



Article An Improved Cellular Automata Traffic Flow Model Considering Driving Styles

Tianjun Feng ^{1,2}, Keyi Liu ^{1,2,*} and Chunyan Liang ^{1,2}

- ¹ School of Transportation Science and Engineering, Jilin Jianzhu University, Changchun 130118, China
- ² Engineering Research Center of Traffic Disaster Prevention and Control in Cold Region,
 - Changchun 130118, China
- * Correspondence: liuky98@yeah.net; Tel.: +86-178-5311-8220

Abstract: An improved cellular automata model (CA model) considering driving styles is proposed to analyze traffic flow characteristics and study traffic congestion's dissipation mechanism. The data were taken from a particular case in the Next Generation Simulation (NGSIM) program, which selected US-101 as the survey location from 7:50 a.m.-8:05 a.m. to investigate vehicle trajectory information. Different driving styles and the differences in vehicle parameters (speed, acceleration, deceleration, etc.) were obtained using principal component analysis and the k-means clustering method. The selected model was proposed for improvement based on analyzing the existing CA models and combining them with the actual road conditions. Considerations of driving styles and two operation mechanisms (over-acceleration and speed adaptation) were introduced in the improved model. The result obtained after the traffic simulation shows that the improved CA model is effective, and the mutual transformation of different traffic flow phases can be simulated. In the improved CA model, dissipating traffic congestion effectively and balancing the overall flow of the road are realized to improve the traffic capacity up to around 115% compared to the NaSch model and meet the demand of all kinds of drivers expecting to drive at the safest distance, which provides a theoretical basis for relieving traffic congestion. The various driving styles in terms of safety, comfort, and effectiveness are performed differently in the improved CA model. An aggressive driving style contributes to increasing traffic capacity up to around 181% compared to a calm driving style, while the calm style contributes to maintaining traffic flow stability.

Keywords: cellular automata model; driving styles; traffic flow; traffic simulation

1. Introduction

With the development of technology and the increase in transportation demand, many scientists have been attracted to the study of traffic problems of high complexity and practical significance. Many models have been proposed to understand the characteristics and mechanisms of traffic flow evolution, which can be broadly classified into microscopic, macroscopic, and mesoscopic models [1–5].

The cellular automata model (CA model) is a type of microscopic model. The basic idea of the CA model is to use a large number of simple structures, simple links, and simple rules running in parallel in time and space to simulate complex and rich phenomena. It has the following advantages.

(1) The complex system's collective phenomena and evolutionary dynamics can be portrayed well.

(2) It has simple and efficient calculation.

(3) The update rule is flexible and intuitive.

The first traffic flow CA model can be traced back to the Wolfram184 model [6]. In a time step, the vehicle either remains motionless (if the preceding cell is occupied) or moves forward one cell (if the preceding cell is empty). Another CA model was proposed by



Citation: Feng, T.; Liu, K.; Liang, C. An Improved Cellular Automata Traffic Flow Model Considering Driving Styles. *Sustainability* **2023**, *15*, 952. https://doi.org/10.3390/ su15020952

Academic Editors: Yusheng Ci, Lina Wu and Ming Wei

Received: 23 November 2022 Revised: 28 December 2022 Accepted: 3 January 2023 Published: 4 January 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). Cremer and Ludwig (1986) [7]. However, these early models did not get attention until the NaSch model was proposed [8]. In the NaSch model, the transition from free flow to congested flow is of the first order. To describe the first-order leap in traffic flow, several scholars introduced the slow-start rule to represent this feature [9–12].

Based on long-term empirical data analysis, Kerner proposed a three-phase traffic theory [13–15], which divides congested traffic into a synchronized flow phase (S) and a wide moving jam phase (J), in addition to a free flow phase (F). In the synchronized flow phase, when the speed is not low (or density is not high), the congestion does not appear spontaneously, then this "synchronized flow" is stable. As the speed decreases (or the density increases), the synchronized flow becomes unstable, and congestion will appear spontaneously.

To reproduce synchronized flow, many CA models have been proposed. The comfortable driving (CD) model was proposed by Knospe et al. in 2000, which considers the driver's requirement for smooth and comfortable driving [16]. The system is a coexistence of the free flow and wide moving jam, but the model cannot reproduce the synchronized flow correctly. Jiang and Wu proposed a modified comfortable driving (MCD) model in 2003 to reproduce the synchronized flow [17]. This model can reproduce synchronized flow, wide moving jam, and the S \rightarrow J transition, but it fails to reproduce the F \rightarrow S transition.

The Kerner–Klenov–Wolf (KKW) model is one of the first CA models in the framework of three-phase traffic theory, in which the two-dimensional region of steady-state and speed adaptation effect is explicitly considered [18]. The updated rules include deterministic and stochastic rules.

Gao proposed a model based on the generalized NaSch model in 2007 and combined the model with the slow-start rule [19]. The basic diagram obtained is similar to the KKW model, and this model can reproduce synchronized flow, wide moving jam, and the $S \rightarrow J$ transition, but it fails to reproduce the $F \rightarrow S$ transition. To overcome this deficiency, Gao et al. later proposed an improved model [20]. However, the velocity of the vehicles fluctuates too much in the synchronized flow, which seems unrealistic.

Tian proposed a two-state model (TS model) in 2015, and the TS model considers two driver states: defensive state and normal state [21]. The model can reproduce free flow, synchronized flow, wide moving jam, and $F \rightarrow S$ and $S \rightarrow J$ transition. To make the TS model more realistic, Tian introduced a logistic function of safe speed and random probability in the two-state model, called the two-state model with safe speed (TSS model) [22]. The model can reproduce the three phases of traffic flow well, and in the improved two-state model, synchronized flow can coexist with free flow.

In previous models, the vehicle has an infinite deceleration and can immediately stop in one step. In some models, a finite deceleration capability of vehicles is considered [23–28].

Driving style is closely related to driving behavior and can be used as a representation to predict and explain driving behavior. As a central part of the traffic system, the driver's behavior plays an important role in the traffic flow.

Kaur et al. introduced driver behavior characteristics into the lattice point model and studied driver behavior during curves using a lattice point hydrodynamic approach [29]. Wang et al. used factor analysis to extract the main factors affecting driving emotion. They established a driving emotion recognition model based on fuzzy integrated judgment and the AD emotion model. The model was validated by actual driving, virtual driving, and interactive simulation experiments [30]. Zheng et al. considered the effect of driver memory and proposed an extended car-following model in which the control signals of vehicles and following vehicle speed contrast were considered. Through numerical simulations, the application of this model was shown to be effective in suppressing traffic congestion [31]. Thompson et al. investigated the effects of habits and expectations on driver behavior and attention allocation in familiar and unfamiliar environments [32]. Peng et al. analyzed the generation and development of overtaking-induced driver road rage using 32 overtaking accidents as examples [33]. Yang et al., based on driving configured on the diversity of driving tendencies, proposed a two-lane CA model to simulate the average speed, flow

rate, and frequency of lane changes under different lane change and deceleration rules [34]. Shi et al. investigated the effects of distracting behaviors such as cell phone use by drivers during driving on traffic safety [35]. Sharma et al. used a lattice-hydrodynamic traffic flow model to study the influence on behavior of driver aggressiveness and conservatism while driving [36]. Li et al. proposed a new grid model to analyze the effect of aggressive driving behavior on traffic flow stability based on consideration of the driver aggression effect [37].

