Modeling Micro Traffic Flow Phenomena Based on Vehicle Types and Driver Characteristics Using Cellular Automata and Monte Carlo

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Abstract*—The modeling of micro traffic flow on a highway has been extensively observed and studied in various aspects, such as driver characteristics in car-following and lane-changing behaviors. Regarding car-following and lane-changing, an interesting aspect is how to model the movement conditions of vehicles on a highway that exhibit unique characteristics regarding the speed of four-wheeled or more vehicles passing through it. This condition occurs on the Porong Highway in Sidoarjo, East Java, Indonesia. Based on these conditions, this study develops a microscopic traffic flow model incorporating driver characteristics categorized into three types: careful drivers, ordinary drivers, and skilled drivers, each with distinct vehicle speed traits. These driver characteristics are integrated into the Nagel-Schreckenberg Stochastic Traffic Cellular Automata (NaSch STCA) model, which we refer to as the Modified NaSch STCA. The Monte Carlo simulation is employed to generate events through random numbers for the Occupied Initial State, Slowdown Probability, and Probability of Lane Changing. These three components are integral parts of the Modified NaSch STCA model. Experiments (simulations) were conducted on the constructed vehicle movement model, and one of the outcomes is that the travel time obtained from the NaSch STCA model is significantly faster than that obtained from the Modified NaSch STCA model. This condition is attributed to the unique vehicle speed characteristics on the Porong Highway, where the average speed v_r = 38 km/h is relatively lower than the average speed typically observed on a highway.

Keywords*—*Micro traffic flow; driver characteristics; cellular automata; Monte Carlo

I. Introduction

Modeling and simulation of microscopic traffic flow have been extensively pursued by researchers, including the development of micro-traffic flow models based on intelligent transportation systems with wireless communication [1]; calibration of microscopic car-following (CF) models to accurately replicate and study traffic behavior and phenomena [2]; estimation and prediction of traffic states by integrating statistical data in both congested and uncongested scenarios [3]. Intelligent transportation systems offer an alternative to enhance traffic environments by integrating the Internet of Things and smart algorithms. These systems collect and process data from various sources to improve transportation efficiency. Research conducted by study [4] reviews the smart techniques employed for predicting traffic flow in urban areas. Additionally, it proposes a general taxonomy where the insights gained from traffic flow analysis merge with computational approaches. Microscopic urban traffic simulation using integrated modeling methods has been conducted, taking into account driver behavior characteristics related to car-following and lane changing. The results indicate that car-following behavior is more sensitive to variations in the status of adjacent vehicles and lane changes compared to lane-changing behavior during the lane-change process. This study also aids in analyzing travel characteristics and the impact mechanisms of vehicles in urban roads, serving as a guide for the development of sustainable transportation and autonomous vehicles in the future, and promoting efficient urban transportation system operations [5].

Microscopic traffic simulations are frequently employed to evaluate the effects of autonomous vehicles on safety and traffic flow. This study examines adaptive driver behavior by having drivers navigate the same route three times, each with a different level of autonomous vehicle penetration. The findings reveal that as the penetration level of autonomous vehicles increases, drivers adopt shorter waiting times, smaller following distances, and more consistent speeds closer to the maximum speed limit. These results indicate that driving behavior changes in response to variations in surrounding traffic composition [6].

Cellular automata have proven highly beneficial, not only in traffic flow simulation but also in diverse fields like pedestrian behavior for example: study a behavior-based cellular automata model that can represent heterogeneous crowd structures and explore the effects of different crowd compositions on pedestrian dynamics, particularly evacuation efficiency [7]. A multi-grid cellular automata model has been utilized to connect vehicle and pedestrian models. The enhanced Kerner-Klenov-Wolf (IKKW) model and a pedestrian movement model that incorporates Time to Collision (TTC) have been proposed. The application of these models to real-life scenarios has shown the impact of pedestrian intrusion behavior on traffic [8]. In the context of disaster mitigation, an expanded cellular automata model has been proposed for emergency evacuation dynamics involving pedestrians, utilizing parameters such as route change probability and group fields. Experiments were conducted to investigate the effects of this new extension, including the verification of related collective phenomena and the evaluation of safety performance metrics [9]. An LSTM-CA simulation for wildfire spread, combining Cellular Automata with Long

Short-Term Memory (LSTM), has been proposed. Real-world wildfire spread simulations have been conducted, and the accuracy of the wildfire spread predictions was verified using KAPPA coefficients, Hausdorff distances, and horizontal comparison experiments based on remote sensing imagery of wildfires [10].

Probabilistic Logistic Cellular Automata (LPCA) modeling has been carried out by integrating a basic logistic growth model with two-dimensional spatial dynamics to simulate the formation of regular patterns. The simulation results indicate that resource scarcity and environmental shape are the primary factors leading to the emergence of various regular patterns [11]. To prevent falling into local optima and to enhance convergence speed and global search potential, an advanced version of the Ant Colony Optimization (ACO) algorithm, known as the Cellular Automata-Based Enhanced Ant Colony Optimization Algorithm (CA-IACOA), has been explored. Simulation results suggest that this algorithm is effective in addressing DDoS attacks, as it achieves high-quality solutions for identifying optimal nodes and reliable routing paths [12]. The phenomena observed in modeling and simulating various aspects using cellular automata indicate its capability to provide solutions to both simple and complex problems.

In the use of cellular automata for a particular problem, the role of randomness and Monte Carlo simulation is crucial. Many researchers emphasize the incorporation of randomness into the rules of cellular automata, such as using randomness in the probability of lane switching [13], [14]. Monte Carlo simulation plays a significant role in modeling and simulating dynamic systems using cellular automata, including calculating simulation data for traffic queuing problems [15] and predicting real-time traffic flow based on normal distribution [16].

In micro traffic flow modeling, driver behavior is a critical parameter. One aspect involves defensive maneuvers by drivers to avoid obstacles and braking, such as encountering a pedestrian appearing suddenly on the road ahead of the vehicle [17]. The smart road stud (SRS) not only drastically alters microscopic driving characteristics but also significantly influences driver decision-making processes during overtaking maneuvers [18]. On the other hand, research on modeling driving behavior in developing countries is conducted using microsimulation approaches with multi-agents, deemed suitable for accurately replicating driving behaviors [19]. Adaptive driver behavior is observed through repeated driving of the same route three times with varying penetration rates of automated vehicles. It is demonstrated that driving behavior changes as the traffic composition around them changes [20]. It is noted that following behavior is more sensitive to variations in lateral vehicle movements and lane changes [21].

In the context of micro traffic flow modeling, many researchers utilize driver behavior as a key parameter. However, this driver behavior is rarely depicted based on the micro traffic flow phenomena observed on highways, especially the phenomenon of vehicle speeds passing through the roadway. Cellular automata, as a method of dynamic system specific to micro traffic flow modeling, employs rules that require processes of randomness, including determining initial density probabilities and lane-changing probabilities. This study employs Monte Carlo simulations for the randomness processes embedded within the cellular automata rules. A survey of vehicle speeds in micro traffic flow was conducted on the Porong Highway in Sidoarjo, East Java, Indonesia, focusing on four-wheeled vehicles: trucks/trailers, buses, public transportation, and private cars. The phenomenon of vehicle speeds passing through this highway served as the basis for categorizing driver characteristics. Based on normalized speed data from each vehicle type, drivers were categorized as follows: careful drivers for truck/trailer drivers, ordinary drivers for bus and public transportation drivers, and skilled drivers for private car drivers. A modified cellular automata model was developed based on these driver characteristic categories, and an analysis of traffic flow simulation results was conducted to assess the accuracy of the model. The results of this study are expected to benefit relevant stakeholders, such as government agencies involved in highway transportation. The findings, which include travel times based on vehicle speed characteristics, can provide valuable insights into the comfort and safety of driving on the Porong-Sidoarjo Highway in East Java, Indonesia.

