A TRAFFIC CELLULAR AUTOMATON MODEL CONSIDERING SPONTANEOUS BRAKING AND DRIVER SCOPE AWARENESS PARAMETERS

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Department of Science and Advanced Technology
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Saga University

STEVEN RAY SENTINUWO

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A dissertation submitted to the Department of Science and Advanced Technology, Graduate School of Science and Engineering, Saga University in partial fulfillment for the requirements of a Doctorate degree in Information Science

by

STEVEN RAY SENTINUWO

Nationality	: Indonesia
Previous Degrees	: Bachelor of Engineering Sam Ratulangi University Indonesia Master of Information Technology University of Indonesia Indonesia

Department of Science and Advanced Technology
Graduate School of Science and Engineering
Saga University
JAPAN

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APPROVAL

Graduate School of Science and Engineering
Saga University
1 - Honjomachi, Saga 840-8502, Japan

CERTIFICATE OF APPROVAL

Dr. Eng. Dissertation

This is to certify that the Dr. Eng. Dissertation of

STEVEN RAY SENTINUWO

has been approved by the Examining Committee for the Dissertation requirements for the Doctor of Engineering Degree in Information Science in September 2013.

Dissertation Committee :

Supervisor, **Prof. Kohei Arai**
Department of Science and Advanced Technology

Member, **Prof. Shinichi Tadaki**
Department of Science and Advanced Technology

Member, **Associate Prof. Hiroshi Okumura**
Department of Science and Advanced Technology

Member, **Associate Prof. Koichi Nakayama**
Department of Science and Advanced Technology

DEDICATION

I want to dedicate this work to my family: Pegy, Cassie, and Chelsea. They have given me the strength to endure hard times and the peace to enjoy the good moments.

I also dedicate this work to my parents. The made the foundations of what I am today.

ABSTRACT

Recently, the field of traffic model and simulation has received growing interest over the last decades. This is due to some reasons: the growing of traffic demand that easily create traffic jam and congestion, the complexity of traffic feature that make them hard to analyze, control, and optimize, and the growing area of potential applications (plan, design, assessing, and provide the alternative layout to optimize transportation system). Traffic systems are inherently dynamic in nature, so that, the number of units in the system varies according to the time and with a considerable amount of randomness. This system formed not only from the interaction between drivers and physical environment, but also much influenced by the interaction between the drivers. The laws of interaction are approximate in nature, so the observations and reactions of drivers are governed by human perception. Since the process of participating in a traffic flow is heavily based on the behavioral aspects associated with human drivers, it would seem important to include these human factors into the modeling equations. Simulation can help to capture some parts of this human behavior that exist in the real traffic situation and converted into the mathematical modeling through the application of computer software. The main issue is to reduce the features complexity that makes a mathematical formulation possible. On the other hand, it also need to capture the characteristic of driver to reproduce the major phenomena that can be observed in real traffic situation.

This dissertation aim to define, investigate, and validate a model for the simulation of spontaneous braking behavior and investigate the effect of driver scope awareness when making a lane changing decision in the traffic flow. In the proposed model, the parameter of spontaneous braking and driver scope of awareness has been introduced. A traffic cellular automata model (TCA) has been enhanced to better capture the behavior of spontaneous braking and scope awareness of the driver. A set of TCA rules are proposed to represent those behaviors. In order to describe their effect in the traffic then the fundamental diagrams have been created: flow-density, speed-density, and space-time diagrams.

Moreover, to evaluate the simulation model and result, simulations for realistic scenarios are performed and compared to the actual data from observations. The actual traffic data have been recorded and analyzed as the comparison data. In the evaluation, the Nagel model for two lane traffic also used as the comparison model. Evaluations results show that the proposed model giving 83.9% accuracy value compare to the actual traffic flow data. While using Nagel and Rickert model, their accuracy is around 75.9% compare to the actual traffic flow data.

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Steven Ray Sentinuwo

Saga, June 2013

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1.
INTRODUCTION

This chapter presents an overview of the topics dealt with in this dissertation. It describes the intention, scope, and limitations of the simulation models for traffic flow analysis and roughly outlines the contents of the succeeding chapters.

Contents

1.1 Background Research

The field of traffic model and simulation has received growing interest over the last decades. This is a due to several reasons:

1. Growing traffic demand: car is the one of the most important form of locomotion when the distance covered is concerned. Since the number of cars has been growing in every day and the capacity of the road is not enough to coup the car number then it is probably time-intensive form of mobility if waiting and queuing are taken into account. In other words, in densely populated areas the capacity of the road network is often at its limits and frequent traffic jams and congestion cause a significant economic damage. To make things even worse, the traffic demand is still growing. For this reason, reliable traffic information systems and traffic management concepts are needed.
2. Feature complexity: the efficient movement of people and goods through physical road and street networks is a fascinating problem. Traffic systems are characterized by a number of features that make them hard to analyze, control, and optimize. Road traffic flow are composed of drivers associated with individual vehicles, each of them

having their own characteristics. The system often cover wide physical areas, the number of active participants is high, the goals and objectives of the participants are not necessarily parallel with each other or with those of the system operator (system optimum vs user optimum), and there are many system inputs that are outside the control of the operator and the participants (the weather condition, the number of users, etc.).

3. In case of an emergency situation, the people and vehicles has to be evacuated within a short time span under stress conditions. Simulations help to analyze traffic condition related to the driver psychology and optimizing the evacuation performance.
4. Numerous traffic phenomena can be observed by simulation. Can they be explained by simple rules and assumptions? To identify those basic principles increases the understanding of traffic dynamics.
5. Growing area of potential applications. Simulation research of road traffic has a connection to several other fields, like driver psychology, safety science, and traffic engineering. This field becomes an important also because it can study models to better help plan, design, and operate transportation system. Deepening this connection might lead to fruitful results and new insight to the development of Intelligent Transport Technologies and Applications.

For these reasons, simulation can help to capture some parts of the real traffic situation and converted into the mathematical modeling through the application of computer software in order to achieve the better plan, design, assessing alternative layouts, and procedure of transportation systems. Simulation in traffic system is important because it can study the complicated models for analytical or numerical treatment, can be used for experimental studies, can study detailed relations that might be lost in analytical or numerical treatment and can produce attractive visual demonstrations of present and future scenarios[1].

Traffic systems are inherently dynamic in nature, so that, the number of units in the system varies according to the time and with a considerable amount of randomness. This system combine man-machine interaction, this mean, there are the interaction between drivers and driver-physical environment. The laws of interaction are approximate in nature, so the observations and reactions of drivers are governed by human perception[1]. Therefore, driver behavior is one of the parameters that affect the road traffic phenomena.

This thesis addresses the challenge of modeling the situation of urban roadway, in particular to capture the spontaneous braking behavior and scope of awareness of the driver into the simulation model. In summary, the aims of this dissertation are the following:

1. Compilation of the basic principles, the aim, and the scope of computer simulations for traffic flow modeling (chapter 2);
2. Developing a traffic model that take into account driver behavior, in particular on spontaneous braking (chapter 3) and driver scope awareness when making a lane changing maneuver (chapter 4);
3. Implementing this model into a simulation and evaluate this model by comparing to the actual traffic condition.

Because the process of participating in a traffic flow is heavily based on the behavioral aspects associated with human drivers[2][3], it would seem important to include these human factors into the modeling equations

1.2 Problem Statement and Motivation

Due to the rapid development of computer technology then research about traffic simulation and modeling has increasingly grown. Computer simulation in traffic model has developed from a research tool of experts to a widely used technology for practitioners and researchers in the research, planning, demonstration, and development of traffic systems. The research about traffic modeling can be divided into two categories: microscopic model and macroscopic model. Microscopic model described traffic behavior as resulting from discrete interaction between vehicles as entities. While the macroscopic models concern to describe the aggregate traffic behavior phenomena by considering the fundamental relationships between vehicles speed, flow, and density.

Most microscopic models (e.g., the car-following model) use the assumption the all the vehicles have a uniform driving behavior. These microscopic models use deterministic approach and, therefore difficult to capture inherent stochastic nature of real traffic. On the other hand, a major limitation of macroscopic models is their aggregate nature. The macroscopic models concern the traffic flow as continuous system, then these models cannot capture the discrete dynamic aspects that arise from vehicles interaction[4].

The interaction between vehicles has strong relationship with the driver behavior. Some research studies have shown that the driver behavior play an important role for the traffic events. One cause of those traffic events is due to the observations and reactions of drivers are governed by human perception. The emotional aspect of the driver contributes to the many situations in traffic such as car crashes and congestion[5]. Another study also shown that the driver behavior is a fundamental factor and a key source of complexity in predicting traffic network states unfolding over time[6].

The recent research from Nagel et.al.[7], discusses two lane traffic and lane changing rules based on a cellular automata model. However, these models just appropriate to be applied into freeway traffic condition and have not considered about spontaneous braking and also drivers' visibility and speed estimation of the vehicles within the monitoring area which may have important influence on human' hazard perception and lane changing decision.

This thesis presents the results of computer simulation study conducted to investigate how the behaviors of driver influence the traffic flow and how these behaviors are related to each other in the traffic flow phenomena. There is a common knowledge that there are differences on the way of braking character of each driver. In the urban roadway traffic situations, vehicle would make a braking as the response to avoid collision with another vehicle or avoid some obstacle like potholes, snow, or pedestrian that crosses the road unexpectedly. In many countries, the reckless driving behaviors such as sudden-stop by public-buses, motorcycle which changing lane too quickly, or tailgating make the probability of braking getting increase.

The new aspect of this thesis is developing the traffic simulation that takes into account the spontaneous braking behavior and scope awareness of the driver and presents the new Cellular Automata model for describing these characteristics. This model is expected to reflect a more realistic the urban roadway traffic behavior.

1.3 Contribution of the Thesis

We introduce a stochastic discrete cellular automata model to simulate the dynamic braking of the driver, in particular for the spontaneous braking behavior, as is observed in urban roadway traffic. Furthermore, we also introduce and present the analysis study about the effect of driver scope awareness in lane changing maneuver. Compare to the real traffic flow data, this proposed model given better accuracy to show traffic flow behavior compare to the previous traffic model.

In the future, this proposed model could be elaborated to improve the development of intelligent transport technologies and applications.

1.4 Scope

Many researches have been proposed the traffic flow model and simulation. The research study, in this thesis, focuses only on the 2-lane urban road traffic model from a cellular automaton point of view in order to describe and analyze the spontaneous braking and scope awareness of driver.

This research will focus on:

1. The fundamental diagram of 2-lane urban roadway traffic simulation.
2. The enhancement of traffic cellular automata model to better capture the spontaneous braking and scope awareness of driver.
3. The evaluation and validation the simulation model to the real traffic data.

1.5 Thesis Outline

This dissertation is organized as follow. Chapter-1 provides an introduction to the research work. Several related issues as the background research are introduced. Problem statement, motivation, contribution, and scope of this study are stated and discussed as well.

Chapter-2 discusses the theoretical background of the traffic simulation and modeling. In this chapter, the previous studies and works for modeling the traffic phenomena by using cellular automata have been reviewed. This chapter has also discussed about driver behavior in the traffic performance.

The description of the proposed model dealing with spontaneous braking behavior is given in Chapter-3. IT consists of model overview, description, and the implementation of the model in simulation. The simulation result of the probability condition of each parameter has been shown in the last part of this chapter.

Chapter-4 describes the parameter of driver scope awareness and the effect to the traffic flow. Brief overview and the description of this parameter is discussed. The results derived from the simulation work are shown in this chapter. The evaluation and comparison study between the proposed model to the actual traffic data and the previous traffic model is also discussed in this chapter.

Chapter-5 draws the conclusion of the overall work in this thesis.

CHAPTER 2.
LITERATURE REVIEW

This chapter contains basic remarks on how to model the traffic flow. It therefore deals with the methodology rather than a specific model in detail. The problem setting, as introduce in the previous chapter, is introduced includes the description and definition of traffic model, and the aspects of traffic flow measurement. Different model classes that comply with the theory will be introduced and briefly described. This is the first step providing the basis for empirical studies, model development, and finally the implementation in the simulation.

Contents

2.1 Traffic Modeling and Analysis

During its more than forty years long history computer simulation in traffic analysis has developed from a research tool of limited group of experts to a widely used technology in the research, planning, demonstration and development of traffic systems. The five driving forces behind this development are the advances in traffic theory, in computer hardware technology and in programming tools, the development of the general information infrastructure, and the society's demand for more detailed analysis of the consequences of traffic measures and plans. The basic application areas of simulation have mainly remained the same, but the applications have grown in size and complexity. In the 1990's demand analysis through simulation has emerged as a new application area. New programming techniques and environments, like object-oriented programming and virtual reality tools are coming to common use. Integrated use of several programs and the applications of parallel computing and GIS databases are some of the latest trends in traffic systems simulation. New ideas, like cellular automata and rule-based simulation with discrete variables have also proven their strength.

