



## Analysis of traffic flow, volume and speed of vehicles in a selected urban area: Prague case

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### ABSTRACT

The dynamic growth of cities and rising mobility demand create major challenges in road traffic management, including congestion, accidents, and environmental impacts. Intelligent Transport Systems (ITS) support monitoring, analysis, and optimization of traffic, but weather conditions remain a significant factor influencing vehicle speed, density, and flow. This study analyzes the impact of weather on traffic dynamics in Prague, focusing on changes in intensity, average speed, and density. Data from traffic detectors on a key road section, collected between October 3–10, 2022, enabled comparisons across different times of day and week. Q-V-K (flow–speed–density) macroscopic modeling, where Q denotes traffic flow (volume), V average vehicle speed, and K traffic density, was applied to identify traffic patterns and their correlation with weather. The results show that rainfall and reduced visibility significantly decrease average vehicle speed and increase congestion. Clear differences between weekdays and weekends were also observed: weekdays show higher intensity during rush hours, while weekends have generally lower volumes. The findings provide practical insights for transport planners and decision-makers. They highlight the importance of integrating weather factors into traffic management strategies and ITS design. Moreover, the study emphasizes the value of long-term data analysis and predictive technologies, such as artificial intelligence and machine learning, to enhance urban transport efficiency and safety.

**Keywords:** traffic flow, weather on traffic dynamics, intelligent transport systems (ITS), modern cities, Q-V-K modelling.

### INTRODUCTION

Modern cities worldwide face growing challenges related to traffic management resulting from the dynamic development of urbanization [1–3], the increase in the number of vehicles [4–6], and the growing demand for mobility [7–9]. Traffic congestion [10–12], increased number of road accidents [13–16], and intensification

of exhaust emissions [17–20] are problems that affect not only the efficiency of transport but also residents' quality of life [21–23]. The issue of road accidents has been the subject of many scientific works, for example [24–26]. The challenge for city administrations and transport infrastructure designers is to develop effective strategies that will allow for sustainable and safe traffic

management [27] in the face of increasing pressure on existing transport systems [28–30].

In addition to problems related to traffic congestion and the environmental impact of transport, road safety is one of the most significant challenges facing modern transport systems. According to European statistics, the Czech Republic records hundreds of fatalities every year, with a high fatality rate that exceeds the long-term goals of the EU's Vision Zero strategy. It should be noted that this situation has gradually improved over the past few decades. However, the high rate of road accidents persists due to speeding, heavy traffic, and unfavorable weather conditions.

In the context of Central Europe, it is particularly important to link congestion problems with road safety and environmental conditions. National data indicate that the Czech Republic continues to suffer relatively high levels of road accident fatalities compared to the EU average, as confirmed by regular reports from European and international institutions. For example, national and European road safety profiles emphasise the need for systemic measures and better risk management in road traffic, including in urban areas [31].

Published studies indicate that unstable traffic and sudden changes in traffic flow increase the risk of road accidents, particularly rear-end collisions and traffic jams. Therefore, taking into account traffic parameters and weather conditions can, on the one hand, contribute to more efficient traffic management and, on the other hand, reduce the number of road accidents.

One of the key tools supporting modern road traffic management is intelligent transport systems (ITS) [32–34]. ITS include a wide range of technologies, such as traffic detectors [35–37], traffic light management systems, as well as real-time data analysis algorithms [38–41]. Thanks to these solutions, it is possible to monitor, analyze and optimize road traffic in a way that is adapted to dynamically changing conditions [42–44]. The implementation of ITS not only improves traffic flow and reduces travel times, but also contributes to reducing the negative impact of transport on the environment by reducing greenhouse gas emissions [45–47].

In the context of modern transport solutions, the analysis of data from traffic detectors has become a key element enabling a better understanding of road user behavior and identification of the main problems related to road capacity, traffic density and vehicle speed [48–51]. This

data is the basis for designing more efficient infrastructure and creating forecasts supporting traffic management in cities [52–55].

For this reason, the integration of weather data with ITS data is justified from the perspective of both capacity efficiency and road safety, and analyses based on Q-V-K relationships can be a practical component of operational decision support (e.g. traffic control, driver warning, dynamic speed limits) [56, 57].

At the same time, traffic engineering literature indicates that meteorological factors (precipitation, fog, reduced visibility, temperature changes) affect drivers' speed choices and behaviour, influencing traffic flow parameters: volume (Q), speed (V) and density (K) [31, 58–60].

In the study presented in this paper, the Q-V-K model addresses the classic macroscopic relationship between traffic volume (Q), average vehicle speed (V), and traffic density (K). These three parameters are fundamental variables in traffic flow theory and describe the quantitative interdependence of vehicles traveling on a specific road section [61, 62].

An important aspect of such analyses is the consideration of external factors, such as weather conditions, which can significantly affect the behavior of road users and the efficiency of transport systems [63–65].

Weather conditions, such as rainfall, fog or temperature changes, can have a significant impact on road traffic [66–68]. Slippery road surfaces, limited visibility or reduced vehicle traction lead to reduced speed, increased risk of accidents and reduced transport efficiency [69–71]. Therefore, the inclusion of weather analysis in road traffic studies is crucial to ensure accurate results and proper infrastructure planning [72, 73].

An analysis of national police statistics reveals that a significant proportion of road accidents in the Czech Republic are caused by limited visibility, rainfall, or slippery roads. These factors directly impact drivers' speeds, braking distances, and traffic flow stability. Therefore, analyzing the relationships among speed, traffic volume, and flow parameters under changing weather conditions is not only important for efficiency but also a key aspect of road safety.

The primary objective of this study is to examine the influence of weather conditions on urban traffic dynamics, with a particular focus on changes in vehicle speed, density, and traffic volume. The analysis was based on data from

traffic detectors that recorded parameters in real-time, combined with meteorological information, including precipitation, fog, and temperature changes. The study was conducted on a selected, key road section in Prague, allowing for the mapping of both daily and weekly mobility patterns.

This paper investigates the influence of weather factors on road traffic dynamics in urban conditions. In particular, it analyzed how rainfall, temperature changes, and other atmospheric variables affect vehicle speed, traffic density, and traffic intensity in the selected research area. These studies were based on data analyzed by traffic detectors, which allowed for identifying traffic patterns in different weather conditions.

The applied research approach combines technological analysis with practical application of the results in designing traffic management strategies [74, 75].

A key goal of the study is to provide practical guidance for decision-makers and transport planners on incorporating weather factors into urban planning and the design of traffic management systems. The authors emphasize the need to integrate meteorological variables with ITS. Furthermore, they highlight the potential of using predictive technologies, such as artificial intelligence and machine learning, in optimizing urban transport.

The ultimate goal of the research is not only to diagnose current traffic conditions but, above all, to seek innovative solutions that can influence the efficiency and safety of urban transport systems, while also meeting the objectives of sustainable development policies.

The authors' research is not limited to a general description of urban transport dynamics. Its primary goal is to deliver results applicable to the real-world conditions across the entire region. It should be noted that in large Central European cities such as Prague, Warsaw, and Budapest, the number of cars and the overall demand for urban mobility have increased significantly over the past few decades. Furthermore, many of these cities have a compact, historical urban structure, which, in practice, hinders significant expansion of road infrastructure. This contributes to traffic congestion and a decline in average travel speeds. Therefore, analyzing the efficiency of transport systems is essential for planning and implementing sustainable mobility strategies in the region. The case of Prague provides a good example of determining typical traffic patterns in Central European cities using empirical data, especially

regarding the relationships among traffic volume, vehicle speed, and traffic density.

The results of the analyses are aimed not only at improving transport efficiency but also at increasing the safety of road users and minimizing the impact of transport on the environment. In the growing demand for sustainable urban infrastructure development, these studies provide valuable advice for designers, urban planners, and decision-makers responsible for planning transport systems in modern agglomerations. Through a detailed analysis of road traffic parameters in different weather conditions, this paper contributes significantly to understanding the impact of external factors on the efficiency of transport systems while providing practical guidelines for traffic management in a dynamically changing urban environment.

## RESEARCH METHODOLOGY

This paper adopts a classic, macroscopic approach to traffic flow described by three variables: traffic volume ( $Q$ ), average vehicle speed ( $V$ ), and traffic density ( $K$ ). The Q-V-K framework is based on the fundamental relationship of traffic flow theory:

$$Q = K \cdot V \quad (1)$$

where:  $Q$  – traffic flow (vehicles per hour),  $K$  – traffic density (vehicles per unit length),  $V$  – average speed (km/h).

This macroscopic formulation enables consistent interpretation of the relationships between congestion, speed reduction, and flow variability.

Data was collected using traffic detectors (R520302-S1 and R520302-S2) placed on a key road section in Prague (Czech Republic) from October 3 to 10, 2022. These detectors provided information on vehicle flow, speed and traffic density on the study days. The analysis covered a full week, which allowed for the assessment of the variability of traffic indicators at different times of the day and week.

After data collection, preliminary verification was carried out to eliminate errors and anomalies. The data was compared with the results of visual observations and information from other sources. Then, a data smoothing process was applied using a time window of 60 minutes, which allowed for the removal of short-term fluctuations and provided a more accurate analysis.