This study continues with an explanation of the stochastic traffic cellular automata (STCA) model and Monte Carlo methods, which are discrete-time simulation models. It then addresses phenomena related to microscopic traffic flow characteristics observed on the Porong-Sidoarjo Highway in East Java, Indonesia, specifically focusing on driver and vehicle characteristics based on vehicle speed in Section II. The micro traffic flow phenomena is given in Section III. Proposed model is given in Section IV. This is followed by a section on testing the developed model and a discussion of the relevant results from these tests in Section V. The study concludes in Section VI with a summary of the research findings.

II. Discrete Time Simulation Model: Cellular Automata-Monte Carlo

A. Stochastic Model: Nagel–Schreckenberg STCA

In the realm of traffic simulation, modeling at the microscopic level has long been recognized as a intricate and time-intensive endeavor, requiring intricate models that portray the behaviors of individual vehicles. However, approximately ten years ago, a novel microscopic model emerged, drawing on the cellular automaton framework rooted in statistical physics. Its principal advantage lies in its efficient and swift performance during computer simulations, although it may exhibit slightly diminished accuracy at the microscopic level. These traffic models based on cellular automata (TCA) are dynamic systems characterized by discrete elements, where time progresses in distinct increments and space is represented in coarse units (for instance, roads divided into 7.5 meter per-cell, each either empty or occupied by a vehicle) [22].

In terms of randomness usage (probability), cellular automata models can be categorized into two types: deterministic models and stochastic models. One deterministic TCA model compares two acceleration models embedded within cellular automata, stating that the Acceleration Time Delay (ATD) model and Speed Adaptation (SA) model exhibit spatiotemporal traffic congestion patterns consistent with empirical findings. In both models, the onset of congestion in free flow conditions on congested roads is associated with a first-order phase transition from free flow to synchronized flow; moving congestion spontaneously emerges only in synchronized flow [23].

Stochastic Traffic Cellular Automata (STCA) are widely used in modeling micro traffic flow. The basic model of STCA introduces a rule involving randomization, utilizing randomness within the TCA rules. This adaptation accounts for natural speed fluctuations caused by human behavior or various external conditions [24]. Incorporating this randomness into TCA transforms it into Stochastic Traffic Cellular Automata (STCA). Many researchers have developed STCA models from various aspects, focusing on updating acceleration in car-following or lane-changing behaviors.

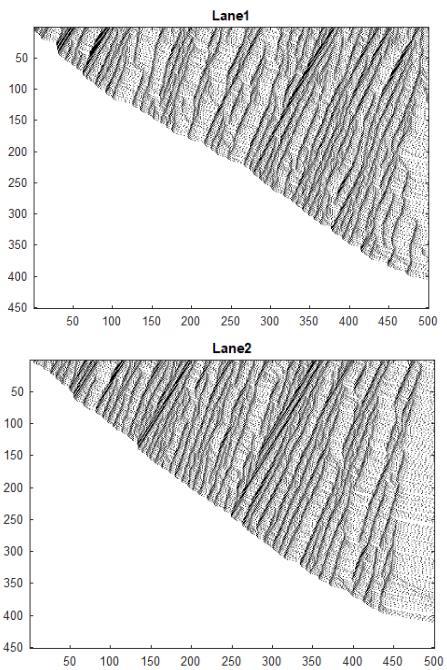

Fig. 1. Time-space diagram of NaSch STCA (two lanes), where the vertical axis represents time-steps and the horizontal axis represents space (cells), road length L = 500 cells, density k = 0.3, slowdown prob. P = 0.3, prob. of lane changing P_{lc} = 0. Top image for lane 1 and bottom image for lane 2.

The STCA developed by Nagel-Schreckenberg is defined on a one-dimensional array with a lattice length L and operates as an open-loop system. Each location (cell) can either be occupied by one vehicle or remain empty. The speed of each vehicle is represented by an integer between zero and $v_{\max}$. Updates in the NaSch STCA system consist of four sequential steps performed in parallel for all vehicles. The update rules in the NaSch STCA system (utilizing two lanes in this study) are as follows [22], [24]:

1) Acceleration: $v_{i,j}(t) \leftarrow v_{i,j}(t-1)+1$

Iϕ $v_{i,j}(t-1) < v_{max}$ αvδ $gs_{i,j}(t-1) > v_{i,j}(t-1)+1$

2) Braking: if $gs_{i,j}(t-1) \leq v_{i,j}(t-1)$,

$$v_{i,j}(t) \leftarrow gs_{i,j}(t-1)-1$$

3) Randomization: with slowdown probability P and random number $\xi(t)$, if $\xi(t) < P \Longrightarrow v_{i,j}(t) \leftarrow v_{i,j}(t-1)-1$.

4) Vehicle movement:

$$x_{i,j}(t) \leftarrow x_{i,j}(t-1)+v_{i,j}(t)$$

where, $v_{i,j}(t)$ is the speed of the vehicle in the i-th lane and j-th position, and $gs_{i,j}(t)$ is space gap, the distance between a vehicle and the vehicle in front of it. Fig. 1 shows one of the simulation results of NaSch STCA for two lanes with the specifications of a lattice length L = 500 cells, density k = 0.3, slowdown probability P = 0.3, probability of lane changing P_{lc} = 0. Vehicles move from left to right, and the system operates as an open-loop system.

B. Monte Carlo Simulation

The Monte Carlo simulation involved generating events through random numbers. This process comprised data collection, assigning random numbers, formulating models, and performing analysis. One reason for using a Monte Carlo simulation is that it typically applies to simulations utilizing stochastic methods to create new configurations of the system being studied [25]. On the other hand, the Monte Carlo Simulation procedure outlined by [15] and utilized in this research involves: (i) Step 1. Data collection, which uses a pseudo-random sequence; (ii) Step 2. Random-number assignment, where events are generated impartially by assigning random numbers in proportion to their probability of occurrence. The standard Monte Carlo method with pseudo-random sequences can achieve good convergence with N sample tests. In predicting traffic flow, the Monte Carlo Simulation serves as a mathematical tool to model risk or uncertainty in a system through the generation of random variables. The Monte Carlo Simulation model is designed to forecast traffic patterns. To create a new dataset with random probabilities, parameters such as the mean and standard deviation from the fitted normal distribution were utilized, as described by [16].

In other areas, the relationship between Cronbach's alpha and randomness was tested using Monte Carlo simulations, as opposed to issues with minimum sample width and bias. Simulation-generated artificial data were used to estimate the alpha coefficient for a K-item scale with a 5-point Likert-type format, answered randomly by 5K individuals, where K denotes the number of items. Each trial was conducted 5000 times, and one finding was that the probability of a Cronbach's alpha coefficient of 0.27 or higher for a K-item 5-point Likert scale, randomly answered by 5K people, is less than 5% [26].

The Monte Carlo simulation procedure, as generally outlined by [15], includes Step 1: Data collection and Step 2: Random-number assignment has been applied in this study. The Monte Carlo Simulation generates random numbers in three areas: the initial state of occupancy, randomization (slowdown probability), and lane-changing probability. These components are integrated into the micro traffic flow modeling addressed in this research. Below is an explanation of each section.

