

Article

Extending the KT Cellular Automata Model for Signalized Urban Traffic

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Abstract

Urban congestion continues to worsen worldwide, underscoring the need for efficient traffic management models. In this study, we extend the existing kinematic theory (KT) cellular automata (CA) model by incorporating a traffic-light module to systematically evaluate how key parameters affect traffic flow and average velocity on a one-lane road containing multiple signalized intersections. Simulations are primarily conducted under periodic boundary conditions to isolate and examine the influence of each parameter. All original KT model features—including the safety-analysis-based determination of velocity and acceleration at each time step—are retained, enabling realistic heterogeneous driving behavior. Additionally, we analyze arrival and departure dynamics under semi-open boundary conditions to gain deeper insight into urban traffic behavior. The results indicate that the maximum traffic flow at a maximum velocity of 60 km/h and a reaction time of 1.0 s is 794 vehicles/h at a density of 0.4 vehicle/cell. Adaptive acceleration increases traffic flow by up to 20% for densities below 0.7 vehicle/cell and even more at higher densities, while reducing the reaction time by 0.2 s increases traffic flow by up to 17%. Increasing the maximum acceleration by 1 m/s² yields only a modest rise of up to 5%. At a maximum velocity of 80 km/h, traffic flow is up to 46% higher relative to 40 km/h, although the effect diminishes at higher densities. Furthermore, semi-open boundary conditions produce consistently higher traffic flow than periodic boundaries. These findings demonstrate that the enhanced KT-CA model can capture the effects of driver behavior and traffic-signal timing, offering an improved framework for analyzing and optimizing urban traffic systems.

Keywords: traffic light model; cellular automata; KT model; heterogeneous conditions; urban traffic



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1. Introduction

Approximately 45% of the world's 8.2 billion people lived in cities in 2025, more than double the urban population share in 1950. Future projections suggest that around two-thirds of global population growth until 2050 will occur in urban areas, with most of the remainder in smaller towns [1]. The 2025 INRIX Global Traffic Scorecard found that congestion worsened in 62% of cities worldwide, while only 26% of cities experienced improvements. In Germany's urban areas, drivers spent up to 67 extra hours in traffic over the year [2]. Mexico City had the highest congestion rate globally at 52%, meaning that typical trips took more than 50% longer than they would under free-flow traffic

conditions [3]. In Ljubljana, Slovenia, the congestion rate reached around 33% in 2023 [4]. In 2020, traffic congestion in New York City resulted in an estimated 1486 USD in cost per driver [5]. These trends underscore the importance of understanding traffic flow patterns in urban areas to identify strategies that improve traffic efficiency and reduce congestion.

Cellular automata (CA) traffic flow models originate from early deterministic and stochastic formulations, such as Wolfram's Rule 184 and the Nagel–Schreckenberg model, which were later extended through various approaches, including safety-based formulations that enable smoother vehicle interactions [6–8]. A literature review of CA traffic models and the development of the kinematic theory (KT) framework is provided in [9].

Although CA models have been extensively developed for traffic flow, their application to urban intersections remains relatively limited. The Biham–Middleton–Levine (BML) model is a simple two-dimensional CA for traffic flow that demonstrates a sharp transition between a free-flow phase, where vehicles move at maximal speed, and a fully jammed phase characterized by complete gridlock [10]. Chowdhury and Schadschneider extended the BML model by incorporating elements of the NaSch model, thus introducing intrinsic stochasticity into the dynamics that triggers the onset of traffic jamming [11]. Fouladvand et al. (2010) described traffic flow at an intersection of two perpendicular streets with fixed-time traffic lights and showed that the model's phase diagram consists of ten phases, depending on the vehicle densities on both roads [12]. Tian et al. (2012) analyzed how the bus flow proportions near intersections affect congestion and found that the critical probability for vehicle entry decreases with increasing bus flow, highlighting the importance of appropriately positioning signalized intersections and selecting suitable signal cycle times [13]. Marzoug et al. (2021) presented another practical application of a CA model by investigating how the time required to clear damaged vehicles and the probability of accident propagation affect traffic flow at intersections [14]. Several studies have applied CA-based models to investigate traffic signalization strategies at urban intersections [15–22].

Lately, different studies have analyzed the characteristics of roundabout traffic using CA models that are relevant for understanding urban traffic flow. The impact of vehicles performing a full turn or U-turn in a single-lane roundabout was investigated by [23]. The results showed that an increase in U-turning vehicles leads to higher capacity in the circulating lanes and reduced capacity at the entry and exit lanes. A CA model was developed to examine the factors influencing fuel consumption and emissions in roundabout traffic. The results showed that driving behavior, particularly during lane entry, is a critical factor affecting fuel consumption and emissions. Optimization strategies improve traffic efficiency and lead to substantial reductions [24]. Liang et al. [25] developed a Three-Stage CA model to analyze and optimize traffic flow at large roundabouts. Simulations show that optimization strategies can improve traffic efficiency and reduce delays and dangerous interactions, with the Path Selection strategy performing best. Urban traffic was investigated by [26] using a cellular automata model, focusing on the effects of traffic density and the proportion of heavy vehicles on moving bottlenecks. The study found that, before traffic saturation, a higher proportion of heavy vehicles leads to a stronger moving bottleneck effect. Marzoug et al. (2025) analyzed traffic emissions and flow dynamics in two-route urban systems using a CA model that integrates key components of urban infrastructure, finding that prioritizing entrance-based feedback most effectively reduces emissions, while lane-changing patterns affect emissions, depending on the entry rate [27].

Outside the scope of CA models, traffic signal control is widely studied subject. Eom and Kim (2020) provided a review of the methods developed and used to improve the efficiency of traffic signal control at intersections [28]. Liu et al. [29] developed a framework of Adaptive Dynamic Programming for traffic signal operation to seek the optimal traffic light

policy, using a macroscopic traffic flow modeling approach. The model can determine both ‘when’ to switch and ‘which mode’ to switch on when controlling the traffic light operation without the need to use the cycle-based average flow approximation typical of state-of-the-art formulations. Alshayeb et al. (2023) developed a new approach by integrating a fuel-consumption surrogate measure, traffic simulation, and signal-timing optimization tools to optimize signal timing under various operating conditions [30]. Agrahari et al. (2024) categorize adaptive traffic signal control systems and show that different artificial intelligence-based approaches offer substantial improvements in managing dynamically varying traffic densities [31].

CA models for urban traffic and intersection simulations have evolved considerably over time. The BML model is an early pioneering CA model for studying urban traffic flow that includes a basic representation of traffic-light operation and is computationally efficient. However, it lacks realistic driving behavior [10]. The model proposed by Fouladvand et al. extends the NaSch framework to signalized intersections and provides a more realistic representation of traffic-light operation than the BML model [12]. Several subsequent extensions of the NaSch framework were developed for analyzing traffic-light control strategies, congestion formation, and traffic-signal optimization [15–17,21,22,27]. These studies include heterogeneous vehicles, multi-lane traffic, and open-boundary conditions, while more recent models also consider vehicle-specific acceleration characteristics, reaction times, and safety constraints [21,26].

Despite these developments, most existing models rely on fixed acceleration and homogeneous reaction times. In contrast, the KT model enables adaptive acceleration and heterogeneous reaction times, allowing a more realistic representation of urban traffic flow under varying traffic conditions. The model is based on physically interpretable parameters, such as the reaction time, acceleration, and speed limits, which facilitates systematic sensitivity analyses and transparent investigation of cause-and-effect relationships between traffic parameters and traffic-flow characteristics. Furthermore, the present study validates the model using empirical traffic measurements aggregated into 5 min intervals. These features are relatively uncommon in CA-based urban traffic flow modeling and contribute to bridging the gap between urban traffic-flow modeling and real-world traffic observations. The evolution of CA models for urban traffic and signalized intersections is summarized in Table 1.

Table 1. Comparison of representative CA models for urban traffic and signalized intersection simulations discussed in the literature review.

Feature	BML [10]	Fouladvand et al. [12]	Wang et al. [21]	Liang et al. [24]	Xiu et al. [26]	KT-CA
Signalized intersections	Yes	Yes	Yes	No	Yes	Yes
Open-boundary conditions	No	No	Yes	Yes	No	Yes
Multiple vehicle types	No	No	No	No	Yes	No
Heterogeneous reaction times	No	No	No	No	No	Yes
Adaptive acceleration	No	No	No	No	No	Yes
Empirical validation with field data	No	No	No	Yes	No	Yes

This study addresses the gap in current traffic flow modeling by extending the KT model to signalized urban traffic. While our previous work [9] developed and validated the KT model for uninterrupted traffic flow under closed boundary conditions, the present study extends the KT framework to signalized urban environments with semi-open and open boundary conditions, thereby enabling the simulation of signalized traffic conditions. Specifically, the present work introduces stochastic vehicle arrivals and departures based on Poisson and Bernoulli processes, intersection-induced queueing and stop-and-go dynamics,

and time-dependent traffic-flow convergence analysis. In addition, the proposed model is quantitatively validated using one month of empirical loop-detector data, enabling comparison between simulated and observed flow–density relationships.

The main contributions of this study are as follows:

- (i) The implementation of a traffic-light module for signalized urban traffic,
- (ii) The introduction of semi-open and open boundary conditions with stochastic vehicle arrivals and departures,
- (iii) The analysis of traffic-flow convergence under signalized conditions,
- (iv) Empirical validation using one month of loop-detector traffic data.

Similar to [9], the effects of the reaction time, maximum acceleration rate, and maximum velocity on traffic flow are investigated but under substantially different operating conditions involving signalized intersections in closed, semi-open and open boundary conditions. Therefore, the present study represents both a methodological extension of the KT framework to signalized urban traffic and an empirical validation of the model using real-world traffic data.

2. Materials and Methods

The kinematic theory (KT) cellular automata model and its car-following rules, including safety-based motion, adaptive acceleration, and heterogeneous driver behavior, are described in detail in [9]. In the present study, these rules are applied unchanged in a signalized urban environment with traffic-light control under closed, semi-open, and open boundary conditions. The variables and parameters used in the KT model are defined as in [9].

2.1. The Traffic Light Model

The traffic light model simulates traffic behavior influenced by traffic lights, maintaining the same distances and operating characteristics as real-world traffic conditions. It incorporates simple decision rules that determine whether a following vehicle should adjust its behavior due to a traffic light, while the movement rules remain consistent with those in the KT model.

From an algorithmic perspective, the integration of traffic lights does not require a modification of the CA structure. The following vehicle simultaneously evaluates the state of the leading vehicle on the traffic lattice and the state of the following traffic signal in a parallel lattice. Safe stopping and motion updates are then determined using the same kinematic safety rules already used for vehicle–vehicle interactions. This parallel-lattice formulation resolves the difficulty of coupling discrete CA dynamics with signalized stopping behavior while preserving the original KT update rules.