Currently, the impact on traffic flow is mainly analyzed qualitatively in terms of individual driver behavior. At the same time, relatively few quantitative studies have been conducted on the effects of drivers on traffic flow. Most previous studies on driving heterogeneity were based on experimental and questionnaire methods, such as in [33–37].

The questionnaire analysis method options are fixed and cannot restore the actual driving condition of the vehicle. The current research on driving style is not comprehensive, so this paper analyzes driving styles from the perspective of a model based on the real driving condition of the vehicle.

The driver's personality characteristics also have an impact on the driving effect. For the same driving scenario, different drivers sustain different physiological and psychological conditions and thus produce different fuel consumption and emissions, affecting the sustainable development of transportation.

Since the daily driving habits of drivers can affect vehicle emissions, some scholars have trained up drivers or made operational recommendations to encourage drivers to adopt ecological driving behaviors, such as avoiding sudden-stop and excessive idling, and accelerating gently, which can significantly reduce vehicle energy consumption and emissions [38].

Miotti et al. states regulating driving styles can help reduce the energy consumption and emissions of driving without requiring infrastructure or vehicle technology change [39].

Meseguer et al. experimentally verified that an aggressive driving style always leads to more energy consumption and CO₂ emissions [40].

Gonder et al. experimented on light vehicles and found that changing the driving style can cause a 20% change in fuel consumption for aggressive drivers, and the change in fuel consumption for drivers compared to mild drivers can also reach 5% to 10% [41].

Rafael et al. evaluated the impact of three driving styles on fuel efficiency and emissions on the chassis dynamometer. The results showed that the aggressive driving style had low fuel efficiency and high emissions [42].

Mansfield et al. studied the pre- and post-intervention bias changes in driving behavior and showed that the effect of intervention on driving behavior depends on individual driver factors and driving motivation [43].

Barth et al. proposed the provision of dynamic driving advice during the driving trip. Dynamic driving advice can reduce fuel consumption and CO_2 emissions by 10–20% and does not affect the overall trip time significantly. The percentage savings also depends on the congestion level, with little effect on free flow and significant savings in congested conditions [44].

Zhai et al. proposed a continuous traffic flow enhancement model considering the effects of driver characteristics and traffic fluctuations, obtaining model stability under linear and nonlinear conditions. The effects of driver characteristics and traffic fluctuations on traffic flow and emissions were investigated [45].

Jiao et al. analyzing the relationship between driver characteristics and following optimal speed by using the grey correlation method, proposed a new optimal speed function (OVF) and vehicle following model, and numerically simulated the influence of different driver characteristics on the vehicle following behavior and fuel economy [46].

Frequent start-stops and idling of vehicles increase fuel consumption and emissions. Therefore, studying the formation and dissipation mechanism of congestion can help implement reasonable traffic control, effectively reducing the waiting time in congested areas and thus can reduce energy consumption and emissions, which is conducive to the sustainable development of transportation. Pan et al. investigated the effect of traffic congestion on particulate matter emissions and the energy consumption of single-lane traffic streams using the NaSch model with periodic and open boundary conditions [47].

Shankar et al. found that if a significant reduction in traffic congestion can be achieved, a significant reduction in energy consumption could be obtained [48].

The rest of this article is arranged as follows: The second part introduces the data processing of driving style classification; the method is introduced, and statistical analysis is performed to obtain the differences in vehicle speed, acceleration, deceleration, etc., under different styles. The third part discusses the classical CA models and the main rules for improving the model. The fourth part focuses on the simulation analysis from the perspective of the fundamental diagram and spatio-temporal characteristics analysis. Finally, in the fifth part, the paper's findings are summarized.

2. Driving Style Analysis

2.1. Data Preparation

In this study, we used NGSIM data to classify driving styles, obtained driving data for the following vehicles, and used the data to validate an improved meta-automata model.

The NGSIM data were obtained from the Next Generation Simulation program [49], which collected vehicle trajectory data on US-101 and Lankershim Avenue in Los Angeles, California, I-80 in Emeryville, California, and Peachtree Street in Atlanta. The data provide precise location information for each vehicle, recorded at 10 Hz, resulting in precise lane locations and positions relative to other vehicles. The data from US-101 were selected for analysis in this study.

The US-101 data contain 25 attributes: vehicle ID, frame ID, global time, local X, and local Y, etc. [49]. The length of the study area is about 640 m, including eight lanes, five driving lanes, two ramp lanes, and one merging lane, shown in Figure 1. The dataset contains 45 min of US-101 vehicle trajectories divided into three 15-min periods: 7:50 a.m.–8:05 a.m., 8:05 a.m.–8:20 a.m., and 8:20 a.m.–8:35 a.m. The trajectory data from 7:50 a.m.–8:05 a.m. was used in this study.

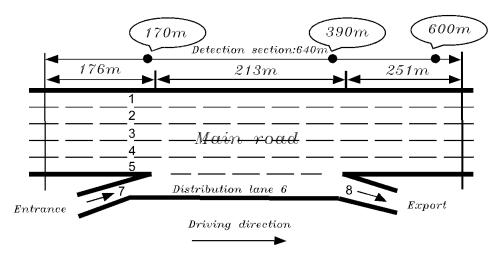


Figure 1. US-101. (Source: Own compilation based on [49]).

To ensure the accuracy of the data, we selected the vehicles on the main lane, which accounted for about 97% of the total, chose the cars as the study object, and then converted the imperial units to international standard units.

The contents of the processed data are shown in Table 1.

2.2. Data Preprocessing

The NGSIM raw data were obtained from video analysis, which contains a lot of errors and noise [50]. Using the raw data directly would lead to greater bias in the analysis results,

affecting the calibration of the microscopic traffic flow model and reducing the accuracy of the subsequent analysis. Therefore, a Savitzky–Golay filter using a third-order polynomial with a window length of 21 was used to smooth the velocity and acceleration data [51].

Table 1. Basic information of NGSIM data.

Number	Name	Unit
1	Vehicle ID	number
2	Frame ID	100 ms
3	Total frames	100 ms
4	Global time	h
5	Local X	m
6	Local Y	m
7	Vehicle length	m
8	Vehicle width	m
9	Vehicle velocity	km/h
10	Vehicle acceleration	m/s^2
11	Lane Identification	number
12	Space headway	m
13	Time headway	S

(Source: Own compilation based on [49]).

2.3. Car-Following Process Extraction

The car-following process is mainly expressed in the process of the following vehicle (FV) to the driving state of the leading vehicle (LV). Figure 2 shows the following scenario. In the same lane, the driver of the following vehicle adjusts the driving speed of his vehicle in real-time according to the driving behavior of the previous vehicle to maintain the desired distance; d is the workshop distance between the two vehicles.

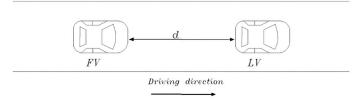


Figure 2. The following scenario. (Source: Own elaboration).

Since vehicle following behavior is driving behavior in a single lane, the data need to be pre-processed. To study the heterogeneity of the following behavior, it is necessary to extract the following vehicle data that meet the requirements from the US-101 dataset, with the following specific screening conditions.