The analysis of atmospheric conditions was carried out based on weather data collected on the study days (October 3–10, 2022) (Figure 1). These data indicate moderate weather conditions with light rainfall on Monday. Temperatures ranged between 3 °C and 17 °C, which could affect traffic variability. In particular, conditions such as rainfall and fog could contribute to reduced vehicle speeds and increased traffic density.

Q-V-K modeling was used to analyze the data [76–78]. The key objective was to understand the impact of weather conditions on vehicle flows and identify traffic patterns [79, 80]. Particular attention was paid to comparing data from weekdays and weekends in order to capture traffic dynamics on different days of the week [81–84].

The study period chosen by the authors (October 3–10, 2022) covered a whole week (Monday–Sunday). This allowed for a comparative analysis of weekday and weekend traffic under similar road and organizational conditions. Furthermore, the short, continuous time window limited the impact of seasonality, long-term roadworks, and significant changes to traffic management. This pilot study aimed to validate the QVK model in real-world urban conditions. The study focused primarily on determining how short-term weather changes may affect traffic, and did not include long-term seasonal trends.

The short observation period (seven consecutive days) was deliberately chosen to maintain methodological consistency and focus on short-term weather effects, without assessing the impact of seasonal variability. It should also be emphasized that the obtained results do not allow for the determination of long-term road traffic behavior. The authors of the paper propose that future research should cover a more extended measurement period (e.g., several months to a year) to account for seasonal changes, extreme weather conditions, and larger structural changes in society’s mobility.

## Q-V-K MODELING IN URBAN CONDITIONS

The authors use an analytical approach based on the Q-V-K (speed-density-traffic volume) model, highlighting its potential as a tool for precisely examining traffic dynamics under variable weather conditions (Formula 1) [58–60]. The Q-V-K model enables the quantitative analysis of basic traffic parameters and their relationships, making it particularly useful in studies of varying traffic volumes and flows, which depend on the time of day and day of the week [85–87]. The fundamental problem the authors highlight is the insufficient consideration of weather conditions in currently used traffic management systems. It should be emphasized that factors such as precipitation, limited visibility, and temperature drops significantly influence driver behavior, traffic density, and average vehicle speeds. Applying the Q-V-K model enables the assessment of these factors and provides a basis for designing traffic management strategies tailored to changing weather conditions. Therefore, according to the authors, the proposed approach is necessary for ITS. Furthermore, it should be emphasized that contemporary predictive modeling, based on artificial intelligence and machine learning methods, provides the foundation for the development of a more effective and flexible road traffic management system. A significant advantage of the adopted methodology is its reliance on real-time data. This approach enables the ongoing identification of traffic problems, planning of appropriate interventions, and implementation of solutions that promote safety, sustainable development, and the convenience of urban mobility.

The Q-V-K model was chosen for its widespread and universal applicability to comprehensive road traffic analysis and its compatibility

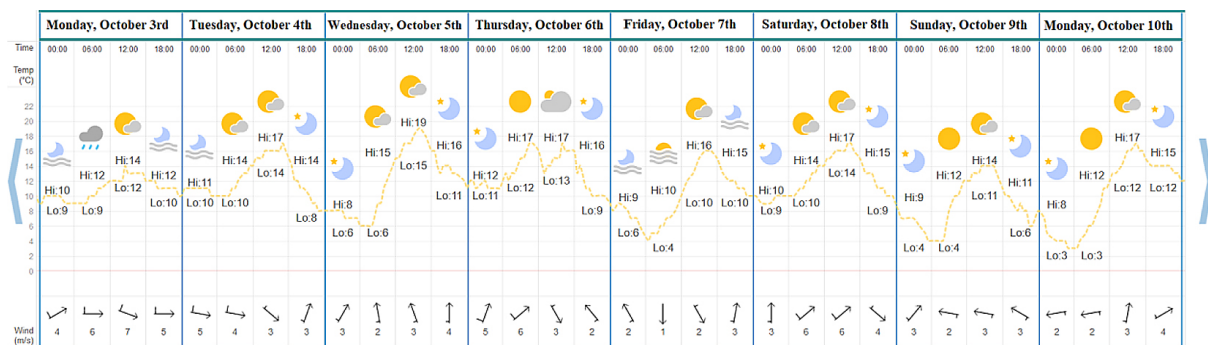


Figure 1. Weather for the study period

with data from urban traffic detectors. Compared to other, more complex microscopic or simulation approaches, the Q-V-K model enables clear interpretation of real-time traffic parameters and allows for integration with ITS.

The innovative nature of this study stems from combining the classic Q-V-K model with current meteorological data. Unlike many studies relying on advanced machine learning techniques for traffic forecasting (Chen et al., 2021; Avila and Mezić, 2020), this study fills a research gap in determining the relations between traffic volume, speed, and density as they behave under short-term changes in environmental conditions based on empirical data.

The main scientific achievements of this study include:

- empirical validation of the Q-V-K relationship under variable atmospheric conditions
- quantitative analysis of the velocity-density-flow relationship during rainfall
- demonstration that the Q-V-K model can provide a basis for further, predictive extensions based on artificial intelligence solutions in urban transport systems

The approach proposed by the authors combines classical macroscopic traffic theory with current variability in environmental conditions. It should be noted, however, that this model is still relatively rarely used in practical ITS implementations.

After acquiring data from traffic detectors, preliminary filtration was performed to eliminate potential inaccuracies. This stage is crucial for ensuring high-quality analytical data, which will

be the basis for further research. The collected data was verified in the context of their compliance with actual traffic conditions. For this purpose, visual observations were used, and the results were compared with those of other available sources of information. This verification process aims to increase the data's reliability and usefulness in the context of road traffic analysis [88–91].

The data from traffic detectors were subjected to advanced statistical analysis, aiming to identify key traffic parameters. The research was based on data from the urban area of Prague, where R520302-S1 and R520302-S2 detectors were used, located on Strakonická Street (section Na Plzeňce – Kotevní) (Figure 2). The road was designed for a maximum speed of 50 km/h and runs near the city center, playing a key role in the functioning of the agglomeration's transport system. The observations were conducted over one week, allowing representative data to be collected for further analysis. The selected observation time provided various traffic conditions, thus enabling a reliable assessment of parameters and their variability depending on the time of day and week.

Analyzing data from the detectors is an important step toward understanding road traffic dynamics in the urban area [92, 93]. The obtained results, based on a solid verification and analysis methodology, have the potential to contribute to the development of more effective traffic management strategies in the urban context.

Road data were used to conduct a detailed analysis of performance indicators and assess the effectiveness of the transport system. The study considered key road traffic parameters,

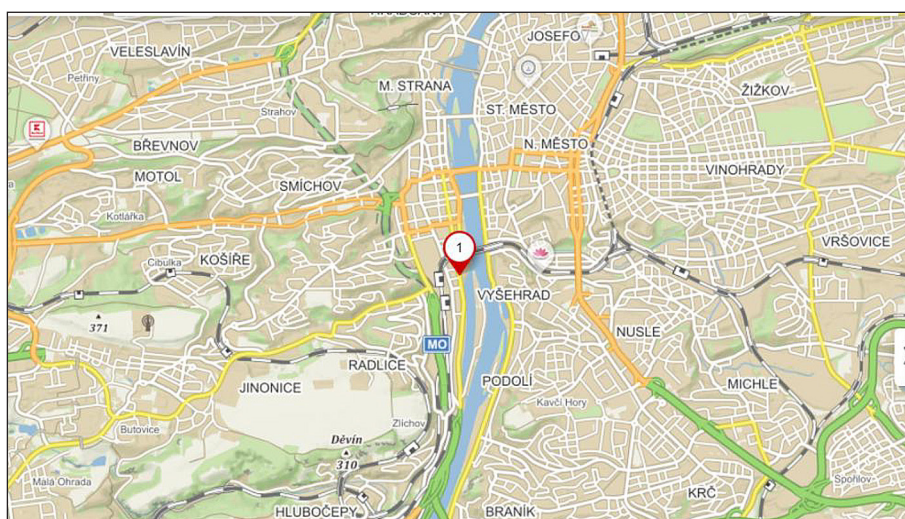


Figure 2. Location of detectors on the map of Prague

i.e., speed, density, and intensity (Q-V-K), which are the foundation of many transport phenomena models. Modeling of Q-V-K dependencies in urban conditions was extended to include additional factors characteristic of urbanized areas, such as traffic lights, intersection structure, and other road infrastructure elements. Particular attention was paid to the analysis of vehicle flow, which is a key indicator of the transport system's performance and reflects the intensity of traffic on a given road. Additionally, the impact of weather on the obtained results was examined.

As part of the study, detailed calculations were made regarding the flow for each lane based on the mathematical relationships presented in Formula 2. This approach allowed for obtaining precise results that can be the basis for further analysis and optimization of transport systems in the urban environment.

$$Q = \frac{N \text{ [vehicle n in time]}}{T \text{ [hour]}} \quad (2)$$

where:  $N$  – number of vehicles passing through a given section;  $T$  – time interval for the analyzed data.