1) Occupied initial state: In this section, random numbers are generated using Monte Carlo, where the random value is generated to be less than a predetermined density percentage k of vehicles. If this condition is satisfied, the initial position of the vehicle is assigned to the corresponding cell, and its initial speed vij(t) is set according to a normal distribution. All vehicles will be moved in parallel per time-step after generating their initial positions and velocities. Based on the density percentage, random positions $x_{ij}(t)$ of vehicles are generated on a lattice length L as specified. The highway specifications used in this experiment replicate conditions on the Porong-Sidoarjo Highway in East Java, Indonesia. The traffic flow direction under study is from the cities of Sidoarjo/Surabaya towards Malang/Banyuwangi (one-way). This highway has two lanes (i = 1-2), and typical straight road length is 3750 meters, thus if 1 cell = 7.5 meters, the lattice length of the road is 500 cells (j = 1-500). In the Cellular Automata model, cells occupied by vehicles are identified with the number 1, while unoccupied cells are identified with 0. Here is the syntax for generating random numbers based on Monte Carlo:

```
for j=1:n
   for i=1:2
      r=rand;
      if(r<k)
         x(1,i,j)=1;
         v(1,i,j)=floor(vmax/2+0.69*randn);
      end
   end
end
```

The initial conditions of vehicle speeds $v_{ij}(t)$ are represented in matrix form with indices $(1,i,j)$. Their values are computed using the floor function with the argument $\frac{v_{max}}{2} + 0{,}69\ x\ randn$, where randn is a function that generates random numbers from a standard normal distribution. Therefore, $v_{ij}(1,i,j)$ will contain the value from this expression after it has been rounded down to the nearest integer using the floor function.

2) Randomization (Slowdown probability): One of the rules in Nagel-Schreckenberg's STCA involves randomization, specifically reducing the speed by 1 cell per time-step for vehicles that satisfy the randomization condition stated in the rule. The value of the random number $\xi(t)$ is generated using Monte Carlo methods, where its magnitude is less than a predefined probability value p (referred to as the slowdown probability). Here is the syntax for generating random numbers based on Monte Carlo, applied from the initial simultaneous movement of vehicles until the end of the specified time period.

```
for j=1:n
   for i=1:2
      if(x(t,i,j)==1)
         r=rand;
         if(r<p)
            if(v(t,i,j)==5)
               ...
               ...
            end
         end
      end
   end
end
```

3) Probability of lane changing: In this study, we refer to the structure of the Porong Sidoarjo highway where each direction has two lanes. Lane changes occur simultaneously between lane 1 and lane 2 as vehicles move over time. Monte Carlo plays a role in generating random numbers to determine which vehicles will change lanes. The random number generated is smaller than a predetermined lane change probability p_{lc}. The syntax for lane change from lane 1 to lane 2 is described below. This condition is equivalent to lane change from lane 2 to lane 1.

```
for j=6:n
if(x(t,1,j)==1)
r=rand;
if (r<plc)
   if(v(t,1,j)==5)
      ...
   end
   ...
   if(v(t,1,j)==1)
      ...
   end
end
end
end
```

III. Micro Traffic Flow Phenomena, Vehicle Types, Driver Characteristics

Traffic flow survey has been conducted in the area of Porong Sidoarjo Highway, East Java, Indonesia, where the traffic direction is specifically from the cities of Sidoarjo/Surabaya towards Malang/Banyuwangi (one-way). This highway serves as a main road connecting major cities including Surabaya, Sidoarjo, Malang, Jember, and

Banyuwangi. The economic growth among these cities is linked to the existence of Porong Sidoarjo Highway. The presence of this highway is highly significant and gives rise to distinct micro-traffic flow phenomena. The survey was conducted from March 23rd to March 30th, 2010. Speed data of vehicles was collected hourly over 24 hours a day for eight days, totaling 190 data points. The surveyed vehicle types included four-wheeled or more vehicles such as trucks/trailers, buses, public transportation, and private cars. Vehicle speed is measured using a speed gun.

A. *Micro Traffic Flow Phenomena*

The survey of speeds from four types of vehicles conducted every hour yielded speed data, where each vehicle type has several speed data points per hour. The mean speed data for each vehicle type per hour was calculated, resulting in 190 mean speed data points per vehicle type. The phenomenon of these mean speeds shows variability in the data. It is desired that the speed data have a normal distribution so that descriptive statistics such as mean and standard deviation can accurately depict the patterns of mean speed and its variability. This includes the potential to determine driver characteristics based on mean speed data. The phenomenon of mean speed data from four types of vehicles over 190 consecutive hours is depicted in Fig. 2.

The results of the vehicle speed survey were analyzed to determine the form of the population distribution or its probability by testing the hypothesis that a specific distribution serves as the model for the speed population. This study conducted hypothesis testing on speed data to assess whether the speed data or population follows a normal distribution or not. The hypothesis test employed a formal goodness-of-fit test procedure based on the chi-square distribution.

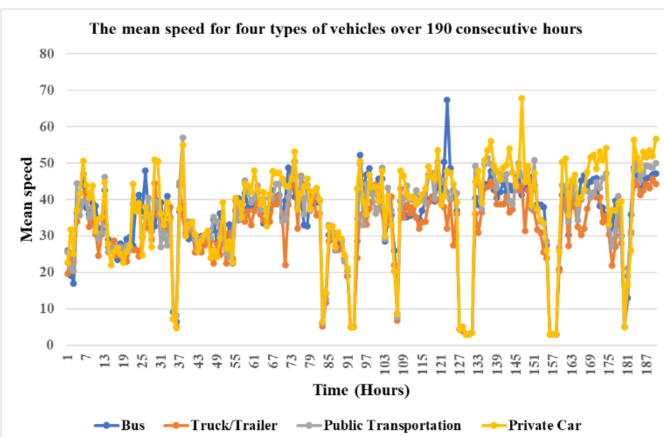

Fig. 2. The mean speed of four types of vehicles for 190 consecutive data points (190 hours).

The testing procedure requires several parameters: a random sample of size n; class interval c; observed frequency in class interval i, O_i; expected frequency in class interval i, E_i (given from the hypothesized probability distribution). Eq. (1) is used as the test statistic to analyze whether the speed data pattern conforms to a normal distribution or not.

$$X_0^2 = \sum_{i=1}^{c} \frac{(O_i - E_i)^2}{E_i} \tag{1}$$

A statistical test is conducted on the population to determine if it follows the hypothesized distribution. The test statistic, X_0^2 has approximately a chi-square distribution with $c - p - 1$ degrees of freedom, where p represents the number of parameters of the hypothesized distribution estimated by sample statistics. The hypothesis is rejected if the calculated value of the test statistic $X_0^2 > \chi^2_{\alpha,c-p-1}$.

In this hypothesis test, conducted on data concerning the mean speeds of all types of vehicles, the sample size $n = 190$ is utilized. With a significance level $\alpha = 0.05$, the hypothesis test aims to determine whether traffic survey data (vehicle speeds) can be adequately modeled by a normal distribution. The test employs $c = 8$ class intervals, which, for a standard normal distribution, divide the distribution area into eight segments with equal probabilities: [0, 0.32), [0.32, 0.675), [0.675, 1.15), [1.15, ∞), and their mirrored intervals on the other side of zero.

Each interval has the probability $p_i = 1/8 = 0.125$, thus the expected cell frequencies $E_i = np_i = 190(0.125) = 23.75$. Note that the parameter values specified are $n = 190$; $\alpha = 0.05$; $c = 8$ cells; $p_i = 1/8 = 0.125$; and $E_i = np_i = 23.75$, which are consistent across all types of vehicles. Di sisi lain sebaran data kecepatan untuk semua jenis kendaraan memiliki mean $\mu = 35$ dan standard deviation Std = 11.32.