- The following behavior data is extracted in a way that the two vehicles driving continuously in the same lane are extracted as a combination.
- The following vehicle and the vehicle in front will not change lanes within a certain time.
- The vehicles of 1–5 lanes are selected for following behavior data extraction. The vehicle driving in or out of the ramp may affect the following behavior.
- The vehicle type as "car" is only considered. The various types of vehicles in the following performance are considered differently, while the car accounts for a large proportion.
- For each data group, the vehicle following time is required to be above 20 s to ensure a relatively stable vehicle following state.
- For each data group, the time headway between the vehicle and the preceding vehicle must be kept within 5 s to ensure that the distance between vehicles will not be too large, resulting in the following effect not being obvious.

According to the above rules, a total of 1104 data sets (653,568 vehicle trajectory samples) were collected from the processed NGSIM data. For the extracted vehicle following data, 70% were used for driving style analysis and determining the model design parameters, and 30% were used to test the model's accuracy.

2.4. Driving Style Division

Driving styles are closely related to driving safety, and aggressive driving styles are usually more likely to lead to traffic accidents. For example, aggressive drivers are easily affected by the road environment (e.g., rainy day, snowy day) and other road users (e.g., disobeying traffic rules) during the driving process, appear driving anger cognition (e.g., frustration, mild irritation) and driving aggressive behavior (e.g., cursing, honking, etc.). To incorporate the actual situation and reduce the influence of subjective questionnaires on the results, vehicle kinematic data were used in this paper.

Velocity and acceleration can show driving habits, and frequency change of velocity and following distance can reflect driving personality. In this paper, 10 evaluation indicators on driving styles were selected, as shown in Table 2.

Table 2. Driving style evaluation index.

Number	Name	Unit	
1	1 Average velocity		
2	The standard deviation of velocity		
3	Average space headway	m	
4	The standard deviation of space headway		
5	Average time headway	s	
6	The standard deviation of time headway		
7	Average acceleration	m/s^2	
8	Average deceleration	m/s^2	
9	Speed difference	m/s	
10	Maximum velocity	km/h	

(Source: Own elaboration).

When classifying driving styles, if all the parameters of the follow-the-leader model are used for classification, all the information about driving behavior is retained. The accuracy and convergence of the analysis results can be affected if the driving style is classified directly using the parameters. Principal component analysis (PCA) is a statistical algorithm that converts correlated variables into linearly uncorrelated variables using orthogonal transformations. The transformed variables are called principal components (PC).

We calculated each PC contribution and cumulative contribution rates, as shown in Figure 3. The first five PCs were selected based on the 85% cumulative contribution principle to reflect the original indicators' information fully. The PC coefficient matrix is shown in Table 3.

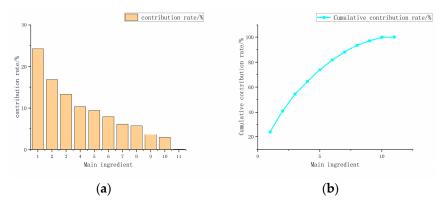


Figure 3. (a) PC contribution, (b) cumulative contribution rates. (Source: Own elaboration).

Standardized Variable	x1	x2	x3	x4	x5
Average velocity	-0.091	0.255	-0.287	0.068	0.538
The standard deviation of velocity	0.023	-0.205	0.272	0.164	0.142
Average space headway	0.237	0.100	-0.304	-0.300	0.091
The standard deviation of space headway	0.320	-0.034	-0.133	-0.334	-0.200
Average time headway	0.248	-0.039	0.123	0.249	0.289
The standard deviation of time headway	0.224	-0.109	0.293	-0.011	-0.156
Average acceleration	-0.368	-0.234	0.255	-0.349	0.468
Average deceleration	0.063	0.284	-0.107	0.360	-0.271
Speed difference	0.205	0.022	0.355	0.380	0.416
Maximum velocity	0.014	0.383	0.319	-0.214	0.176

Table 3. The PC coefficient matrix.

(Source: Own elaboration).

The scores of each PC were calculated based on the PC score coefficient matrix and used as the input for the subsequent classification and driving style recognition models. Among them, the main influencing factors of the first three PCs are average acceleration, maximum velocity, and average deceleration.

Then the number of driving style classifications was determined using cluster analysis methods. In this paper, the k-means algorithm was used to classify driving styles. The essence of the algorithm is to determine new cluster centers through iterative operations, and the calculation converges when the cluster centers do not change.

However, the disadvantage of k-means is that it is difficult to determine the number of "k" clusters. The main methods to determine the value of k are the silhouette measure and elbow method. The elbow method is based on the idea that the number of clusters k is taken from 1 to k = 8, with each step of 1. The sum of squared errors (SSE) is calculated for each value of k. The formula is shown in Equation (1).

$$SSE = \sum_{h=1}^{k} \sum_{p \in s_h} \|p - c_h\|_2^2$$
(1)

where c_h is the cluster midpoint in cluster S_h , p is the sample in cluster S_h , and k is the total number of clusters in the dataset.

When the number of clusters increases, the degree of aggregation of each cluster also increases, and the SSE decreases gradually. When the value of *k* is less than the correct number of clusters, the increase in the value of *k* will significantly increase the degree of aggregation of each cluster, and the decrease in SSE is greater. However, when *k* reaches the optimal number of clusters and then increases the number, the decrease of SSE will become slow and eventually level off. Therefore, the relationship between SSE and *k* is in the shape of an elbow, and the value of *k* corresponding to that elbow is the optimal number of data clusters. It is calculated that when the value of k is greater than 3, the SSE change tends to level off. Therefore, the number of driving styles classified in this study was three, and the three driving styles were named: calm, moderate, and aggressive.

Then the first three principal components were derived from arriving at the driving style identification results, shown in Figure 4. The clustering results show that 24% of the vehicles are of aggressive driving style, 54% of vehicles are of moderate driving style, and 22% of vehicles are of calm driving style.

To characterize the parametric features of the following behavior under different driving styles, the cluster centers in each cluster are taken to represent the following behavior of the class of drivers, shown in Table 4. According to the analysis of the clustering results, the aggressive driver will be close to the preceding vehicle, drive fast, and likely act boldly in the following process; acceleration and deceleration are greater than in the other

two styles. Calm drivers always stay away from the vehicle in front of them and drive cautiously and slowly. The surroundings have less influence on moderate drivers.

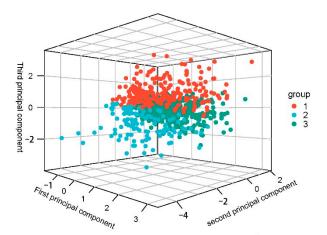


Figure 4. Driving style recognition results. (Source: Own elaboration).

Table 4. Clustering centers	of car-following	variables for di	fferent driving styles.

Driving Style	Driver Number	Maximum Velocity (km/h)	Average Acceleration (m/s ²)	Average Deceleration (m/s ²)	
Aggressive Style	936	73.21	4.32	4.74	
Moderate Style	2467	65.18	2.62	2.43	
Calm Style	771	60.86	1.58	1.33	
(Source: Own elaborat	ion).				

(Source: Own elaboration).

3. Model Description

3.1. NaSch Model

The NaSch model is a classical single-lane CA model, and the evolutionary rules mainly include acceleration, deceleration, random slowing rule, and update rule. The random slowing rule is set, so that the vehicle does not drive on the road at a fixed speed, and the vehicle will randomly slow down with a certain probability p. The evolution rules of the NaSch model in the one-time step are as follows.