First, the following vehicle checks if the red light is on ($s(t) = 1$). Then, it evaluates whether it can stop safely in front of the traffic light. The distance to the traffic light, $d_{\text{trafficlight}}(t)$, must be greater than the distance $d_{\text{mintrafficlight}}(t)$, the minimum stopping distance, which is defined as follows:

$$d_{\text{mintrafficlight}}(t) = v_f(t)t_r - \frac{a_{\max_f}t_r}{2} + \frac{(v_f(t) - a_{\max_f}t_r)^2}{2a_{\max_f}}. \quad (1)$$

The model is programmed such that the following vehicle treats a traffic light ahead as a leader vehicle with $v_l(t) = 0$ and $a_{\max_l} = 0$, effectively interpreting the light as a stop condition. Third, the following vehicle checks whether its distance to the traffic light, $d_{\text{trafficlight}}(t)$, is shorter than the sum of its distance to the leader vehicle and the minimum distance the leader needs to stop using the emergency deceleration, given by the following:

$$\left(d_{stop_l}(t) = d_n(t) + \frac{v_l^2(t)}{2a_{max_l}} \right), \quad (2)$$

where $d_{stop_l}(t)$ represents the stopping distance of the leader vehicle.

If all three conditions are satisfied, the model considers the traffic light position in the next time step. Otherwise, the following vehicle continues to follow the leader vehicle. The model does not include yellow lights explicitly, but the duration of the red light encompasses the duration of the yellow light to avoid introducing additional parameters, as its effects are implicitly captured within the red phase. When the red light turns on, and the following vehicle cannot stop safely in front of the traffic light, it bypasses the traffic light and continues to follow the leader vehicle. This rule mimics the behavior of vehicles at yellow lights. The red lights remain on long enough to allow for the clearance of vehicles at the intersection. The yellow signal is modeled in accordance with Slovenian traffic regulations, which prohibit driving through a yellow light except in cases where a vehicle, traveling at the permitted speed, cannot safely stop due to insufficient distance from the signal [32]. This modeling choice does not artificially affect the capacity or queue formation, as vehicles are still constrained by safety-based stopping conditions and signal timing.

The safe following distances that the following vehicle considers when approaching the traffic light are derived from [9]. Three safe following distance values are then calculated, depending on the different actions the following vehicle (f) intends to take at time t , as follows:

$$d_{acc}^{trafficlight} = \frac{(v_f(t) + a_f(t)t_r)^2}{2a_{max_f}} + \frac{a_f(t)t_r^2}{2} + v_f(t)t_r, \quad (3)$$

$$d_{keep}^{trafficlight} = \frac{(v_f(t) + a_f(t)t_r)^2}{2a_{max_f}} + v_f(t)t_r, \quad (4)$$

$$d_{dec}^{trafficlight} = \frac{(v_f(t) + a_f(t)t_r)^2}{2a_{max_f}} - \frac{a_f(t)t_r^2}{2} + v_f(t)t_r. \quad (5)$$

Here, $d_{acc}^{trafficlight}$, $d_{keep}^{trafficlight}$, and $d_{dec}^{trafficlight}$ represent the safe following distances required by the following vehicle to accelerate, maintain its velocity, or decelerate, respectively, in the next time step.

Updating Rules for the Traffic Light Model

The logic for updating rules in the traffic light model follows the same structure as in the KT model, with a few enhancements. These enhancements override specific rules from [9].

S1: Safe distances.

$$\begin{aligned} &\text{If } (s(t) = 1) \wedge (d_{trafficlight}(t) \geq d_{mintrafficlight}(t)) \wedge (d_{trafficlight}(t) \leq d_{stop_l}(t)), \\ &\quad \text{then } (d_{acc} = d_{acc}^{trafficlight}, d_{keep} = d_{keep}^{trafficlight}, d_{dec} = d_{dec}^{trafficlight}). \\ &\text{Otherwise, } (d_{acc} = d_{acc}^{stop} \vee d_{acc}^{move}, d_{keep} = d_{keep}^{stop} \vee d_{keep}^{move}, d_{dec} = d_{dec}^{stop} \vee d_{dec}^{move}). \end{aligned} \quad (6)$$

Here, d_{acc}^{stop} , d_{keep}^{stop} , and d_{dec}^{stop} represent safe following distance to accelerate, keep velocity or decelerate while stopped, while d_{acc}^{move} , d_{keep}^{move} , and d_{dec}^{move} represent the safe following distances to accelerate, keep velocity or decelerate while moving.

S2: Slow to acceleration.

There is no “slow-to-acceleration” rule when the following vehicle is approaching the traffic light position.

For clarity, Table 2 summarizes the variables introduced for the traffic light extension of the KT model.

Table 2. Variables introduced for the traffic light model.

Variables	Descriptions
$d_{trafficlight}(t)$	Distance to the traffic light
$d_{mintrafficlight}(t)$	Minimum stopping distance in front of the traffic light
$d_{acc}^{trafficlight}, d_{keep}^{trafficlight}, d_{dec}^{trafficlight}$	Safe following distance required to accelerate, maintain velocity, or decelerate in front of a traffic light
$s(t)$	Traffic light state indicator (0 = green, 1 = red)

2.2. Arrivals and Departures Modules

Based on the computed traffic flow on Dunajska Road and the relative importance of the side roads, arrival and departure probabilities were derived for vehicles entering and leaving Dunajska Road. Vehicles entering Dunajska Road at signalized intersections arrive are modeled as a Poisson process. The number of arriving vehicles in each discrete time step follows a Poisson distribution with rate μ . When the traffic light is red, arriving vehicles queue and wait, consistent with real traffic behavior. The numerical values of the Poisson parameter μ and the Bernoulli probability p used in the simulations are provided in Tables A1 and A2. Parameter μ_1 represents vehicle arrivals at the beginning of the road segment, while the remaining μ values correspond to arrivals from individual side roads and intersections.

The probability mass function of a random variable following a Poisson distribution is defined as

$$p_Y(y) = \frac{-\mu \mu^y}{y!}, \quad (7)$$

where μ denotes the expected value of the random variable Y , and y represents the number of events occurring within a given time interval. The support of this random variable is unbounded, allowing for an arbitrary number of arrivals within the considered period [33].

In contrast, vehicle departures from Dunajska Road are modeled using a Bernoulli distribution, since each vehicle independently decides, with a given probability, whether it exits the road segment. A Bernoulli trial has two possible outcomes, and its result is a random variable X following a Bernoulli distribution. The probability mass function of x is given by

$$p_X(x) = \begin{cases} (1-p) & X = x_1 = 0 \\ p & X = x_2 = 1 \end{cases} \quad (8)$$

The support of the Bernoulli random variable consists of two values, commonly denoted as 0 and 1 [33]. In the present case, a value of 1 indicates that a vehicle turns from the main road onto the side road with probability p , while a value of 0 corresponds to the vehicle remaining on the main road with probability $(1-p)$. In the simulations, this decision is implemented such that each vehicle approaching the intersection independently determines whether to turn or continue straight.

The expected numbers of arrivals and departures over the entire simulation are comparable for both distributions. The arrival probability depends on a predefined traffic flow rate expressed as a function of traffic density, which is obtained from simulations performed

under closed-boundary conditions. In contrast, the departure probability depends on the instantaneous traffic state on Dunajska Road.

2.3. Locations of the Traffic Lights

The simulations are conducted on a one-lane road with traffic lights for pedestrians, meaning that vehicles neither enter nor exit the road (Figure 1). The traffic lights in the model are positioned to match those on a 1500 m section of Dunajska Road in Ljubljana, Slovenia. The section starts at the intersection of Tivolska and Dunajska Roads and ends just after the intersection with Dimičeva Street (Figure 1).

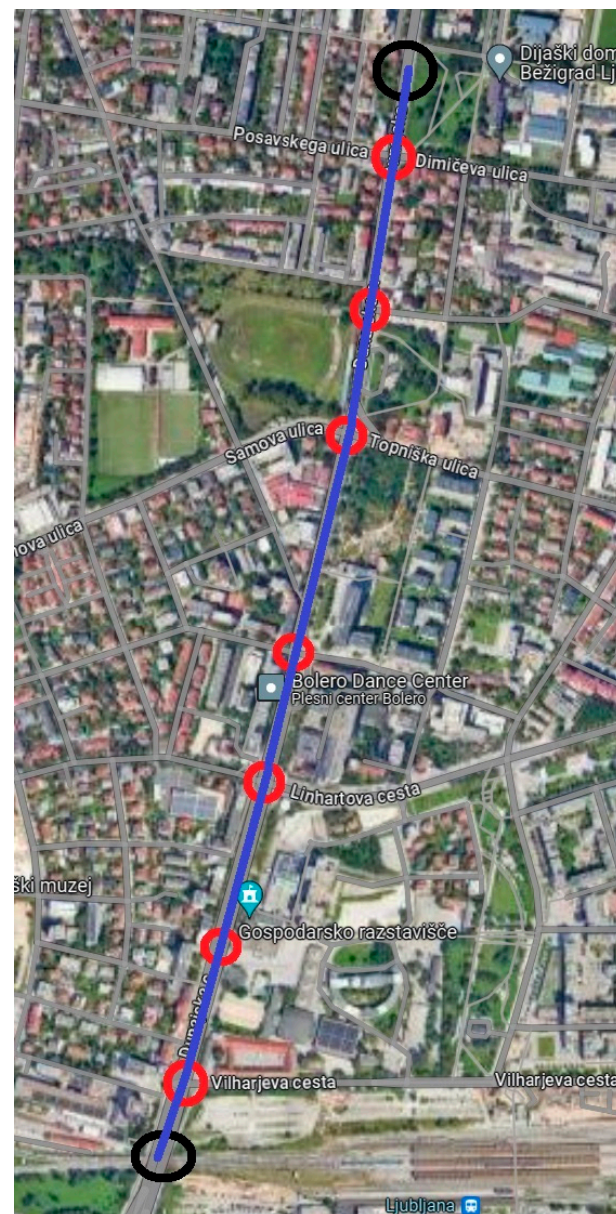


Figure 1. The section of Dunajska Road used in the traffic CA model for this study. The black circles indicate the start and end of the section, while the red circles mark the locations of the traffic lights [34].

In Table 3, the delay for traffic lights is determined. Since only traffic lights with a 90 s cycle are synchronized, the delay is calculated only for these. Traffic lights with a 120 s cycle have a different green light duration; so, they do not impact the total flow.

Table 3. Locations of traffic lights along the studied section of Dunajska Road.

Traffic Light Location	Distance from the Start of the Studied Area (m)	Traffic Light Cycle Time Duration (s)	Green Light Duration on Dunajska Road (s)	Green Light Delays Relative to the First Traffic Light (s)
Dunajska Road, Vilharjeva Road	112.5	120	70	Not synchronized with other intersections due to differing cycle lengths
Dunajska Road, Gospodarsko razstavišče	322.5	120	90	Not synchronized with other intersections due to differing cycle lengths
Dunajska Road, Linhartova road	540.5	90	40	0
Dunajska Road, Kržičeva Street	742.5	90	60	82
Dunajska Road, Topniška Street	1057.5	90	36	55
Dunajska Road, Ptujška Street	1267.5	90	65	72
Dunajska Road, Dimičeva Street	1455	90	50	55

2.4. Acceleration, Deceleration, and Reaction Time Parameters

The acceleration, deceleration, and driver reaction time parameters used in this study are based on those defined and validated in [9], which were derived from empirical traffic studies [8,35–40]. In that study, parameter ranges were selected based on empirical findings reported in the literature and shown to be consistent with the observed traffic behavior. In the proposed framework, the same parameter ranges are employed unless stated otherwise.