2.1.1 Traffic Characteristics

Road traffic flows are the combination of drivers associated with individual vehicles, each of them having their own characteristics. These characteristics are called *microscopic* when a traffic flow is considered as being composed of such a stream of vehicles[3]. Through the interactions between the drivers of the vehicles, then formed the dynamical aspects of these traffic flows. These dynamic conditions are largely determined by the behavior of each driver, as well as the physical characteristics of the vehicles.

Since the process of participating in a traffic flow is heavily based on the behavioral aspects associated with human drivers[2], it would seem important to include these human factors into the modeling equations. However, this leads to a severe increase in complexity, which is not always a desired artifact[3].

2.1.1.1 Variables related with vehicle

Referring to Maerivoet[8], the following is expressed some variables related with vehicle. Let considering individual vehicles, each vehicle i in a lane of a traffic stream have the following informational variables:

- a length, denoted by l_i;
- a longitudinal position, denoted by x_i;
- a speed, denoted by $v_i = \frac{dx_i}{dt}$;
- an acceleration, denoted by $a_i = \frac{dv_i}{dt} = \frac{d^2x_i}{dt^2}$.

Note that the position x_i of a vehicle is typically taken to be the position of its rear bumper. In this approach, a vehicle's other spatial characteristics (i.e., its width, height, and lane number) are neglected.

2.1.1.2 Characteristics of traffic flow

We quote from Gartner[2] and Maerivoet[3], they explained that, we can consider two consecutive vehicles in the same lane in a traffic stream: a follower *i* and its leader i + 1. Referring to Figure 2-1, it can be seen that vehicle *i* has a certain *space headway* h_{s_i} to its predecessor (it is expressed in meters), composed of a distance (called a space gap) g_{s_i} to this leader and its own length l_i:

$$h_{s_i} = g_{s_i} + l_i \quad \text{Eq.2-1}$$

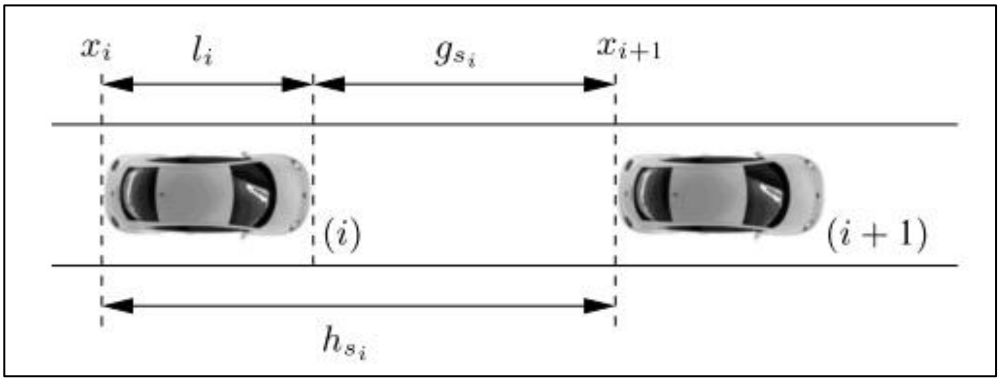

Figure 2-1. Two consecutive vehicles

In the context of the space headway, by taking the rear bumper as the vehicle's position then the space headway $h_{s_i} = x_{i+1} - x_i$. The space gap is thus measured from the follower vehicle's front bumper to its leader rear bumper. Maerivoet also stated that analogously to Eq.2-1, each vehicle has a time headway h_{t_i} (expressed in seconds) which is consist of a time gap g_{t_i} and an occupancy time ρ_i:

$$h_{t_i} = g_{t_i} + \rho_i \quad \text{Eq. 2-2}$$

By using a time-space diagram, the space and time headways can be visualized. Figure 2-2 presents a time-space diagram showing two vehicles trajetories i and i+1, as well as the space and time headway h_{s_i} and h_{t_i} of vehicle i. Both headways are composed of a space gap g_{s_i} and the vehicle length l_i, and the time gap g_{t_i} and the occupancy time ρ_i, respectively. The time headway can be seen as the difference in time instants between the passing of both vehicles, respectively at $t_i + 1$ and t_i, (diagram based on [3]). In other words, Figure 2-2 also informs that the position of both vehicles can be plotted with respect to time, tracing out two *vehicle trajetories*. Time direction has drawn horizontal and space direction in vertical way, then the vehicles' respective speeds can be derived by taking the tangents of the trajectories (for simplicity, we have assumed that both vehicles travel at the same con- stant speed, resulting in parallel linear trajectories). Accelerating vehicles have steep inclining trajectories, whe- reas those of stopped vehicles are horizontal.

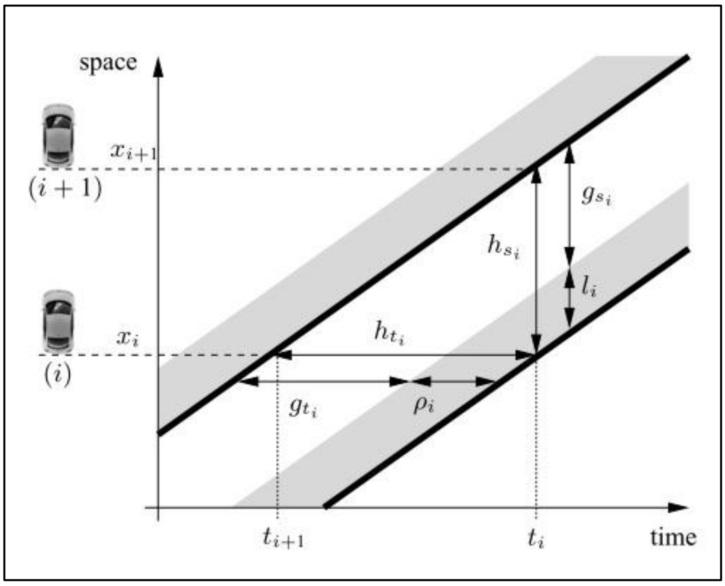

Figure 2-2 A time-space diagram shows two vehicle trajectories i and i + 1.

When the vehicle's speed is constant, the time gap is the amount of time necessary to reach the current position of the leader when travelling at the current speed (i.e., it is the elapsed time an observer at a fixed location would measure between the passing of two consecutive vehicles). In single-lane traffic, vehicles always keep their relative order, a principle sometimes called first-in, first-out (FIFO). For multi-lane traffic however, this principle is no longer obeyed due to overtaking maneuvers, resulting in vehicle trajectories that cross each other. If the same time-space diagram were to be drawn for only one lane (in multi-lane traffic), then some vehicles' trajectories would suddenly appear or vanish at the point where a lane change occurred[3].

2.1.1.3 Density, Flow, and Speed

Discussing the traffic flow to a more aggregate macroscopic level (traffic streams are regarded as a fluid) then there are three important macroscopic traffic flow characteristics: density, flow rates, and mean speed.

A synonym of density is concentration. However, refer to Hall et.al., there is difference between them. The former is a measure of concentration over space, while the latter measures a concentration over time of the same vehicle stream. Density can be measured only along a length. If only point measurements are available, density needs to be calculated either from occupancy or from speed and flow. This density value allows us to get an idea of how crowded a certain section of a road is. It is typically expressed in number of vehicles per kilometer (or mile). Note that the concept of density totally ignores the effects of traffic composition and vehicle lengths, as it only considers the abstract quantity 'number of vehicles'[3]. When density cannot be exactly measured or computed, or when density measurements are faulty, it has to be *estimated*. To this end, several available techniques exist e.g., based on explicit simulation using a traffic flow propagation model[9], based on a vehicle re-identification system[10], based on a complete traffic state estimator using an extended Kalman filter[11], or based on a non-linear adaptive observer[12].

Using the spatial region R_s, the density *k* for single-lane traffic is defined as:

$$k = \frac{N}{K} \qquad \text{Eq. 2-3}$$

with *N* the number of vehicles present on the road segment. If we consider multi-lane traffic, we have to sum the partial densities k_l of each of the L lanes as follow[3]:

$$k = \sum_{l=1}^{L} k_l = \frac{1}{K} \sum_{l=1}^{L} N_l, \qquad \text{Eq. 2-4}$$

2.2 Traffic Cellular Automata Models for the Micro Traffic Flow

Cellular automaton (CA), at the basis of the model presented in this dissertation, is a discrete model studied in computability theory, mathematics, physics, complexity science, theoretical biology and microstructure modeling. Currently, various fields have been using CA models to model the phenomena of their system, such as vehicular traffic flow, pedestrian behavior, escape and panic dynamic, collective behavior, and self-organization. CA model uses a simple approach for modeling and simulation of complex dynamical systems. The behavior of complex systems can be described by considering at the local interactions between their elementary parts. CA decomposes a complex phenomenon into a finite number of elementary processes.

The CA model consists of two components, a cellular space and a set of state. A set of rules specify the time and space evolution of the system, which is discrete in both variables. The state of a cell is completely determined by its nearest neighborhood cells. All neighborhood cells have the same size in the lattice. Each cell can either be empty, or is occupied by exactly one node. There is a set of local transition rule that is applied to each cell from one discrete time step to another (i.e., iteration of the system). This parallel updating from local simple interaction leads to the emergence of global complex behavior. All vehicles have the same length l_i=1 cell, with traffic considered as homogeneous, so all vehicles‘ characteristics are assumed to be the same[13].

By using illustrative time-space diagrams, each Traffic Cellular Automata (TCA) models can shows its qualitative behavioral characteristics; these diagrams can represent all traffic operations that occur in the system. The paths of all the vehicles' movements are traced, resulting in a set of trajectories (the space direction is vertical, the time direction is horizontal); each vehicle is represented by a pixel. In the trajectories, congestion waves clearly appear as they move upstream with time: vehicles entering such a wave reduce their speed (nearly horizontal trajectories) for a while, until they can accelerate again (steep ascending trajectories). The time axis direction starts from left to right, while the space axis direction is upward, so vehicles drive diagonally upwards to the right and congestion waves propagate diagonally downwards to the right.

Many studies of TCA models have been performed by scientists/researchers, some of them are [14], [15], [16], [17], [18], [19]. In this overview of the TCA models, we refer to Maerivoet and De Moor[13]

2.2.1 Overview and physical setup

This section describes the overview of the historic origins of cellular automata (CA), as they were conceived around 1950. The origin of CA consists four main ingredients constitute a cellular automaton: the physical environment, the cells' states, their neighborhoods, and finally a local transition rule. Subsequently, there is a general description on how cellular automata are applied to vehicular road traffic, discussing their physical environment and the accompanying rule set that describes the vehicles' physical propagation. In this overview of the cellular automata (CA), we refer to the study from Maerivoet and De Moor[13].

2.2.1.1 Origin of cellular automata

The mathematical concepts of cellular automata (CA) models can be traced back as far as 1948, when Johann Louis von Neumann introduced them to study (living) biological systems[20]. Von Neumann's work, was the notion of *self-reproduction* and theoretical machines (called *kinematons*) that could accomplish this. As his work progressed, von Neumann started to cooperate with Stanislaw Marcin Ulam, who introduced him to the concept of *cellular spaces*. These described the physical structure of a cellular automaton, i.e., a grid of cells which can be either 'on' or 'off' [21]. Interestingly, Alan Mathison Turing proposed in 1952 a model that illustrated reaction–diffusion in the context of *morphogenesis* (e.g., to explain the patterns of spots on giraffes, of stripes on zebras, etc). His model can be seen as a type of continuous CA, in which the cells have a direct analogy with a simplified biological organism.

In the 1970s, CA models found their way to one of the most popular applications called ‘simulation games’, of which John Horton Conway’s *“Game of Life”*[22] is probably the most famous. The game found its widespread fame due to Martin Gardner who, at that time, devoted a Scientific American column, called *“Mathematical Games”*, to it. Life, as it is called for short, is traditionally ‘played’ on an infinitely large grid of cells. Each cell can either be ‘alive’ or ‘dead’. The game evolves by considering a cell’s all surrounding neighbors, deciding whether or not the cell should live or die, leading to phenomenon called ‘birth’, ‘survival’, and ‘overcrowding’ (or ‘loneliness’).

