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Time Period Analysis of Traffic Flow around Scenic Spots in Small Towns Based on K-Means Clustering

Kai Jiang[1], Yujie Long[2], Zejian Li[1], Zhilan Zhou[2], Junwei Liang[1,*]

[1]*School of Computer and Software, Shenzhen Institute of Information Technology, Shenzhen, China, 518172*
[2]*School of Artificial Intelligence, Shenzhen Institute of Information Technology, Shenzhen, China, 518172*
**Corresponding author: jwliang@sziit.edu.cn*

Abstract: *With rapid urbanization and the proliferation of motor vehicles, traffic congestion in small towns featuring renowned scenic areas has escalated, posing challenges for roads that must accommodate both local commuters and tourist vehicles. Tourist vehicles frequently idling on roads for parking exacerbate traffic inefficiencies. To address this, this study innovatively excludes statutory holiday traffic (e.g., Tomb Sweeping Day, Labor Day) to focus on a targeted dataset from April 8th to April 21st, 2024. By integrating the K-means clustering algorithm, this research introduces a novel temporal segmentation approach to analyze traffic flow patterns. This method dynamically partitions time periods into clusters, estimates traffic volume variations across phases within each cluster, and reveals distinct temporal traffic profiles. Unlike traditional static analyses, this study provides granular, time-sensitive insights that enable precise traffic management strategies, such as adaptive signal control and parking optimization, to alleviate congestion around scenic spots in small towns. The findings offer a robust framework for addressing traffic challenges in tourism-dependent small towns, bridging gaps in existing literature on dynamic traffic flow modeling.*

Keywords: *Traffic Flow, K-Means Clustering, Genetic Algorithm (GA)*

1. Introduction

The analysis of traffic flow dynamics around scenic spots has gained critical importance amid the global surge in tourism demand. Early studies established foundational frameworks through predictive traffic volume models, exemplified by the ESE Gravity Model[1]. Subsequent advancements incorporated machine learning techniques, including deep learning models for traffic correction[2], LSTM networks augmented by Markov state descriptions[3], lightweight finite-data-driven approaches[4], and spatiotemporal networks for short-term forecasting[5]. These contributions collectively advanced the comprehension of spatiotemporal traffic patterns.

Concurrently, technological innovations in traffic detection have emerged, such as smart traffic light systems leveraging real-time vehicular monitoring[6] and optimized YOLO-based algorithms for vehicle detection[7,8]. These innovations enhance the precision and granularity of traffic flow analysis.

Analytical frameworks for traffic optimization have also been developed, encompassing crowdsourced ITS data applications[9], signal control algorithms to mitigate vehicle queue times[10], and systematic reviews of vehicular connectivity challenges[11]. Despite these efforts, the literature has largely overlooked the distinct traffic patterns of small towns experiencing seasonal tourist influxes[12]. While K-means clustering has been utilized for urban traffic segmentation, its applicability to temporal periodicity analysis around scenic spots remains underexplored.

This paper addresses this research gap by proposing a K-means-based temporal segmentation framework to dissect traffic flow dynamics in small-town tourist areas, thereby bridging predictive modeling with adaptive traffic management strategies.

The empirical analysis in this study is based on data from the Mathematical Contest in Modeling (MCM) organized by the China Society for Industrial and Applied Mathematics (https://www.mcm.edu.cn/).

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2. Time Period Division Based on the K-means Algorithm

2.1 Traffic Volume Calculation

The traffic volume is defined as the number of vehicles passing through a certain road segment within a unit of time. Over a specific period, the number of vehicles passing through a particular point on a highway can be calculated using the following formula:

$$Q = \frac{N}{\Delta t} \tag{1}$$

Wherein, N represents the number of vehicles passing through a certain intersection, and Δt denotes the time interval.

2.2 Time Period Division for April Based on Clustering Algorithm

In this study, traffic flow data representative of weekdays and weekends in April were analyzed. The dataset provides comprehensive records of the time and direction of vehicles passing through intersections. Initially, the time field in the dataset was converted to an hourly granularity to enable a more detailed hourly analysis of traffic flow.