3. Results

The simulations use the KT model with AA and FA modes as described in [9]. The results are presented in the same order and in a similar manner to study [9] to facilitate clearer comparisons between the two studies. However, the results in this paper differ substantially because they are obtained under fundamentally different conditions. Unlike [9], where simulations were performed on a 1500 m long one-lane circular road without any obstacles, the present study uses simulations on a 1500 m long one-lane circular road with a series of traffic lights and considers periodic, semi-boundary, and open-boundary conditions. A 1500 m long one-lane circular road corresponds to 200 cells, where each cell represents 7.5 m and contains at most one vehicle. Vehicle positions and velocities are initialized according to the method in [9]. The maximum velocity is set to 60 km/h unless stated otherwise, and all stochastic parameters follow models from [8,9] ($R_d = 1$, $R_0 = 0.8$, $v_s = 8$ m/s and $R_s = 0.01$). The present study investigates the effects of different reaction times (0.8 s, 1.0 s, 1.2 s) and maximum acceleration rates (2, 3, 4 m/s²) in homogeneous and heterogeneous traffic conditions. Each simulation ran for 10,000 time steps, and the results are compared between AA and FA modes to assess the influence of adaptive acceleration on traffic flow. The simulation results are presented with dots for the AA mode and continuous lines for the FA mode.

3.1. Different Reaction Times

In the following section, different reaction times are employed in the simulations on the road with traffic lights. Figure 2 shows the flow–density relationship under heterogeneous conditions. As shown in the figure, the reaction time has a significant impact on the traffic flow. For a reaction time of 1.0 s, the traffic flow increases rapidly with the density until it reaches 740 vehicles/hour at a density of 0.2 vehicle/cell. The flow then remains almost constant until the density exceeds 0.6 vehicle/cell, at which point it peaks at 795 vehicles/hour. Beyond this density, the traffic flow begins to decrease nearly linearly until reaching maximum density.

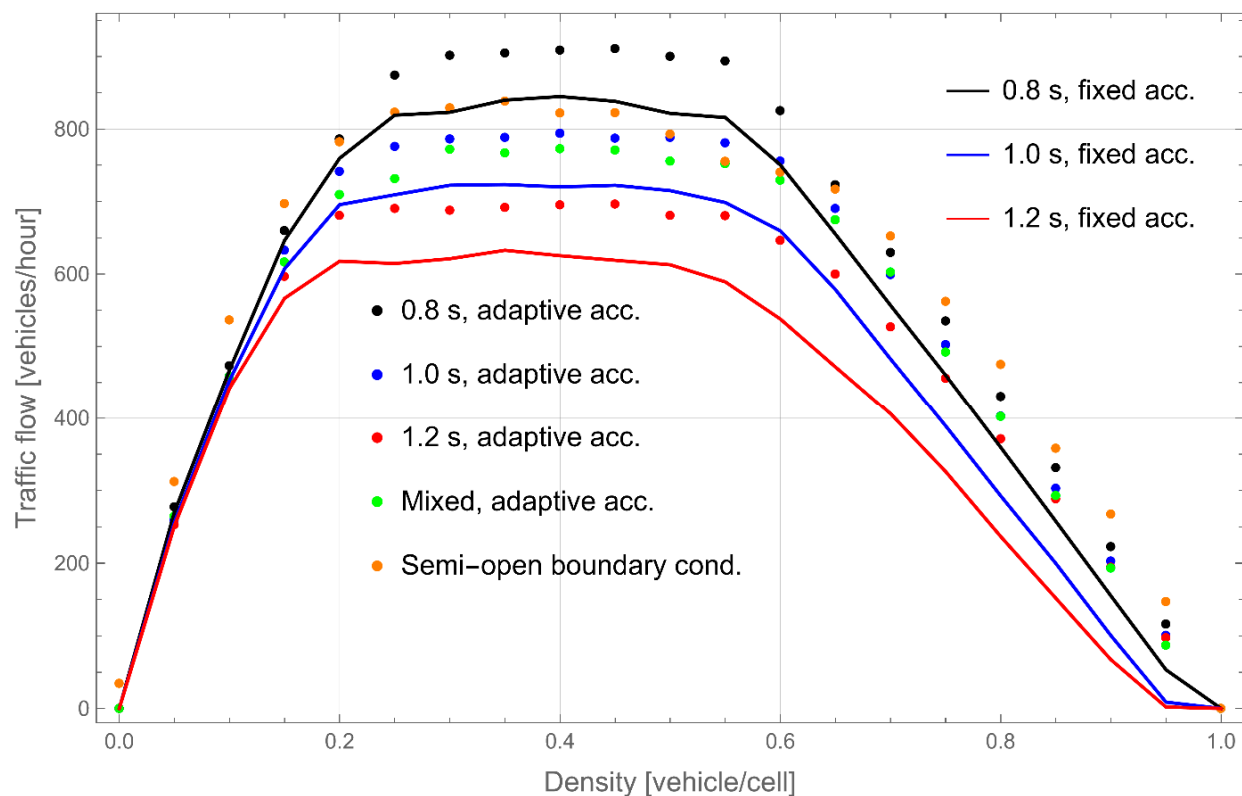


Figure 2. The flow–density diagram for the road with traffic lights, obtained using the new KT model with the AA mode and the FA mode, for different reaction times and a maximum velocity of 60 km/h.

On roads with traffic lights, the traffic flow is either in a free-flow or congestion phase, with no synchronized phase due to the traffic lights disrupting the flow. The duration of congestion depends on density: the higher the density, the longer the congestion. The traffic characteristics are similar for reaction times of 0.8 s and 1.2 s. However, for a reaction time of 0.8 s, the traffic flow is up to 14% higher than for 1.0 s, while a reaction time of 1.0 s results in traffic flow up to 14% higher than for 1.2 s. In heterogeneous conditions, where 20% of vehicles have a reaction time of 0.8 s, 60% have 1.0 s, and 20% have 1.2 s, the traffic flow is up to 6% lower compared to a scenario where all vehicles have a reaction time of 1.0 s. This suggests that the traffic flow improves with shorter reaction times.

Under semi-open boundary conditions, where vehicles arrive at and depart from intersections in proportion to the importance of the road, the traffic flow is consistently higher than under closed boundary conditions. The maximum flow is approximately 5% higher; however, at both lower and higher density values, the difference can reach up to 20%. Vehicle departures reduce the local density at intersections and thereby enhance the traffic flow. This effect is further pronounced by vehicle arrivals during red phases on the

main road, when vehicles would otherwise remain stationary. The impact of departures becomes especially significant at higher densities, where the overall traffic flow is reduced.

Figure 3 presents the spatiotemporal diagrams for different traffic phases on the one-lane road with traffic lights under periodic boundary conditions. These diagrams were generated for the AA mode with a reaction time of 1 s. As shown in Figure 4, the blue and red dots represent the movement of two vehicles over time. From these, it is evident that the average velocity decreases at higher density values compared to lower densities. The black dots, which also represent vehicles, indicate larger congestion at higher densities, particularly in front of the traffic lights.

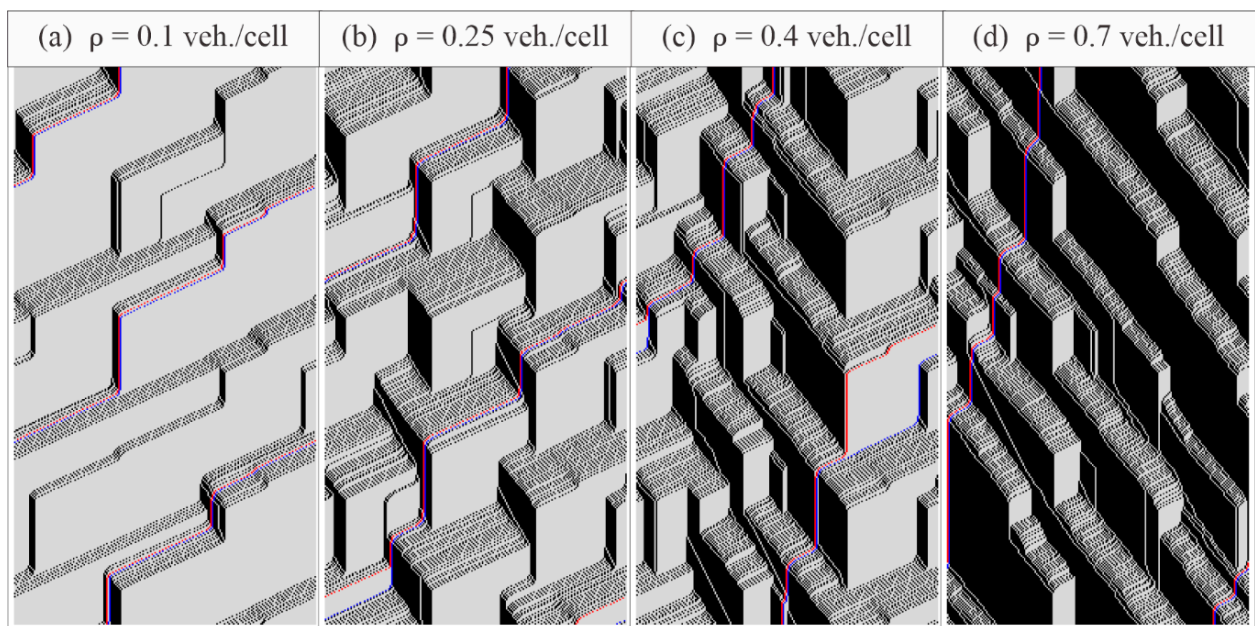


Figure 3. The spatiotemporal diagrams generated with the new KT model for the road with traffic lights, showing different traffic phases with a reaction time of 1.0 s and a maximum velocity of 60 km/h. (a) represents flow with a density of $\rho = 0.1$ vehicle/cell; (b) represents synchronized flow with a density of $\rho = 0.25$ vehicle/cell; (c,d) represent wide moving jam with a density value of $\rho = 0.4$ vehicle/cell, and $\rho = 0.7$ vehicle/cell, respectively. Blue and red dots represent two vehicles.

In contrast, the average velocity decreases with the increasing density and does not remain relatively constant as in the first case. The presence of traffic lights prevents vehicles from maintaining free-flow conditions continuously, forcing them to stop occasionally, regardless of the density. As the density increases, the congestion in front of the traffic lights becomes more pronounced, which further reduces the average velocity. For a reaction time of 1.0 s and a density of 0.05 vehicle/cell, the average velocity in the AA mode is 39 km/h. Up to a density of 0.35 vehicle/cell, the average velocity decreases more rapidly with density, after which it declines almost linearly.

The average velocity decreases with the increasing density, regardless of the reaction time. For example, at a reaction time of 0.8 s, the average velocity is up to 15% higher than at 1 s, with variations generally between 7% and 15%. The difference between the reaction times of 1.0 s and 1.2 s follows a similar pattern. In heterogeneous conditions, the average velocity is up to 6% lower compared to when all vehicles have a reaction time of 1 s. As expected, the average velocity is higher when vehicles have shorter reaction times. Additionally, as shown in the traffic flow results, the average speed in the AA mode is consistently higher than in the FA mode.