The widespread popularization of CA models was achieved in the 1980s through the work of Stephen Wolfram. Based on empirical experiments using computers, he gave an extensive classification of CA models as mathematical models for self-organizing statistical systems[21]. Wolfram’s work culminated in his mammoth monograph, called *A New Kind of Science*[23]. In this book, Wolfram related cellular automata to all disciplines of science (e.g., sociology, biology, physics, mathematics, etc.).

2.2.1.2 Ingredients of a cellular automaton

From a theoretical point of view, four main ingredients play an important role in cellular automata models:

A. The physical environment

This defines the *universe* on which the CA is computed. This underlying structure consists of a *discrete lattice of cells* with a rectangular, hexagonal, or other topology, the examples shown by Figure 2-3. Typically, these cells are all equal in size; the lattice itself can be finite or infinite in size, and its dimensionality can be a linear string of cells called an *elementary cellular automaton* or ECA, or a grid, or even higher dimensional. In most cases, a common—but often neglected—assumption, is that the CAs lattice is embedded in a *Euclidean space*.

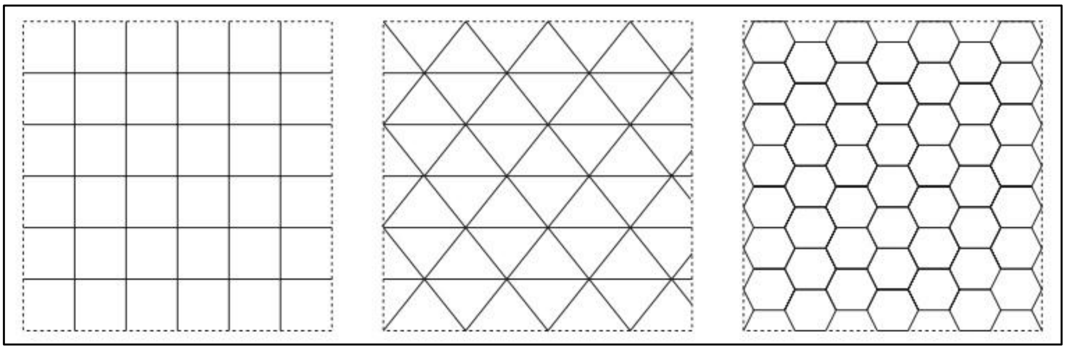

Figure 2-3. Some examples of different Euclidean lattice topologies for a cellular automaton in two dimensions

B. The cells' states

Each cell can be in a certain state, where typically an integer represents the number of distinct states a cell can be in, e.g., a binary state. Note that a cell's state is not restricted to such an integer domain (e.g.,$\mathbb{Z}_2$), as a continuous range of values is also possible (e.g.,$\mathbb{R}^+$), in which case we are dealing with *coupled map lattices* (CML). We call the states of all cells collectively a CAs *global configuration*. This convention asserts that states are local and refer to cells, while a configuration is global and refers to the whole lattice.

C. The cells' neighborhoods

For each cell, we define a neighborhood that locally determines the evolution of the cell. The size of neighborhood is the same for each cell in the lattice. In the simplest case, i.e., a one-dimensional lattice, the neighborhood consists of the cell itself plus its adjacent cells. In a two-dimensional rectangular lattice, there are several possibilities, e.g., with a radius of 1 there are, besides the cell itself, the four north, east, south, and west adjacent cells (*von Neumann neighborhood*), or the previous five cells as well as the four north–east, south–east, south–west, and north–west diagonal cells (*Moore neighborhood*); see Figure 2-4 for an example of both types of neighborhoods. Figure 2-4 shows the von Neumann neighborhood (left) consisting of the central cell itself plus 4 adjacent cells, and the Moore neighborhood (right) where there are 8 adjacent cells. Note that for one-dimensional CA's, both types of neighborhoods are the same Note that as the dimensionality of the lattice increases, the number of direct neighbors of a cell increases exponentially.

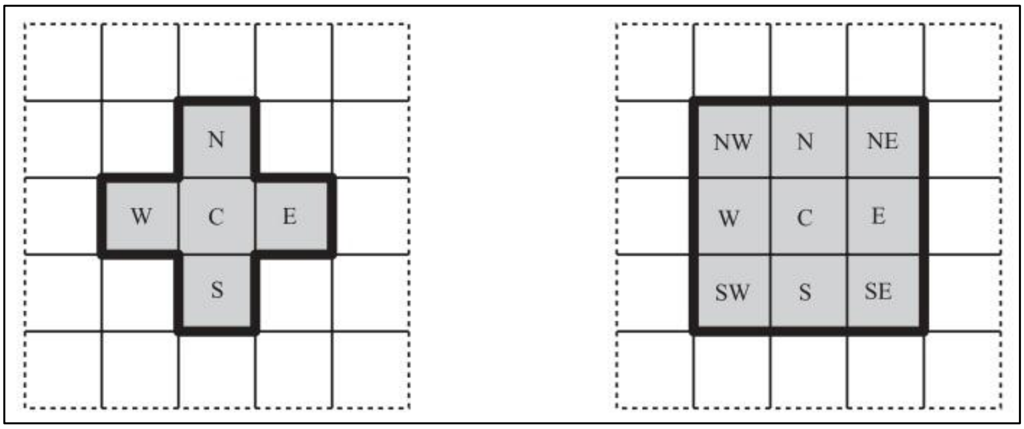

Figure 2-4. Two commonly used two-dimensional CA neighbourhoods with a radius of 1 (figure source:[13]).

C. A local transition rule

This rule (also called function) acts upon a cell and its direct neighborhood, such that the cell's state changes from one *discrete time step* to another (i.e., the system's iterations). The CA evolves in time and space as the rule is subsequently applied to all the cells *in parallel*. Typically, the same rule is used for all the cells (if the converse is true, then the term *hybrid* CA is used). When there are no stochastic components present in this rule, we call the model a *deterministic* CA, as opposed to a *stochastic* (also called *probabilistic*) CA.

As the local transition rule is applied to all the cells in the CAs lattice, the global configuration of the CA changes. This is also called the CAs *global map*, which transforms one global configuration into another. Sometimes, the CAs evolution can be reversed by computing past states out of future states. By evolving the CA backwards in time in this manner, the CAs *inverse global map* is computed. If this is possible, the CA is called *reversible*, but if there are states for which no precursive state exists, these states are called *Garden of Eden* (GoE) states and the CA is said to be *irreversible*.

Finally, when the local transition rule is applied to all cells, its global map is computed. In the context of the theory of dynamical systems, this phenomenon of *local simple interactions* that lead to a *global complex behavior* (i.e., the spontaneous development of order in a system due to *internal* interactions), is termed *self-organization* or *emergence*. Whereas the previous parts discussed the classic approach to CA models, the following parts will focus on vehicular traffic flows, leading to traffic cellular automata (TCA) models.

2.2.1.3 Road layout and the physical environment

When applying the cellular automaton analogy to vehicular road traffic flows, the physical environment of the system represents the road on which the vehicles are driving. In a classic single-lane setup for traffic cellular automata, this layout consists of a one-dimensional lattice that is composed of individual cells (our description here thus focuses on unidirectional, single-lane traffic). Each cell can either be empty, or is occupied by *exactly* one vehicle; we use the term *single-cell models* to describe these systems. Another possibility is to allow a vehicle to span several consecutive cells, resulting in what we call *multi-cell models*. Because vehicles move from one cell to another, TCA models are also called *particle–hopping models*[16].

An example of the tempo-spatial dynamics of such a system is depicted in Figure 2-5, where two consecutive vehicles i and j are driving on a one-dimensional lattice. A typical discretization scheme assumes $\mathrm{t} = 1\ \mathrm{s}$ and $x = 7.5\mathrm{m}$, corresponding to speed increments of $\mathrm{v} = \mathrm{x}/\mathrm{t} = 27\ \mathrm{km}/\mathrm{h}$. The spatial discretisation corresponds to the average length a conventional vehicle occupies in a closely jam packed (and as such, its width is neglected), whereas the temporal discretization is based on a typical driver's reaction time and we implicitly assume that a driver does not react to events between two consecutive time steps[24].

With respect to the layout of the system, we can distinguish two main cases: closed versus open systems. They correspond to periodic (or cyclic) versus open boundary conditions. The former is usually implemented as a closed ring of cells, sometimes called the *Indianapolis scenario*, while the latter considers an open road. This last type of system is also called the *bottleneck scenario*. The name is derived from the fact that this situation can be seen as the outflow from a jam, where vehicles are placed at the left boundary whenever there is a vacant spot. Note that, in closed systems, the number of vehicles is always conserved, leading to the description of *number conserving cellular automata* (NCCA)[13].

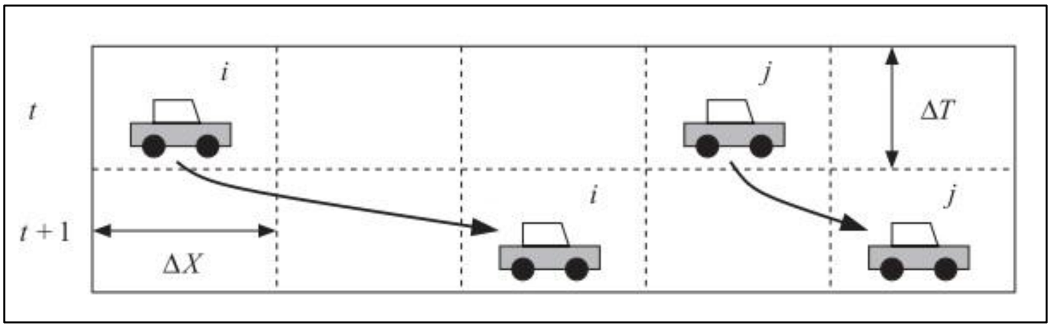

Figure 2-5. Schematic diagram of the operation of a single-lane traffic cellular automaton (TCA)

2.2.1.4 Vehicle movements and the rule set

The propagation of the individual vehicles in a traffic stream, is described by means of a rule set that reflects the car-following and lane-changing behavior of a traffic cellular automaton evolving in time and space. The TCAs local transition rule actually comprises this set of rules. They are consecutively applied to all vehicles in parallel (called a *parallel update*). So in a classic setup, the system's state is changed through *synchronous position updates* of all the vehicles: for each vehicle, the new speed is computed, after which its position is updated according to this speed and a possible lane-change maneuver. Note that there are other ways to perform this update procedure, e.g., a random sequential update. Because time is discretized in units of ΔT seconds, an *implicit reaction time* is assumed in TCA models. It is furthermore assumed that a driver does not react to events between consecutive time steps.

For single-lane traffic, we assume that vehicles act as *anisotropic particles*, i.e., they only respond to frontal stimuli. So typically, the car-following part of a rule set only considers the direct frontal neighborhood of the vehicle to which the rules are applied. The radius of this neighborhood should be taken large enough such that vehicles are able to drive collision-free. Typically, this radius is equal to the maximum speed a vehicle can achieve, expressed in cells per time step.

From a microscopic point of view, the process of a vehicle following its predecessor is typically expressed using a *stimulus–response relation*[8]. Typically, this response is the speed or the acceleration of a vehicle; in TCA models, a vehicle's stimulus is mainly composed of its speed and the distance to its leader, with the response directly being a new (adjusted) speed of the vehicle. In a strict sense, this only leads to the avoidance of accidents. Some models however, incorporate more detailed stimuli, such as anticipation terms. These forms of 'anticipation' only take leaders' reactions into account, *without predicting* them. When these effects are taken into account together with a safety distance, strong accelerations and abrupt braking can be avoided. Hence, as the speed variance is decreased, this results in a more stable traffic stream[25][26][27].

Interestingly, a TCA model can also be derived from a so-called Gipps car-following model. All speeds in this Gipps model are directly computed from one discrete time step to another[13]. If now the spatial dimension is also discretized (a procedure called *coarse graining*), then this will result in a TCA model.