Acceleration :
$$v_n = \min(v_n + 1, v_{\max})$$
 (2)

Deceleration :
$$v_n = \min(d_n + 1, v_{n+1}).$$
 (3)

Random slowing rule :
$$v_{n+1} = \max(v_{n+1} - 1, 0)$$
 (4)

Update rule :
$$x_{n+1} = x_n + v_{n+1}$$
 (5)

where, v_{max} is the maximum velocity, d_n is the distance between two vehicles, x_n , v_n are the position and velocity of the vehicle at the moment *n*, respectively.

3.2. KKW Model

This subsection briefly introduces the core part of the KKW model, the speed adaptation rules [52]. The updated rules include dynamic rules and stochastic rules.

Step 1. Dynamical part of the KKW model:

$$\widetilde{v} = \max(0, \min(v_{\max}, v_s, v_c)) \tag{6}$$

in which v_c is calculated by the following equation:

$$v_{c} = \begin{cases} v_{n} + at, & \text{if } dis > D_{n} \\ v_{n} + at \times sign(v_{lead} - v_{n}), & \text{if } dis \leq D_{n} \end{cases}$$
(7)

In the above equation, v_{max} is the maximum speed of the vehicles, v_s is the safe speed that the vehicle cannot exceed to avoid a collision, v_c is the adaptation speed of the vehicles within the synchronized flow distance and the preceding vehicle's speed. t is the time step, set to 1 s. a is the acceleration or deceleration. The sign(x) is a sign function, if x > 0, sign(x) = 1, if x = 0, sign(x) = 0, otherwise sign(x) = -1. D_n is the synchronized distance, *dis* is the distance between the following vehicle and the preceding vehicle.

The updated rule of v_c reflects the "speed adaptation". The "speed adaptation" means that when the front vehicle is within the synchronization distance, the following vehicle will judge whether to accelerate according to the preceding vehicle's speed. When the distance is greater than D_n , the influence of the preceding car on the following car is weak, and the acceleration of the following car is almost not affected by the speed of the preceding car. When the distance is less than D_n , the front car acts powerfully on the following car, and the following car adjusts its speed to approach the speed of the preceding car. The "speed adaptation" ensures that the speed of the following car can be very close to the speed of the front car in a certain distance range, which causes a synchronized flow state.

Synchronized flow distance is a function of the speed. In the literature [15], Kerner gives the following linear and nonlinear relations for

$$D_n = d + k v_n t \tag{8}$$

$$D_n = d + v_n t + \beta v_n^2 / (2a) \tag{9}$$

where *d*, *k*, and β are constants. In this paper, the linear relationship of D_n is selected as the improved model parameter design.

Step 2. Stochastic part of KKW models:

$$v' = \max(0, \min(\tilde{v} + a\eta t, v + at, v_{\max}, v_s))$$
(10)

In which *a* is the vehicle's acceleration. η is the parameter set to control the speed disturbance, its value is set by setting a random number, representing the slow start and "pinch" phenomena, depending on the corresponding conditions, as in Equation (11).

$$\eta = \begin{cases} -1, & if \ r < p_b, \\ 1, & if \ p_b \le r < p_b + p_a, \\ 0, & otherwise. \end{cases}$$
(11)

$$p_b = \begin{cases} p_1, & \text{if } v = 0, \\ p_2, & \text{if } v > 0. \end{cases}$$
(12)

$$p_{a} = \begin{cases} p_{a1}, & if \ v < v_{p}, \\ p_{a2}, & if \ v \ge v_{p}. \end{cases}$$
(13)

where *r* is a random number between 0 and 1. p_a and p_b are functions used to control the rate of addition and subtraction.

 p_1 and p_2 are constants between 0 and 1, and $p_1 > p_2$. p_{a1} , p_{a2} , v_p are constants, $p_{a1} > p_{a2}$.

Step 3. Vehicle movement:

$$x_{n+1} = x_n + v't \tag{14}$$

3.3. The Improved CA Model

Based on the previous presentation, a new CA model was proposed by considering the driving styles and introducing two principles (the speed adaptation principle and the over-acceleration principle), which are improved and combined with the NaSch model.

Over-acceleration rule on a single lane [53]: in the current driving lane, when the distance between a car and the preceding car is within the synchronized flow distance and the speed of the preceding car is less than or equal to its speed, the following car will accelerate with probability in addition to adapting to the speed of the preceding car; this probability is related to the current speed and the difference of the synchronized flow speed. The over-acceleration rule was modified to make it more suitable for the model proposed in this paper.

$$v_{n+1} = \min(v_{n+1} + acc, v_{\max}) \quad if \quad d_n \le D_n \text{ and } v_n \ge v_{lead} \tag{15}$$

The over acceleration occurs in the lane when

$$r < p_a$$
 (16)

where *r* is a random number between 0 and 1, v_{lead} is the preceding vehicle's velocity, p_a is the same as defined in the previous section.

r

To describe the diversity of driving styles, the vehicle's maximum speed and acceleration are subdivided according to the driving types. The subscripts denote variables regarding aggressive, moderate, and calm styles, respectively. Consequently, $v_{max,agg}$, acc_{agg} , and dec_{agg} are the vehicle parameters of aggressive style. $v_{max,mod}$, acc_{mod} , and dec_{mod} are the vehicle parameters of moderate style. $v_{max,calm}$, acc_{calm} , and dec_{calm} are the vehicle parameters of calm driving style.

The evolution rules for the improved CA model are given here.

Rule (a): Classification of driving style characteristics

$$v_{\max} = \begin{cases} v_{\max,agg} & if \ driver \ is \ aggressive \ style, \\ v_{\max,mod} & if \ driver \ is \ moderate \ style, \\ v_{\max,calm} & if \ driver \ is \ calm \ style. \end{cases}$$
(17)

$$acc = \begin{cases} acc_{agg} & if \ driver \ is \ aggressive \ style, \\ acc_{mod} & if \ driver \ is \ moderate \ style, \\ acc_{calm} & if \ driver \ is \ calm \ style. \end{cases}$$
(18)

$$dec = \begin{cases} dec_{agg} & if \ driver \ is \ aggressive \ style, \\ dec_{mod} & if \ driver \ is \ moderate \ style, \\ dec_{calm} & if \ driver \ is \ calm \ style. \end{cases}$$
(19)

Rule (b): determine whether the distance is within the synchronization distance

$$if \ d_n \le D_n \tag{20}$$

Follow rules (c), (d), skip rule (e),

$$if \ d_n > D_n \tag{21}$$

Skip rules (c), (d), follow rule (e).

Where, d_n is the distance between the following vehicle and the preceding vehicle. Rule (c): the improved speed adaptation rules

$$\widetilde{v} = \begin{cases} v_n + acc \times t, & \text{if } v_{lead} > v_n, \\ v_n - dec \times t, & \text{if } v_{lead} < v_n, \\ v_n, & \text{if } v_{lead} = v_n. \end{cases}$$
(22)

 $v_{n+1} = \begin{cases} \max(0, \min(\widetilde{v} - dec \times t, v - dec \times t, v_{\max}, d_n)), & \text{if } r < p_b, \\ \max(0, \min(\widetilde{v} + acc \times t, v + acc \times t, v_{\max}, d_n)), & \text{if } p_b \le r < p_b + p_a, \\ \max(0, \min(\widetilde{v}, v + acc \times t, v_{\max}, d_n)), & \text{otherwise.} \end{cases}$ (23)

$$p_b = \begin{cases} p_{sts}, & if \ v_n = 0, \\ p_{slow}, & if \ v_n > 0. \end{cases}$$
(24)

$$p_{a} = \begin{cases} p_{a1}, & if \ v_{n} < v_{p}, \\ p_{a2}, & if \ v_{n} \ge v_{p}. \end{cases}$$
(25)

where, p_{sts} is the slow start probability when the vehicle's speed is 0, p_{slow} is the random slowing probability, and r is a random number between 0 and 1.