TABLE I. TEST THE DISTRIBUTION OF SURVEY DATA (MEAN SPEED) FOR ALL TYPES OF VEHICLES (FOUR TYPES OF VEHICLES)

Class Interval	Observed Frequency o_i	Expected Frequency E_i	oi - Ei	(oi - Ei)^2	(oi - Ei)^2/Ei
x < 22	19	23,75	-4,75	22,56	0,95
22 ≤ x < 27	12	23,75	-11,75	138,06	5,81
27 ≤ x < 31	21	23,75	-2,75	7,56	0,32
31 ≤ x < 35	19	23,75	-4,75	22,56	0,95
35 ≤ x < 39	28	23,75	4,25	18,06	0,76
39 ≤ x < 43	41	23,75	17,25	297,56	12,53
43 ≤ x < 48	41	23,75	17,25	297,56	12,53
48 ≤ x	9	23,75	-14,75	217,56	9,16
Total	**190**	**190**			**43,01**

A hypothesis testing procedure is employed to determine if the sample data set of mean speeds follows a normal distribution.

H_0: The distribution takes on a normal form

H_1: The distribution does not adhere to a normal form

The test statistic is

$$X_0^2 = \sum_{i=1}^{c} \frac{(O_i - E_i)^2}{E_i} = \frac{(19 - 23.75)^2}{23.75} + \frac{(12 - 23.75)^2}{23.75} + \cdots + \frac{(9 - 23.75)^2}{23.75} = 43.01$$

Table I shows observed and expected frequencies for each cell, as well as the results of the chi-square distribution calculation.

- The chi-square table with $\alpha = 0.05$ and degrees of freedom $= c - p - 1 = 8 - 2 - 1 = 5$ (p represents the number of parameters in the hypothesized distribution, which in this instance are the parameters of the normal distribution specifically, the mean μ and the variance σ^2. Thus, there are two parameters, so $p = 2$).

$$\chi^2_{\alpha,c-p-1} = \chi^2_{0.05,5} = 11.07$$

- Conclusion: since $X_0^2 = 43.01 > \chi^2_{0.05,5} = 11.07$, rejecting H_0 suggests that the speed data for all vehicles does not follow a normal distribution.

The results of the hypothesis test using a chi-square distribution indicate that the distribution is not normal, meaning that the mean speed data (survey results) from four types of vehicles do not exhibit a normal distribution. As mentioned above, transforming traffic flow survey data (vehicle speed data) into a normal distribution provides a strong basis for more in-depth statistical analysis, simplifies data interpretation, and enhances the validity of the analysis results to support decision-making.

Normalization of the mean speed data for four types of vehicles was conducted individually for each vehicle due to varying extreme data (outliers) they possess. Below is the normalization applied to the mean speed data of the truck/trailer.

Normalizing the speed of trucks/trailers.

Here is the normalization mechanism for the mean speed data of trucks/trailers.

- Transform the data using the natural logarithm function.
- Remove the outlier data. After removal, the dataset consists of 170 entries, down from the original 190.
- The mean is 3.53 and the standard deviation is 0.20.
- Appling the hypothesis-testing procedure:

  H_0: The distribution follows a normal form.

  H_1: The distribution does not follow a normal form
- The statistical test value is

$$X_0^2 = \sum_{i=1}^{c} \frac{(O_i - E_i)^2}{E_i}$$
$$= \frac{(27 - 21.25)^2}{21.25} + \frac{(17 - 21.25)^2}{21.25} + \cdots + \frac{(21 - 21.25)^2}{21.25} = 8.26$$

Each interval has a probability $p_i = 1/8 = 0.125$, thus the expected cell frequencies $E_i = np_i = 170(0.125) = 21.25$ for each interval.

Table II shows observed and expected frequencies for each cell, as well as the results of the chi-square distribution calculation.

- The chi-square table with $\alpha = 0.05$ and degrees of freedom $= c - p - 1 = 8 - 2 - 1 = 5$ (p represents the number of parameters in the hypothesized distribution, which in this instance are the parameters of the normal distribution specifically, the mean μ and the variance σ^2. Thus, there are two parameters, so $p = 2$).

$$\chi^2_{\alpha,c-p-1} = \chi^2_{0.05,5} = 11.07$$

- Conclusion: Since $X_0^2 = 8.26 < \chi^2_{0.05,5} = 11.07$, accepting H_0 indicates that the speed data for the truck/trailer follows a normal distribution.

TABLE II. NORMALIZATION OF MEAN SPEED SURVEY DATA FOR TRUCK / TRAILER

Class Interval (Natural logarithmic numbers)	Observed Frequency o_i	Expected Frequency E_i	oi - Ei	(oi - Ei)^2	(oi - Ei)^2/Ei
x < 3,300	27	21,25	5,75	33,06	1,56
3,300 ≤ x < 3,395	17	21,25	-4,25	18,06	0,85
3,395 ≤ x < 3,466	13	21,25	-8,25	68,06	3,20
3,466 ≤ x < 3,530	18	21,25	-3,25	10,56	0,50
3,530 ≤ x < 3,594	22	21,25	0,75	0,56	0,03
3,594 ≤ x < 3,665	26	21,25	4,75	22,56	1,06
3,665 ≤ x < 3,760	26	21,25	4,75	22,56	1,06
3,760 ≤ x	21	21,25	-0,25	0,06	0,00
Total	**170**	**170**			**8,26**

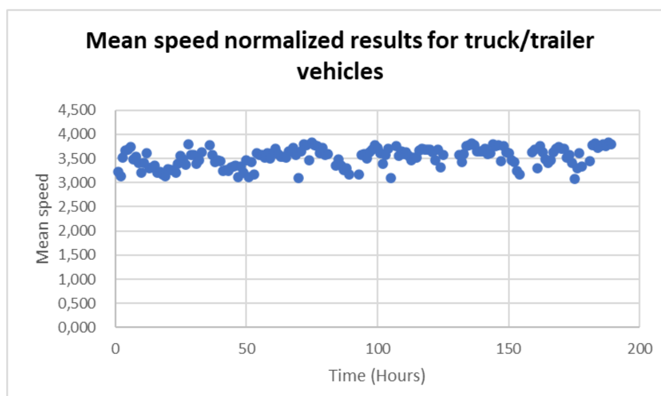

Fig. 3. Mean speed normalized results for truk/trailer vehicles.

Fig. 3 illustrates the normalized mean speed results for trucks/trailers, based on 170 data points (after removing outliers). The normalized mean speed data yielded a minimum of 3.086 and a maximum of 3.839, with respective actual mean speeds of 22 and 47.

Using the same method, normalization was also performed on the mean speed data for buses, public transportation, and private cars. Table III summarizes the normalization process for these three vehicle types. The normalized data counts for buses, public transportation, and private cars are 160, 170, and

160 respectively. The degrees of freedom used for all three types of vehicles are the same, which is 5. However, the significance levels (alpha) differ: 0.05 for buses, 0.005 for public transportation, and 0.010 for private cars. All chi-square distribution calculations for the mean speed data of these three vehicle types yielded values smaller than the chi-square values in the table. This condition indicates that the distribution of mean speed data for buses, public transportation, and private cars can be assumed to be normal.