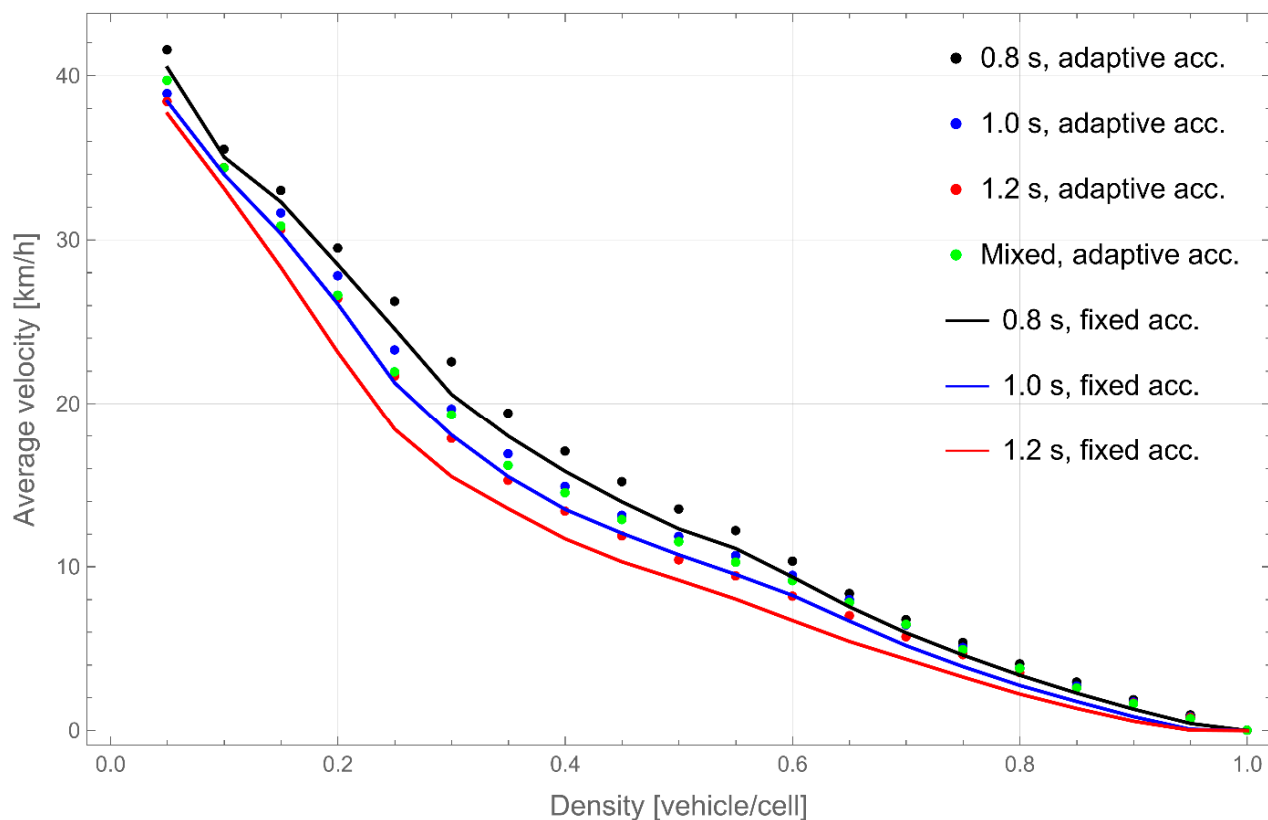


Figure 4. The speed–density diagram for the road with traffic lights, comparing the AA mode and the FA mode at different reaction times, with a maximum velocity of 60 km/h.

3.2. Different Maximum Acceleration Rates

This section examines the effect of different maximum acceleration rates while keeping the reaction time constant at 1.0 s in the simulations. Unlike the previous analysis, which involved varying reaction times in heterogeneous conditions, the current analysis is conducted under homogeneous conditions. In this case, only one type of vehicle or driver is represented in each simulation. While the previous analysis considered a mix of drivers with maximum acceleration rates of 2, 3, and 4 m/s², this part uses a single driver type with a fixed maximum acceleration rate of 2, 3, or 4 m/s² for each simulation.

The purpose of this section is to examine the influence of different maximum acceleration rates on traffic flow. Since the essential characteristics of the traffic flow—such as the average speed–density profile—are like those in the previous section, we focus here only on presenting the flow–density relationship for the road with traffic lights. The results of the simulations are shown in Figure 5.

The maximum traffic flow values for maximum acceleration rates of 4, 3, and 2 m/s² are 846, 816, and 793 vehicles/hour, respectively. In general, the traffic flow values at different maximum acceleration rates on the road with traffic lights are quite similar. These results indicate that the traffic flow is not highly sensitive to the maximum acceleration rate. Additionally, Figure 5 also illustrates that, on the road with traffic lights, the traffic flow in the AA mode is slightly higher than in the FA mode.

3.3. Different Maximum Velocities

This section presents simulations conducted with different maximum velocities. All vehicles have a constant reaction time of 1.0 s and varying maximum acceleration rates, as detailed in [9]. All simulations are performed in the AA mode.

As seen in Figure 6, typical patterns emerge regarding the influence of maximum velocity on traffic flow. Higher maximum velocities, especially at lower densities result in greater traffic flow. However, at densities of 0.65 vehicles/cell and higher, the maximum velocity has almost a negligible impact on the traffic flow, as higher velocities are seldom achieved due to congestion.

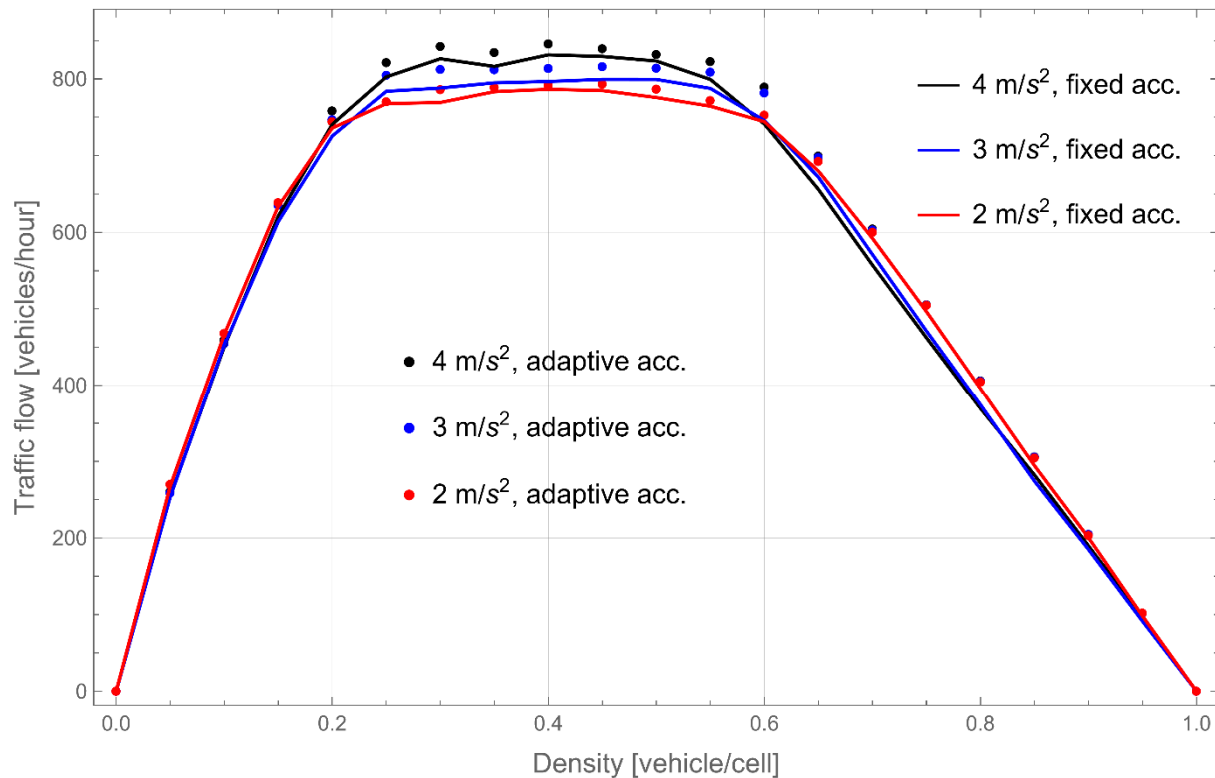


Figure 5. The flow-density diagram for the road with traffic lights, generated using the new KT model with the AA mode and the FA mode, for a reaction time of 1 s, different maximum acceleration rates, and a maximum velocity of 60 km/h.

The effect of the maximum velocity is more pronounced at lower maximum velocities, where vehicles can reach maximum speeds before encountering congestion caused by traffic lights. For example, the difference in traffic flow between speed limits of 80 km/h and 70 km/h is a maximum of 4%, while the difference between 50 km/h and 40 km/h reaches up to 13%.

The traffic flow at different speed limits demonstrates a clear dependence on the maximum velocity. At a speed limit of 80 km/h, the maximum traffic flow reaches 844 vehicles/hour at a density of 0.35 vehicles/cell. At 70 km/h, the flow decreases slightly to 808 vehicles/hour at the same density. For a maximum velocity of 60 km/h, the maximum flow is 794 vehicles/hour at a density of 0.4 vehicles/cell. Further reductions in the maximum velocity to 50 km/h and 40 km/h result in maximum traffic flows of 762 and 721 vehicles/hour, respectively, both occurring at a density of 0.4 vehicles/cell.

Given that traffic flow depends on the speed limit only at densities less than 0.7 vehicle/cell, the average velocity at higher densities remains similar across all maximum velocity values, as shown in Figure 7. At speed limits of 70 km/h and 80 km/h, the average velocity at a density of 0.05 vehicle/cell reaches its peak, around 44 km/h. At 60 km/h, it decreases by approximately 5 km/h, while at 50 km/h and 40 km/h, it drops by an additional 9 km/h. At higher densities, the variations in average velocity become smaller. By the time the density reaches 0.65 vehicle/cell, the average velocity stabilizes

across all speed limits. In fact, at higher densities, the speed limit has less influence on the average velocity, as higher speeds become increasingly rare.