The analysis of vehicle flows enabled the identification of characteristic patterns related to peak hours when the highest traffic volumes were recorded (Figure 3). Using data from different days of the week, significant differences in traffic volume were identified between weekdays and weekends. The obtained research results indicate

complex traffic dynamics, reflecting transport system users' daily and weekly activity cycles. Such observations provide valuable information on the variability of traffic volume, which is crucial for designing and optimizing traffic management strategies in the urban environment.

The second important indicator analyzed in the study was the weighted average speed of vehicles measured on the lanes. This value was calculated using precise mathematical methods in accordance with the relationship presented in Formula 3. The inclusion of the weighted average speed of vehicles allowed for the differentiation of traffic on the lanes, which provides a more complete picture of the efficiency of the transport system and allows for a more accurate interpretation of the dynamics of road traffic in the analyzed area.

$$V = \frac{(Q_{R1} \cdot V_{R1} + Q_{R2} \cdot V_{R2})}{Q} \quad (3)$$

where:  $Q_{R1}$  – number of vehicles passing through the first lane;  $V_{R1}$  – speed of the analyzed vehicles passing through the first lane;  $Q_{R2}$  – number of vehicles passing through the second lane;  $V_{R2}$  – speed of the analyzed vehicles passing through the second lane;  $Q$  – total number of all vehicles passing through the tested section.

The application of the described method made it possible to obtain a representative image of the speed distribution for the entire analyzed road section, taking into account differences in

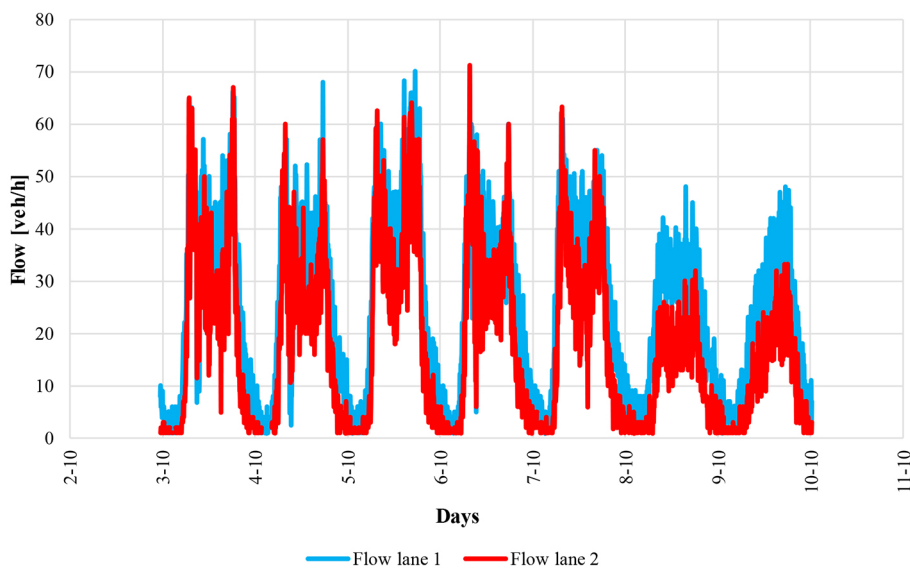


Figure 3. Weekly vehicles flow for two lanes of traffic

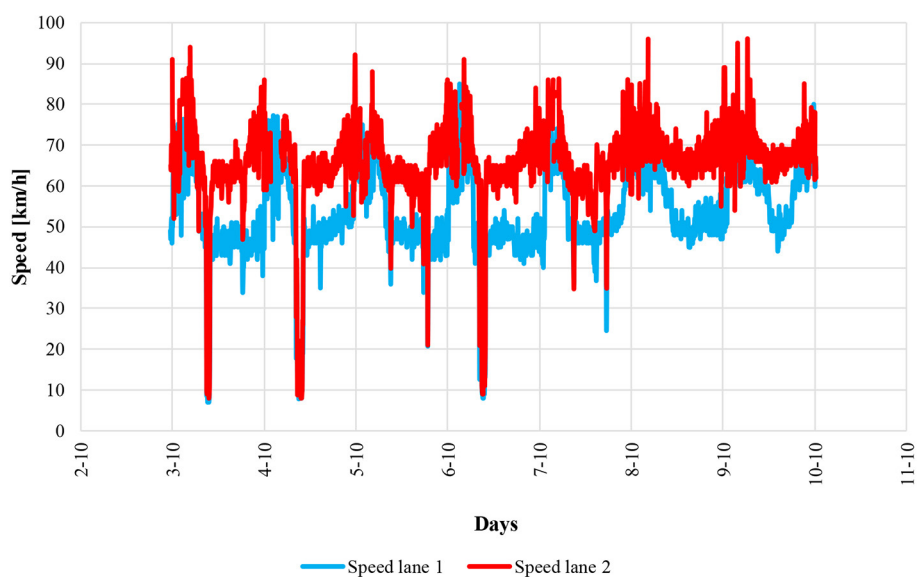


Figure 4. Weekly vehicle speed for two lanes of traffic

Table 1. Pearson correlation - weekly vehicle speed for two lanes of traffic

Parameter	Parameter	Flow lane 1	Speed lane 1	Flow lane 2	Speed lane 2
Flow lane 1	Pearson correlation	-	-0.4609	0.8960	-0.3421
	p-value	-	0.00	0.00	0.00
Speed lane 1	Pearson correlation		-	-0.4875	0.7472
	p-value		-	0.00	0.00
Flow lane 2	Pearson correlation			-	-0.4318
	p-value			-	0.00
Speed lane 2	Pearson correlation				-
	p-value				-

vehicle flow on individual lanes (Figure 4). The observed speed reduction during rush hours, resulting from increased traffic congestion, was in full compliance with the identified vehicle flow patterns. These results confirm the consistency of the analysis with actual road traffic conditions, which emphasizes the validity of the applied research approach.

Based on the correlation analysis (Table 1) between traffic parameters in the two observed lanes, several control parameters can also be applied. The presented Pearson correlation coefficient values are statistically significant (p-value  $\approx 0.000$ ), confirming the indicated significance and allowing interpretation with a non-primary probability. The results indicate a limited correlation between traffic access and speed in the same lane ( $r = -0.4609$  for lane 1 and  $r = -0.4318$  for lane 2), confirming the basic assumption of traffic control theory. In practice, this means that with

more vehicles traveling at a time when there is less space for free movement, the gaps between cars decrease, and additional entry becomes more frequent. This results in a decrease in average vehicle speed. Furthermore, considering that the numerical values are not extremely high, this is considered stable, but not very cumulative. Based on this, it can be assumed that the road section under investigation poses a threat to traffic congestion, which is physically harmful to the city, and that your capacity is insufficient to address it.

However, a robust positive correlation was observed between traffic volumes in both lanes ( $r = 0.896$ ). This indicates that vehicle flows are synchronized mainly, meaning that nearly parallel changes (load increases or decreases) occur in both lanes. Therefore, the analyzed road section constitutes a coherent system. Both lanes respond similarly to external factors, such as time of day, fluctuations in transport demand, and

weather conditions. The lack of significant differences in load levels between lanes confirms that the analyzed road section functions as a coherent vehicle flow system. Analyzing vehicle speeds, a strong positive correlation is observed between the speeds in both lanes ( $r = 0.7472$ ). Accordingly, vehicles slow down or accelerate in both lanes. This is most likely because both lanes are equipped with the same traffic lights, similar vehicle types use them, and the frequent occurrence of so-called braking waves in urban traffic. It should be noted, however, that the value of the coefficient is not equal to 1; it indicates minor, local differences, including, among others, momentary acceleration in one lane, lane changes by drivers, or other minor traffic disruptions.

Based on statistical analysis, it can also be concluded that there is a negative correlation between traffic volume in one lane and vehicle speed in the adjacent lane ( $r = -0.3421$  and  $r = -0.4875$ ). This relationship indicates that an increase in traffic volume in one lane reduces the average speed in the parallel lane, confirming the presence of inter-flow interactions and the lack of complete independence of flows. This phenomenon can be interpreted as the transfer of local traffic disturbances from one lane to another, which is characteristic of sections with limited capacity. Deteriorating traffic conditions (e.g., increased traffic volume) in one lane lead to secondary disturbances (e.g., reduced speed) in the adjacent lane, confirming the presence of coupling between lanes. The unequal strength of the correlation indicates asymmetry

in interactions between lanes, which may result from the cross-sectional geometry, the adopted traffic management, the location of merge and merge points, and the vehicle mix.

In a synthetic approach, the results confirm the basic relationship described in the Q–V–K model: as traffic volume (Q) increases, flow density (V) increases, leading to a decrease in speed (V). At the same time, the conducted research allows us to conclude that the analyzed road section does not function as two independent lanes, but as a single integrated flow. Changes in parameters in one lane affect traffic conditions in the adjacent lane. The empirical results obtained in real-world conditions are consistent with the classical assumptions of road traffic theory for urban environments.

The data was subjected to a smoothing process, which was performed using a time window of 60 minutes. This procedure allowed the removal of noise and fluctuations that may result from short-term traffic events or irregularities in traffic. Obtaining more stable data on flow and speed allows for a better understanding of general traffic trends, identification of peak hours, determination of seasonal and weekly changes, and comparisons between different periods (Figure 5).