TABLE III. SUMMARY OF MEAN SPEED SURVEY DATA NORMALIZATION FOR BUS, PUBLIC TRANSPORTATION, AND PRIVATE CAR VEHICLES

Vehicle	Steps	Data Specifications	Decision
Bus	▪Change the mean speed data to the function of natural logarithmic ▪Delete the extreme data (outlier's data) ▪Appling the hypothesis-testing procedure (H_o = normal distribution, H_1 = not normal distribution)	Normalized amount of data = 160; Degree of freedom = 5; alpha = 0.05; Mean = 3,66; Std = 0,14; Chi-square Dist. = 8,93; Chi-square Table = 11,07; Chi-square Dist. (=8,93) < Chi-square Table (=11,07)	H_o accepted; Normal Distribution
Public Transportation		Normalized amount of data = 170; Degree of freedom = 5; alpha = 0.005; Mean = 3,62; Std = 0,20; Chi-square Dist. = 15,98; Chi-square Table = 16,75; Chi-square Dist. (=15,98) < Chi-square Table (=16,75)	H_o accepted; Normal Distribution
Private Car		Normalized amount of data = 160; Degree of freedom = 5; alpha = 0.010; Mean = 3,70; Std = 0,21; Chi-square Dist. = 13,70; Chi-square Table = 15,09; Chi-square Dist. (=13,70) < Chi-square Table (=15,09)	H_o accepted; Normal Distribution

B. Driver Characteristics Based on Vehicle Speed Phenomena

The phenomenon of micro-traffic flow on Porong Sidoarjo Highway has been investigated. Based on speed surveys conducted on four types of vehicles (trucks/trailers, buses, public transportation, and private cars), mean speed data requiring normalization due to non-normal data distribution was obtained. The normalized mean speed data (in natural logarithm and real numbers) with min-max speed values are shown in Table IV. The vehicle speed phenomenon from the survey results and the normalization process of speed data are used as a basis to establish the characteristics of drivers passing through Porong Sidoarjo Highway. The normalized vehicle speed data obtained from the survey depict the characteristics of drivers crossing Porong Sidoarjo Highway more accurately. This condition considers how they regulate their speed according to their skill levels and safety preferences. Under these circumstances, driver characteristics are categorized into three groups: (i) Careful driver (for truck or trailer drivers); (ii) Ordinary driver (for bus and public transportation drivers); and (iii) Skilled driver (for private vehicle drivers).

TABLE IV. THE PHENOMENON OF VEHICLE SPEED TO DETERMINE DRIVER CHARACTERISTICS

Vehicle	Mean speed (natural logarithmic number)	Mean speed (real number)	(min - max) normalized speed	Driver characteristics
Truck/Trailer	3,53	34	22 - 47	Careful driver
Bus	3,66	39	27 - 52	Ordinary driver
Public Transportation	3,62	37	21 - 52	Ordinary driver
Private Car	3,7	41	26 - 57	Skilled driver

Characteristics of careful drivers regarding the speed phenomenon that occurs on Porong Sidoarjo Highway, East Java, Indonesia: (i) They are cautious, prioritizing safety over speed; (ii) They drive at a moderate speed, maintain distance from the vehicle ahead, and are ready to react quickly to changes in traffic; (iii) They drive at a speed lower than average to ensure safety and comfort. As for ordinary drivers, their characteristics are: (i) They typically follow basic traffic rules and drive at a comfortable speed that is appropriate for traffic conditions; (ii) They carefully follow the flow of traffic, adjusting their speed to the surrounding traffic conditions; (iii) They exhibit speeds close to the average. The characteristics of skilled drivers are: (i) They have a higher level of expertise in handling various driving situations; (ii) They can make quick decisions and maneuver vehicles effectively without compromising safety; (iii) They are capable of driving at speeds higher than average, yet within safe limits and well-controlled.

IV. THE PROPOSED MODEL OF MICRO TRAFFIC FLOW PHENOMENA

In the previous section, the characteristics of drivers were categorized based on the speed phenomena observed on Porong Highway in Sidoarjo, East Java, Indonesia. Using the results of a vehicle speed survey conducted on this highway, these characteristics were classified into three types: careful driver, ordinary driver, and skilled driver. This section involves mathematical modeling of the vehicle speeds for each driver type based on the phenomena observed on Porong Highway in Sidoarjo. Subsequently, these speed models are integrated into the NaSch STCA rules. Lane-changing behavior is also incorporated into the STCA model, considering two lanes as per the real conditions on Porong Highway in Sidoarjo.

A. Driver Characteristics Modeling

The three predefined driver characters exhibit fundamental differences in their speeds. Careful drivers maintain lower driving speeds below the average to prioritize safety and comfort. Ordinary drivers typically drive at speeds close to the average. Skilled drivers are capable of driving at speeds higher than the average, yet within safe limits and well-controlled. Here are the statements regarding the speed modeling for each driver character:

- careful driver: $1 \leq v_{cd} \leq \bar{v}_r$
- ordinary driver: $v_{od} = \bar{v}_r \pm 1$
- skilled driver: $\bar{v}_r \leq v_{sd} \leq v_{max}$

where, v_{cd}, v_{od}, and v_{sd} are the respective speeds of careful drivers, ordinary drivers, and skilled drivers in sequence, while $\bar{v}_r$ represents the average speed for all vehicle types passing through Porong Highway in Sidoarjo.

Based on the speed data from the survey conducted on Porong Highway in Sidoarjo over 190 consecutive hours (eight days), the average speed for all vehicle types (referring to Table IV) $\bar{v}_r$ is 38 km/h. Converting this to computational terms, where 1 cell equals 7.5 meters and 1 second corresponds to 1 time-step, the average vehicle speed passing through Porong Highway in Sidoarjo $\bar{v}_r$ becomes 1.4 cells/time-step. In computational calculations, this is rounded up to 2 cells/time-step.

B. *Lane Changing*

The Porong Sidoarjo Highway features two lanes in each direction. An illustration of two lanes in one direction is shown in Fig. 4. A vehicle is represented by a small box. If a vehicle intends to change lanes, it must satisfy the condition that on the new lane, there is a distance of b units between itself and the vehicle behind, and a distance of a units between itself and the vehicle in front. By meeting these conditions, collisions between vehicles can be avoided.

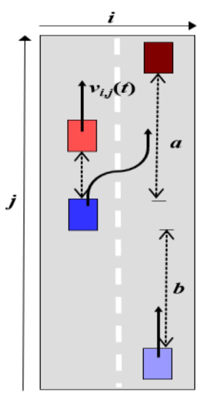

Fig. 4. Illustration of a two-lane highway with lane-changing dynamics.

Many studies have focused on lane-changing behavior in multi-lane and dual-lane scenarios. One such study examines lane-changing on a two-lane highway, as investigated by [27]. Based on the illustration in Fig. 4, the lane-changing used in this research must satisfy the following conditions:

$gs_{i=1,j}(t-1) < \min\{v_{i=1,j}(t-1), v_{max}\}$

$gs_{i=2,j-b}(t-1) > v_{max}$ and

$gs_{i=2,j+a}(t-1) > gs_{i=1,j}(t-1)$ with probability of lane changing P_{lc}.

C. *Modified NaSch STCA*

The vehicle movement model in the micro-traffic flow simulation conducted on Porong Sidoarjo Highway refers to the phenomenon of vehicle speeds observed on that highway. Based on the survey results of vehicle speed measurements, drivers' characteristics are categorized into three types: careful drivers, ordinary drivers, and skilled drivers. The fundamental difference among them lies in the typical driving speeds they maintain while traversing Porong Sidoarjo Highway.

In this study, the proposed vehicle movement is a modification of the NaSch STCA vehicle movement, where vehicle speeds are differentiated into three types according to predefined driver characteristics. The modified NaSch STCA follows these rules:

1) Acceleration: $v_{i,j}(t) \leftarrow v_{i,j}(t-1) + 1$

Iϕ $v_{i,j}(t-1) < v_{max}$ ανδ $gs_{i,j}(t-1) > v_{i,j}(t-1) + 1$

Where

- for careful drivers applies $1 \leq v_{i,j}(t-1) \leq \bar{v}_r$
- for ordinary drivers applies $\bar{v}_r - 1 \leq v_{i,j}(t-1) \leq \bar{v}_r + 1$
- for skilled drivers applies $\bar{v}_r \leq v_{i,j}(t-1) \leq v_{max}$

2) Braking: if $gs_{i,j}(t-1) \leq v_{i,j}(t-1)$,

$$v_{i,j}(t) \leftarrow gs_{i,j}(t-1) - 1$$

3) Randomization: with slowdown probability P and random number $\xi(t)$, if $\xi(t) < P \Longrightarrow v_{i,j}(t) \leftarrow v_{i,j}(t-1) - 1$.