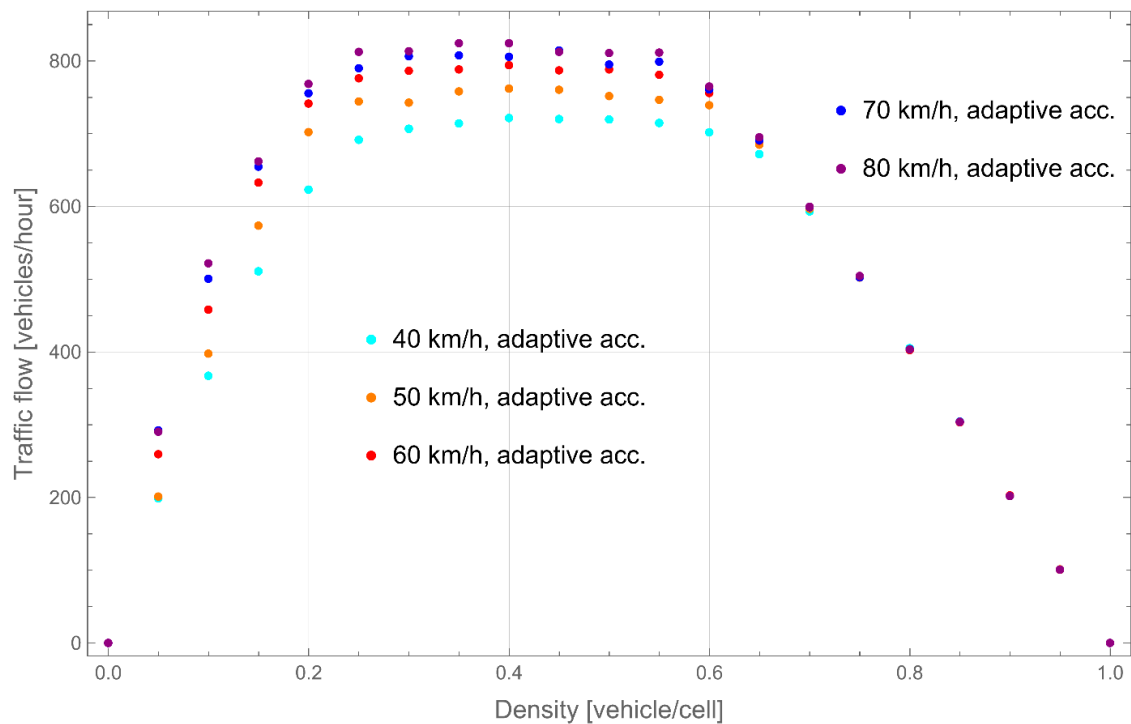


Figure 6. The flow-density diagram for the road with traffic lights, obtained using the new KT model with the AA mode, for a reaction time of 1.0 s and varying maximum velocities.

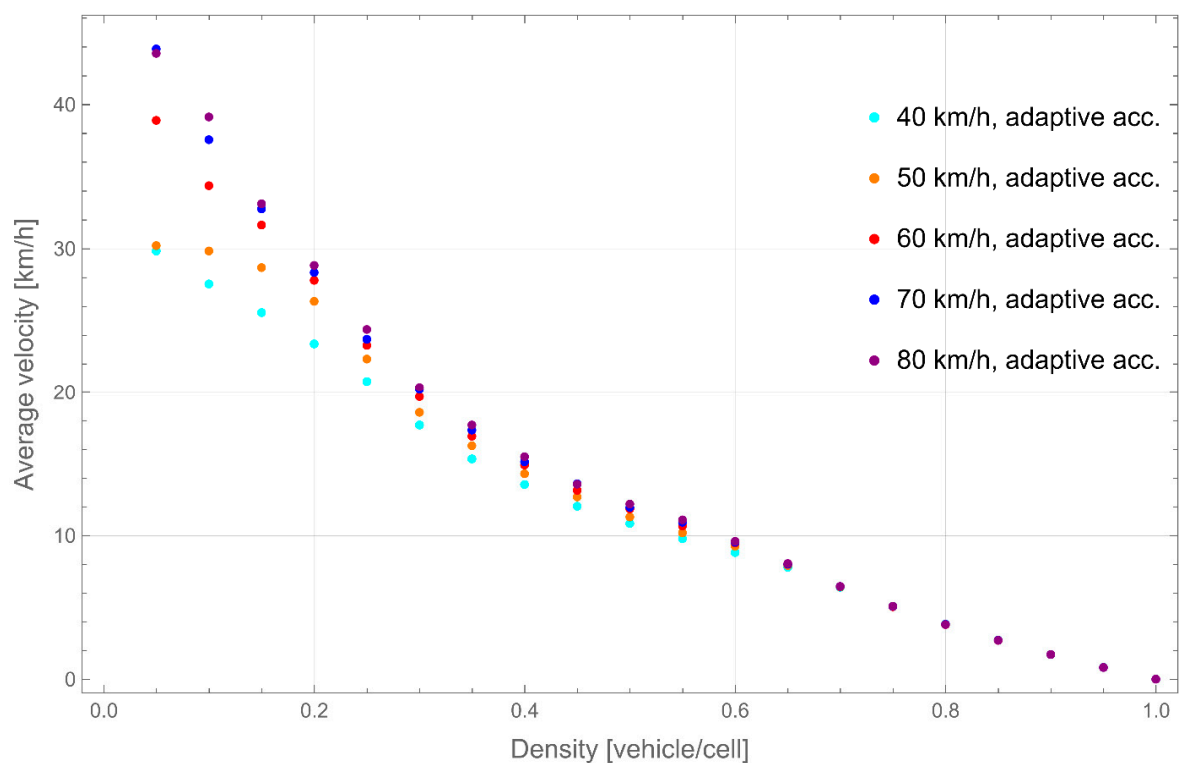


Figure 7. The speed-density diagram for the road with traffic lights, obtained using the new KT model with adaptive acceleration mode, for a reaction time of 1.0 s and varying maximum velocities.

4. Discussion

4.1. Theoretical and Literature-Based Validation

While the KT model was previously validated in [9], the results of the extended version with traffic lights were compared with simulations by [41], who used the SUMO model on a 4.2 km one-lane road with closed boundary conditions, five traffic lights, and a speed limit of 50 km/h with cycle lengths differing from those in this study. Despite these differences, our study produced similar results of around 800 vehicles/hour/lane under a basic scenario with a 60 km/h speed limit, 1 s reaction time, and standard acceleration values, confirming the robustness of the model under comparable traffic conditions. The capacity of the 8.5 km long Grand River Boulevard (M-5) in Detroit is designed for approximately 825 vehicles/hour/lane [42], providing a reference for realistic urban arterial traffic flow.

Based on an assumed base saturation traffic flow rate of 1900 vehicles/hour/lane and the effective green time, the effective capacity of a single signalized movement c can be expressed as follows:

$$c = s \frac{g}{C}, \quad (9)$$

where s is the saturation flow, g is the effective green time, and C is the cycle length [43]. Using a typical effective green ratio of 0.45, which is commonly reported for coordinated urban arterials, yields an effective capacity of approximately 860 vehicles/hour/lane [44]. For an arterial with multiple consecutive signalized intersections, the effective flow is expected to be lower due to interactions between signals, queue formation, and offsets. In this context, the simulated flow of 832 vehicles/hour/lane reflects these combined effects, including the presence of a green wave, supporting the realism of the extended KT-CA model predictions.

4.2. Validation Using Empirical Traffic Data

Figure 8 compares the simulated and empirical flow–density relationships derived from one month of loop-detector measurements aggregated into 5 min intervals on Tržaška Road in Ljubljana. There were no empirical observations above approximately 100 vehicles/km for the analyzed road segment. Therefore, the comparison is limited to the observed density range [45]. In the validation procedure, the same model settings for the speed limit of 60 km/h as in previous analyses were used. We decided to not apply any additional tuning of the parameters.

Using baseline model settings in an open-loop configuration, the proposed KT-CA model reproduces the characteristic macroscopic behavior of signalized urban traffic. The red curve represents a least-squares polynomial approximation of the empirical observations and is included to visualize the general flow–density tendency.

In this study, the normalized root mean square error $NRMSE$ and the coefficient of determination (R^2) were selected as evaluation metrics to quantify the agreement between the simulated traffic flow and the polynomial approximation of the observed traffic flow. The metrics were calculated as follows:

$$NRMSE = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (q_i - \check{q}_i)^2}}{q_{\max} - q_{\min}} \quad (10)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (q_i - \check{q}_i)^2}{\sum_{i=1}^N (q_i - \bar{q})^2} \quad (11)$$

where q_i denotes the empirical value, $\check{q}_i$ the simulated value, N the number of observations, $q_{\max} - q_{\min}$ the range of empirical values, and $\bar{q}$ the mean empirical value.

The obtained values ($NRMSE = 0.058$, $R^2 = 0.95$) indicate strong agreement between the simulated and observed traffic dynamics within the observed density range.

Additional simulations were performed for Jamova Road, which differs from Dunajska Road in terms of the speed limit and signal configuration. The results show a similar flow–density relationship, although some differences in the magnitude of traffic flow were observed. These differences are related to differences in traffic-light configuration. This indicates that the KT model is capable of reproducing traffic dynamics under different urban traffic conditions and is not limited to a single road configuration.

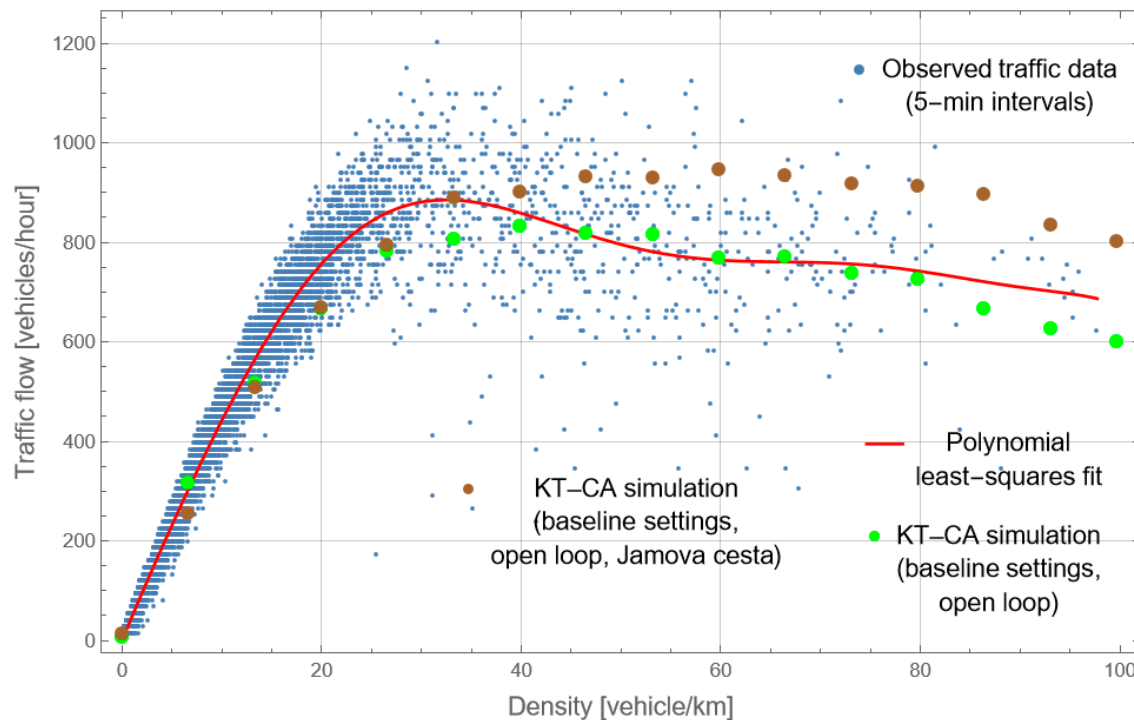


Figure 8. Comparison of empirical and simulated flow–density relationships for urban arterial roads in Ljubljana. Blue dots represent loop-detector measurements from Tržaška Road aggregated into 5 min intervals, while the red curve denotes the polynomial least-squares approximation of the empirical observations. Green dots indicate KT-CA simulation results for Dunajska Road, and brown dots represent KT-CA simulation results for Jamova Road, both obtained using baseline model settings in an open-loop configuration.