Such analyses are important for making decisions on traffic management and planning actions to improve road capacity and travel comfort for users. Proper understanding and interpretation of data allows for more effective implementation of optimization strategies, which contributes to increasing the efficiency of the transport system in urban areas.

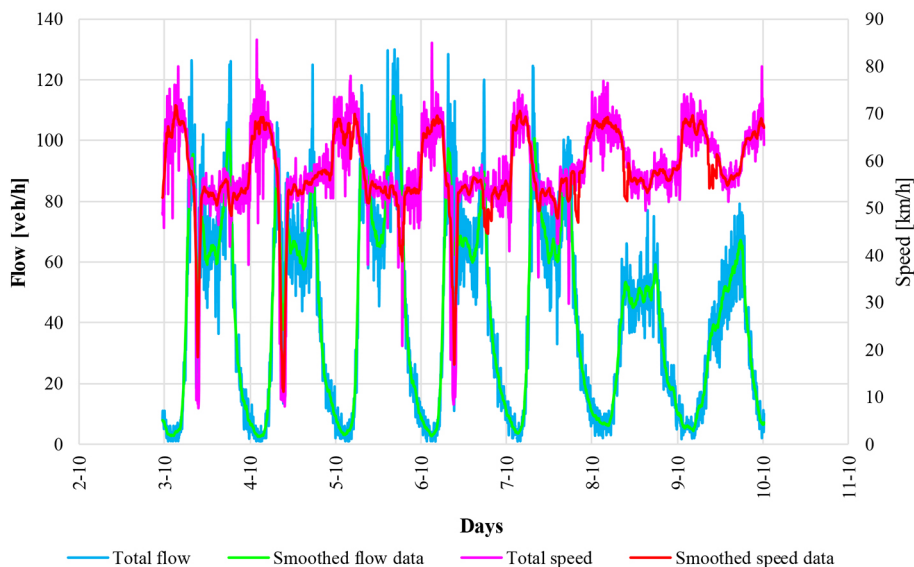


Figure 5. Weekly flow and vehicle speed chart

**Table 2.** Pearson correlation - weekly flow and vehicle speed

Parameter	Parameter	Total flow	Total speed	Smoothed flow data	Smoothed speed data	Day	Hour
Total flow	Pearson correlation	-	-0.4404	0.9630	-0.5373	-0.1753	0.2574
	p-value	-	0.00	0.00	0.00	0.00	0.00
Total speed	Pearson correlation		-	-0.4728	0.9012	0.2501	-0.3165
	p-value		-	0.00	0.00	0.00	0.00
Smoothed flow data	Pearson correlation			-	-0.5660	-0.1848	0.2658
	p-value			-	0.00	0.00	0.00
Smoothed speed data	Pearson correlation				-	0.2562	-0.3842
	p-value				-	0.00	0.00
Day	Pearson correlation					-	-0.0221
	p-value					-	0.324
Hour	Pearson correlation						-
	p-value						-

Table 2 presents the results of the Pearson correlation. The very high correlation between the original and smoothed data indicates that the applied smoothing arranges the time series without altering its overall course – it mainly removes short-term fluctuations. The moderate negative correlation between Total flow and Total speed ( $r = -0,45$  to  $-0,50$ ) accurately reflects the classic Q-V-K model relationship, i.e., as traffic volume increases, average speed decreases. This indicates conditions typical of urban traffic with increased density, but not yet reaching full critical capacity. The positive correlation between Total flow and Hour confirms that changes in traffic volume are strongly related to the circadian rhythm, particularly peak hours (e.g., commuting to and from work/school). In turn, the negative correlation between Total speed and Hour confirms that average speeds decrease significantly during peak hours, a direct result of increased road congestion. The weaker correlations with the Day variable indicate that differences between days are less significant than variation within a day. This indicates that the hourly cycle, rather than the inter-day cycle, has the greatest impact on traffic congestion.

There are some patterns observed. Vehicle flows are higher in the morning and afternoon and lower at night. This suggests peak traffic times when more vehicles are on the road, probably related to commuting to and from work. Lower flows during night hours may indicate lower traffic volumes at these times. There is an apparent

reduction in vehicle flows at weekends. This may be due to reduced travel for work, excursions, or school trips. There may be changes in traffic patterns due to changes in travel and social activity patterns at weekends. There are spikes in the opposite direction of the flow. This means that speeds are lower in the morning and during the day and increase at night. This pattern may be related to morning traffic jams, heavier traffic during the day, and more relaxed movement at night. Displaying the flow and speed data in a “Weekly Flow and Speed” histogram allows you to visualize how these parameters change over the week. The data presented in the histogram enables the identification of traffic patterns such as peak hours, flow and speed fluctuations, and other factors affecting road traffic. This allows for a better understanding of traffic dynamics and appropriate actions to be taken to optimize traffic management. The 24-hour timeline shows individual days in parallel, using smoothed data obtained in earlier stages of the analysis (Figure 6).

Table 3 presents the results of the Pearson correlation. Very high correlations between weekdays indicate a stable and repeatable daily traffic rhythm, confirming the systemic nature of urban mobility described in the study. Slightly lower correlation values for Monday compared to other weekdays indicate some partial differentiation, which may most likely result from increased travel intensity after the weekend break. Slightly lower values correlations between weekdays and

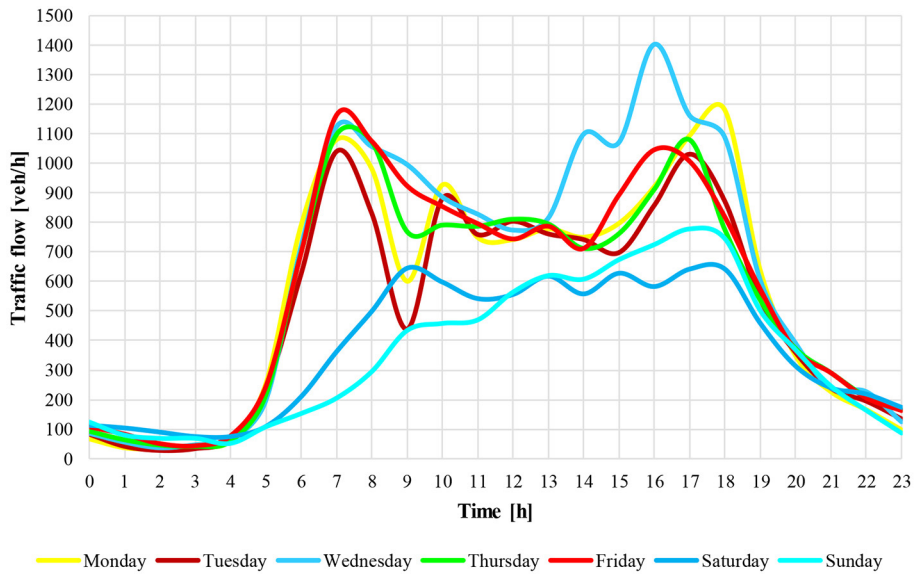


Figure 6. Traffic flow variability graph

Table 3. Pearson correlation - Traffic flow variability - days

Parameter	Parameter	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Monday	Pearson correlation	-	0.9813	0.9471	0.9636	0.9551	0.8539	0.7778
	p-value	-	0.000	0.000	0.000	0.000	0.000	0.000
Tuesday	Pearson correlation		-	0.9365	0.9706	0.9507	0.8523	0.7805
	p-value		-	0.000	0.000	0.000	0.000	0.000
Wednesday	Pearson correlation			-	0.9548	0.9707	0.8975	0.8241
	p-value			-	0.000	0.000	0.000	0.000
Thursday	Pearson correlation				-	0.9899	0.8600	0.7378
	p-value				-	0.000	0.000	0.000
Friday	Pearson correlation					-	0.8680	0.7357
	p-value					-	0.000	0.000
Saturday	Pearson correlation						-	0.9278
	p-value						-	0.000
Sunday	Pearson correlation							-
	p-value							-

weekends indicate a clearly variable vehicle flow pattern on Saturdays and Sundays. Reduced morning peaks and more dispersed traffic patterns are observed. The lowest coefficient values for Sundays compared to midweek days indicate the most distinct mobility profile. This indicates varying flows depending on the day of the week. The high statistical significance of all correlations indicates that the observed inter-day variability is structural and reproducible, not random. Regarding the

results presented in the article, the analysis confirms that the road section under study exhibits a precise weekly segmentation. This means that the day of the week should be treated as a significant explanatory variable in both the Q-V-K model and the solutions used in ITS systems. This also justifies conducting comparative analyses between weekdays and weekends, which are a key element of the adopted methodology and allow for capturing the actual variation in traffic patterns.