The primary objective was to discern the inherent characteristics of different time periods and segment the 24-hour day into distinct clusters. Clustering algorithms are well-suited for grouping time periods with similar traffic characteristics, facilitating a nuanced understanding of traffic patterns. In this study, the classic K-means clustering algorithm was employed to cluster the extracted data.

To determine the optimal number of time period clusters (K value), the Elbow Method was utilized. The Elbow Method operates on the principle that as the number of clusters (K) increases, the partitioning of samples becomes more refined, and the Sum of Squared Errors (SSE) gradually decreases. The relationship between SSE and K forms an elbow-shaped curve, with the K value corresponding to the elbow representing the true number of clusters in the data. The SSE is calculated as follows:

$$SSE = \sum_{(i=1)}^{k} \sum_{c \in C_1} |p - m_i|^2 \tag{2}$$

Where C_i is the i-th cluster, p represents all sample points in cluster C_i, and mi is the centroid of cluster C_i (the mean of all samples in C_i). According to the Elbow Method, as K increases, SSE gradually decreases and then stabilizes. The inflection point in the SSE decrease curve is identified as the optimal number of clusters.

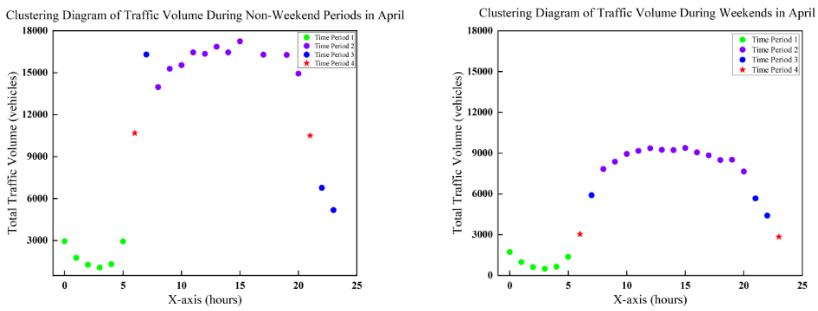

Figure 1 K-means Clustering Effect Diagram

By applying the Elbow Method, it was determined that the optimal number of clusters for the best clustering effect is 4. The visualization of the clustering effect is shown in Figure 1.

2.3 Description of Traffic Flow During Weekend Time Periods in April

Finally, by calculating the Euclidean distances between traffic flows during different time periods to assess their similarity, the hours of the day were divided into time periods with similar traffic flow characteristics. Based on the clustering results, a total of four distinct time periods were identified for the weekends from April 8th to April 21st, 2024, along with the hours they encompass, as shown in Table 1:

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Table 1 Clustering Results for Weekend Time Periods from April 8th to April 21st, 2024

Time Period Number	Included Hours
Time Period 1	0, 1, 2, 3, 4, 5
Time Period 2	8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20
Time Period 3	7, 21, 22
Time Period 4	6, 23
Time Period Number	Included Hours

Note: Here, "0" represents 0:00-1:00, "1" represents 1:00-2:00, and so on.

Based on the clustering analysis results, the traffic flow characteristics during different time periods of a weekend day from April 8th to April 21st, 2024, are as follows:

(1)Time Period 1: [0, 1, 2, 3, 4, 5]

This period includes late night to early morning, with low traffic flow and similar characteristics, making it suitable for analysis as a single unit.

(2)Time Period 2: [8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]

This period covers most of the daytime, including the morning peak, midday, and evening peak, with high and complex traffic flow variations. A longer time period is needed to capture these changes.

(3)Time Period 3: [7, 21, 22]

This period includes the morning peak and evening peak, marking the beginning of increased traffic flow, with distinct peak characteristics.

(4)Time Period 4: [6, 23]

This period includes the end of the early morning and the beginning of late night, with traffic flow decreasing again, similar to Time Period 1 but with subtle differences.