2.2.2 Wolfram's rule 184 (CA-184)

One of the deterministic models is one-dimensional TCA model with binary state introduced by Stephen Wolfram[21]. As using one dimensional then this model is called an elementary cellular automaton (ECA). Assuming a local neighborhood of three cells wide in the radius of 1, then there are $2^{2^3} = 256$ different rules possible. Around1983, Stephen Wolfram classified all these 256 binary ECAs. One of these is called rule 184, its name is derived from Wolfram's naming scheme.. Wolfram's scheme is based on the representation of how a cell's state evolves in time, depending on its local neighborhood. Figure 2-6, presents a convenient visualization for the evolution of the state in a binary ECA. This figure shows the state $\sigma_i(t)$ of a central cell i at time step t, together with the state $\sigma_{i-1}(t)$ and $\sigma_{i+1}(t)$ of its two direct neighbors $i - 1$ and $i + 1$, respectively. All three of them constitute the local neighborhood $N_i(\mathrm{t})$ of radius 1. Because states are binary, we can indicate them with a color (e.g., state $\sigma_{i+1}(t)$ in Figure 2-6), whereas an empty (white) square represents a state of 0. According to the local transition rule $\delta(i, t)$, the local neighborhood $N_i(\mathrm{t})$ is then mapped from t to $t + 1$ onto a new state $\sigma_i(t + 1)$. The graphical representation in Figure 2-6, thus provides us with an illustrative method to indicate the evolution of $\{\sigma_{i-1}(\mathrm{t}), \sigma_i(\mathrm{t}), \sigma_{i+1}(\mathrm{t})\} \rightarrow \sigma_i(t + 1)$.

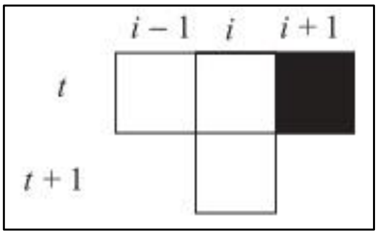

Figure 2-6. Evolution of cell's state in time, based on its local neighborhood

Considering the transition depicted in Figure 2-6, we can see that a complete neighborhood contains three cells, each of which can be in a 0 (white) or 1 (black) state. So in total, there are $2^3 = 8$ possible configurations for such a local neighborhood. Wolfram's naming scheme for the binary ECAs is now based on an integer coding of this neighborhood. Indeed, the local transition rule δ(*i*, *t*) is given by a table lookup containing eight entries, one for each of the possible local neighborhoods. If we binary sort these eight configurations in the descending order (1 1 1), (1 1 0), (1 0 1), (1 0 0), (0 1 1), . . ., then we obtain a graphic scheme such as the one in Figure 2-7. As can be seen, for each of the local configurations, a resulting 0 or 1 state is returned for cell *i* at time step *t* + 1. Collecting all resulting states, and writing them in base 2, results in the number $(1\ 0\ 1\ 1\ 1\ 0\ 0\ 0)_2$. This has the physical meaning that a particle (black-square) moves to the right if its neighboring cell is empty. Converting this code to base 10, we obtain the number 184. Wolfram now coded all 256 possible binary ECAs by a unique number in the range from 0 to 255, resulting in 256 rules for these CAs.

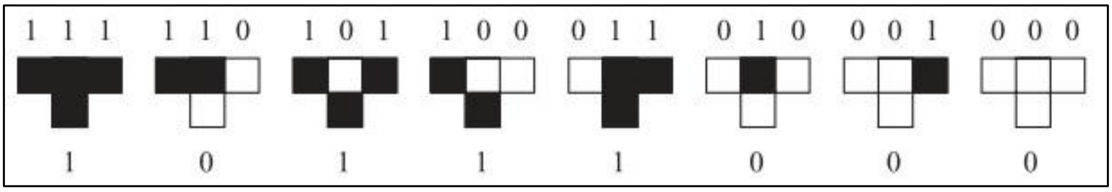

Figure 2-7. A graphical representation of Wolfram's rule 184

Rule 184 (abbreviate as CA-184) is an *asymmetrical* rule because $\delta((1\ 1\ 0)_2, t) = 0 \neq \delta((0\ 1\ 1)_2, t) = 1$. It is also called a *quiescent* rule because

$\delta((0\ 0\ 0)_2, t) = 0$ (so all zero-initial conditions remain zero). As an example of the rule's evolution, Figure 2-7 shows that the local neighborhood $(100)_2$ gets mapped onto a state of 1. If we consider these 1 states as *particles* (i.e., vehicles), and the 0 state as *holes*, then rule 184 dictates that all particles move one cell to the right, on the condition that this right neighbor cell is empty. Equivalently, all holes have the tendency to move to the left for each particle that moves to the right, a phenomenon which is termed the *particle-hole symmetry*.

For a TCA model, we can rewrite the previous actions as a set of rules that are consecutively applied to all vehicles in the lattice. For the CA-184, we have the following two rules:

(R1) acceleration and braking

$$v_i(t) \leftarrow \min\{g_{s_i}(t-1), 1\} \qquad \text{Eq. 2-5}$$

(R2) vehicle movement

$$x_i(\mathrm{t}) \leftarrow x_i(t-1) + v_i(t) \qquad \text{Eq. 2-6}$$

Rule R1, Eq. 2-5, sets the speed of the *i*th vehicle, for the current updated configuration of the system; it states that a vehicle always strives to drive at a speed of 1 cell/time step, unless it's impeded by its direct leader, in which case $g_{s_i}(t-1) = 0$ and the vehicle consequently stops in order to avoid a collision. The second rule R2, Eq. 2-6, is not actually a 'real' rule; it just allows the vehicles to advance in the system.

Figure 2-8 have applied these rules to a lattice consisting of 300 cells (closed loop), showing the evolution over a period of 580 time steps. The time and space axes are oriented from left to right, and bottom to top, respectively. The left part, shows a free-flow regime with a global density *k* = 0.2 vehicles/cell, and the right part has a congested regime with *k* = 0.75 vehicles/cell. Each vehicle is represented as a single colored dot; as time advances, vehicles move to the upper right corner, whereas congestion waves move to the lower right corner, i.e., backwards in space. From both parts of Figure 2-8, we can see that the CA-184

TCA model constitutes a fully deterministic system that continuously repeats itself. A characteristic of the encountered congestion waves is that they have an eternal life time in the system.

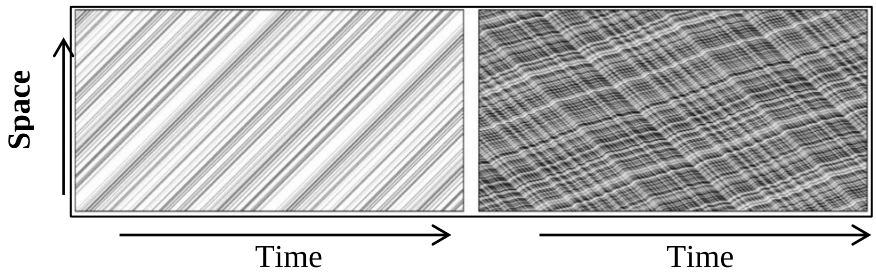

Figure 2-8. Typical time–space diagrams of the CA-184 TCA model

Figure 2-9 plots both the $(k, \bar{v}_s)$ and (k, q) diagrams. As can be seen from the left part, the global space-mean speed remains constant at $\bar{v}_s = 1$ cell/time step, until the critical density $k_c = 0.5$ is reached, at which point $\bar{v}_s$ will start to diminish towards zero where the critical density $k_j = 1$ is reached. Similarly, the global flow first increases and the decreases linearly with the density, below and respectively above, the critical density. Here, the capacity flow $q_{cap} = 0.5$ vehicles/time step is reached. The transition from the free-flowing to the congested regime is characterized by a first-order phase transition. As is evidenced by the *isosceles triangular shape* of the CA-184's resulting (k, q) fundamental diagram, there are only two possible kinematic wave speeds, i.e., $+1$ and -1 cell/time step. Both speeds are also clearly visible in the left, respectively right, time-space diagrams of Fig. 2.7.

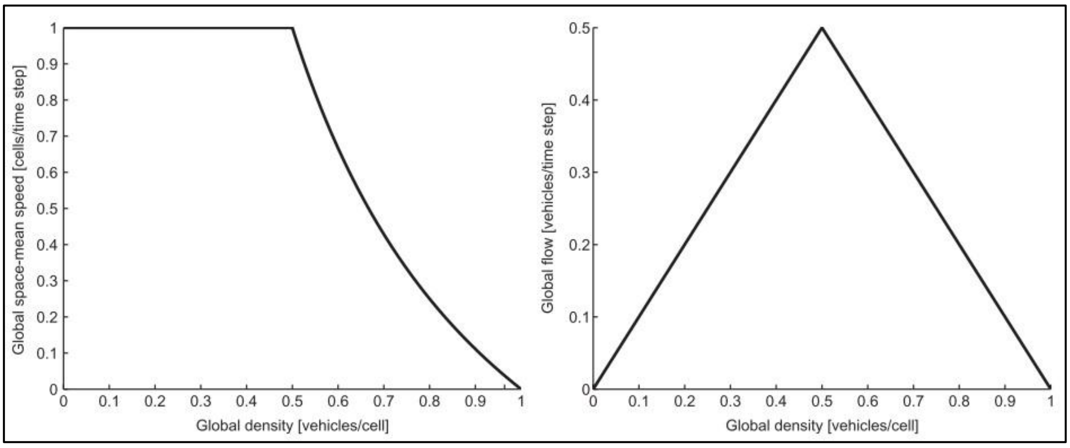

Figure 2-9. Fundamental diagrams for the CA-184

2.2.3 Deterministic Fukui-Ishibashi TCA (DFI-TCA)

In 1996, Fukui and Ishibashi constructed a generalization of the prototypical CA-184 TCA model[28]. Although their model is essentially a stochastic one, but we also discussed its deterministic one. Fukui and Ishibashi's idea was two-fold: on the one hand, the maximum speed was increased from 1 to $v_{\max}$ cell/time step, and on the other hand, vehicles would accelerate *instantaneously* to the highest possible speed. Corresponding to the definitions of the rule set of a TCA model, the CA-184's rule R1, Eq. 2-5, changes as follows:

(R1) *acceleration and braking*

$$v_i(t) \leftarrow \min\{g_{s_i}(t-1), v_{\max}\} \qquad \textit{Eq. 2-7}$$

Just as before, a vehicle will now avoid a collision by taking into account the size of its space gap. To this end, it will apply an instantaneous deceleration: for example, a fast-moving vehicle might have to come to a complete stop when nearing the end of a jam, thereby *abruptly* dropping its speed from $v_{\max}$ to 0 in one time step.

Due to the strictly deterministic behavior of the system, the time-space diagrams of the DFI-TCA do not differ much from those of the CA-184. The only difference is the speed of the vehicles in the free-flow regime, leading to steeper trajectories. It is however interesting to study the $(k, \bar{v}_s)$ and (k, q) diagrams in

Figure 2-10. The left-diagram $(k, \overline{v_s})$ shows several plots for the deterministic DFI-TCA each for a different $v_{max} \in \{1, \ldots, 5\}$. Similarly to the CA-184, the global space-mean speed remains constant, until the critical density is reached, at which point $\overline{v_s}$ will start to diminish towards zero. While in the right-diagram (k, q) shows that each plots having a triangular shape, with the slope of the congestion branch invariant for the different v_{max}. Here we can see that increasing the maximum speed $v_{\max}$ creates-as expected-a steeper free-flow branch in the (k, q) diagram. Interestingly, the slope of the congested branch does not change, logically implying that the kinematic wave speed for jams remains constant, i.e., -1 cell/time step. This can be confirmed with an analytical kinematic wave analysis, as explained by Nagel[17].

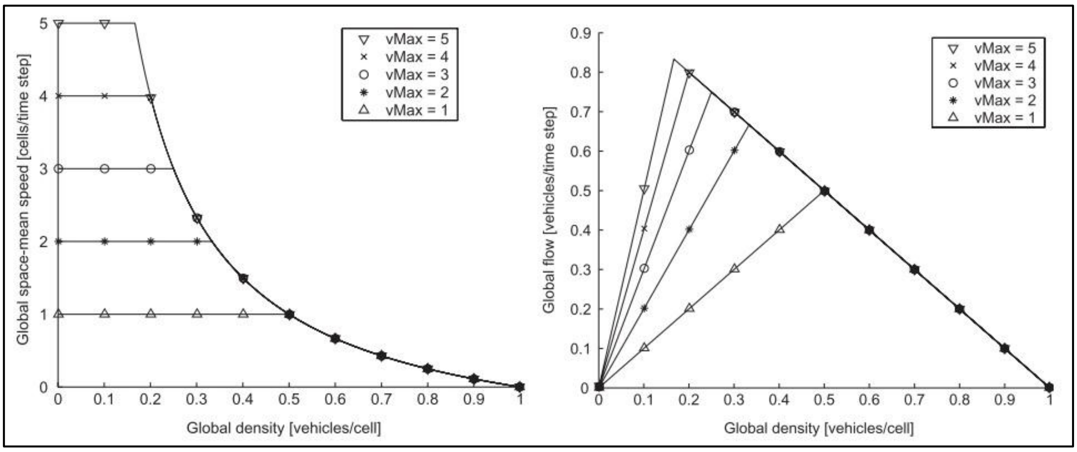

Figure 2-10. Fundamental diagrams for the DFI-TCA model

Based on the behavior of the vehicles near the critical density, we can analytically compute the capacity flow as follows: in the free-flow regime, all vehicles move with a constant speed of $v_{\max}$ cells/time-step. When the critical density is reached, all vehicles drive collision-free at this maximum speed, which implies that $g_{s_i} = v_{\max}$ cells. The space headway $h_{s_i} = v_{\max} + 1$ (because $l_i = 1$ for single-cell models). Consequently, the value for the critical density as[3]:

$$k_c = \frac{1}{\bar{h}_{s_c}} = \frac{1}{v_{max} + 1} \qquad \textit{Eq. 2-8}$$

The capacity flow is now computed by means of the fundamental relation, i.e., $q_{\mathrm{cap}} = k_{\mathrm{c}} v_{\max}$:

$$q_{\mathrm{cap}} = \frac{v_{\max}}{v_{\max} + 1} \qquad \textit{Eq. 2-9}$$

Applying *Eq. 2-8* and *Eq. 2-9*, for e.g., $v_{\max} = 5$ cell/time step, result in $k_c \approx 0.167$ vehicles/cell and $q_{\mathrm{cap}} \approx 0.83$ vehicles/time step. If we furthermore assume $\Delta X = 7.5$ m and $\Delta T = 1$ s, then both values correspond to 22 vehicles/km and 3000 vehicles/h, respectively.