4.3. The Convergence Test

To evaluate the numerical convergence of the KT model, a convergence test was first conducted on a road segment without traffic lights. Simulations were performed at a density of 0.3 vehicles per cell, with a reaction time of 1.0 s and a maximum velocity of 60 km/h, under two different initial conditions: a mega-jam and a uniform vehicle distribution. The results were then compared with simulations carried out under identical conditions on a road segment with a series of traffic lights. For the road without traffic lights, simulations starting from mega-jam initial conditions—where all vehicles are initially at rest—show that the traffic flow rapidly converges to a steady state with only minor fluctuations (Figure 9).

Simulations with initially uniformly distributed vehicles (Figure 10) show that the traffic flow remains steady from the start of the simulation, with only minor fluctuations.

When traffic lights are introduced, the traffic flow no longer converges to a single steady-state value. Instead, persistent oscillations emerge due to the periodic stopping and releasing of vehicles at intersections. These oscillations remain bounded over time, indicating that the numerical stability is preserved, while the absence of classical steady-state

convergence reflects the inherently time-dependent nature of traffic flow on a signalized road (Figure 11).

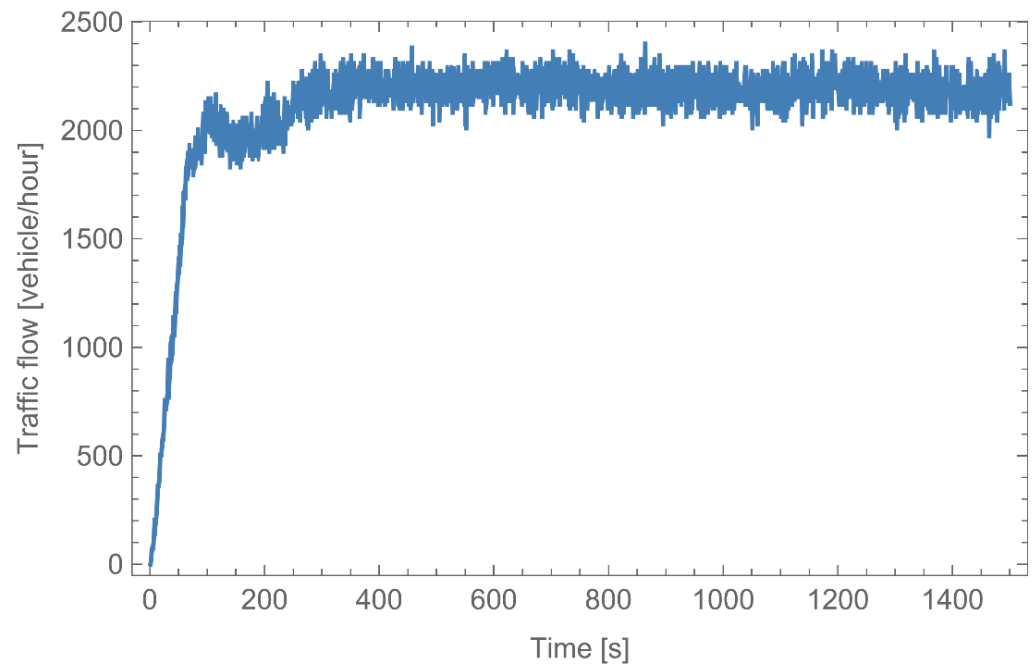


Figure 9. Traffic flow evolution on a one-lane road without traffic lights, using a reaction time of 1 s, a maximum velocity of 60 km/h, a density of 0.3 vehicles per cell, and initial mega-jam conditions (all vehicles at rest).

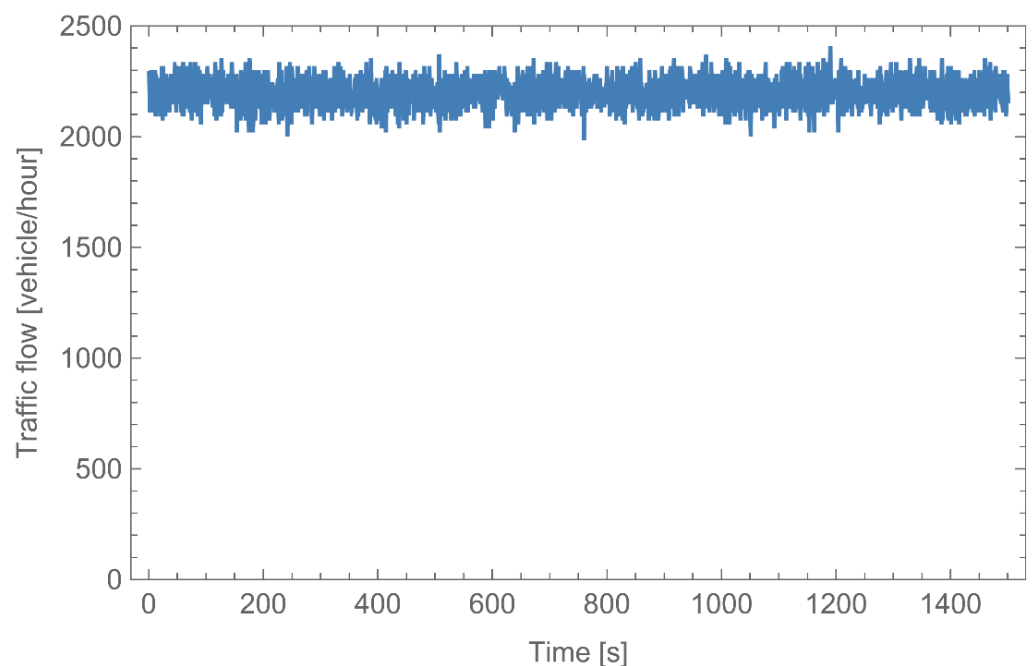


Figure 10. Traffic flow on a one-lane road without traffic lights, using a reaction time of 1 s, a maximum velocity of 60 km/h, a density of 0.3 vehicles per cell, and initially uniformly distributed vehicles, as described in [9].

The traffic flows from Figures 9–12 are random processes. In the case of initially uniformly distributed vehicles, the random process is stationary over the entire observation period (1500 s). This can be proven by the estimation of the moving average and autocorrelation function, which are constant in any arbitrarily chosen sub-period. The

autocorrelation function R as a function of time-lag τ is defined as a correlation between the process values observed a time-lag τ apart and is one of the characteristics of random processes [46]. Autocorrelation functions with a time lag between 10 and 200 s were estimated for different sub-periods. The results are shown in Figures 13 and 14.

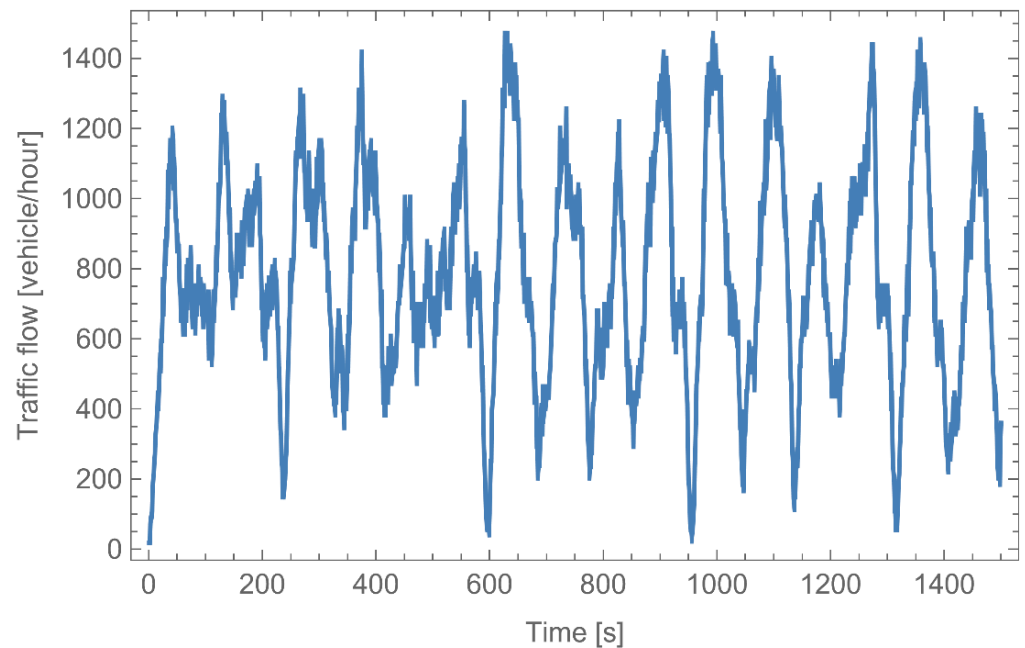


Figure 11. Traffic flow on a one-lane road with traffic lights, using a reaction time of 1 s, a maximum velocity of 60 km/h, a density of 0.3 vehicles per cell, and initial mega-jam conditions (all vehicles at rest).

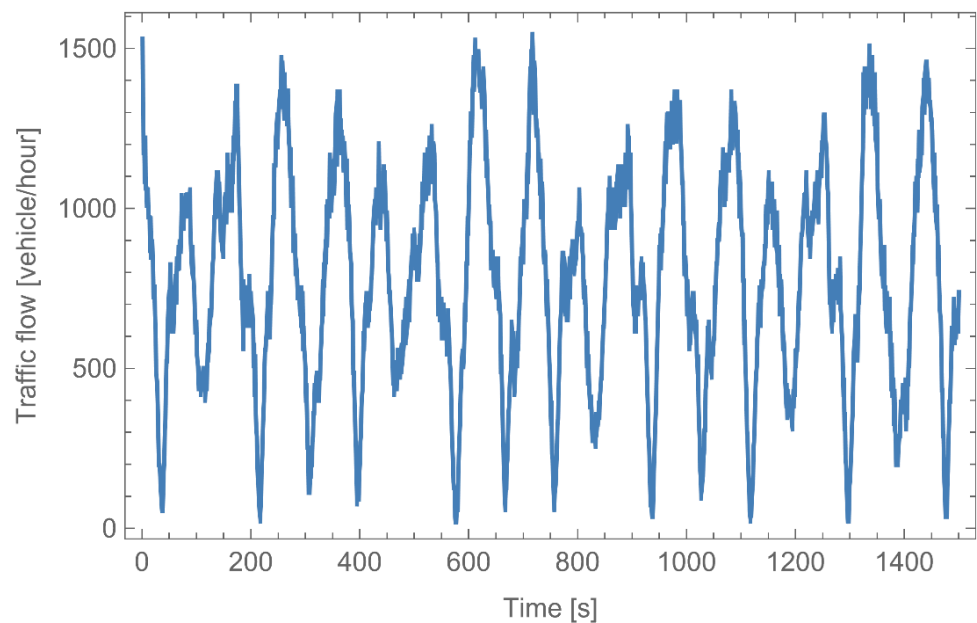


Figure 12. Traffic flow on a one-lane road with traffic lights, using a reaction time of 1 s, a maximum velocity of 60 km/h, a density of 0.3 vehicles per cell, and initially uniformly distributed vehicles, as described in [9].