Finally, by calculating the average traffic flow for each time period during the weekends in April, descriptive statistics were performed on the distribution of traffic flow for different phases across different time periods. The results are shown in Figure 2:

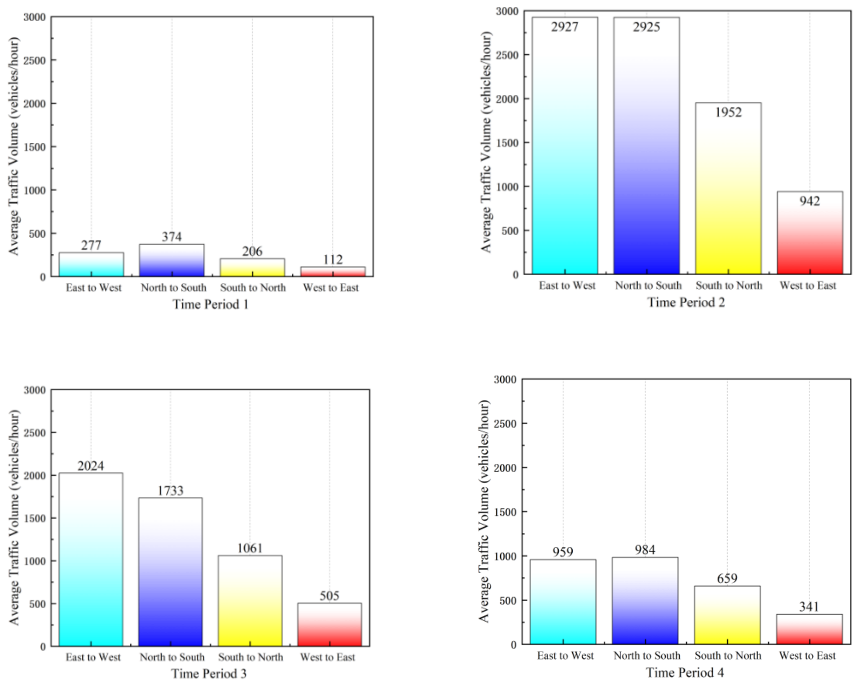

Figure 2 Traffic Flow Statistics for Four Time Periods and Four Phases During Weekends from April 8th to April 21st, 2024

(1)Time Period 1: [0, 1, 2, 3, 4, 5]

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Characteristics: Low traffic flow, especially in the west-to-east direction, with small variations in traffic flow across all directions. Overall, traffic is relatively stable, consistent with off-peak characteristics.

(2)Time Period 2: [8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]

Characteristics: Significant increase in traffic flow, with east-to-west and north-to-south directions approaching 3000 vehicles, showing strong commute peak characteristics. There are large differences in traffic flow across directions, with east-to-west and north-to-south being the main traffic flows and west-to-east traffic being relatively low.

(3)Time Period 3: [7, 21, 22]

Characteristics: Although traffic flow is high, it is lower than during the daytime peak, especially in the south-to-north and west-to-east directions. These time points reflect the transition period between traffic peaks, with still significant traffic volume but not as high as during the daytime peak.

(4)Time Period 4: [6, 23]

Characteristics: Low traffic flow, especially in the west-to-east direction. This is the off-peak period in the early morning and late night, with overall sparse traffic, consistent with the characteristics of early morning and late night low-traffic periods.

2.4 Description of Traffic Flow During Non-Weekend Time Periods in April

During the weekdays from April 8th to April 21st, 2024, the time period differentiation followed the same method as described above, utilizing K-means clustering to identify four distinct time periods and the hours they encompass.

Ultimately, based on the clustering results, four different time periods were identified for the weekdays from April 8th to April 21st, 2024, along with the hours they include, as shown in Table 2:

Table 2 Clustering Results for Weekday Time Periods from April 8th to April 21st, 2024

Time Period Number	Included Hours
Time Period 1	0, 1, 2, 3, 4, 5
Time Period 2	7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 20
Time Period 3	22, 23
Time Period 4	6, 21
Time Period Number	Included Hours

Note: Here, "0" represents 0:00-1:00, "1" represents 1:00-2:00, and so on.