4) Vehicle movement:

$$x_{i,j}(t) \leftarrow x_{i,j}(t-1) + v_{i,j}(t)$$

Together with the lane-changing rules stated in the previous session: $gs_{i=1,j}(t-1) < \min\{v_{i=1,j}(t-1), v_{max}\}$

$$gs_{i=2,j-b}(t-1) > v_{max} \text{ ανδ}$$

$$gs_{i=2,j+a}(t-1) > gs_{i=1,j}(t-1)$$

with probability of lane changing P_{lc}.

V. Experimental Results and Discussion

In this session, a trial was conducted on vehicle movement using a predetermined model known as the Modified NaSch STCA. As explained in the previous session, drivers are categorized into three types based on speed, which is characteristic of each driver (careful, ordinary, and skilled drivers). The determination of the number of each type of driver is based on probabilities (percentages) relative to the predetermined vehicle density. The probabilities for careful drivers, ordinary drivers, and skilled drivers are denoted as P_{cd}, P_{od}, and P_{sd} respectively.

A. *Experimental Results*

Fig. 5 illustrates a time-space diagram, one of the outcomes of the trial (simulation) of vehicle movement using the Modified NaSch STCA, replicating the phenomenon of vehicle movement on the Porong-Sidoarjo Highway. The specifications of this vehicle movement simulation are as follows: a two-lane highway with a lattice length of L = 500 cells, density k = 0.3, slowdown probability P = 0.1, probability of lane changing P_{lc} = 0.4, probability of careful drivers P_{cd} = 0.1, probability of ordinary drivers P_{od} = 0.3, and probability of skilled drivers P_{sd} = 0.6. The vehicles move in one direction, from left to right, replicating the movement from the city of Sidoarjo / Surabaya towards Banyuwangi / Malang, and this movement system operates as an open-loop system.

Based on Fig. 5, it can be seen that with a vehicle density of k = 50% (0.5), where the probability of trucks/trailers (careful drivers) being present is 10% (0.1), the probability of buses and public transportation (ordinary drivers) is 30% (0.3), and the probability of private cars (skilled drivers) is 60% (0.6), all vehicles cover a distance of 500 cells = (500 x 7.5 meters) = 3750 meters. This results in a total travel time of t = 3161 time-steps ≈ 3161 seconds ≈ 52.68 minutes. This condition indicates that with the average speed per type of vehicle passing through the Porong Sidoarjo highway as shown in Table IV, where the minimum speed value of all types of vehicles = 22 km/h and the maximum = 57 km/h, the average speed for all types of vehicles = 38 km/h. This phenomenon highlights that with a vehicle density of k = 50% and an average speed $\bar{v}_r$ = 38 km/h, the travel time for all vehicles over a distance of 3750 meters is 3161 seconds (52.68 minutes).

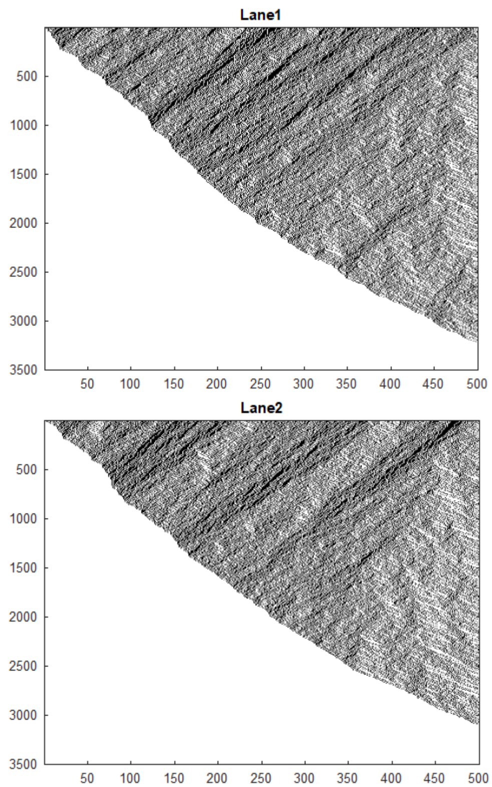

Fig. 5. Time-space diagram of Modified NaSch STCA (two lanes), where the vertical axis represents time-steps and the horizontal axis represents space (cells), road length L = 500 cells, density k = 0.5, slowdown prob. P = 0.3, prob. of lane changing P_{lc} = 0.4, prob. of careful drivers P_{cd} = 0.1, prob. of ordinary drivers P_{od} = 0.3, and prob. of skilled drivers P_{sd} = 0.6. Top image for lane 1 and bottom image for lane 2.

The comparison of the time-space diagram between NaSch STCA and Modified NaSch STCA is illustrated by one of the test results (simulations) as shown in Fig. 6. The test specifications employed are as follows: the road length 500 cells, with a vehicle density of k = 0.3, there is a 30% probability of slowdown (P = 0.3) and a 0% probability of lane changing (P_{lc} = 0.0). In the Modified NaSch STCA model, the probabilities P_{cd} = 0.1 for careful drivers, P_{od} = 0.3 for ordinary drivers, and P_{sd} = 0.6 for skilled drivers. It can be seen that with the same specifications, over a distance of 500 cells (3750 meters), the travel time for all vehicles in the NaSch STCA model is 409 time-steps (409 seconds), while the modified model takes 1934 time-steps (1934 seconds). This indicates that the travel time in the NaSch STCA model is significantly faster than in the modified model. This phenomenon occurs because the average speed of vehicles traveling on the Porong Highway tends to be lower than usual.

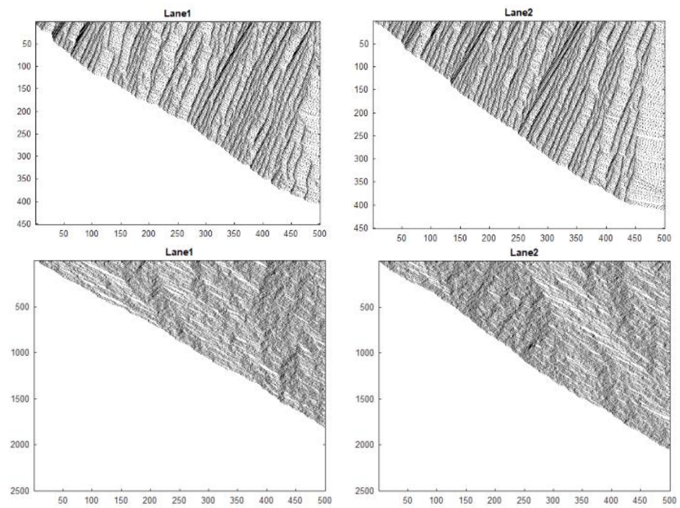

Fig. 6. A comparison of time-space diagrams for two lanes between the NaSch STCA model and the Modified NaSch STCA. In this visualization, the vertical axis corresponds to time-steps, while the horizontal axis represents space measured in cells. The road length is L = 500 cells, with a density of k = 0.3. The probability of slowdown is P = 0.3, and the probability of lane changing is P_{lc} = 0.0. For the Modified NaSch STCA model, the probabilities are as follows: P_{cd} = 0.1 for careful drivers, P_{od} = 0.3 for ordinary drivers, and P_{sd} = 0.6 for skilled drivers. The top image shows the time-space diagram for the NaSch STCA model, while the bottom image depicts the Modified NaSch STCA model.