Rule (d): The over-acceleration rule within the synchronized flow distance is shown in Formulas (14) and (15) for details.

Rule (e): The process of acceleration

$$v_{n+1} = \min(v_n + acc, v_{\max}) \tag{26}$$

Rule (f): The process of deceleration

$$v_{n+1} = \min(v_{n+1}, d_n)$$
(27)

Rule (g): Improved random slowing rule

$$r > p_b \tag{28}$$

$$v_{n+1} = \max(v_{n+1} - dec, 0) \tag{29}$$

Rule (h): Update location

$$loc_{n+1} = loc_n + v_{n+1}t (30)$$

where, loc_n is the vehicle position when the timestep is n.

4. Simulation and Analysis

In the model of this paper, Simulations are carried out on a circular road with the periodic boundary condition. In the model, each cell represents 1 m. Each vehicle occupies 7 cells, the road length is 2000 cells, and the simulation time is 2000 s. Referring to the driving style analysis results in Section 2, 20% of the vehicles are of aggressive driving style, 60% of vehicles are of moderate driving style, and 20% of vehicles are of calm driving style, while the parameters of driving styles are set as shown in Table 5 and the model parameters in Table 6.

Table 5. The parameters of driving styles.

Driving Style	Maximum Velocity (Cell/s)	Acceleration (Cell/s ²)	Deceleration (Cell/s ²)	
Aggressive Style	19	4	4	
Moderate Style	18	2	2	
Calm Style	16	1	1	

(Source: Own elaboration).

Table 6. The model parameters.

k	d	p_{a1}	p_{a2}	p_{sts}	p_{slow}	t	v_p
2	0	0.3	0.2	0.3	0.2	1 s	9 cell/s

(Source: Own elaboration).

4.1. Fundamental Diagram Analysis

Figure 5 represents the flow-density diagram of the NaSch model and the improved CA model. When the NaSch model's density increases, the traffic flow also increases. The traffic flow reaches a maximum value of 0.751 when the density reaches 0.165, which means the optimal density is 0.165. Before reaching the optimal density, the traffic flow on the road is generally in a free-flow phase. After reaching the optimal density, the traffic flow changes from the free-flow phase to the congestion phase. The traffic flow starts to decrease, similar to the traditional traffic fundamental diagram. Analysis of the flow density diagram of the improved CA model shows that when the density reaches 0.133, the maximum flow is 0.896, and the optimal density is 0.133. The flow has a sudden drop process when the optimal density is reached. When the density is less than 0.133, the few vehicles on the road can all drive at the desired speed without being affected by the previous vehicle. The traffic flow can maintain a steady state at a higher speed, and the flow increases linearly, that is, the free flow phase. When the density falls between 0.103 and 0.26, the number of congested vehicles increases, and the distance between vehicles decreases. When the speed fluctuation amplitude exceeds the critical limit, the free flow turns into the synchronized flow, and the spontaneous phase transition for $F \rightarrow S$ occurs. Flow drops sharply, but no serious congestion occurs on the road. When the density is greater than 0.26, the traffic flow changes from a synchronized flow to a wide moving jam, and the spontaneous phase transition for $S \rightarrow J$ occurs.

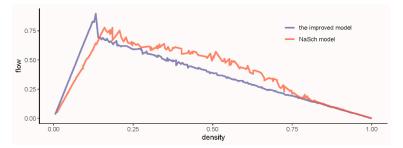


Figure 5. Averaged flow-density diagram for different models. (Source: Own elaboration).

When the density of the two models is in the range of 0.143 to 0.805, the NaSch model traffic flow is slightly larger than the improved CA model. This is because the improved model considers the speed adaptation principle. When the distance between the preceding and following two vehicles is less than the synchronization distance, as well as the slower speed of the front vehicle, the following vehicle will choose to slow down to ensure a safe distance, while the NaSch model only considers whether the distance between the preceding and the following two cars can guarantee that the following car will not collide with the preceding car in the next time step. So, in this density, the average speed of the NaSch model will be slightly larger than the improved CA model's, resulting in a slightly higher density. However, as the density gradually increases, the gap between the two models becomes smaller and eventually converges.

Figure 6a,b represent the flow-density diagram and the velocity-density diagram for the CA model considering only style and all styles. As can be seen from Figure 6a,b, the overall trends in speed and flow for different driving styles for the same model are similar. Still, all have some variability in the values, which becomes more pronounced as the density increases. In particular, this difference is greatest at densities of 0.165 to 0.26, where the spontaneous phase transition $F \rightarrow S$ occurs. Aggressive drivers are the first to end the free-flow phase, which is because aggressive drivers have the highest speed and the largest safety distance. Due to the existence of various types of traffic flow and the interaction between various types, all style phase transition is induced, thus making the density of the $F \rightarrow S$ transition in the mixed traffic flow approximately the same as that of the aggressive flow. In addition, the speed and flow curves output oscillate to some extent. The reason is that vehicles frequently perform acceleration and deceleration to obtain the best

speed as the vehicle density increases. The mutual interference between vehicles makes the average velocity show an unstable oscillating downward trend. However, when the density is greater than 0.441, regardless of the driving styles, the traffic flow is basically in the wide moving jam phase, and eventually, all the curves converge.

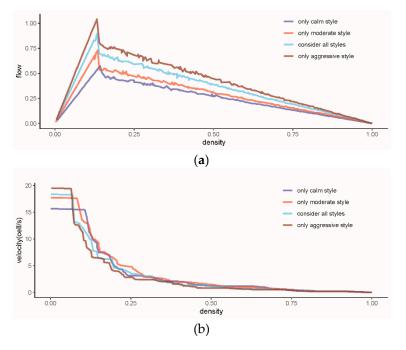


Figure 6. Fundamental diagram. (a) Averaged flow-density diagram for different styles and (b) velocity-density diagram for different styles. (Source: Own elaboration).

4.2. Thermodynamic Diagram Analysis

Thermodynamic diagrams are created based on the speed of vehicles on the road. In this experiment, the vehicle speed is divided into 20 levels from 0 to 20, where red is the maximum speed of 20 cells/s and blue is the stationary state, 0 cells/s. The diagrams' abscissa indicates the cell's location, while the ordinate indicates the simulation time. The driving direction is from left to right, and the time moves in the direction from bottom to top. The spatio-time region consisting of spatial location 0–2000 cells and simulation time 1000–2000 s is selected for thermodynamic diagrams analysis.