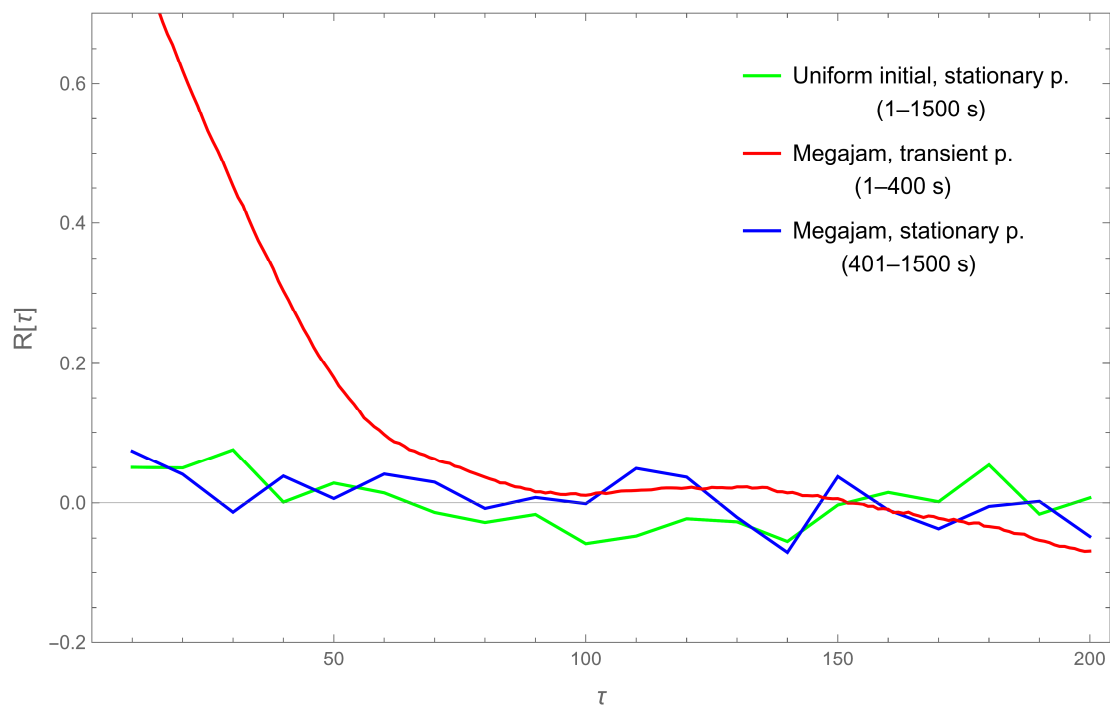


Figure 13. The autocorrelation function for time lags between 10 and 200 s for a road without traffic lights at a density of 0.3 vehicle/cell. The green line corresponds to a 1500 s simulation with initially uniformly distributed vehicles. The red and blue lines correspond to simulations with initial mega-jam conditions for the intervals 1–400 s and 401–1500 s, respectively.

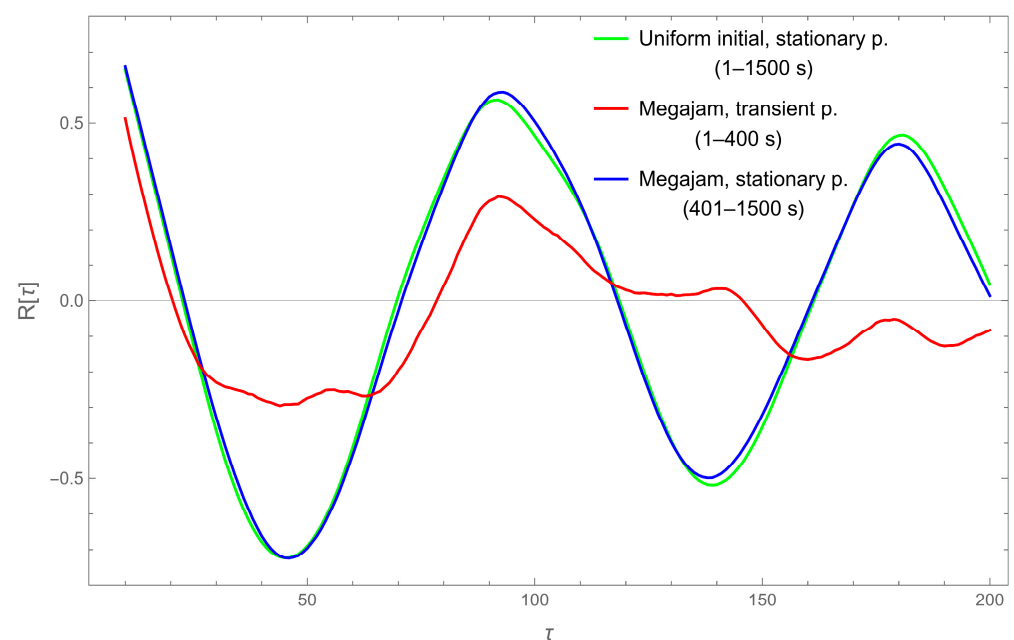


Figure 14. The autocorrelation function for time lags between 10 and 200 s for a road with a series of traffic lights at a density of 0.3 vehicle/cell. The green line corresponds to a 1500 s simulation with initially uniformly distributed vehicles, while the red and blue lines correspond to simulations with initial mega-jam conditions for the intervals 1–400 s and 401–1500 s, respectively.

The green line in Figure 13 represents the autocorrelation function obtained from a 1500 s simulation on a road without traffic lights, with a density of 0.3 vehicles/cell and initially uniformly distributed vehicles. The blue line corresponds to the autocorrelation function computed for the interval from 401 to 1500 s in simulations with initial mega-jam

conditions. The similarities between these two curves indicate that the traffic flow modeled with the KT model converges to the same stationary state. The first 400 s presents a transient phase of the simulation with initial mega-jam conditions. The autocorrelation function for the transient phase is represented by the red line.

The green and blue curves in Figure 14 represent autocorrelation functions for whole period in the case of uniform initial distribution and the stationary phase (401–1500 s) for mega-jam initial conditions, respectively. These two curves show close agreement, indicating that, also in the presence of traffic lights, the KT model converges to a stationary traffic flow after the transient phase, similarly to the case without traffic lights shown in Figure 13. The red curve in Figure 14 represents the autocorrelation curve for the transient phase in the case of mega-jam initial conditions and a road with traffic lights.

4.4. Open-Boundary Conditions

To better approximate real-world traffic dynamics, simulations were performed under open-boundary conditions (Figure 15). Vehicles were initially distributed along the road according to the specified density. Subsequently, they entered the road with an arrival rate corresponding to the traffic flow at that density and exited freely at the end of the road segment. The simulation results show qualitative agreement with those obtained under semi-open boundary conditions, with the primary difference being enhanced traffic flow at higher densities, as vehicles are able to leave the road segment without restriction. Another notable difference is the variability in traffic flow observed at the same density across different simulation runs, which arises from the stochastic nature of vehicle arrivals.

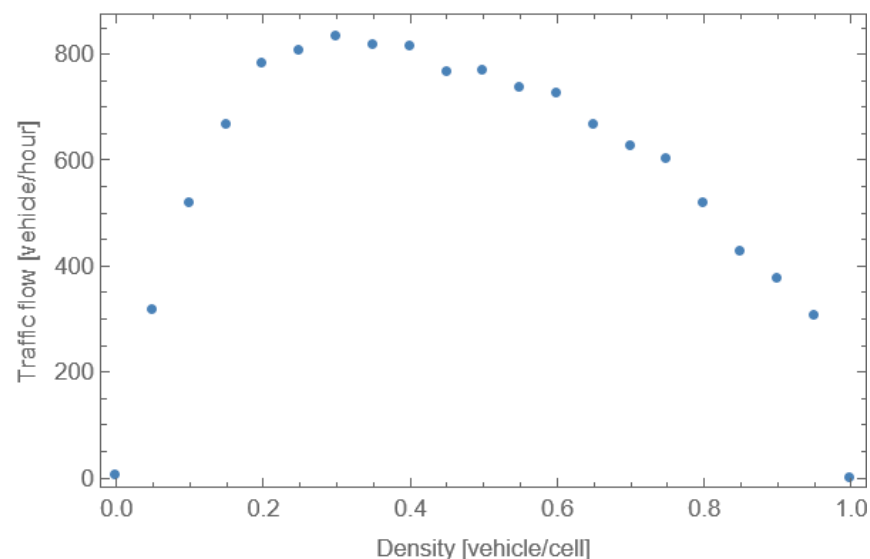


Figure 15. The flow–density diagram for the road with traffic lights in open-boundary conditions, obtained using the new KT model with the AA mode, for the reaction times of 1 s and a maximum velocity of 60 km/h.

Real traffic environments involve numerous factors that are not captured by the present model but can significantly influence the traffic flow. These include heterogeneous driving speeds and overtaking behavior on multi-lane urban arterials, as well as the presence of different vehicle types, such as buses, alongside passenger cars. Moreover, pedestrian activity—particularly at intersections—can slow turning vehicles and affect traffic conditions over a broader area. Finally, drivers with exceptionally long reaction times may trigger localized congestion and traffic jams. As a result, identical traffic densities may correspond to different traffic flow values under varying real-world conditions.

4.5. Sensitivity Analysis of Yellow-Phase Duration

A targeted sensitivity analysis was conducted to assess the influence of yellow-phase treatment and the associated stopping behavior near intersections. Since safety analysis governs stopping decisions during the yellow phase in the KT-CA model, the sensitivity test was performed by varying the yellow-phase duration at all signalized intersections by ± 2 s while preserving all other model parameters.

Figure 16 shows the resulting flow–density relationships for the reduced yellow phase, baseline signal timing, and extended yellow phase scenarios. The results show only limited changes in maximum traffic flow and the overall shape of the flow–density relationship. The relative differences between the baseline signal timing and the other two scenarios generally remained below 6%, while at high densities, the differences became negligible, indicating the limited sensitivity of the model to reasonable variations in yellow-phase duration.