A comparison of travel time versus vehicle density was conducted between the NaSch STCA model and the Modified NaSch STCA model. The simulation specifications include a road length of 500 cells, a slowdown probability P = 0.3, and a lane-changing probability P_{lc} = 0.3. For the Modified NaSch STCA model, the probabilities for careful drivers, ordinary drivers, and skilled drivers are P_{cd} = 0.1, P_{od} = 0.2, and P_{sd} = 0.7, respectively. Travel time for vehicles was calculated for each density value incrementing by 0.1, ranging from 0.1 to 0.9. Detailed travel time results for each density value k increasing by 0.1 are shown in Table V. It can be observed that, for both models, travel time increases with higher vehicle density. At the same density value, the NaSch STCA model exhibits significantly faster travel times compared to the Modified NaSch STCA model. This condition is consistent across all density values. For instance, in this simulation, the NaSch STCA model yields a travel time of 138 time-steps for a density of k = 0.1, increasing to 1196 time-steps for a density of k = 0.9. Meanwhile, for the Modified NaSch STCA model, the travel time is 1364 time-steps at a density of k = 0.1, increasing further with each increment in vehicle density, reaching 5641 time-steps at k = 0.9. It can be stated that the travel time for the NaSch STCA model is significantly faster than for the Modified NaSch STCA model. This condition is attributed to the unique vehicle speed characteristics on the Porong Sidoarjo highway, where the average speed for all vehicle types $\bar{v}_r$ = 38 km/h is lower than the general average speed.

It is also noted the difference in travel time between the Modified NaSch STCA model and the NaSch STCA model. Table V shows that the difference for a density of k = 0.1 is 1226 time-steps. The travel time difference increases as vehicle density rises. For a density of k = 0.9, the travel time difference is 4445 time-steps. The simulation results are also generally illustrated in the line graph shown in Fig. 7.

TABLE V. VEHICLE TRAVEL TIME AND THE DIFFERENCES BETWEEN THE NSCH STCA MODEL AND THE MODIFIED NSCH STCA MODEL

Density *k*	The travel time (time-steps)		Difference (time-steps)
	NSch STCA	Modified NSch STCA	
0,1	138	1364	1226
0,2	252	1698	1446
0,3	394	1999	1605
0,4	509	2284	1775
0,5	672	3208	2536
0,6	802	3510	2708
0,7	939	4360	3421
0,8	1041	5094	4053
0,9	1196	5641	4445

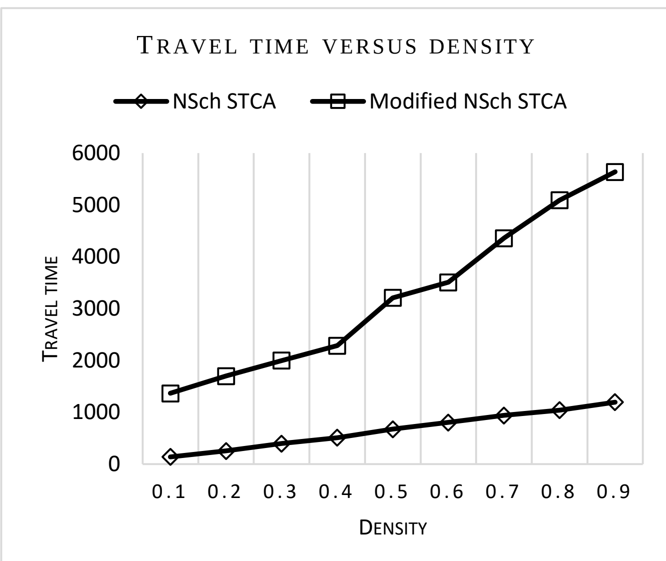

Fig. 7. Comparison of travel time with vehicle density between the NaSch STCA model and the Modified NaSch STCA model. The road length is L = 500 cells, the probability of slowdown is P = 0.3, and the probability of lane changing is P_{lc} = 0.3. Specifically for the Modified NaSch STCA model, the probabilities of the presence of careful drivers, ordinary drivers, and skilled drivers are P_{cd} = 0.1, P_{od} = 0.2, and P_{sd} = 0.7, respectively.

This study also examined vehicle travel time relative to the set travel distance, ranging from 100 cells to 500 cells. A comparison was made between the travel times of the NaSch STCA model and the Modified NaSch STCA model. Fig. 8 shows that the Modified NaSch STCA model exhibits significantly greater travel times for each specified distance compared to the NaSch STCA model.

The mean speed values produced by the modified NaSch STCA model were analyzed in relation to vehicle density. Simulation results with specifications of road length L = 500 cells; slowdown probabilities P = 0.1, 0.50, and 0.9 in sequence; and lane-changing probability P_{lc} = 0.3 are shown in Fig. 9. It is observed that higher vehicle densities lead to a decrease in mean speed. This condition aligns with the $(k, \bar{v}_r)$ diagram model described.

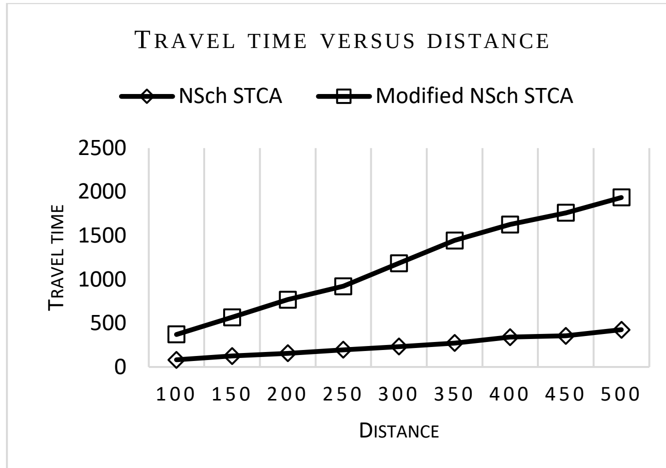

Fig. 8. Comparison of travel time with distance traveled between the NaSch STCA model and the Modified NaSch STCA model. The road length is L = 500 cells, density k = 0.3, the probability of slowdown is P = 0.3, and the probability of lane changing is P_{lc} = 0.3. Specifically for the Modified NaSch STCA model, the probabilities of the presence of careful drivers, ordinary drivers, and skilled drivers are P_{cd} = 0.1, P_{od} = 0.2, and P_{sd} = 0.7, respectively.

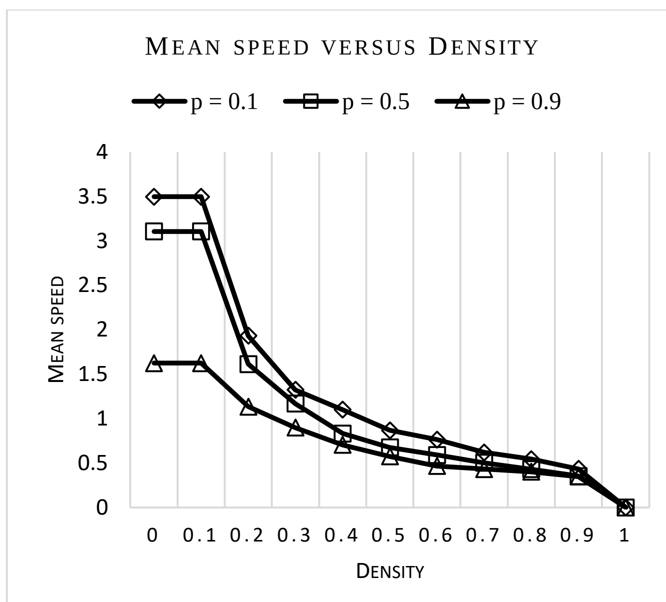

Fig. 9. Several $(k, \bar{v}_r)$ diagrams from the modified NaSch STCA model (mean speed versus density) with the specifications: road length L = 500 cells; slowdown probability P = 0.1, 0.5, and 0.9 in sequence; lane-changing probability P_{lc} = 0.3.