Figure 7a–d represents the thermodynamic diagrams of the NaSch model at a density of 0.4, the improved CA model at a density of 0.4, and the free flow and $F \rightarrow S \rightarrow F$ transition, respectively. Analysis of Figure 7a shows that vehicles present high speeds when there is no congestion on the road. When the road is congested, the vehicle speed drops directly from the maximum speed to 0 until the road is no longer congested. However, during the following process, the vehicle's speed will not maintain the maximum speed state for a long time due to the preceding vehicle's speed and distance. The thermodynamic diagram of the improved CA model at a density of 0.4 is shown in Figure 7b, where the blockage zone narrows and decreases as time passes, and the number of vehicles traveling at the desired safe distance increases due to the speed adaptation principle, where the vehicle speed changes frequently. Compared with Figure 7a, the improved CA model improves road congestion, the vehicle's free and synchronized flow area increases, and most vehicles are in normal driving conditions. Therefore, the improved CA model can effectively dissipate traffic congestion, balance the overall flow rate of the road, and meet the needs of all types of drivers who expect to drive at the safest distance.



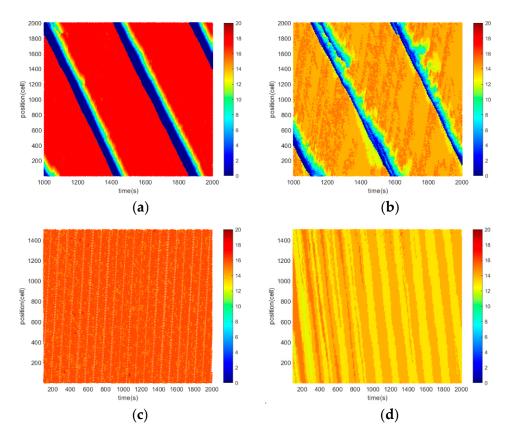


Figure 7. Thermodynamic diagram. (a) NaSch model; (b) improved CA model; (c) free-flow phase; (d) $F \rightarrow S \rightarrow F$ transition. (Source: Own elaboration).

The improved CA model presents a free-flow phase at lower density, shown in Figure 7c. The distance between vehicles is large and not affected by the speed adaptation principle. Most vehicles take the highest speed that can be taken in the current situation without congestion. Traffic flow occurs in the state of mutual transformation between free flow and synchronized flow, shown in Figure 7d. The road will not be congested, but the principle of speed adaptation will control the vehicles. When the preceding vehicle is approaching, the vehicle will decelerate and traffic flow occurs, $F \rightarrow S$ transition. However, when the distance becomes larger, the vehicle will return to the highest speed that can be taken in the current situation, and the traffic flow returns to the free flow state, and traffic flow occurs, $S \rightarrow F$ transition.

4.3. Trajectory Diagram Analysis

Figure 8a,b represents the trajectory diagrams of the NaSch model and the improved CA model considering a density of 0.42, respectively. The diagrams' abscissa indicates the spatial location of the cell, and the ordinate indicates the simulation time. The most representative spatial locations 0–2000 cell and simulation times 1000–2000 s are selected to form the trajectory diagrams. The white area in the graph indicates no vehicle at that location, and the black lines indicate the vehicles' driving trajectory. The vehicles travel from bottom to top, and the time goes from left to right.

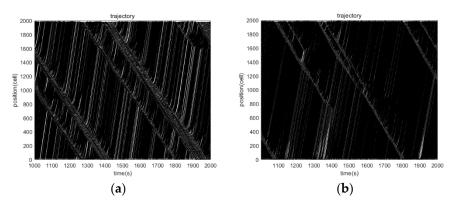


Figure 8. Diagram of trajectories. (a) NaSch model; (b) improved CA model. (Source: Own elaboration).

As shown in Figure 8a, the NaSch model indicates that traffic congestion gradually propagates upstream of the roadway over time and that there are large bands of wide congestion. The improved CA model changes the rules of operation of vehicles on the road, which is more consistent with the reality of vehicles moving forward. As shown in Figure 8b, the number of blocking strips decreases. The wide moving jam narrows over time, the traffic congestion on the upstream side of the road gradually dissipates, the free-flow area within the lane becomes larger, and there is no large-scale wide moving jam. Compared with the NaSch model, the improved CA model significantly reduces the number of congestion zones and traffic congestion is greatly improved.

The F-S-J transition fragment is selected further to investigate the speed perturbation under different traffic phases and justify the speed adaptation principle. The trajectory and speed of individual vehicles are analyzed as follows. The trajectory fragment in Figure 9a, the blue and red trajectories indicate the aggressive and the calm cars, respectively. The thermodynamic diagram shown in Figure 9b indicates the vehicle's current speed.

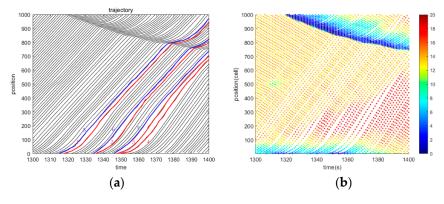


Figure 9. (a) Trajectory diagram, (b) thermodynamic diagram. (Source: Own elaboration).

In Figure 9, it can be seen that when the time is at 1345 s, the vehicle (vehicle 2 in Figure 6) is slower and is not affected by the change in speed of the aggressive preceding vehicle (vehicle 6 in Figure 6) because they are far away from each other. The vehicle will close the distance between the two vehicles at a higher speed and take the same action to adapt to the shifting behavior of the preceding vehicle, with the final distance remaining relatively safe for the vehicle. This interaction between vehicles generates disturbance and spreads backward into the traffic flow (e.g., vehicles 3, 4, and 7 in Figure 6). From the vehicle trajectories (e.g., vehicles 3, 4, and 7 in Figure 6), it can be found that aggressive vehicles have a relatively small distance from the vehicle in front during acceleration. However, calm vehicles choose to adjust their acceleration at a safer distance to accommodate the speed of the vehicle in front.

5. Discussion and Conclusions

The primary purpose of traffic flow modeling and simulation is to analyze traffic flow characteristics and study the formation and dissipation mechanism of traffic congestion to better guide real traffic. Research on the formation and dissipation mechanism of congestion can help implement reasonable traffic control, and reduce energy consumption and emissions, which is conducive to the sustainable development of transportation [47,48]. In this paper, we extended the NaSch and KKW models, and proposed an improved CA model to reproduce various traffic phenomena and behaviors on the single-lane road. Compared to the previous models, the improved CA model takes into account the effect of driving style, refines the length of each cell so that each car can fully occupy each cell as it travels, and introduces two operational mechanisms (over-acceleration and speed adaptation) to simulate the transformation among different traffic flow phases.

The specific research results are as follows.

- Unlike the general questionnaire survey method, we used a particular case in NGSIM data as the research object, extracted 1104 data sets that reflect the characteristics of driving styles, used the PCA method to reduce the dimensionality of the resulting data, then used the k-means method for driving style classification and parameter calibration. Compared with the general questionnaire survey method, our method considers the vehicle kinematic data, which can truly reflect the actual motion of the vehicle and not be affected by the subjective factors of the driver.
- In the process of modeling, we introduced two operational mechanisms and linear equations to express the synchronous flow distance and combined them with the driving style. We compared the results of the improved CA model and the NaSch model through numerical experiments. It was shown that the improved CA model has a 15% higher traffic flow rate. When the optimal density is exceeded, the flow rate of the improved CA model is slightly lower than the NaSch model due to the two operating mechanisms, which are in good agreement with the results obtained from the previous literature [52].
- In the simulation process, the calm style will choose a safer and more secure way to travel during the following process, and the road can remain stable for a longer time, but the maximum flow is lower. The aggressive style is more reckless, and the traffic flow cannot maintain a free flow state for a long time, but the aggressive style increases the traffic capacity up to around 181% more than the calm driving style.
- Furthermore, the simulation results also show that the improved CA model can generate well the free flow phase, the synchronized flow phase, the wide moving jam phase, and the transition among the phases. Compared with the NaSch model, the improved CA model has fewer congested areas, decreasing gradually over time. Due to the speed adaptation principle, the overall vehicle speed is not high, but the vehicles can maintain a uniform speed for a long time. The improved CA model can effectively relieve road congestion and accelerate the dissipation of traffic congestion, which can largely meet the drivers' requirements and provide a theoretical basis for relieving traffic congestion, which is conducive to the sustainable development of transportation.