**Table 4.** Pearson correlation – traffic flow variability – hours

Parameter		Midnight	1 A. M.	2 A. M.	3 A. M.	4 A. M.	5 A. M.	6 A. M.	7 A. M.	8 A. M.	9 A. M.	10 A. M.	11 A. M.	Noon	1 P. M.	2 P. M.	3 P. M.	4 P. M.	5 P. M.	6 P. M.	7 P. M.	8 P. M.	9 P. M.	10 P. M.	11 P. M.
Mid-night	Pearson correlation		0.8810	0.8213	0.7466	0.1003	-0.7664	-0.8168	-0.7388	-0.6761	-0.0983	-0.8602	-0.7092	-0.7337	-0.7226	-0.5324	-0.3612	-0.4459	-0.7673	-0.8291	-0.7669	-0.1669	0.3182	0.0483	0.1811
	p-value		0.009	0.023	0.054	0.831	0.044	0.025	0.058	0.095	0.834	0.013	0.074	0.061	0.067	0.219	0.426	0.316	0.044	0.021	0.044	0.721	0.487	0.918	0.698
1 A. M.	Pearson correlation			0.9332	0.7948	0.4345	-0.7145	-0.7135	-0.6344	-0.5122	0.1285	-0.7090	-0.5931	-0.7298	-0.6629	-0.5248	-0.3099	-0.4485	-0.8001	-0.8056	-0.7468	-0.4383	0.3164	0.3211	0.4863
	p-value			0.002	0.033	0.330	0.071	0.072	0.126	0.240	0.784	0.074	0.160	0.063	0.105	0.227	0.499	0.313	0.031	0.029	0.054	0.325	0.489	0.483	0.269
2 A. M.	Pearson correlation				0.9382	0.2437	-0.8587	-0.8564	-0.8281	-0.7159	-0.1257	-0.8366	-0.7993	-0.8914	-0.8500	-0.6345	-0.5079	-0.6392	-0.9255	-0.7575	-0.8008	-0.6049	0.0432	0.1179	0.2889
	p-value				0.002	0.598	0.013	0.014	0.021	0.070	0.788	0.019	0.031	0.007	0.015	0.126	0.244	0.122	0.003	0.049	0.030	0.150	0.927	0.801	0.530
3 A. M.	Pearson correlation					0.0182	-0.9389	-0.9012	-0.9169	-0.8227	-0.2120	-0.8788	-0.8830	-0.9658	-0.8971	-0.4931	-0.4357	-0.5588	-0.8891	-0.5590	-0.6881	-0.5170	-0.2271	-0.0355	-0.0210
	p-value					0.969	0.002	0.006	0.004	0.023	0.648	0.009	0.008	0.000	0.006	0.261	0.328	0.192	0.007	0.192	0.087	0.235	0.624	0.940	0.964
4 A. M.	Pearson correlation						0.1540	0.0981	0.2043	0.2449	0.4225	0.2538	0.2167	-0.0149	0.0608	-0.1119	0.0868	-0.0176	-0.1878	-0.2325	-0.1180	-0.4596	0.2300	0.5690	0.7349
	p-value						0.742	0.834	0.660	0.597	0.345	0.583	0.641	0.975	0.897	0.811	0.853	0.970	0.687	0.616	0.801	0.299	0.620	0.182	0.060
5 A. M.	Pearson correlation							0.9487	0.9407	0.8772	0.3084	0.9294	0.8844	0.8841	0.8923	0.4157	0.4645	0.5298	0.8466	0.6282	0.7911	0.3605	0.2363	-0.0140	0.0516
	p-value							0.001	0.002	0.009	0.501	0.002	0.008	0.008	0.007	0.354	0.294	0.221	0.016	0.131	0.034	0.427	0.610	0.976	0.912
6 A. M.	Pearson correlation								0.9821	0.9617	0.5049	0.9590	0.9604	0.9195	0.9742	0.6234	0.6498	0.7055	0.9351	0.7185	0.8522	0.4664	0.2156	0.1631	0.0727
	p-value								0.000	0.001	0.248	0.001	0.001	0.003	0.000	0.135	0.114	0.077	0.002	0.069	0.015	0.291	0.642	0.727	0.877
7 A. M.	Pearson correlation									0.9768	0.5535	0.9552	0.9898	0.9446	0.9812	0.6170	0.6541	0.7137	0.9094	0.6068	0.7665	0.4788	0.3128	0.2863	0.2058
	p-value									0.000	0.197	0.001	0.000	0.001	0.000	0.140	0.111	0.072	0.005	0.148	0.044	0.277	0.495	0.534	0.658
8 A. M.	Pearson correlation										0.6835	0.9083	0.9779	0.8915	0.9676	0.6128	0.6959	0.7259	0.8719	0.5603	0.7372	0.4549	0.3980	0.3829	0.2992
	p-value										0.090	0.005	0.000	0.007	0.000	0.143	0.083	0.065	0.011	0.191	0.059	0.305	0.377	0.397	0.515
9 A. M.	Pearson correlation											0.4409	0.6239	0.3726	0.5932	0.6150	0.8303	0.7470	0.4541	0.2399	0.4058	0.4032	0.4628	0.7022	0.4355
	p-value											0.322	0.134	0.410	0.160	0.142	0.021	0.054	0.306	0.604	0.366	0.370	0.296	0.079	0.329
10 A. M.	Pearson correlation												0.9386	0.8765	0.9137	0.6175	0.5974	0.6527	0.8562	0.7190	0.8012	0.3081	0.0457	0.2273	0.1192
	p-value												0.002	0.010	0.004	0.140	0.157	0.112	0.014	0.069	0.030	0.501	0.923	0.624	0.799
11 A. M.	Pearson correlation													0.9402	0.9836	0.6914	0.7126	0.7713	0.9070	0.5859	0.7318	0.5156	0.3109	0.3993	0.2496
	p-value													0.002	0.000	0.085	0.072	0.042	0.005	0.167	0.062	0.236	0.497	0.375	0.589
Noon	Pearson correlation														0.9473	0.5940	0.5285	0.6461	0.9209	0.5264	0.6533	0.5706	0.3025	0.2339	0.1462
	p-value														0.001	0.160	0.223	0.117	0.003	0.225	0.112	0.181	0.510	0.614	0.754
1 P. M.	Pearson correlation															0.7168	0.7390	0.8049	0.9624	0.6542	0.8024	0.6176	0.3067	0.2775	0.1087
	p-value															0.070	0.058	0.029	0.001	0.111	0.030	0.139	0.504	0.547	0.817
2 P. M.	Pearson correlation																0.9056	0.9495	0.7683	0.7131	0.6809	0.7012	-0.1384	0.3948	-0.1786
	p-value																0.005	0.001	0.044	0.072	0.092	0.079	0.767	0.381	0.702
3 P. M.	Pearson correlation																	0.9792	0.7282	0.6370	0.7251	0.6998	0.1345	0.4089	-0.0578
	p-value																	0.000	0.064	0.124	0.065	0.080	0.774	0.362	0.902
4 P. M.	Pearson correlation																		0.8186	0.6681	0.7434	0.7839	0.1169	0.3790	-0.1007
	p-value																		0.024	0.101	0.055	0.037	0.803	0.402	0.830
5 P. M.	Pearson correlation																			0.7637	0.8605	0.7181	0.1551	0.0953	-0.1454
	p-value																			0.046	0.013	0.069	0.740	0.839	0.756
6 P. M.	Pearson correlation																				0.9378	0.3970	-0.4167	-0.2002	-0.5294
	p-value																				0.002	0.378	0.352	0.667	0.222
7 P. M.	Pearson correlation																					0.5093	-0.0952	-0.1583	-0.3826
	p-value																					0.243	0.839	0.735	0.397
8 P. M.	Pearson correlation																						0.3091	0.0531	-0.3087
	p-value																						0.500	0.910	0.501
9 P. M.	Pearson correlation																							0.3128	0.5853
	p-value																							0.495	0.167
10 P. M.	Pearson correlation																								0.7744
	p-value																								0.041
11 P. M.	Pearson correlation																								
	p-value																								

Table 4 presents the results of the Pearson correlation. Very high correlations between morning rush hours suggest that commutes are consistent and repetitive, confirming the observed traffic concentration at a specific time. A strong correlation was also observed in the afternoon hours, confirming that the second peak has a similarly structured and regular character. High correlations during night hours, despite low flow values, indicate stable free-flow traffic and low volume variability. Low correlations between night and peak hours indicate completely different operating conditions for the road system. The correlation structure confirms the division of the day into functional traffic phases and justifies the use of the Q-V-K model separately for these intervals, which was one of the main methodological assumptions of the article.

The pattern observed in the data analyzed is consistent with typical morning and afternoon peak hours when people travel to and from work or school. Lower traffic flows during night hours suggest lower road activity and reduced vehicle traffic. There are apparent weekly changes in traffic flows, with lower traffic flows on weekends than on weekdays. This pattern may be due to several factors, including fewer work-related trips, reduced school travel, and reduced weekend social activity. The observed lower traffic flows on weekends indicate changing travel patterns and varying demand levels for transport services during this period. Seasonal patterns also emerge from the data presented in Figure 7, which may be related to factors such as weather conditions,

school holidays, and Traffic congestion, as a measure of the number of vehicles per unit length of road plays a key role in assessing the efficiency of a transport system.