As opposed to the instantaneous acceleration in rule R1, *Eq. 2-7*, we can also assume a *gradual acceleration* of one cell per time step (the braking remains instantaneous):

(R1) *acceleration and braking*

$$v_i(t) \leftarrow \min\{v_i(t-1) + 1, \mathrm{g}_{s_i}(t-1), v_{\max}\} \qquad \textit{Eq. 2-10}$$

However, experimental observations have indicated that there is no difference in global system dynamics, with respect to either adopting gradual or instantaneous vehicle accelerations[13].

There exist a strong relation between the previously discussed deterministic TCA models, and the macroscopic first-order LWR model with a triangular $q_e(k)$ fundamental diagram[8]. Some of finer results in this case, are the work of Nagel who extensively discusses some analytical result of both deterministic and stochastic TCA models[16], and the work of Daganzo who explicitly proves an equivalency between two TCA models and the kinematic wave model with a triangular $q_e(k)$ fundamental diagram[29].

As can be seen in Figure 2-11, for the limiting case when $v_{\max} \to \infty$, the congested branches in both $(k, \bar{v}_{\mathrm{s}})$ and (k, q) diagrams grow, at the cost of the free-flow branches which disappear. In such a simplified system, the critical density $k_c = 0$, with a capacity flow $q_{\text{cap}} = 1$.

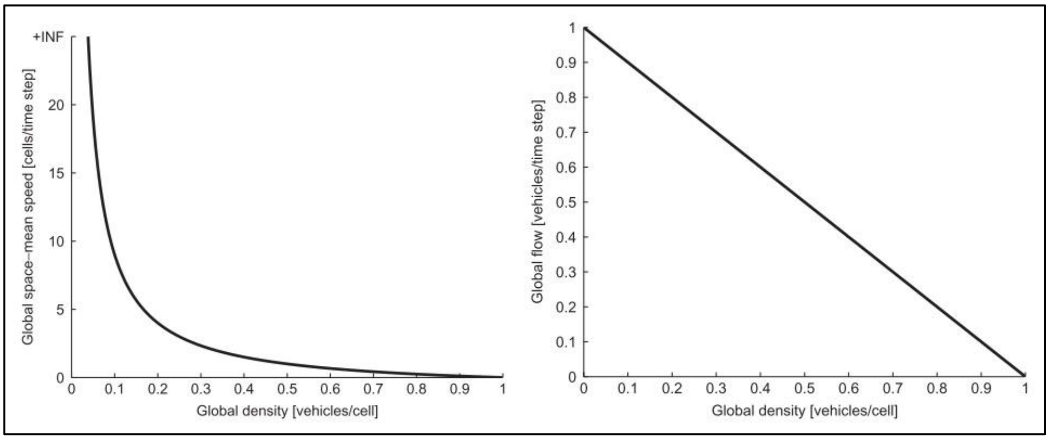

Figure 2-11. Fundamental diagrams for the deterministic CA-184 using $\boldsymbol{v_{max}} \rightarrow \propto$

2.2.4 Nagel-Schreckenberg model (NaSch)

The Nagel-Schreckenberg (NaSch) model is one of the theoretical CA models for the simulation of freeway traffic[24]. In 1992, Nagel and Schreckenberg proposed a TCA model that was able to reproduce several characteristics of real-life traffic flows. Their model is called the *NaSch TCA*, but is more commonly known as the *stochastic traffic cellular automaton* (STCA) This model is essentially a simple cellular automaton model for road traffic flow that can reproduce the spontaneous emergence of traffic jams, i.e., show a slowdown in average car speed when the road is crowded due to the high density of cars. This model shows how traffic jam can be thought of as an emergent or collective phenomenon due to interactions between cars on the road, then when the density of cars is high and so cars are close to each on average.

The NaSch model also known as stochastic traffic cellular automaton (STCA) because it included a stochastic term in one of its rules. Like in deterministic traffic CA models (e.g., CA-184 or DFI-TCA), this NaSch model contains a rule that reflect vehicle increasing speed and braking to avoid collision. However, the stochasticity term also introduced in the system by its additional rule. In one of its rules, at each time-step *t*, a random number $\xi(t) \in [0,1]$ is generated from a uniform distribution. This random number is then compared with a stochastic noise parameter $p \in [0,1]$, this is called the *slowdown probability*. For it is based on this probability p then a vehicle will slow down to $v_i(t) - 1$ cells/time-step. According to Nagel and Schreckenberg, the randomization rule captures natural speed fluctuations due to human behavior or varying external conditions[13].

In this NaSch model, a road is divided into cells. The original model uses cells that aligned in a single row whose ends are connected so that all cells make up a circle. This condition is called periodic boundary conditions. Each cell is either empty road or contains a single car. This means one car can occupy exactly one cell at any time. Each car is assigned a velocity which is an integer between 0 and a maximum velocity. Nagel and Schreckenberg uses maximum velocity v_{max} = 5 in their original work. In this model, a cell represents a car length and the maximum velocity as being the speed limit on the road. However, the model can also be thought as just a way to understand or to model features of traffic jams by showing how interactions between nearby cars cause the cars to slow down. One time step of this model is equal to 1 second in the real traffic situation. In each time step, the procedure is as follows[24].

In each step, the following four actions are conducted in order from first to last, and all are applied to all cars. For an arbitrary configuration, one update of the system consists of the following four consecutive steps, which are performed in parallel for all vehicles:

1. Acceleration: if the velocity v of a vehicle is lower than v_{max} and if the distance to the next car ahead is larger than v + 1 the speed is advanced by one $[v \rightarrow v + 1]$.
2. Slowing down (due to other cars): if the vehicle at site i sees the next vehicle at site $i + j$ (with $j \leq v$), it reduces its speed to $j - 1$ $[v \rightarrow j - 1]$.
3. Randomization: with probability p, the velocity of each vehicle (if greater than zero) is decreased by one $[v \rightarrow v - 1]$.
4. Car motion: each vehicle is advanced v sites.

Through the steps one to four very general properties of single lane traffic are modeled on the basis of integer valued probabilistic cellular automaton rules.

Already this simple model shows nontrivial and realistic behavior. Step 3 is essential in simulating realistic traffic flow since otherwise the dynamics is completely deterministic. It takes into account natural velocity fluctuations due to human behavior or due to varying external conditions. Without this randomness, every initial configuration of vehicles and corresponding velocities reaches very quickly a stationary pattern which is shifted backwards (i.e. opposite the vehicle motion) one site per time step. This step introduces overreactions of drivers when braking, providing the key to the formation of the spontaneously emerging jams. This STCA model is called a minimal model, in the sense that all these rules are a necessity for mimicking the basic features of real-life traffic flow. Although the rationale of step 3 is widely agreed upon, much critism was however expressed due to this second rule. For example, Brilon and Wu [30] believe that this rule has no theoretical background and is in fact introduced quite heuristically[13].

Figure 2-12 shows an intuitive feeling for the STCA's system dynamics. Both diagrams show the evolution for a global density of k = 0.2 vehicles/cell, but with p set to 0.1 for the left diagram, and p =0.5 for the right diagram. As can be seen in both diagrams, the randomization in the model gives rise to many unstable artificial phantom mini-jams. The downstream fronts of these jams smear out, forming *unstable interfaces*[17].

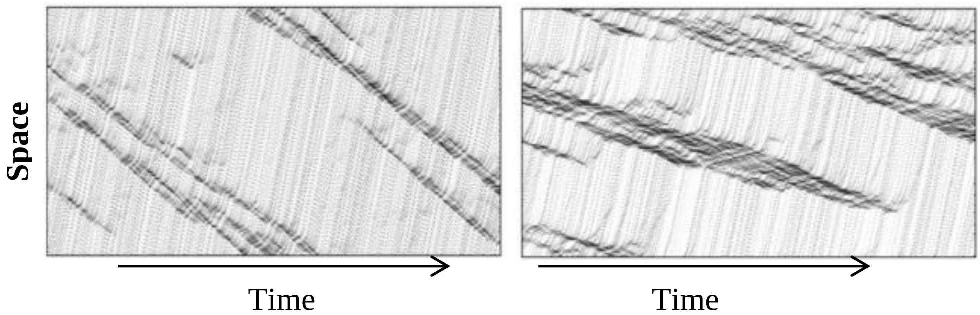

Figure 2-12. Typical time-space diagram of the STCA model

This is a direct result of the fact that the intrinsic noise (as embodied by p) in the STCA model is too strong: a jam can always form at any density, meaning that breakdown can (and will) occur, even in the free-flow traffic regime. For low enough densities however, these jams can vanish as they are absorbed by vehicles with sufficient space headways, or by new jams in the system. It has been experimentally shown that below the critical density, these jams have finite life times with a cut-off that is about $5\ x\ 10^5$ time steps and independent of the lattice size. When the critical density is crossed, these long-lived jams evolve into jams with an infinite life time, i.e., they will survive for an infinitely long time[31][32].

2.2.5 Stochastic Fukui-Ishibashi TCA (SFI-TCA)

In chapter 2.2.2, we have discussed the deterministic FI-TCA (DFI-TCA) which is a generalization of the CA-184 TCA model. From their original formulation, Fukui and Ishibashi later introduced stochasticity, but now only for vehicles driving at the highest possible speed of $v_{\max}$ cells/time step[28].

Before we continue the discussion of SFI-TCA, it should be better to know the main difference between DFI-TCA models and SFI-TCA models. The DFI-TCA models have stated that there can be no spontaneous formation of jam structures. All congested conditions produced in those models, essentially come from the assumed initial conditions. Whereas the SFI-TCA models (i.e. these mean probabilistic CA) allow for the spontaneous emergence of phantom jams. All these models explicitly incorporate a stochastic term in their equations, in order to the TCA models is more realistic reflected to the real-life behavior[33].

We can express the rules of this model, by considering step-3 and step-4 of the NaSch model for randomization and vehicle movement, respectively, but now complemented with the DFI-TCA's rule R1 for instantaneous accelerations, i.e., *Eq. 2-7* of chapter 2.2.2, and an extra rule R0, as introduced by Nagel and Pazcuski[34], so the complete rules of SFI-TCA are:

(R0) *determine stochastic noise*

$$\begin{aligned} v_i(t-1) = v_{\max} &\Rightarrow p' \leftarrow p \\ v_i(t-1) < v_{\max} &\Rightarrow p' \leftarrow 0 \end{aligned} \qquad \textit{Eq. 2-11}$$

(R1) *acceleration and braking*

$$v_{\mathrm{i}}(t) \leftarrow \min\{\mathrm{g}_{\mathrm{s_i}}(t-1), \mathrm{v}_{\max}\} \qquad \textit{Eq. 2-12}$$

(R2) *randomization*

$$\xi(t) < p \Longrightarrow v_i(t) \leftarrow max\{0, v_i(t) - 1\} \qquad \textit{Eq. 2-13}$$

(R3) *vehicle movement*

$$x_i(\mathrm{t}) \leftarrow x_i(\mathrm{t} - 1) + v_i(\mathrm{t}) \qquad \textit{Eq. 2-14}$$

With now p replaced by $p'(t)$ in the randomization rule R2. It can be seen that for $v_{\max} = 1$, the SFI-TCA and STCA models are the same. Furthermore, for $p = 0$ the SFI-TCA becomes fully deterministic, and in contrast to the STCA's zero-flow behavior, the SFI-TCA's $p = 1$ case corresponds to the STCA with $p = 0$ and $v_{\max} - 1$.