6. Future Work

First, the CA model proposed in this paper is a single-lane model. However, multilane highways are more common in real traffic. Therefore, our next focus is to extend our single-lane model into a multi-lane one and study the impact of vehicle differences and speed fluctuations on traffic flow at the micro-scale; we will carry out a detailed comparison with real-world traffic.

Second, traffic flow studies are an extremely complex problem. Multi-lane lane change problems, weather influencing factors, etc., need to be considered, as well as whether the model applies to mixed traffic flows; all still needs to be discussed and studied.

Finally, as time progresses, transportation systems are gradually entering the Internet and automated driving era. It is imperative to consider the influence of connected automated vehicles in the design of future models.

Author Contributions: Conceptualization; Funding acquisition, T.F., C.L.; Software, K.L.; Data curation, K.L.; Writing—original draft preparation, K.L., T.F.; investigation, K.L.; Writing—review and editing, K.L., T.F., C.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by Science and Technology Research Planning Project of the Jilin Provincial Department of Science and Technology (20220402030GH).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflict of interest.

References

- 1. Daganzo, C.F. Requiem for second-order fluid approximations of traffic flow. *Transp. Res. Part B-Methodol.* **1995**, *29*, 277–286. [CrossRef]
- 2. Helbing, D. Derivation and empirical validation of a refined traffic flow model. Phys. A 1996, 233, 253–282. [CrossRef]
- 3. Yu, S.W.; Liu, Q.L.; Li, X.H. Full velocity difference and acceleration model for a car-following theory. *Commun. Nonlinear Sci. Numer. Simul.* **2013**, *18*, 1229–1234. [CrossRef]
- 4. Jamshidnejad, A.; Papamichail, I.; Papageorgiou, M.; De Schutter, B. A mesoscopic integrated urban traffic flow-emission model. *Transp. Res. Part C-Emerg. Technol.* 2017, 75, 45–83. [CrossRef]
- Di Gangi, M.; Cantarella, G.E.; Di Pace, R.; Memoli, S. Network traffic control based on a mesoscopic dynamic flow model. *Transp. Res. Part C-Emerg. Technol.* 2016, 66, 3–26. [CrossRef]
- 6. Wolfram, S. 20 Problems in the theory of cellular automata. *Phys. Scr.* **1985**, *9*, 170–183. [CrossRef]
- Cremer, M.; Ludwig, J. A fast simulation-model for traffic flow on the basis of boolean operations. *Math. Comput. Simul.* 1986, 28, 297–303. [CrossRef]
- 8. Nagel, K.; Schreckenberg, M. A cellular automaton model for freeway traffic. J. De Phys. I 1992, 2, 2221–2229. [CrossRef]
- 9. Fukui, M.; Ishibashi, Y. Effect of delay in restarting of stopped cars in a one-dimensional traffic model. *J. Phys. Soc. Jpn.* **1997**, *66*, 385–387. [CrossRef]
- Benjamin, S.C.; Johnson, N.F.; Hui, P.M. Cellular automata models of traffic flow along a highway containing a junction. J. Phys. A Math. Gen. 1996, 29, 3119–3127. [CrossRef]
- 11. Schadschneider, A.; Schreckenberg, M. Traffic flow models with 'slow-to-start' rules. Ann. Der Phys. 1997, 6, 541–551. [CrossRef]
- 12. Barlovic, R.; Santen, L.; Schadschneider, A.; Schreckenberg, M. Metastable states in cellular automata for traffic flow. *Eur. Phys. J. B* **1998**, *5*, 793–800. [CrossRef]
- 13. Kerner, B.S. Experimental features of self-organization in traffic flow. Phys. Rev. Lett. 1998, 81, 3797–3800. [CrossRef]
- 14. Kerner, B.S.; Rehborn, H.; Aleksic, M.; Haug, A. Recognition and tracking of spatial-temporal congested traffic patterns on freeways. *Transp. Res. Part C-Emerg. Technol.* **2004**, *12*, 369–400. [CrossRef]
- 15. Kerner, B.S.; Klenov, S.L. A Study of Phase Transitions on Multilane Roads in the Framework of Three-Phase Traffic Theory. *Transp. Res. Rec.* **2009**, 2124, 67–77. [CrossRef]
- 16. Knospe, W.; Santen, L.; Schadschneider, A.; Schreckenberg, M. Towards a realistic microscopic description of highway traffic. *J. Phys. A Math. Gen.* **2000**, *33*, L477–L485. [CrossRef]
- 17. Jiang, R.; Wu, Q.S. Cellular automata models for synchronized traffic flow. J. Phys. A Math. Gen 2003, 36, 381–390. [CrossRef]
- 18. Kerner, B.S.; Klenov, S.L.; Wolf, D.E. Cellular automata approach to three-phase traffic theory. *J. Phys. A Math. Gen* **2002**, 35, 9971–10013. [CrossRef]
- 19. Gao, K.; Jiang, R.; Hu, S.X.; Wang, B.H.; Wu, Q.S. Cellular-automaton model with velocity adaptation in the framework of Kerner's three-phase traffic theory. *Phys. Rev. E* 2007, *76*, 026105. [CrossRef]
- Gao, K.; Jiang, R.; Wang, B.H.; Wu, Q.S. Discontinuous transition from free flow to synchronized flow induced by short-range interaction between vehicles in a three-phase traffic flow model. *Phys. A Stat. Mech. Its Appl.* 2009, 388, 3233–3243. [CrossRef]
- 21. Tian, J.F.; Treiber, M.; Ma, S.F.; Jia, B.; Zhang, W.Y. Microscopic driving theory with oscillatory congested states: Model and empirical verification. *Transp. Res. Part B-Methodol.* **2015**, *71*, 138–157. [CrossRef]
- 22. Tian, J.F.; Li, G.Y.; Treiber, M.; Jiang, R.; Jia, N.; Ma, S.F. Cellular automaton model simulating spatiotemporal patterns, phase transitions and concave growth pattern of oscillations in traffic flow. *Transp. Res. Part B-Methodol.* **2016**, *93*, 560–575. [CrossRef]
- Ci, Y.S.; Wu, L.N.; Ling, X.Z.; Pei, Y.L. Operation reliability for on-ramp junction of urban freeway. J. Cent. South Univ. Technol. 2011, 18, 266–270. [CrossRef]