Calculating traffic congestion can be extremely useful in planning and assessing ongoing traffic performance for road infrastructure. To determine traffic congestion, you can use two key pieces of information: traffic flow ( $Q$ ) and vehicle speed ( $V$ ). According to the fundamental macroscopic relationship (Formula 1), traffic density ( $K$ ) can be expressed as (Formula 4):

$$K = \frac{Q}{V} \tag{4}$$

where:  $K$  – traffic density (vehicles per unit length),  $Q$  – traffic flow (vehicles per hour),  $V$  – average speed (km/h).

It should be noted, however, that the calculations are based on a simplified model that does not consider all the factors that affect road traffic. Differences in vehicle types, changing road conditions, and traffic flow variations at different times can significantly affect actual congestion (Figure 7). Therefore, the calculation results should be interpreted in the broader context of traffic efficiency analysis. This will allow for a more comprehensive understanding of traffic dynamics and better management decisions.

Figure 7 shows the changes in traffic congestion over time, considering the flow of vehicles at different speeds. When analyzing traffic

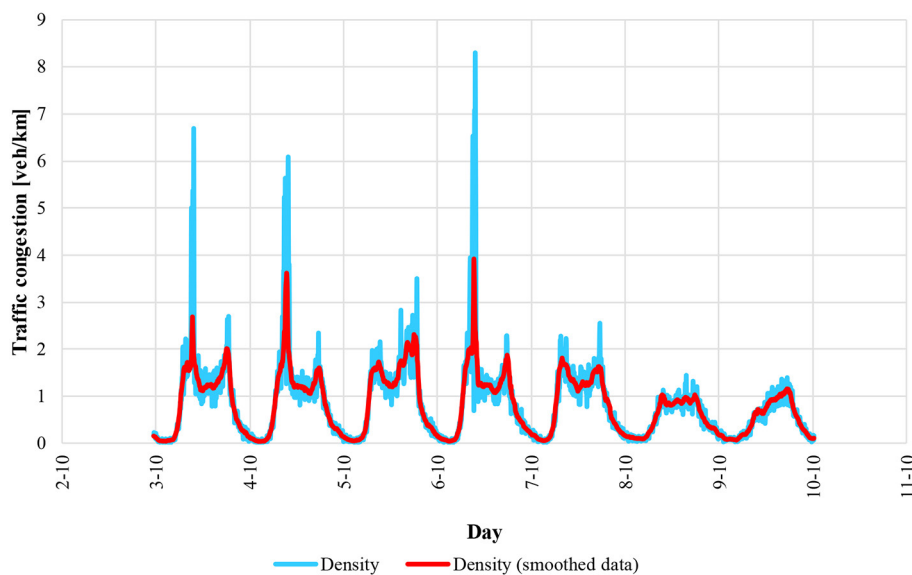


Figure 7. Weekly traffic congestion

**Table 5.** Pearson correlation - weekly traffic congestion

Parameter	Parameter	Density	Density (smoothed data)	Hour	Day
Density	Pearson correlation	-	0.8754	0.1626	-0.2123
	p-value	-	0.00	0.000	0.00
Density (smoothed data)	Pearson correlation		-	0.2265	-0.2273
	p-value		-	0.00	0.00
Hour	Pearson correlation			-	-0.0243
	p-value			-	0.277
Day	Pearson correlation				-
	p-value				-

congestion patterns, clear trends related to the flow dynamics can be seen.

Table 5 presents the results of the Pearson correlation. The very high agreement between the Density and Density (smoothed data) variables demonstrates that smoothing data does not distort the overall structure of traffic congestion, but merely facilitates trend analysis. This confirms the methodological validity of the approach used in this paper. The weak positive correlation between Density and Hour allows us to conclude that the main factor determining traffic volume is the time of day. This result confirms the importance of peak hours. The correlation between Density and Hour is lower but still significant. This indicates that there are differences in traffic volume between days, but their impact is smaller than that of daily variability. Correlation analysis indicates that urban traffic jams are cyclical and result more from circadian rhythms than from differences between individual days of the week. These conclusions support the central thesis adopted in the article, which states that the QVK model in urban environments should primarily consider time division by hour of the day, and only then by day of the week. The strong statistical confirmation of the correlation indicates that the observed traffic jams are not random, but rather result from repetitive mechanisms in the operation of the transportation system.

During the week, especially in the morning hours, a significant increase in traffic congestion

is observed. This is the effect of traffic intensity during rush hours, when people travel to work, schools, and other places of employment. In contrast to weekdays, weekends (Saturdays and Sundays) usually have lower traffic. The highest traffic congestion values occur on Wednesdays, as well as on Mondays and Tuesdays. These days, society is usually more focused on professional tasks, resulting in increased road traffic. Traffic congestion is a key indicator of the efficiency of the transport system. It is used to assess the road infrastructure’s effectiveness and plan future actions in this area (Table 6).

There is a strong positive correlation (0.78) between the percentage of road occupancy and the number of total vehicles and traffic density. This indicates that higher road occupancy leads to more vehicles and higher traffic density. A negative correlation (-0.65) between the percentage of road occupancy and average vehicle speed suggests that higher traffic congestion often leads to lower speeds (Figures 8, 9). Traffic congestion analysis provides valuable information for decision-makers and transport researchers, enabling a better understanding of road traffic dynamics.

In road traffic analysis, the key issue is the relationship between the percentage of traffic density and the average speed of all vehicles. Higher traffic density often leads to a lower average speed, which is important for understanding traffic dynamics and the efficiency of the transport

**Table 6.** Key statistical indicators for traffic congestion

Indicator	Average	Standard deviation
Road occupancy	2.62 [%]	2.73 [%]
Number of vehicles	24.82 [pieces]	16.54 [pieces]
Average vehicle speed	53.42 [km/h]	11.75 [km/h]
Traffic density	4.96 [vehicles/minute]	3.31 [vehicles/minute]

