development of Internet of Things technology, shared bikes can be more customized, such as real-time data analysis to automatically adjust the allocation of bikes to better meet user needs.

To better manage and develop bike-sharing, city managers need to develop reasonable strategies and policies, such as optimizing the urban traffic layout, providing more special bicycle lanes, and establishing reasonable charging and weak mechanisms.

At the same time, the government and enterprises should strengthen cooperation to jointly promote the sustainable development of shared bikes and provide more convenient, efficient, and environmentally friendly travel options to urban residents.

6 CONCLUSION

This paper studies the challenges and opportunities of bike-sharing management through data analysis, and puts forward corresponding management suggestions. As a convenient and environmentally friendly means of transportation, shared bike has developed rapidly in cities in recent years. However, with the increasing number of shared bikes, a series of management problems have also emerged. This paper first analyzes the imbalance between supply and demand faced by shared bikes. Due to the uneven distribution of shared bikes, there may be a surplus in some areas, while others may have insufficient bikes. In addition, shared bikes are also prone to excessive aggregation of bikes, making it difficult for users to find available bikes. To address these problems, this paper proposes a data-driven management decision strategy. Through the data analysis of user behavior and demand, the demand change of shared bikes can be predicted, and the allocation of vehicles can be adjusted in advance to achieve the goal of supply and demand balance. Secondly, this paper also studies the impact of the weather on the use of shared bikes. Weather is one of the most important factors for people to choose their travel tools. For example, in bad weather, people prefer to use public transport or taxis rather than ride shared bikes. Therefore, this paper believes that weather factors need to be taken into account when formulating scheduling strategies to better allocate shared bikes and improve their utilization rate and management efficiency.

Finally, this paper puts forward some suggestions for the management of shared bikes. First of all, a standardized bike-sharing management system should be established. Through unified management and scheduling, the balanced distribution of bikes can be realized and the user experience can be optimized. Secondly, the government can formulate corresponding strategies and policies to support the development of shared bikes, such as optimizing the transportation layout, establishing special bicycle lanes, and formulating charging and weak mechanisms. For future studies, this paper suggests that the sustainability of shared bike management can be further explored. For example, how to achieve a balanced allocation of shared bikes, improve utilization and management efficiency, and how to optimize the user experience. In addition, the coordinated development of shared bikes and other vehicles, and the impact of shared bikes on the urban environment and traffic conditions can also be studied. The significance of these studies is to provide a scientific basis for the management of shared bikes and promote the intelligent and sustainable development of urban traffic.

In conclusion, this paper studies the challenges and opportunities of bike-sharing management. Further research can provide more profound theoretical and practical guidance for the management of bike-sharing, and promote the sustainable development of the bike-sharing industry. Through continuous exploration and innovation, bike-sharing can truly become an important part of urban transportation and provide residents with more convenient, efficient, and environmentally friendly travel options.

REFERENCES

Z. Lei, T. Liu, L. Yang, et al. Urban traffic research based on shared bicycle data. Urban Transportation, 14(2), 123-132, (2017).

H. Wang, T. Xu, X. Jia, & W. Li. Shared bicycle management in a smart city: A case study of Hangzhou, China. Transportation Research Part C: Emerging Technologies, 90, 58-71,. (2018).

Y. Zhang & J. Zhou. Intelligent control of shared bike in smart city environment. Communications in Computer and Information Science, 1048, 287-296,. 2019.

J. M. Burda & S. Hakim. Shared bikes and the city: Strategies for implementing public bike-sharing in a city of Dhaka. IATSS Research, 41(2), 102-109,. 2017.

S. Shaheen, E. Martin, N. Chan, A. Cohen, & J. M. Pogodzinski.. Public bikesharing in North America: early operator understanding and emerging trends. Transportation Research Record: Journal of the Transportation Research Board, 2534(1), 78-87, 2015.

L. Sun, Y. Zhang, X. Wang, et al.. Research on the relationship between shared bicycles and urban air quality. Transportation and Transportation Research, 17(4), 65-71, (2018).

L. Sun, Y. Chen, C. Liu, & P. Yang.. Optimizing docking station allocation in bike-sharing systems. IEEE Transactions on Intelligent Transportation Systems, 20(10), 3950-3961, (2019).

M. Li, K. Chen, T. Wang, et al. Research on the layout model of shared bicycle parking areas. Transportation Planning and Management, 39(5), 94-100,(2020). .

J. Zhang, Z. Gui, S. Wang, & Y. Xu.The Application of Shared Bicycles in Smart Cities. In International Conference on Data Mining and Big Data (pp. 776-783). Springer, Singapore. (2020).

Y. Zhang & S. Qi. A Research on Management of Shared Bike in Smart City Based on Internet of Things. In 2018 13th International Conference on Computer Science & Education (ICCSE) (pp. 897-902). IEEE.(2018).