- 24. Pottmeier, A.; Thiemann, C.; Schadschneider, A.; Schreckenberg, M. Mechanical restriction versus human overreaction: Sccident avoidance and two-lane traffic simulations. In Proceedings of the 6th International Conference on Traffic and Granular Flow, Berlin, Heidelberg, 10–12 October 2005. [CrossRef]
- 25. Larraga, M.E.; Alvarez-Icaza, L. Cellular automaton model for traffic flow based on safe driving policies and human reactions. *Phys. A Stat. Mech. Its Appl.* **2010**, *389*, 5425–5438. [CrossRef]
- 26. Jin, C.J.; Wang, W. The influence of nonmonotonic synchronized flow branch in a cellular automaton traffic flow model. *Phys. A Stat. Mech. Its Appl.* **2011**, 390, 4184–4191. [CrossRef]
- 27. Kokubo, S.; Tanimoto, J.; Hagishima, A. A new Cellular Automata Model including a decelerating damping effect to reproduce Kerner's three-phase theory. *Phys. A Stat. Mech. Its Appl.* **2011**, *390*, 561–568. [CrossRef]
- 28. Chmura, T.; Herz, B.; Knorr, F.; Pitz, T.; Schreckenberg, M. A simple stochastic cellular automaton for synchronized traffic flow. *Phys. A Stat. Mech. Its Appl.* **2014**, 405, 332–337. [CrossRef]
- Kaur, R.; Sharma, S. Analysis of driver's characteristics on a curved road in a lattice model. *Phys. A Stat. Mech. Its Appl.* 2017, 471, 59–67. [CrossRef]
- Wang, X.Y.; Liu, Y.Q.; Wang, F.; Wang, J.Q.; Liu, L.P.; Wang, J.H. Feature extraction and dynamic identification of drivers' emotions. *Transp. Res. Part F-Traffic Psychol. Behav.* 2019, 62, 175–191. [CrossRef]
- 31. Zheng, Y.M.; Cheng, R.J.; Ge, H.X.; Lo, S.M. An extended car-following model with consideration of the driver's memory and control strategy. *Asian J. Control.* 2018, 20, 689–696. [CrossRef]
- 32. Thompson, C.; Sabik, M. Allocation of attention in familiar and unfamiliar traffic scenarios. *Transp. Res. Part F-Traffic Psychol. Behav.* **2018**, *55*, 188–198. [CrossRef]
- 33. Peng, Z.Y.; Wang, Y.; Chen, Q. The generation and development of road rage incidents caused by aberrant overtaking: An analysis of cases in China. *Transp. Res. Part F-Traffic Psychol. Behav.* **2019**, *60*, 606–619. [CrossRef]
- Yang, L.H.; Zhang, X.Q.; Ji, W.C. A divided two-lane cellular automaton model of traffic flow considering driving tendency. *Ksce J. Civ. Eng.* 2018, 22, 5187–5194. [CrossRef]
- Shi, J.; Xiao, Y.; Atchley, P. Analysis of factors affecting drivers' choice to engage with a mobile phone while driving in Beijing. *Transp. Res. Part F-Traffic Psychol. Behav.* 2016, 37, 1–9. [CrossRef]
- 36. Sharma, S. Modeling and analyses of driver's characteristics in a traffic system with passing. *Nonlinear Dyn.* **2016**, *86*, 2093–2104. [CrossRef]
- Li, X.Q.; Fang, K.L.; Peng, G.H. A new lattice model of traffic flow with the consideration of the drivers' aggressive characteristics. *Phys. A Stat. Mech. Its Appl.* 2017, 468, 315–321. [CrossRef]
- 38. Günther, M.; Kacperski, C.; Krems, J.F. Can electric vehicle drivers be persuaded to eco-drive? A field study of feedback, gamification and financial rewards in Germany. *Energy Res. Soc. Sci.* **2020**, *63*, 101407. [CrossRef]
- 39. Miotti, M.; Needell, Z.A.; Ramakrishnan, S.; Heywood, J.; Trancik, J.E. Quantifying the impact of driving style changes on light-duty vehicle fuel consumption. *Transp. Res. Part D-Transp. Environ.* **2021**, *98*, 102918. [CrossRef]
- 40. Meseguer, J.E.; Toh, C.K.; Calafate, C.T.; Cano, J.C.; Manzoni, P. DrivingStyles: A Mobile Platform for Driving Styles and Fuel Consumption Characterization. *J. Commun. Netw.* **2017**, *19*, 162–168. [CrossRef]
- 41. Gonder, J.; Earleywine, M.; Sparks, W. Analyzing vehicle fuel saving opportunities through intelligent driver feedback. *SAE Int. J. Passeng. Cars–Electron. Electr. Syst.* **2012**, *5*, 450–461. [CrossRef]
- 42. Rafael, M.; Sanchez, M.; Mucino, V.; Cervantes, J.; Lozano, A. Impact of driving styles on exhaust emissions and fuel economy from a heavy-duty truck: Laboratory tests. *Int. J. Heavy Veh. Syst.* **2006**, *13*, 56–73. [CrossRef]
- 43. Mansfield, L.R.; Guros, F.; Truxillo, D.M.; MacArthur, J. Individual and contextual variables enhance transfer for a workplace eco-driving intervention. *Transp. Res. Part F Traffic Psychol. Behav.* **2016**, *37*, 138–143. [CrossRef]
- 44. Barth, M.; Boriboonsomsin, K. Energy and emissions impacts of a freeway-based dynamic eco-driving system. *Transp. Res. Part D Transp. Environ.* **2009**, *14*, 400–410. [CrossRef]
- Zhai, C.; Wu, W. Analysis of drivers' characteristics on continuum model with traffic jerk effect. *Phys. Lett. A* 2018, 382, 3381–3392. [CrossRef]
- Jiao, S.; Zhang, S.; Zhou, B.; Zhang, Z.; Xue, L. An Extended Car-Following Model Considering the Drivers' Characteristics under a V2V Communication Environment. *Sustainability* 2020, 12, 1552. [CrossRef]
- 47. Pan, W.; Xue, Y.; He, H.-D.; Lu, W.-Z. Impacts of traffic congestion on fuel rate, dissipation and particle emission in a single lane based on NaSch Model. *Phys. A Stat. Mech. Its Appl.* **2018**, *503*, 154–162. [CrossRef]
- 48. Shankar, R.; Marco, J. Method for estimating the energy consumption of electric vehicles and plug-in hybrid electric vehicles under real-world driving conditions. *IET Intell. Transp. Syst.* **2013**, *7*, 138–150. [CrossRef]
- U.S. Department of Transportation Federal Highway Administration. Next Generation Simulation (NGSIM) Vehicle Trajectories and Supporting Data. 2016. Available online: https://data.transportation.gov/stories/s/Next-Generation-Simulation-NGSIM-Open-Data/i5zb-xe34 (accessed on 23 December 2022).
- Coifman, B.; Li, L.Z. A critical evaluation of the Next Generation Simulation (NGSIM) vehicle trajectory dataset. *Transp. Res. Part B-Methodol.* 2017, 105, 362–377. [CrossRef]
- Savitzky, A.; Golay, M.J.E. Smoothing + differentiation of data by simplified least squares procedures. Anal. Chem. 1964, 36, 1627–1639. [CrossRef]

- 52. Tian, J.F.; Zhu, C.Q.; Jiang, R.; Treiber, M. Review of the cellular automata models for reproducing synchronized traffic flow. *Transp. AE Transp. Science.* **2021**, *17*, 766–800. [CrossRef]
- 53. Boris, S.; Kerner, S.L.K.; Gerhard, H.; Michael, S. Effect of driver over-acceleration on traffic breakdown in three-phase cellular automaton traffic flow models. *Phys. A Stat. Mech. Its Appl.* **2013**, 392, 4083–4105. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.