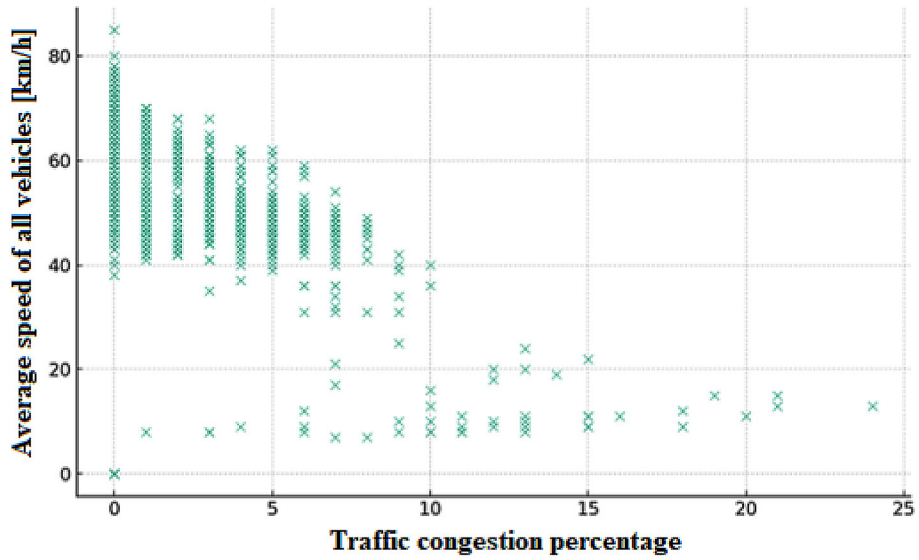


Figure 8. Relationship between traffic congestion and average speed

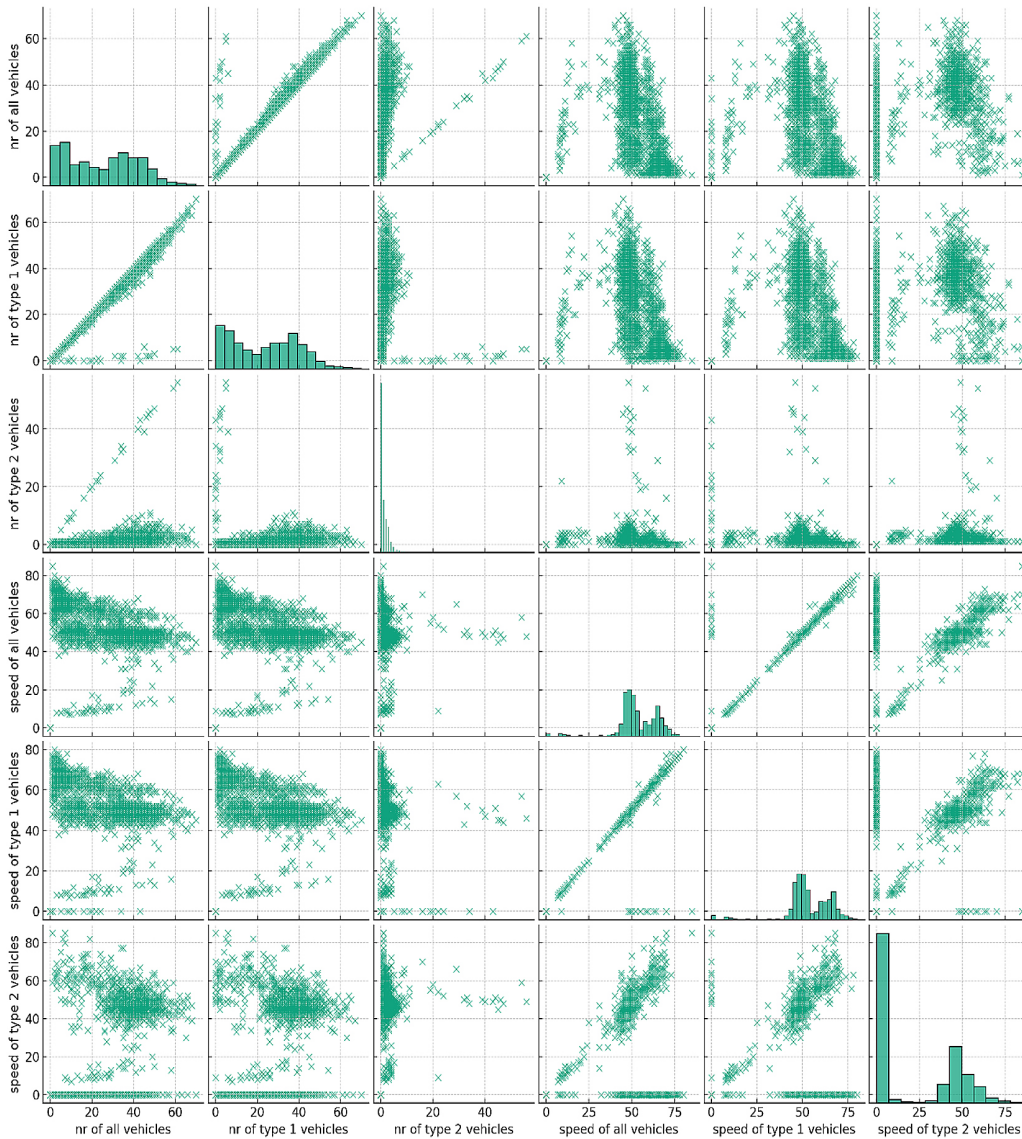


Figure 9. Influence of vehicle type (type 1 and type 2) on density

system [11, 93]. The analysis pays special attention to the number of vehicles of different types and their impact on the overall traffic statistics, such as speed or density. The analysis is based on data from the study area in the city of Prague, from detectors R520302-S1 and R520302-S2, which provide important information about the efficiency of the transport system.

The parameters Q-V-K are considered and are the basis of most road traffic models. Vehicle flow reflects the traffic density on the road and is an essential indicator of the efficiency of the transport system. The analysis reveals significant patterns related to rush hours when traffic volume reaches its highest values within 24 hours. Significant differences in traffic volume were observed between weekdays and weekends. On weekends, the traffic flow is lower, possibly due to fewer people traveling for work or education. Vehicle speeds were lower in the morning and during the day and increased during the night. Factors influencing these changes include morning traffic jams and higher daily traffic volumes. The data were subjected to a smoothing process, which allowed for obtaining more stable information on flow and speed, which is important for analyzing general traffic trends.

Traffic congestion calculated from the flow and speed of vehicles provided important information on the efficiency of the transport system [12, 94]. In the context of modern traffic management, the use of advanced models based on advanced forecasting techniques is a key element. There is a growing trend to focus on predictive models that use a wide range of data. In the context of making decisions about road infrastructure and traffic management, forecasting future values becomes essential. The research results reflect the current state of knowledge, indicating the importance of parameter analysis in the context of transport system efficiency. Further research in this area can contribute to a better understanding of road traffic dynamics and more effective transport infrastructure management.

In recent years, there has been a significant trend towards using predictive models in road traffic analysis. These models use a wide range of data, including traditional traffic measurements and data from telematics systems and sensors. The study using the **\*\*TRAFICAM CollectR\*\*** system illustrates how advanced analytical techniques can contribute to a better understanding and effective road traffic management. The study focused on a short-term traffic analysis covering seven days.

In order to understand how different geographical and urban conditions affect traffic dynamics, it was suggested that the study be extended to other regions or cities. Comparison of data from different areas can provide valuable insights into observed trends and the specifics of individual locations. The proposal to conduct a long-term analysis is crucial to consider changes in traffic flows during different seasons and differences between weekdays and weekends. Additionally, the analysis could include possible changes due to long-term urban and demographic trends, allowing for a more complete picture of road traffic dynamics. The study used standard data analysis methods. However, it is recommended that more advanced techniques, such as machine learning or multivariate analysis, be implemented to extract deeper relationships and patterns from the data. This approach can lead to a better understanding of road traffic dynamics and more effective management methods. Additionally, it is suggested that research be conducted focusing on the impact of different weather conditions, such as precipitation, temperature, visibility, etc., on traffic flow, safety, and driving efficiency. Understanding these relationships can improve road safety and optimize traffic management systems.

## DISCUSSION

The research indicates that weather conditions play a key role in shaping road traffic dynamics. Higher vehicle speeds and lower traffic density were recorded on dry days, characterized by higher visibility and better road grip. On the other hand, rainfall on Wednesdays and Saturdays significantly reduced speeds and increased vehicle density on the roads. This results from drivers' more cautious driving style, who adapt their behavior to the worsening road conditions. These data confirm that road traffic planning and management should consider weather variability integral to transport strategies.

The results indicate that weather conditions significantly influence the speed, density, and stability of traffic flow, and are consistent with previous studies. Other authors systemic influence of weather and climate on transport operation [66] and noted that extreme weather events cause significant disruptions to mobility [67]. Empirical studies by [69, 70] found that precipitation reduces mobility and alters road user behavior.

The results confirm that precipitation significantly decreases average vehicle speed and increases traffic density. Similar conclusions were drawn by [66], who found that weather variability affects the efficiency of the entire transportation system. Other authors noted that unfavorable weather conditions decrease traffic flow [67].

The observed speed limits during rainfall in Prague are consistent with previous studies and indicate that drivers adapt their driving behavior to prevailing weather conditions, such as reduced visibility or slippery surfaces. The cited studies primarily focused on how travel needs and driver behavior change. In this paper, the authors focused on quantifying how speed, density, and traffic flow change in adverse weather conditions.

Analysis of the differentiation of traffic dynamics between weekdays and weekends provides interesting conclusions. On weekdays, morning and afternoon rush hours are visible, associated with regular commuting to work and school [11, 95]. On weekends, traffic is less intensive, which suggests reduced mobility of residents related to professional duties. These results are consistent with typical patterns of social activity, which emphasizes the importance of adapting traffic management strategies to the specifics of individual days of the week.

The research confirms three key relationships, which have also been described in the literature:

- the higher the traffic volume, the lower the average speed;
- rainfall impairs traffic flow and contributes to traffic jams;
- the pattern of rush hour traffic on weekdays differs significantly from that observed on weekends.

These results are consistent with both classical traffic flow theory and previous empirical studies.

The applied Q-V-K models, including speed, density, and traffic volume, enabled precise analysis of road traffic. The obtained results indicate the consistency of the measurements with actual traffic conditions. For example, analyzing speed and flow during rush hours provided valuable information on congestion on key road sections [2, 51]. Q-V-K models provide a solid basis for predicting the behavior of road users, especially in changing weather conditions.

They found that an increase in traffic density is associated with a decrease in average speed (negative correlation), consistent with traditional

traffic flow theory and simulation studies [77, 78]. Unlike the cited studies, the authors of this paper verify these relationships using data from detectors in a densely populated urban area.

Despite the increasingly widespread use of machine learning models for road traffic prediction, their effectiveness depends largely on reliable macroscopic relationships among the parameters. The Q-V-K model provides a transparent, interpretable framework that can serve as a basis for more advanced, complex approaches. Therefore, the use of the Q-V-K model should be considered a foundation for future predictive modeling.

Most studies published to date focus primarily on mobility demand, accident statistics, or the number of public transport passengers. In contrast, this study provides a macroscopic analysis of the relationship between speed, traffic volume, and density (QVK model), taking into account various weather conditions on a selected (real-world) section of an urban road.

The innovative nature of this study does not focus on modifying the traditional QVK model. Instead, it expands its interpretive scope to include sensitivity analysis to environmental factors in urban environments. Specifically, the study integrates real-time traffic detector data with meteorological observations. This approach enables a detailed assessment of how changing weather conditions modify the fundamental relationships between speed, density, and traffic flow.

Compared to research methodologies based on simulation or predictive machine learning models [43, 89], this study focuses on the empirical validation of macroscopic traffic relationships in a real environment monitored by ITS.

The presented approach integrates classical traffic flow theory with practical aspects of traffic management, providing a transparent, fully interpretable analytical tool that can serve as the basis for advanced forecasting systems based on artificial intelligence. Previous studies on traffic flow modeling have primarily relied on simulations and forecasting models using neural networks [76, 82, 83]. It should be noted that, while these methods exhibit high predictive accuracy, they also lack full interpretability and direct connections to measurable macroscopic traffic parameters.

Therefore, the authors' proposed research methodology addresses the existing research gap in this area and enables a structured macroscopic assessment based on observations of Q-V-K model parameters. This approach is characterized

by comprehensive data interpretability, which is crucial for the practical implementation of ITS systems.