The rationale behind the specific randomization in the SFI-TCA model is that drivers who are moving at a high speed, are not able to focus their attention indefinitely. As a consequence, there will be fluctuations at these high speeds. There will be no capacity drop, but the effect on the $(k, \bar{v}_s)$ diagram is that its free-flow branch will become slightly downward curving, starting at $\bar{v}_s = v_{\max} - p$ for $k = 0$.

To conclude, we mention the related work of Wang et al. who studied the SFI-TCA both analytically and numerically, providing an exact result for $p = 0$, and a close approximation for the model with $p \neq 0$ [77]. Based on the SFI-TCA, Wang et al. developed a model that is subtly different. They assumed that drivers do not suffer from concentration lapses at high speeds, but are instead only subjected to the random deceleration when they are driving close enough to their direct frontal leaders [78]. And finally, we mention the work of Lee et al. who incorporate anticipation with respect to a vehicle's changing space gap g_s as its leader is driving away. This results in a higher capacity flow, as well as the appearance of a synchronized-traffic regime, in which vehicles have a lower speed, but are *all* moving[79].

The other study of traffic flow model using the SFI-TCA has been performed by Wang, B.H., et al.[35], both analytically and numerically. They have obtained an exact result for p =0, and a close approximation for the model with p ≠ 0. They developed traffic flow model related with the SFI-TCA, their model is subtly different. Through the other study, Wang, L.,et al., assumed that drivers do not suffer from concentration lapses at high speeds, but are instead only subjected to the random deceleration when they are driving close enough to their direct frontal leaders[36]. The SFI-TCA is also used by Lee, K., et al.[37], related with anticipation of movement of the car ahead. They have considered anticipation with respect to a vehicle changing space gap g_s when its leader is driving away. This results in a higher capacity flow, as well as the appearance of a synchronized-traffic regime, in which vehicles have a lower speed, but are all moving.

2.3 Driver Behavior

Road traffic flows are the combination of drivers associated with individual vehicles, each of them having their own characteristics. These characteristics are called *microscopic* when a traffic flow is considered as being composed of such a stream of vehicles[3]. Through the interactions between the drivers of the vehicles, then formed the dynamical aspects of these traffic flows. These dynamic conditions are largely determined by the behavior of each driver, as well as the physical characteristics of the vehicles.

Since the process of participating in a traffic flow is heavily based on the behavioral aspects associated with human drivers[2], it would seem important to include these human factors into the modeling equations. However, this leads to a severe increase in complexity, which is not always a desired artifact[3].

2.3.1 Driving task

The driving task had been considered by Lunenfeld[38] to be a hierarchical process, with three levels: (1) Control, (2) Guidance, and (3) Navigation. Most control activities, it is pointed out, are performed "automatically," with little conscious effort. In short, the control level of performance is *skill based*, in the approach to human performance and errors set forth by Jens Rasmussen as presented in *Human Error*[39]. For the guidance level, Lunenfeld also said that guidance level inputs to the system are dynamic speed and path responses to roadway geometrics, hazards, traffic, and the physical environment. Information presented to the driver-vehicle system is from traffic control devices, delineation, traffic and other features of the environment; continually influence the driver response to change his performance depends on the situation that they experienced.

The third level, in which the driver acts as a supervisor apart, is *navigation*. One example the characteristic of the navigation level is route planning and guidance while reroute, for example, correlating directions from a map with guide signage in a corridor. This level is called *knowledge-based behavior*. Knowledge based behavior will become increasingly more important to traffic flow theorists as Intelligent Transportation Systems (ITS) mature.

2.3.2 Braking behavior and response

The speed limit for detection of oncoming collision or pull-away has been studied in collision-avoidance research. The study has estimated that drivers can detect a change in distance between the vehicle they are driving and the one in front when it has varied by approximately 12 percent. If a driver were following a car ahead at a distance of 30 m, at a change of 3.7 m the driver would become aware that distance is decreasing or increasing, i.e. a change in relative velocity[40].

This would suggest that a change of distance of 12 percent in 5.6 seconds or less would trigger a perception of approach or pulling away. Mortimer concludes that "...unless the relative velocity between two vehicles becomes quite high, the drivers will respond to changes in their headway, or the change in angular size of the vehicle ahead, and use that as a cue to determine the speed that they should adopt when following another vehicle."[40].

2.3.3 Acceleration Performance

The characteristics of the driver are the boundary on how fast the driver can accelerate his vehicle. The actual acceleration rates in a traffic stream are typically much lower than the performance capabilities of the vehicle, particularly a passenger car. Refer to a data from American Association of State Highway and Transportation Officials (AASHTO, 1990), a nominal range for "comfortable" acceleration at speeds of 48 km/h and above is about $0.6\ \mathrm{m/sec^2}$ to $0.7\ \mathrm{m/sec^2}$. The other nominal acceleration rate, many drivers prefer to use under "unhurried" circumstances at approximately 65 percent of maximum acceleration for the vehicle, it is around 1 $\mathrm{m/sec^2}$[41]. When the driver removes his foot from the accelerator pedal (or equivalent control input), then the deceleration will occur at about the same level as "unhurried" acceleration, approximately 1 $\mathrm{m/sec^2}$ at speeds of 100 km/h or higher. In contrast to operation of a passenger car, light truck, or heavy truck; their acceleration change are much more limited by the performance capabilities of the vehicle.

2.3.4 Gap Acceptance

When the driver want to enter or cross a traffic stream, he has to evaluate the space between a nearest vehicle with him in the traffic stream that he wants and himself, then make a decision whether to cross or enter or not. The time between the arrivals of successive vehicles at a point is the time gap, and the critical time gap is the least amount of successive vehicle arrival time in which a driver will attempt a merging or crossing maneuver. There are five different gap acceptance situations. These are[40]:

- left turn across opposing traffic, no traffic control,
- left turn across opposing traffic, with traffic control (permissive green),
- left turn onto two-way facility from stop or yield controlled intersection,
- crossing two-way facility from stop or yield controlled intersection,
- turning right onto two-way facility from stop or yield controlled intersection.

2.3.5 Lane changing

In real traffic, most highways consist two or more lanes. Regarding this road condition, there are a few analytical models for multi-lane traffic. Nagatani was one of the first researchers that introduced a CA model for two lane traffic[42]. His model used deterministic approach and the maximum velocity $v_{max} = 1$. Then, building on Nagatani's model, Rickert et.al.[43], considered a model with $v_{max} \geq 1$. Rickert proposed a symmetric rule set where the vehicle changes lanes if the following criteria are fulfilled:

$$gap(i) < l \qquad \text{Eq. 2-15}$$

$$gap_0(i) > l_0 \qquad \text{Eq. 2-16}$$

$$gap_{0,back}(i) > l_{0,back} \qquad \text{Eq. 2-17}$$

Meanwhile, Nagel et.al.[7] also discussed two lane traffic and lane changing rules based on a cellular automata model. Furthermore, we enhanced the original NaSch model by introduced the spontaneous braking parameter as a driver behavior that periodically affect the traffic flow and lane changing decision[44]. However, these models have not considered about drivers' visibility and speed estimation of the vehicles within the monitoring area which may have important influence on human' hazard perception and lane changing decision.

Toledo, T., et. al.[45], develop, implements, and tests a framework for driving behavior modeling that integrates the various decisions, such as acceleration, lane changing and gap acceptance (they give the name: integrated driving behavior model). The proposed framework is based on the concepts of short-term goal and short-term plan. Drivers are assumed to conceive and perform short-term plans in order to accomplish short-term goals. This behavioral framework supports a more realistic representation of the driving task, since it captures drivers' planning capabilities and allows decisions to be based on anticipated future conditions.

The model captures both lane changing and acceleration behaviors. The driver's short-term goal is defined by the target lane. Before change lanes, a driver selects a short-term plan to perform the desired lane change. Short-term plans are defined by the various gaps in traffic in the target lane. Drivers adapt their acceleration behavior to facilitate the lane change using the target gap. Inter-dependencies between lane changing and acceleration behaviors are obtained by the model.

2.3.6 Aggressive driver

Many study have been performed related with the driving behaviors, one of them is about aggressive behavior. In the vehicle-driver systems, vehicle behavior is influenced by the driver behaviors, e.g. aggressive behavior. Vehicle enters the network at certain entry points and tries to reach his destination by calculating the shortest path, in which vehicle behavior is determined by: car following; lane changing; and gap acceptance[5].

In the aggressive driving, Shinar[46] proposed that the classical frustration-aggression hypothesis provides a useful tool for understanding driver aggression. He had stated that driver aggression is caused by frustration because of traffic congestion and delays. In the other study performed by Lajunen, T., et al.[47], have stated about the relationships between exposure to congestion (rush-hour driving) and aggressive violations (DBQ) were investigated in Great Britain, Finland and the Netherlands. Partial correlations showed that the frequency of rush-hour driving did not correlate statistically significantly with driver aggression. Correlations between driving during rush-hour and aggression did not differ in magnitude from those between driving on country roads and aggressive violations. In addition, correlations between exposure to congestion and aggressive violations in countries with large number of vehicles per road kilometer (UK, Netherlands) were not higher than those in a sparsely populated country (Finland). These results from three countries suggest that congestion does not increase driver aggression as directly as suggested by Shinar[46].

CHAPTER 3.
SPONTANEOUS BRAKING AND LANE CHANGING EFFECTS ON TRAFFIC CONGESTION

In the real traffic situations, vehicle would make a braking as the response to avoid collision with another vehicle or avoid some obstacle like potholes, snow, or pedestrian that crosses the road unexpectedly. However, in some cases the spontaneous-braking may occur even though there are no obstacles in front of the vehicle. In some country, the reckless driving behaviors such as sudden-stop by public-buses, motorcycle which changing lane too quickly, or tailgating make the probability of braking getting increase. The new aspect of this research is the simulation of braking behavior of the driver and presents the new Cellular Automata model for describing this characteristic. Moreover, this research also examines the impact of lane-changing maneuvers to reduce the number of traffic congestion that caused by spontaneous-braking behavior of the vehicles.

Contents

3.1 Overview

The study of traffic flow has received a lot of attention for the past couple of decades. The simulations of traffic congestion become the most important aspect in the field of traffic analysis and modeling. Traffic congestion can be defined as the saturation condition of road network that occurs as increased traffic volume or interruption on the road, and is characterized by slower speed, longer trip times, and increased vehicular queuing. The investigated situations in the real traffic condition are those of traffic congestion caused by some main reason, such as insufficient road capacity, incidents, work zones (e.g., road maintenance or constructions near the road that requires space), weather events (e.g., in the case of rain or snow) which can hampers visibility therefore a driver have to slowdown its vehicle to compensate, or emergencies situations (e.g., hurricanes or severe snowstorms). However, in this research, we concern to investigate the effect of individual braking behavior of the driver on traffic congestion.

In more detail, this research interests to describe and reproduce the characteristic of spontaneous-braking probability and its effects to the traffic behavior. In the real traffic situations, vehicle would make a braking as the response to avoid collision with another vehicle or avoid some obstacle like potholes, snow, or pedestrian that crosses the road unexpectedly. However, in some cases the spontaneous-braking may occur even if there are static obstacles in front of the vehicle. In some country, the reckless driving behaviors such as sudden-stop by public-buses, motorcycle which changing lane too quickly, or tailgating make the probability of braking getting increase.

This research presents a new Cellular Automata model for describing the phenomena of spontaneous-braking behavior and lane-changing character in traffic flow. In this model, the effect of spontaneous-braking probability and lane-changing maneuver in two-lane highway with one-way traffic character are investigated. This proposed model extends the NaSch[24] model that first introduced CA for traffic simulation. The set of rules in NaSch model are modified to better capture and describe the behavior of the driver while making spontaneous-braking and lane-changing maneuver in traffic flow. The base deceleration rule of NaSch[24] model is applicable only to stationary vehicles, which is vehicles that are blocked by the leading vehicle in the previous time step. This rule is not applicable to two conditions, in the condition of those vehicles which are stopped due to spontaneous-braking behavior, and in the two-lane highway that allows vehicle to make lane-changing maneuvers. Compared with the original NaSch model, this proposed model exhibits spontaneous-braking probabilities effect combined with acceleration, deceleration, and lane-changing maneuvers effects. Though it is well known that spontaneous-braking is extremely reducing the local speed of vehicles, the impact on the global system has not been studied.