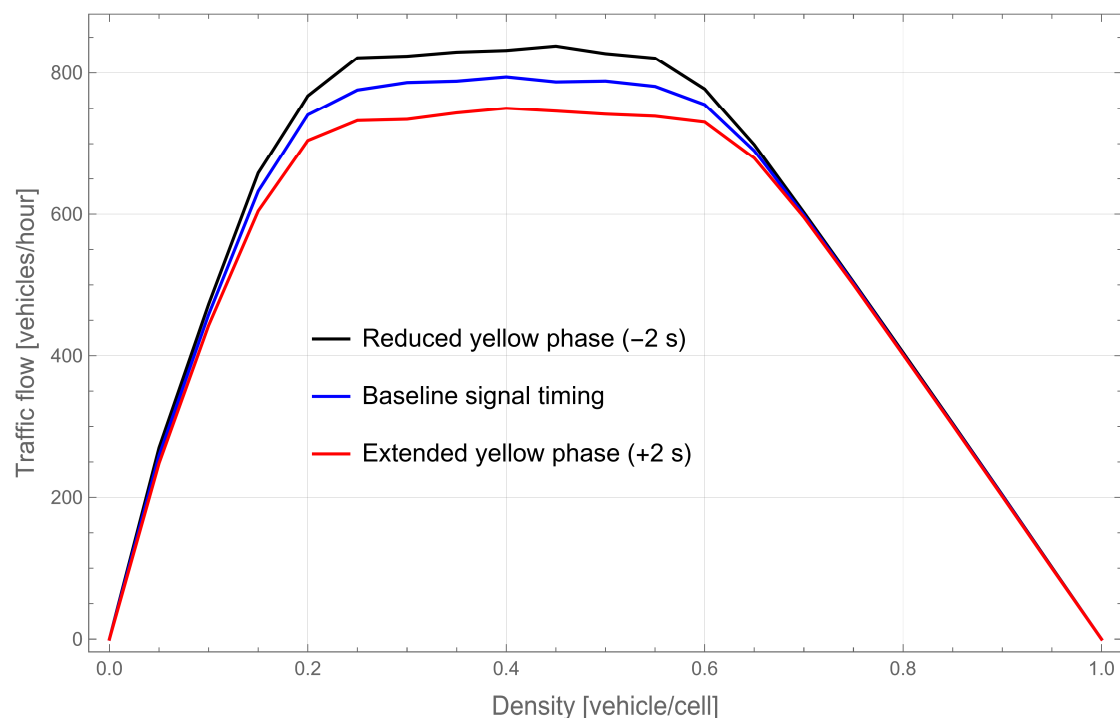


Figure 16. Sensitivity analysis of the yellow-phase duration on the flow–density relationship.

4.6. Model Advantages and Limitations

The obtained flow–density relationships are consistent with the general behavior reported by established microscopic traffic simulation tools and empirical traffic observations within the observed density range [41,45]. Recent comparative studies have shown that no single traffic simulator is universally optimal and that the choice of model depends on the intended application. For example, SUMO and MATSim emphasize computational efficiency and scalability, whereas VISSIM provides a more detailed representation of vehicle interactions and driving behavior [47]. Microscopic simulation platforms such as VISSIM provide detailed representations of traffic operations and allow the simulation of heterogeneous traffic consisting of different vehicle types with varying speeds, sizes and maneuverability characteristics through numerous user-defined parameters. In contrast, the KT-CA model was designed to facilitate systematic investigation of the influence of individual traffic parameters on traffic-flow dynamics. The model uses a limited number of physically interpretable parameters, such as the reaction time, maximum acceleration and speed limit, allowing systematic sensitivity analyses and transparent interpretation of the obtained results. Despite its relatively simple structure and the absence of additional

parameter tuning, the model reproduced the observed flow–density relationship with good accuracy (NRMSE = 0.058; $R^2 = 0.95$), indicating that the main characteristics of signalized urban traffic can be captured without extensive calibration procedures. Previous studies have noted that microscopic simulators such as VISSIM often require extensive calibration because several driver-behaviour parameters cannot be directly measured in the field and therefore must be adjusted to reproduce observed traffic conditions. Moreover, the calibration can be challenging due to the large number of user-defined parameters and their interactions [48]. Consequently, the proposed model facilitates the investigation of cause-and-effect relationships between traffic parameters and traffic-flow characteristics.

To summarize, the KT–CA model represents a compromise between model simplicity and traffic-flow realism. Its main advantages are the limited number of physically interpretable parameters, transparent model structure, efficient execution of sensitivity analyses, and reduced calibration requirements. However, the current implementation does not explicitly account for lane-changing behavior, detailed driver behavior, or heterogeneous vehicle fleets. Consequently, the model is particularly suitable for investigating the influence of individual traffic parameters on traffic-flow dynamics, while more detailed microscopic simulators may be preferable when analyzing complex traffic operations involving multiple vehicle types and driving behaviors.

5. Conclusions

This study introduces an extended KT model for heterogeneous traffic operating under periodic, semi-boundary and open-boundary conditions on a road segment with a series of traffic lights. Compared with an equivalent road segment without signalization, the introduction of traffic lights—representative of a typical urban arterial—reduces traffic flow by more than a factor of two and a half. In the proposed framework, vehicles accelerate progressively by adjusting their acceleration rate when insufficient space prevents acceleration at the maximum allowable value. This adaptive acceleration (AA) mode provides more flexibility than the fixed acceleration (FA) mode.

The study presents speed–density and flow–density relationships for various reaction times, maximum acceleration rates, and maximum velocities, with reaction time effects analyzed for both homogeneous and heterogeneous traffic conditions. Furthermore, traffic flow under semi-open boundary conditions—where vehicles enter and exit at signalized intersections—is investigated, thereby improving the representativeness of urban traffic simulations. Validation using observed traffic data, convergence tests, and open-boundary simulations provided additional insights into urban traffic dynamics. While absolute flow values may vary across cities and roadway configurations, the relative sensitivities identified here are robust with respect to parameter variation. The results can be summarized as follows:

1. Similarly to the road without traffic lights [9], the AA mode where vehicles can adjust their accelerations and decelerations, increases the traffic flow and average velocity on the road with a series of traffic lights by more than 30% at higher densities and up to 20% at lower densities (Figure 2). Namely, when the available space is insufficient for maximum acceleration, vehicles can use lower acceleration rates instead of maintaining their current velocity. This improves the utilization of available road space and reduces the delays during queue discharge at signalized intersections, resulting in higher traffic flow, particularly under high-density conditions.
2. Semi-open boundary conditions, where vehicles arrive at and depart from intersections, result in a maximum traffic flow approximately 5% higher than that under closed boundary conditions. At both lower and higher density values, this difference can reach up to 20%, as vehicle departures reduce local density at intersections and

thereby improve traffic flow. Furthermore, the traffic flow is additionally enhanced by vehicle arrivals during red phases at intersections on the main road. (Figure 2).

3. A shorter reaction time has a similar effect to the AA mode, with a 0.2 s reduction leading to up to a 17% increase in traffic flow and average velocity. In heterogeneous reaction time conditions, the traffic flow and average velocity are slightly lower than in homogeneous conditions, with all of them having a 1.0 s reaction time. Namely, vehicles with slower reaction times tend to slightly slow the flow when following faster-reacting vehicles (Figure 2). However, the impact of driver reaction is higher on a road without traffic lights because there are no obstacles to interrupt the traffic flow.
4. As in [9], the maximum acceleration rates have a minimal effect on both the traffic flow and average velocity because vehicles typically lack sufficient space to fully utilize their maximum acceleration rates, and even when they do, the impact is limited to the next few time steps (Figure 5).
5. Higher maximum velocities increase the traffic flow at lower densities but have little impact at higher densities. At a maximum velocity of 80 km/h, the maximum traffic flow is 17% higher compared to a speed limit of 40 km/h. However, as the speed limit increases, its impact on the traffic flow diminishes (Figure 6).
6. Quantitative validation using one month of empirical loop-detector measurements on Tržaška Road in Ljubljana showed strong agreement between the simulated and observed flow–density relationships (NRMSE = 0.058, $R^2 = 0.95$), supporting the applicability of the proposed KT–CA model to signalized urban traffic (Figure 8).

This paper provides a comprehensive characterization of traffic behavior on signalized roadways, offering valuable insights for traffic planners involved in urban traffic management. The proposed model can be applied to assess the effects of speed limits on traffic flow and travel times, as well as to evaluate the efficiency of different traffic signal coordination strategies. The semi-open boundary extension of the traffic light model enables the investigation of how varying vehicle arrival and departure rates influence traffic flow at individual intersections and along entire road segments. These rates may also be used to optimize traffic signal timing or to determine appropriate lengths of widened traffic lanes. Furthermore, different maximum acceleration rates are examined to evaluate their impact on traffic flow; these parameters can also be employed to estimate traffic emissions by incorporating an emission model into the KT framework.

The results obtained in this study may have practical implications for traffic management on signalized urban arterial roads. The sensitivity analyses demonstrated that reaction time, speed limits and signalized interruptions significantly influence traffic flow and road capacity. Therefore, the proposed KT–CA model may be useful for evaluating the potential effects of traffic-control measures on urban traffic flow.

While this study provides useful information about urban traffic dynamics, several limitations should be acknowledged. The extended KT model is currently restricted to a single-lane road with traffic lights. Consequently, lane-changing behavior and the effects of drivers with different maximum velocities are not yet examined. Additionally, further improvements could be achieved by incorporating dynamically varying reaction times at both the individual driver level and across the entire driver population. The present model also does not explicitly consider pedestrian crossings, variations in signal timing parameters (e.g., cycle length, green ratio, and offsets), adaptive signal control strategies, or heterogeneous driver decision-making during the yellow phase.

6. Future Work

Although this paper focuses on assessing the influence of various driving parameters on traffic flow along a signalized road, several extensions are planned for future research and practical applications:

1. The evaluation of different traffic signal control and coordination strategies, including the effects of cycle length, green ratio, signal offsets, and adaptive signal control on traffic-flow characteristics.
2. Extension of the model to a multi-lane framework incorporating heterogeneous driver types with varying maximum velocities, enabling a more detailed investigation of driving styles and lane-changing behavior.
3. Investigation of the impact of connected and automated vehicles (CAVs) with reduced reaction times, including an assessment of how varying CAV penetration rates affect traffic efficiency, especially in urban areas at signalized intersections.

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Data Availability Statement: The code is available from the authors upon request. Additionally, the code will be uploaded to the repository of the University of Ljubljana. No empirical data was used for the research described in this article.

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Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this review.

Appendix A. Boundary-Condition Parameters

Table A1. Poisson arrival rates (μ_1 – μ_5) corresponding to the target density level g .

Density (g)	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6
0.0	0.0134	0.0019	0.0023	0.0027	0.0013	0.0008
0.1	0.1198	0.0171	0.0204	0.024	0.012	0.0072
0.2	0.2262	0.0323	0.0385	0.0452	0.0226	0.0136
0.3	0.2458	0.0351	0.0418	0.0492	0.0246	0.0147
0.4	0.2418	0.0345	0.0411	0.0484	0.0242	0.0145
0.5	0.2378	0.034	0.0404	0.0476	0.0238	0.0143
0.6	0.2338	0.0334	0.0397	0.0468	0.0234	0.014
0.7	0.1771	0.0253	0.0301	0.0354	0.0177	0.0106
0.8	0.1193	0.017	0.0203	0.0239	0.0119	0.0072
0.9	0.0615	0.0088	0.0104	0.0123	0.0061	0.0037
1.0	0.0036	0.0005	0.0006	0.0007	0.0004	0.0002

Table A2. Bernoulli departure probabilities (p_1 – p_5) used in all simulation scenarios.

p_1	p_2	p_3	p_4	p_5
0.14	0.17	0.20	0.10	0.06

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