By combining classic macroscopic traffic models with real-time observation of variable environmental conditions, this study attempts to move from traditional, static traffic assessment towards adaptive urban mobility management systems. The results clearly show that even well-known models such as Q–V–K can provide new knowledge necessary for developing intelligent traffic forecasting and control systems.

The innovative nature of this study stems from combining the classic Q–V–K model with current meteorological data. Unlike many studies relying on advanced machine learning techniques for traffic forecasting (Chen et al., 2021; Avila and Mezić, 2020), this study fills a research gap in determining the relationships between traffic volume, speed, and density as they behave under short-term changes in environmental conditions based on empirical data.

The presented research results indicate that the well-known theoretical relationships between traffic volume, speed, and density (Q–V–K) respond to changing weather conditions, which can be measured and expressed quantitatively. In practice, this means that modern ITS-based traffic management systems should take into account changing weather conditions and respond accordingly.

The observation that the presented model is primarily applicable to Prague, and therefore its generalization may be limited, is understandable and partially justified. However, it is worth emphasizing that this stems, to some extent, from a misunderstanding of the study's purpose. The analytical framework, based on the Q–V–K model (speed – V, density – K, and traffic volume – Q), was not designed exclusively for a single city but represents a flexible approach applicable to a variety of urban environments. The case study conducted in Prague was intended as a verification study – its goal was to confirm the model's effectiveness in real-world traffic conditions in a large metropolitan area, rather than limit its usefulness to this specific area. The methodology used in the study, which focuses on analyzing real-time data from traffic detectors and collecting information on atmospheric conditions, can be adapted for use in other cities. However, the basic requirement is the availability of measurement infrastructure (vehicle counters, speed sensors, weather stations). One of the advantages of the Q–V–K model is its

universal applicability. The variables describing vehicle flow (Q), density (K), and speed (V) can be directly measured and compared in any transportation system. As a result, adapting the model to new conditions requires only minimal technical modifications. The authors also emphasize the need for continued research across a broader geographic and temporal scope, which will enable further refinement of the model, taking into account regional, seasonal, and infrastructure differences. In this context, the Prague study should be viewed as a pilot project, designed to empirically validate the model's usefulness and practical value in real-world urban settings. The obtained results provide valuable insights into, among other things, traffic management during peak hours, the impact of weather conditions on transportation flow, and variations in traffic patterns between weekdays and weekends. These phenomena are universal and can be observed in most urban environments, not just in Prague. Furthermore, the Q–V–K model can be easily extended to incorporate specific local factors, such as road network layout, the importance of public transportation, and demographic structure. This enables the Q–V–K model to be tailored to the specific conditions of a particular region. In summary, the application of the Q–V–K model is not limited to the case study. It is worth noting that the design of this model is based on universal principles of road traffic. After introducing appropriate modifications, the Q–V–K model can be effectively used to assess and optimize traffic dynamics in various cities and regions.

The results obtained from the conducted research indicate that the correlation between traffic volume and vehicle speed on the analyzed road section is similar to that observed in other Central European cities. During morning and afternoon rush hours, traffic increases significantly, which translates into a decrease in average vehicle speed. This is typical for large cities in the region, where many people travel at similar times of day, primarily commuting to and from work or school. Analysis of data from Prague also shows that the traffic patterns are very similar on weekdays. It is worth noting that road traffic volumes follow a similar pattern during specific hours of the day. The situation is completely different on weekends, when traffic is lower and more evenly distributed throughout the day. It is important to emphasize that the obtained results fit into the overall picture of the operation of urban transport systems in Central European cities.

Despite the valuable results, these studies have some limitations. The observation period covered only one week, which limits the possibility of capturing long-term trends and seasonal changes in traffic dynamics. In addition, the data do not include extreme weather conditions, such as heavy storms, snowfall or severe frost, which can significantly impact road user behavior.

To obtain a more complete picture of road traffic dynamics, extending the study period to several months or a whole year is necessary. This will allow for the inclusion of seasonal variability, such as differences in traffic volume in summer and winter. These studies can also be extended to other urban areas, allowing for comparison of traffic specifics in different locations and urban conditions.

Future research should consider extreme weather conditions, such as intense storms, fog, snowfall, or strong winds. Analyzing their impact on traffic flow, speed, and safety can provide valuable information for traffic management in crisis situations. Implementing predictive models based on artificial intelligence and machine learning can significantly increase the effectiveness of traffic management. These models can use historical data and current traffic and weather conditions information to predict traffic patterns in real-time.

Another direction of research is to analyze the impact of additional factors, such as the technical condition of the road surface, the presence of roadworks, or demographic variability in different urban areas. Complementing the analysis with these variables will allow a more comprehensive understanding of road traffic dynamics [55, 96, 97]. The use of new technologies, such as IoT sensors [36, 37, 98], video monitoring systems [99, 100], or data from autonomous vehicles [98, 101–103], can provide more detailed information about road traffic. Research in this direction can focus on assessing the effectiveness of technologies in improving traffic flow and increasing safety.

## CONCLUSIONS

This paper provides a comprehensive analysis of road traffic dynamics in urban conditions, considering the impact of weather conditions on basic transport parameters such as speed, flow, and vehicle density. Studies conducted based on data from traffic detectors have shown significant differences in road user behavior between

weekdays and weekends, as well as depending on the weather. The results indicate that weather conditions such as rainfall or reduced visibility significantly reduce speed and increase traffic density, which is crucial for city traffic management.

The conclusions of this work emphasize the need to integrate weather data, ITS technologies, and adaptive traffic management models in modern urban transport strategies. The results can serve as a valuable basis for planning a more efficient and sustainable transport system adapted to changing urban and climatic conditions. This research provides theoretical knowledge and practical recommendations that can improve city residents' quality of life and their transport infrastructure's efficiency.

The applied Q-V-K models proved effective in data analysis and provided consistent results. These results allowed for identifying traffic patterns during peak hours and different trends on weekdays and weekends. Additionally, the analysis showed significant differences in traffic intensity depending on the time of day and week, emphasizing the importance of adaptive road transport management strategies.

Although the study lasted only one week (Monday to Sunday), it allowed for controlled evaluation of the QVK model's suitability for changing weather conditions. The results suggest that short-term analyses can be a first (preliminary) step in developing long-term predictive road traffic management systems. The road section under study experienced moderate traffic volume, averaging approximately 24.82 (approximately 25) vehicles. However, peak hour traffic was significantly higher than the weekly average. Furthermore, the average vehicle speed during the analyzed period was 53.42 km/h, with a deviation from the weekly average of 11.75 km/h during peak hours.

The study showed that 4.96 vehicles per minute traveled on the analyzed road section, with an increase in vehicle traffic during morning and afternoon peak hours during working hours. Furthermore, a strong positive correlation (0.78) was observed between road occupancy and traffic density, and a negative correlation (-0.65) between road occupancy and average vehicle speed. In practice, this means that the more cars on the road, the higher the traffic density, while the more congested the road, the lower the average vehicle speed.

The studied road section in Prague is characterized by moderate speeds, averaging approximately 53 km/h, and typical weekday traffic, where speed and vehicle density are strongly correlated. It should also be emphasized that weather conditions significantly impact vehicle traffic. Moderate rainfall causes drivers to drive more slowly and increases their concentration on the road. Analysis of weather conditions and road traffic:

- dry days (Monday, Tuesday, Thursday, Friday, and Sunday): The flow of vehicles on these days was characterized by a higher average speed, which suggests fewer restrictions resulting from weather conditions.
- days with precipitation (Wednesday, Saturday): A decrease in vehicle speed and increased traffic density were observed, typical in conditions of limited visibility and slippery road surfaces.

During rainfall, vehicles traveled at a lower average speed, and more vehicles accumulated on the road than on dry days. This relationship indicates that basic traffic parameters are clearly sensitive to changing weather conditions.

The obtained results can also be considered in a broader, regional context. Transport systems in Central European cities often have similar traffic patterns, largely driven by residents' daily commutes to work and school. The correlations between traffic volume, vehicle speed, and traffic density (Q–V–K) identified in this study are consistent with findings presented in other publications. Prague is a particularly interesting study in this case, primarily because its transport infrastructure and residents' mobility patterns are in many respects typical of other Central European cities. Therefore, the obtained research results are characterized by a certain universality and can be interpreted not only in local conditions but also in a broader regional perspective. Furthermore, the obtained research results should be considered useful in the context of improving the management of urban transport systems, particularly the development of ITS.

Incorporating weather analysis into road traffic dynamics research enables more precise traffic management models that consider weather variability's impact on transport systems' performance. The paper also indicates significant limitations, such as the limited duration of the study or the lack of analysis of extreme weather conditions, which may affect the results.

Based on the results, several further research directions were proposed, including extending the research to other urban areas and for longer periods, analyzing the impact of extreme weather conditions, and using advanced technologies such as artificial intelligence in traffic forecasting and management. The use of predictive models and advanced analytical techniques in road traffic research is a promising path to improving the effectiveness of transport management. Proposals for expanding research and using innovative analysis methods can contribute to a better understanding of traffic dynamics and the challenges facing modern transport infrastructure.

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