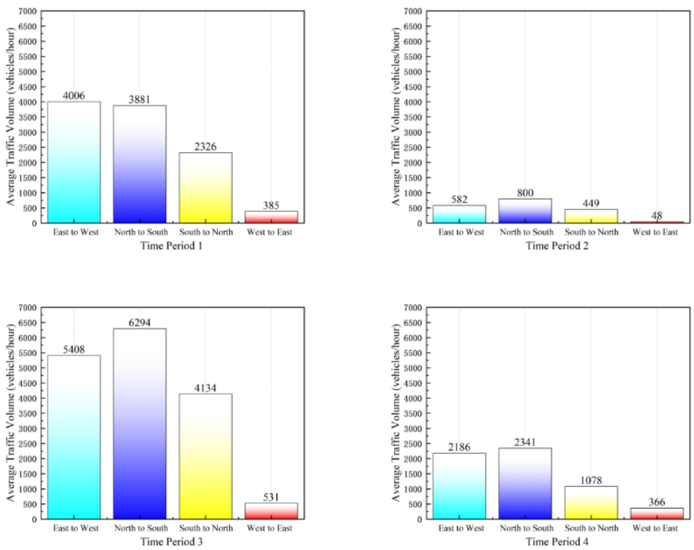

Figure 3 Traffic Flow Statistics for Four Time Periods and Four Phases During Weekdays from April 8th to April 21st, 2024

From the table, we can observe:

(1)Time Period 1: [0, 1, 2, 3, 4, 5] and Time Period 3: [22, 23] exhibit relatively low traffic flow, which is associated with reduced travel during nighttime on non-weekends.

(2)Time Period 2: [7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 20] represents the peak hours of the day, with a significant increase in traffic flow, coinciding with people's daily commutes and peak activity periods.

(3)Time Period 4: [6, 21] also shows relatively high traffic flow, albeit slightly lower than Time Period 2, which is related to the morning and evening commute peaks.

Finally, by calculating the average traffic flow for each time period during the weekdays in April, descriptive statistics were performed on the distribution of traffic flow for different phases across different time periods. The results are shown in Figure 3.

3. Statistics on Turning and Through Traffic Flow by Phase

3.1 Turning and Through Traffic at Each Phase During Weekends in April

Based on the previous analysis, we have obtained the traffic flow for all four phases within four different time periods. Subsequently, we selected all traffic flow data from the intersection of Jingzhong Road-Weizhong Road and its four adjacent intersections for analysis, namely: Weizhong Road-Scenic Area Entrance/Exit, Jingzhong Road-Weiyi Road, Jingzhong Road-Huannan Road, and Jingsan Road-Weizhong Road. Vehicles that appeared repeatedly within adjacent time periods and maintained the same phase when passing through two intersections were considered as through traffic, while those with inconsistent phases were considered as turning traffic (including left turns, right turns, and U-turns).

The calculation results are presented in Table 3:

Table 3 Proportions of Through and Turning Traffic During Rest Days from April 8th to April 21st, 2024, by Time Period

Time Period	Phase	Through Traffic Count	Turning Traffic Count	Through Traffic Proportion	Turning Traffic Proportion
Time Period 1	East-West	1	0	100.00	0.00
	North-South	1736	2475	41.23	58.77
	South-North	1315	1930	40.52	59.48
	West-East	3	37	7.50	92.50
Time Period 2	East-West	29	16	64.44	35.56
	North-South	36787	47623	43.58	56.42
	South-North	22985	39489	36.79	63.21
	West-East	6	29	17.14	82.86
Time Period 3	East-West	6	3	66.67	33.33
	North-South	4188	6464	39.32	60.68
	South-North	3214	4764	40.29	59.71
	West-East	0	1	0.00	100.00
Time Period 4	East-West	0	0	0.00	0.00
	North-South	1458	2366	38.13	61.87
	South-North	1163	1540	43.03	56.97
	West-East	1	1	50.00	50.00

Note: The "Through Traffic Proportion" and "Turning Traffic Proportion" are rounded results.

(1)Time Period 1: [0, 1, 2, 3, 4, 5]

During this stage, traffic flow is at a relatively low level. Northbound traffic is primarily through traffic, accounting for 41.23%, while turning traffic accounts for 58.77%, initially revealing the beginning of the morning commute pattern.

(2)Time Period 2: [8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]

Traffic flow reaches its peak during this period. Northbound traffic consists of 43.58% through traffic and 56.42% turning traffic, indicating the stability and complexity of daytime traffic flow.