Delayed acceleration and slowdown probability have been incorporated into the modified NaSch STCA model. Regarding delayed acceleration, this study references, which is described by Takayasu–Takayasu TCA (T^2-TCA) in R2 as follows:

(R2) delayed acceleration:

$$v_i(t) = 0 \wedge g_{si}(t) \geq 2 \Longrightarrow v_i(t+1) \leftarrow 1$$

The presence of delayed acceleration and slowdown probability complements each other, as both impact the overall performance of the traffic system and contribute to increased travel time or congestion. When many vehicles experience delayed acceleration and there is also a high probability of slowdown, traffic can become more unstable and inefficient. This study demonstrates the effect of slowdown probability on travel time, with delayed acceleration incorporated into the Modified NaSch STCA model. It can be stated that the effect of slowdown probability on travel time is also influenced by the presence of delayed acceleration within the system. Simulation results for travel time in relation to slowdown probability are shown in Fig. 10. Observations were made for low, medium, and high densities, specifically k = 0.3, 0.5, and 0.9, with a lane-changing probability P_{lc} = 0.3.

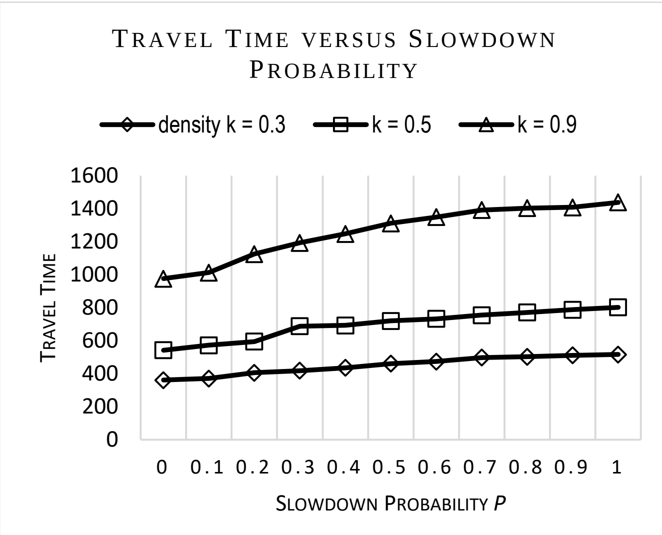

Fig. 10. Travel time observed as a function of slowdown probability P for densities k = 0.3, 0.5, and 0.9 sequentially; with a lane-changing probability P_{lc} = 0.3.

B. Discussion

The workflow of this study is as follows: (i) Conduct a survey of traffic phenomena on the Porong Highway in East Java, Indonesia. The survey data includes vehicle types, vehicle speeds, traffic density, and questionnaire responses about the conditions experienced by road users on Porong Highway. (ii) Process the survey data and analyze the observed phenomena. (iii) Examine the patterns emerging from the data analysis. (iv) Identify research topics that can be pursued based on the available data.

Based on the phenomena observed from the survey data, a unique finding is the variation in vehicle speeds, where different vehicle types exhibit different average speeds. Consequently, a microscopic traffic flow model was developed based on the speed characteristics of each vehicle type. Since vehicles are driven by individuals who influence their speed by accelerating or decelerating, the vehicle characteristics are inherently linked to the driver.

The discrete dynamic system model used is Cellular Automata, specifically the NaSch STCA model, which is a stochastic method utilizing random number generation. The random number generator employed in this model is the Monte Carlo method, integrated into the NaSch STCA with three components utilizing Monte Carlo simulation: the Occupied Initial State, Slowdown Probability, and Probability of Lane Changing. The innovation in this microscopic traffic flow modeling is the categorization of driver characteristics based on vehicle speeds observed on the Porong-Sidoarjo Highway, categorized into: careful driver, ordinary driver, and skilled driver, each with specific vehicle speed profiles.

The anticipated outcome is the alignment of the developed microscopic traffic flow model with the indications of vehicle travel times in relation to parameters such as density, travel distance, and slowdown probability. Traffic flow simulations on the Porong Highway have been conducted, producing vehicle travel times that replicate the actual traffic conditions on that road. The simulation specifications were adapted to match the conditions of the Porong Highway: the traffic flow under examination is from the Sidoarjo/Surabaya area towards Malang/Banyuwangi (one-way). This highway features two lanes (i = 1-2) and a typical straight road length of 3750 meters. Therefore, with each cell representing 7.5 meters, the lattice length of the road is 500 cells (j = 1-500).

For example, when using a slowdown probability P = 0.3 and a lane-changing probability P_{lc} = 0.3, the Modified NaSch STCA model assigns probabilities of P_{cd} = 0.1, P_{od} = 0.2, and P_{sd} = 0.7 for careful, ordinary, and skilled drivers, respectively. Vehicle travel times were computed for each density value incrementing by 0.1, from 0.1 to 0.9. Detailed results of travel times for each density increment are presented in Table V. For instance, the NaSch STCA model has a travel time of 138 time-steps at a density of k = 0.1, which increases to 1196 time-steps at k = 0.9. In contrast, the Modified NaSch STCA model shows a travel time of 1364 time-steps at k = 0.1, which grows to 5641 time-steps at k = 0.9. This indicates that the NaSch STCA model has significantly faster travel times compared to the Modified NaSch STCA model. This disparity is due to the unique vehicle speed characteristics on the Porong-Sidoarjo highway, where the average speed $\bar{v}_r$ =38 km/h is lower than the general average speed.

VI. Conclusion

The phenomenon of micro traffic flow on the Porong Highway in East Java, Indonesia, exhibits distinctive characteristics. A survey of vehicles with four or more wheels was conducted over eight days (190 hours) on this highway. The survey identified four types of vehicles: trucks/trailers, buses, public transportation, and private cars. The survey data revealed that these vehicles have average speeds of 34 km/h, 39 km/h, 37 km/h, and 41 km/h, respectively. Based on these speed characteristics, drivers of each vehicle type were categorized as careful drivers for trucks/trailers, ordinary drivers for buses and public transportation, and skilled drivers for private cars.

Vehicle movement modeling was performed using the NaSch STCA (NaSch STCA) model, specifically the Modified NaSch STCA (Modified NaSch STCA), tailored to simulate conditions on the surveyed Porong Sidoarjo highway. The road length was 3750 meters (L = 500 cells), straight with two lanes in each direction. Simulation results with specific parameters (road length of 500 cells, density k = 0.3, slowdown probability P = 0.3, and probability of lane changing P_{lc} = 0.0) compared data between the NaSch STCA and Modified NaSch STCA models. The Modified NaSch STCA model included specific driver presence probabilities: 0.1 for careful drivers, 0.3 for ordinary drivers, and 0.6 for skilled drivers.

One of the comparisons between these models is their travel time, where the NaSch STCA model significantly outperformed the Modified NaSch STCA model. This outcome reflects the characteristic vehicle speeds on the Porong Sidoarjo highway, with an average speed for all vehicle types $\bar{v}_r$ = 38 km/h.

For future research, it is essential to develop micro traffic flow modeling based on driver characteristics on a particular roadway, in collaboration with local government authorities. A more effective approach would be to combine Cellular Automata with artificial intelligence, enhancing the modeling of dynamic micro traffic systems and driver characteristic classification.

ACKNOWLEDGMENT

Special thanks to the Knowledge Engineering research team at the Politeknik Elektronika Negeri Surabaya (PENS), East Java, Indonesia, for their support and motivation throughout the completion of this research. Particularly, heartfelt gratitude goes to Professor Kohei Arai from Saga University, Japan, for his comprehensive guidance and in-depth discussions on the cellular automata methods employed in the modeling and simulation aspects of this research.

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Authors' Profile

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