This research uses a two-lane highway character with a periodic boundary condition. The periodic boundary approach has been used to conserve the number of vehicles and the stability of the model. The goal of this research is to analyze the phenomena of spontaneous-braking behavior in traffic flow then propose a new cellular automata model to describing this phenomena. Moreover, this paper also investigates the impact of lane-changing maneuvers towards traffic congestion that is caused by spontaneous-braking behavior.

3.2 Model Description

As mentioned before, research extends a probabilistic CA model that introduced by Nagel-Schrekenberg (NaSch)[24] for the description of single-lane highway traffic. While the original NaSch model uses a single lane that is represented by a one-dimensional array of L sites (cells), this research considers two-lane highway with unidirectional traffic character in periodic boundaries condition. The two-lane model is needed to describe the more realistic traffic condition which has several types of vehicles with multiple desired velocities. In single-lane model, the vehicles with multiple desired velocities just resulting in the platooning effect with slow vehicle being followed by faster ones and the average velocity reduced to the free-flow velocity of the slowest vehicle[43].

The simulation model in this research presents two additional elements. The first additional element is spontaneous-braking parameter. This element is needed to illustrate the probability of spontaneous-braking behavior of the vehicle that occur in the real traffic situation. The concept of spontaneous-braking probability is introduced for the description of the spontaneous reaction of the drivers while making a vehicle-braking behavior. This reaction can be caused by several things e.g., as the response to avoid collision with another vehicles, the reckless driving behaviors such as sudden-stop by public-buses, motorcycle which changing lane too quickly, or tailgating. Those behaviors make the probability of braking getting increase.

In original NaSch model[24], there is no rule accommodate the spontaneous-braking behavior. NaSch model introduced a stochastic noise parameter $p \in [0,1]$ that can make a slowdown vehicle to $v(i) - 1$ cells/time-step. However, in real traffic situations this rule is difficult to describe the nature of the braking, especially on spontaneous-braking behavior of the vehicle. In our opinion, the value of braking is a variable number and the spontaneous-braking represent the extreme value of a braking behavior. Thus, the slow-down rule of vehicle $v(i)-1$ cells/time-step cannot describe the characteristic of spontaneous-braking. This paper introduces a new additional rule to represent the behavior of spontaneous-braking by using a spontaneous-braking probability $Pb: v(i) \rightarrow v(i)-b$. Here $b$is the braking parameter, denotes the characteristic of driver while make a braking. The value of bx is equal or less than the current speed $v_{(i)}$. This rule takes into account the dynamic characteristic of the driver while make a braking of its car. Already mentioned before, a two-lane unidirectional highway model with periodic boundary system is used in this computational model. Refer to the discrete NaSch model, a one-dimensional chain of L cells of length 7.5 m represents each lane. There are just two possibility states of each cell. Each cell can only be empty or containing by just one vehicle. The speed of each vehicle is integer value between $v = 0, 1, \ldots, v_{max}$. In this model, all vehicles are considered as homogeneous then have the same maximum speed vmax. In order to investigate the effect of spontaneous-braking behavior then the state of a road cell at the next time-step, from t to $t+1$ is dependent on the states of the direct frontal neighborhood cell of the vehicle and the core cell itself of the vehicle. The state of the road cells can be obtained by applying the following rules to all cells (vehicles) by parallel updated:

R(1) Acceleration

$$v_{(i)} \rightarrow min(v_{(i)}+1, v_{max}) \qquad \textit{Eq. 3-1}$$

R(2) Deceleration

$$v_{(i)} \rightarrow min(v_{(i)}, gap_{(i)}) \qquad \textit{Eq. 3-2}$$

R(3) Spontaneous braking probability

$$Pb : v_{(i)} \rightarrow v_{(i)} - b \qquad \textit{Eq. 3-3}$$

R(4) Driving

$$x_{(i)} \rightarrow x_{(i)} + v_{(i)} \qquad \textit{Eq. 3-4}$$

As this simulation model try to investigate the effect of spontaneous-braking behavior on traffic flow then this model deliberately eliminates the randomization rule of original NaSch: ($v_{(i)}$− 1 cells/time-step). Here for the reason to avoid the speed reduction of vehicles caused by this rule that could influence our simulation results. The variable $gap_{(i)}$ indicates the distance between a vehicle $x_{(i)}$ and its predecessor $x_{(i)+1}$. While v_{max} represents the maximum speed of the vehicle.

The second additional element is lane-changing parameter. By using two-lane highway model and applying multiple desired velocity types, then this research also accommodates the lane-changing maneuvers of vehicles. In the real traffic situation, driver tends to make a lane-changing maneuver while encounter traffic congestion along its lane. This research also intends to evaluate the impact of lane-changing maneuvers towards the traffic congestion that caused by spontaneous-braking behavior of the driver. In this model, the lane-changing maneuver is analogous as the movement of liquid. There is a different from the lane-changing model of Ricket et, al[43]. In this model, a vehicle would consider changing its lane only if the vehicles "see" another vehicle on its cell ahead and do so if possible. It means, as long as there is a cell free ahead on their lane then the vehicles would still remain on their lane. This lane-changing model will preserve the deceleration rule in our model that is showed in Eq. 3-5.

The lane-changing rule is applied to vehicles to change from right lane to left lane and conversely. Vehicles are only move sideways and they do not advance. Figure 3-1 shows the schematic diagram of lane-changing operation. A vehicle changes to the next lane if all of the following conditions are fulfilled:

$$Cell_{next} > 0 \qquad \textit{Eq. 3-5}$$

$$Cell_{target} = 0 \qquad \textit{Eq. 3-6}$$

$$x_{cellsback} + v_{cellsback_{t+1}} \neq cell_{target} \qquad \textit{Eq. 3-7}$$

$Cell_{next}$, $Cell_{target}$, and $Cell_{back}$ are the parameters that inform the state of one cell ahead, state of next cell, and state of cells behind on the other lane, respectively. If one cell is unoccupied or free-cell then its state is 0. In the real traffic situation, a driver also has to look back on the other lane and estimate the velocity of another cars-behind to avoid a collision. Therefore, Eq. 3-7 accommodates the driver behavior to estimate the velocity of vehicles before change its lane.

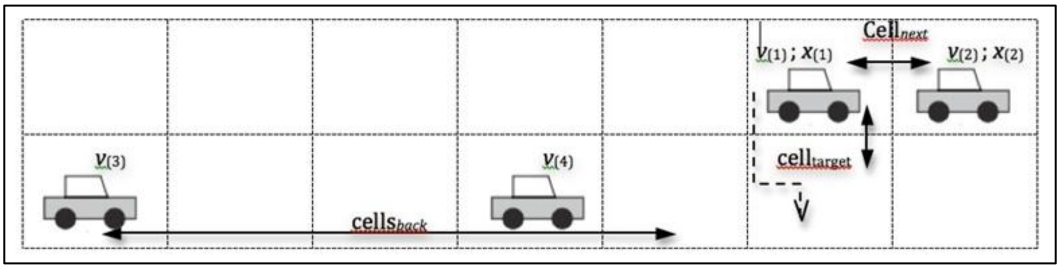

Figure 3-1. Schematic diagram of a lane-changing operation.

3.3 The Implementation of the Model into a Simulation

The simulation starts with an initial configuration of N vehicles, with random distributions of positions on both lanes. This simulation use the same initial velocity for all vehicle $v_{\min}$ = 0 and the maximum vehicle speed has been set to $v_{\max}$ = 5 cell/time-step. Each time-step has been setup to $\mathrm{t} = 1\ \mathrm{s}$ and $x = 7.5\mathrm{m}$, then corresponding to speed increments of $\mathrm{v} = \mathrm{x}/\mathrm{t} = 27\ \mathrm{km/h}$. Therefore, a vehicle's speed in this simulation model has a minimum value $v_{\min}$ = 0 km/h and maximum value $v_{\max}$ = 135 km/h, corresponded to the value of real traffic condition. A one-lane loop consists of 100 cells. Many simulations performed with different density ρ. The density ρ can be defined as number of cars N along the highway over number of cells on the highway L. During one simulation, the total number of cars on the highway cannot change. Vehicles go from left to right. If a vehicle arrives on the right boundary then it moves to the left boundary. Figure 3-2 illustrates an environment, which exhibits a certain configuration.

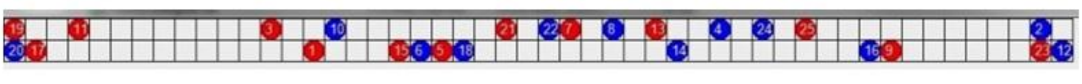

Figure 3-2. An environment with a certain configuration

This research divides the analysis into two stages. The first stage investigates the effect of spontaneous-braking on the traffic flow. In this simulation stage, we analyze the traffic flow for the spontaneous-braking probability Pb = 0; 0.3; and 0.7. The simulation was running 1000 time steps to let the system reaches its stable condition. The system automatically increase the vehicles density from minimum density $\rho = 0$ until maximum density $\rho = 100$ percent. Once the transient dies out, then the data extraction was started. The data was analyzed using fundamental diagrams, which plot the velocity of vehicle *vs* vehicle flow *vs* global density. To show the system dynamics then the graph had written the last ten steps for each density before the end of simulation. Figure 3-3 and Figure 3-4 present the fundamental diagrams of this model. Figure 3-3 shows the measurement of the average velocity $v(t)$ over all vehicles at each density. The red color, black color, and blue color of scatter graph present the average velocity in the condition with spontaneous-braking probability $P_b = 0$, $P_b = 0.3$, and $P_b = 0.7$, respectively. One can be observed that in the traffic without spontaneous braking probability, the maximum velocity 5 unit of distance per unit of time could be achieved in the density $\rho \leq 0.12$. When the probability of spontaneous-braking increased then the critical density point that maximum velocity can be achieved became lower than normal condition. For the spontaneous-braking probability $P_b = 0.3$, the critical point of maximum velocity $v_{max} = 5$ is around $\rho = 0.04$. While in the situation that spontaneous-braking probability $P_b = 0.7$, the vehicles were very difficult to reach their maximum speed $v_{max} = 5$.

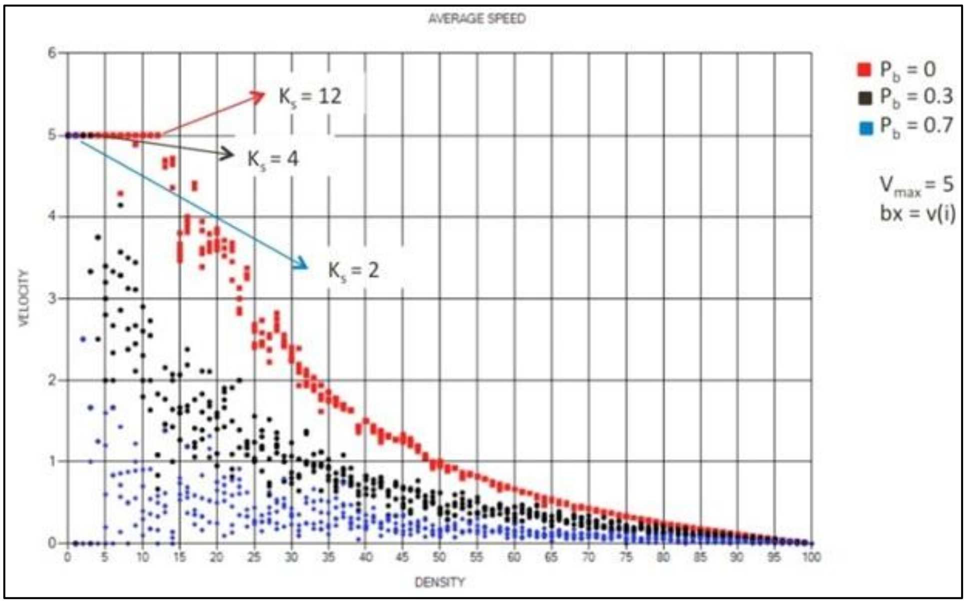

Figure 3-3. Average velocity (cell/time-step) vs density (cars/highway site).