(3)Time Period 3: [7, 21, 22]

During the morning and evening peak hours, northbound traffic consists of 39.32% through traffic and

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60.68% turning traffic, indicating increased traffic mobility and more diverse travel directions during peak hours.

(4)Time Period 4: [6, 23]

During the late night to early morning period, traffic flow drops to its lowest level. Northbound traffic has nearly equal proportions of through and turning traffic, each accounting for 50%, reflecting the reduction in nighttime traffic activity and the balance in travel behavior.

3.2 Turning and Through Traffic at Each Phase During Non-Weekend Days in April

Similar to the previous analysis, vehicles that appeared repeatedly within adjacent time periods and maintained the same phase when passing through two intersections were considered as through traffic, while those with inconsistent phases were considered as turning traffic (including left turns, right turns, and U-turns). The calculation results are presented in Table 4:

Table 4 Proportions of Through and Turning Traffic During Weekdays from April 8th to April 21st, 2024, by Time Period

Time Period	Phase	Through Traffic Count	Turning Traffic Count	Through Traffic Proportion	Turning Traffic Proportion
Time Period 1	East-West	2	2	50.00	50.00
	North-South	3524	3692	48.84	51.16
	South-North	2317	3813	37.80	62.20
	West-East	0	1	0.00	100.00
Time Period 2	East-West	60	34	63.83	36.17
	North-South	75813	80730	48.43	51.57
	South-North	57088	76884	42.61	57.39
	West-East	10	102	8.93	91.07
Time Period 3	East-West	3	3	50.00	50.00
	North-South	3312	3741	46.96	53.04
	South-North	2474	4692	34.52	65.48
	West-East	2	2	50.00	50.00
Time Period 4	East-West	7	5	58.33	41.67
	North-South	5659	6229	47.60	52.40
	South-North	3986	6418	38.31	61.69
	West-East	2	5	28.57	71.43

Note: The "Through Traffic Proportion" and "Turning Traffic Proportion" are rounded results.

(1)Time Period 1: [0, 1, 2, 3, 4, 5]

During this stage, road traffic flow is generally low, and the distribution of through and turning behaviors is relatively balanced. Particularly in the east direction, the proportion of through traffic is higher, indicating that vehicles tend to follow straight paths during this time.

(2)Time Period 2: [7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 20]

During this period, traffic flow increases significantly, with a particular concentration of traffic in the north direction, where both through and turning behaviors are frequent. The proportion of through traffic in the north direction is slightly lower than that of turning traffic, which may reflect the complexity of traffic dynamics during the daytime peak hours and the diversity of vehicle travel directions at intersections.

(3)Time Period 3: [22, 23]

During this stage, traffic flow remains at a low level, with the proportion of through traffic slightly higher than that of turning traffic, similar to Time Period 1, but with overall lower traffic volume, indicating reduced road traffic activity during late-night hours.

(4)Time Period 4: [6, 21]

During this stage, traffic flow is at a moderate level, with a relatively balanced distribution of through and turning behaviors, although the proportion of turning traffic is slightly higher, which may be related to the traffic flow patterns during specific time periods.

4. Conclusions

This study utilized principal component analysis (PCA) and K-means clustering to explore temporal traffic patterns around a scenic area in a small town. PCA reduced data dimensionality, revealing underlying traffic trends, while K-means clustering categorized time periods based on traffic characteristics. Key findings indicate pronounced traffic flow variations: low, uniform traffic during late-night to early-morning hours versus high, directionally diverse traffic during peak daytime. Weekday and weekend traffic also differed, with distinct through-to-turning traffic ratios across time periods.

However, the study has limitations. The limited data collection window may constrain generalizability, and external factors like weather and tourism policy changes were not fully considered.

Future research should expand data collection across seasons and years and integrate external influences for a more comprehensive traffic analysis. Advanced machine learning, such as deep learning, could enhance traffic prediction accuracy. Practically, traffic management could adopt dynamic signal control strategies and optimized parking plans based on our findings, aiming to alleviate congestion and foster a sustainable urban traffic system.

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