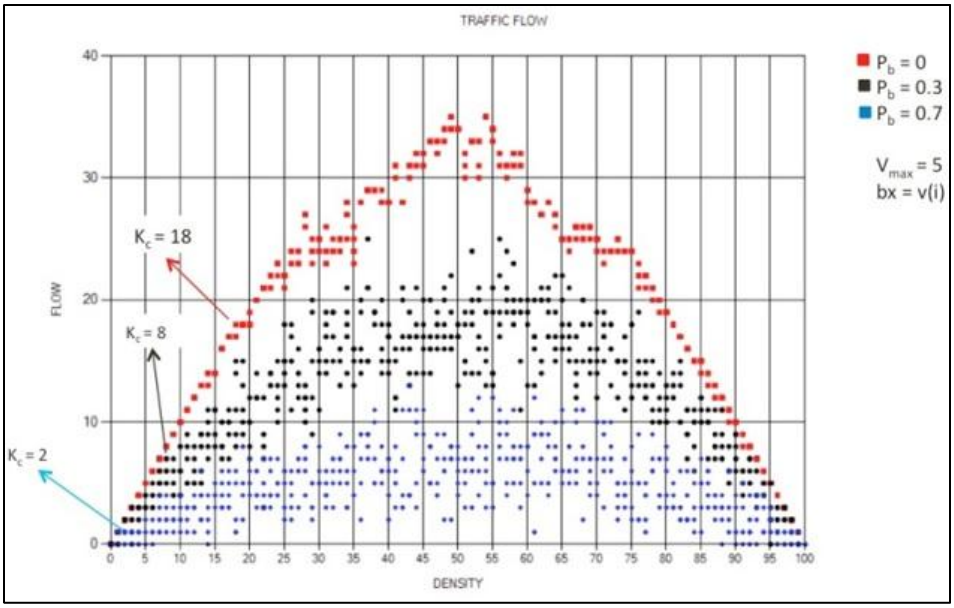

Figure 3-4. Traffic flow (cars/time step) vs density (cars/highway site).

In the phase after the critical density point of maximum velocity was reached, the vehicles reduced their velocity to synchronize with the gap between them and the vehicle ahead. However, in the transition phase after the critical density point of maximum velocity, the vehicles still maintained their velocity. Regarding this average velocity graph, the traffic jam obviously appeared when the average velocity $v < 1$ cell/time.

Figure 3-4 illustrates the traffic flow over vehicles density for the spontaneous-braking probability $P_b = 0$, $P_b = 0.3$, and $P_b = 0.7$, respectively. The traffic flow indicates the number of moving vehicles per unit of time. While the density parameter means the number of vehicles per unit area of the highway. As can be seen from the graph, there is a reduction in traffic flow in the presence of spontaneous-braking parameter. We also consider the critical density k_c that appeared in each traffic flow. Here, the critical density means a maximum density achievable under free flow. In the traffic flow with $P_b = 0$, the critical density k_c situated at the density $\rho = 0.18$.

The critical density k_c was getting lower when the spontaneous-braking parameter increased. Below the critical density k_c, all vehicles can make a movement. However, in the density after the critical density point, not every vehicle can move at each time step. This critical density point also indicates when the traffic congestion started to happen. To get an intuitive feel for the dynamics, we provide a set of space-time diagrams in Figure 3-5, Figure 3-6, and Figure 3-7 for various density values.

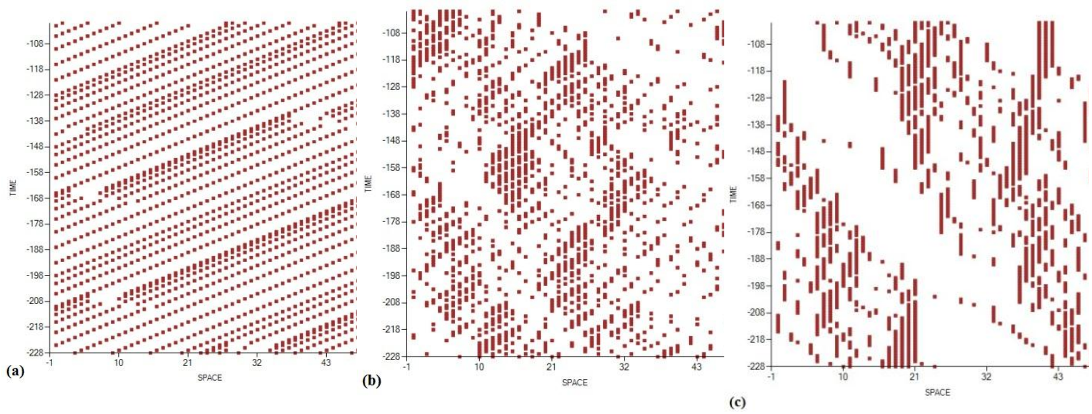

Figure 3-5. Space-time diagram for density $\rho = 0.25$ and $P_b = 0$ (a), $P_b = 0.3$ (b), and $P_b = 0.7$ (c); without lane-changing maneuvers.

The horizontal axis represents space and vertical axis represents the time. In order to get data to analyze, we simulate this model for density $\rho = 0.25$; 0.50; and 0.75 that represent light traffic, moderate traffic, and heavy traffic situations. For density $\rho = 0.25$, it can be seen that the spontaneous-braking behavior has given a significant impact to produce traffic congestion (Figure 3-5). The single vertical line which is shown in these time-space diagrams represents a stationary vehicle that is making a spontaneous-braking behavior. In the traffic with density value ρ = 0.50, there is a moderate impact of the spontaneous-braking behavior on the traffic congestion.

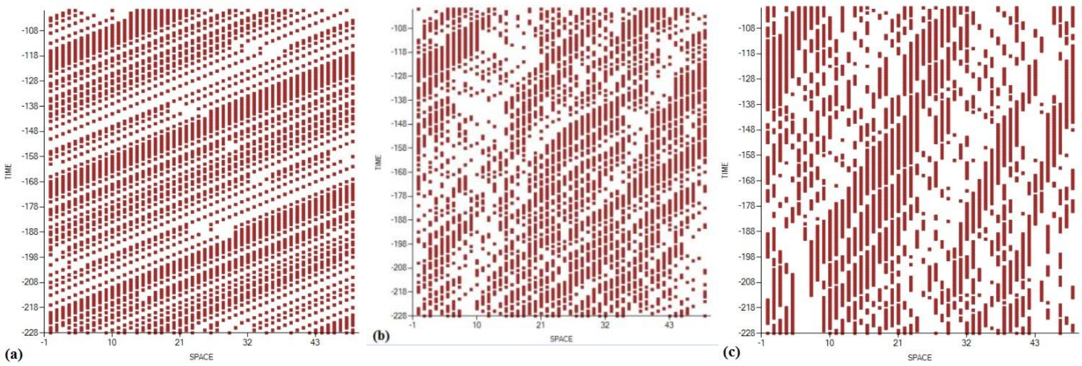

Figure 3-6. Space-time diagram for density $\rho = 0.50$ and $P_b = 0$ (a), $P_b = 0.3$ (b), and $P_b = 0.7$ (c); without lane-changing maneuvers.

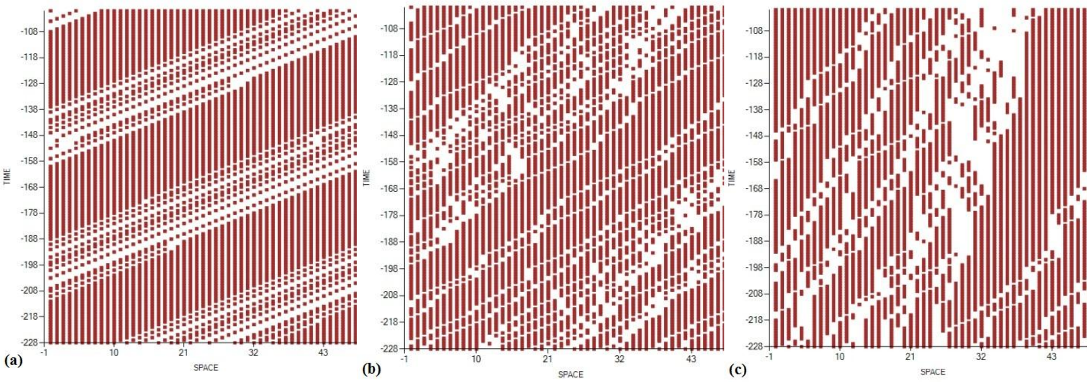

Figure 3-7. Space-time diagram for density $\rho = 0.75$ and $P_b = 0$ (a), $P_b = 0.3$ (b), and $P_b = 0.7$ (c); without lane-changing maneuvers.

It can be seen that before the spontaneous-braking parameter was applied, the congestion already occurred on the traffic (Figure 3-6). While in Figure 3-7, the effect of spontaneous-braking on traffic congestion just a slightly impact is shown. That because in density value ρ = 0.75, the traffic congestion already appeared although in the condition without spontaneous-braking behavior.

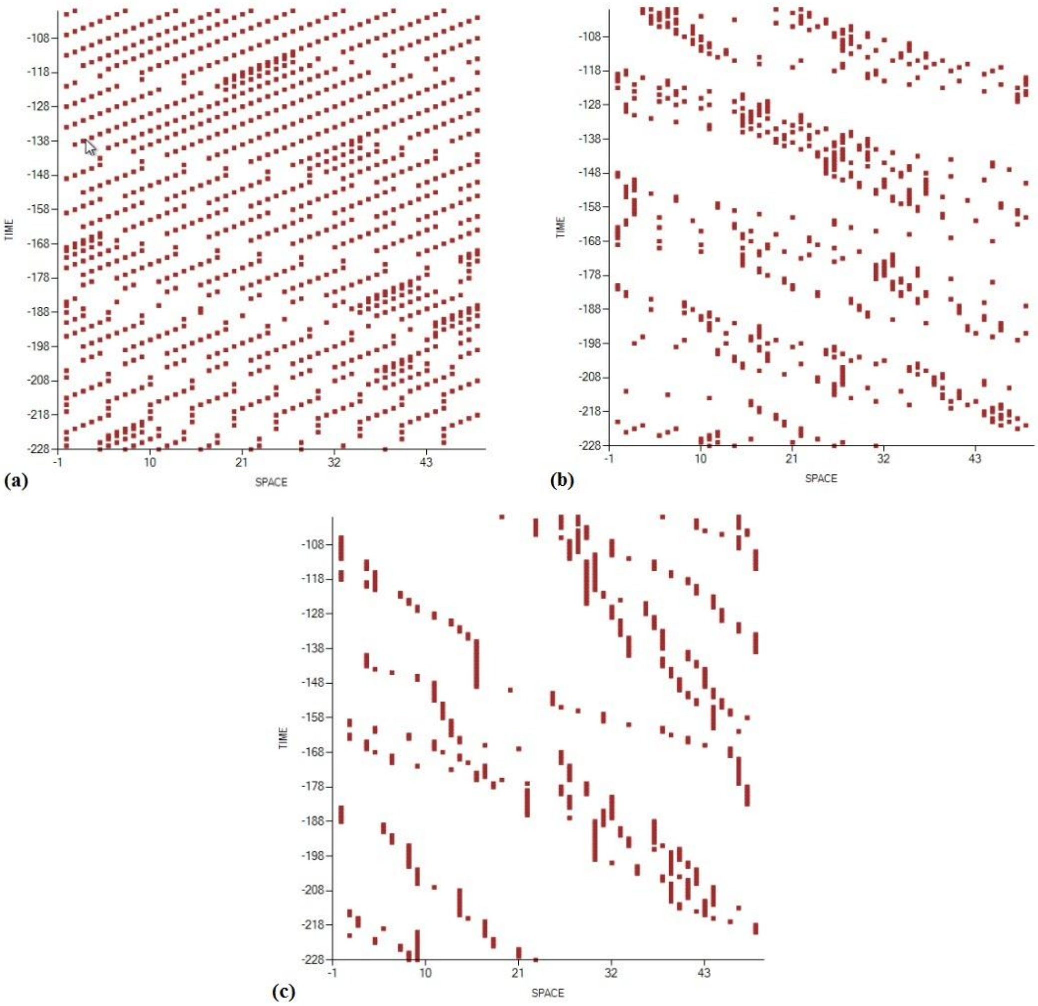

Figure 3-8. Space-time diagram for density ρ = 0.25 and P_b = 0 (a), P_b = 0.3 (b), and P_b = 0.7 (c); with lane-changing maneuvers.

The lane-changing effect on traffic congestion is discussed from here. As shown before that the spontaneous-braking behavior can contribute to the traffic congestion.

Therefore, in this section we evaluate the effect of lane-changing to reduce the congestion level. This lane-changing model was applying the Eq. 3-5, Eq. 3-6, and Eq. 3-7. In this simulation, the vehicles can look back and estimate the situation along 5 cells behind on the other lane before make a lane-changing. We provide a set of space-time diagrams in Figure 3-8, Figure 3-9, and Figure 3-10 for the density values ρ = 0.25; 0.50; and 0.75.

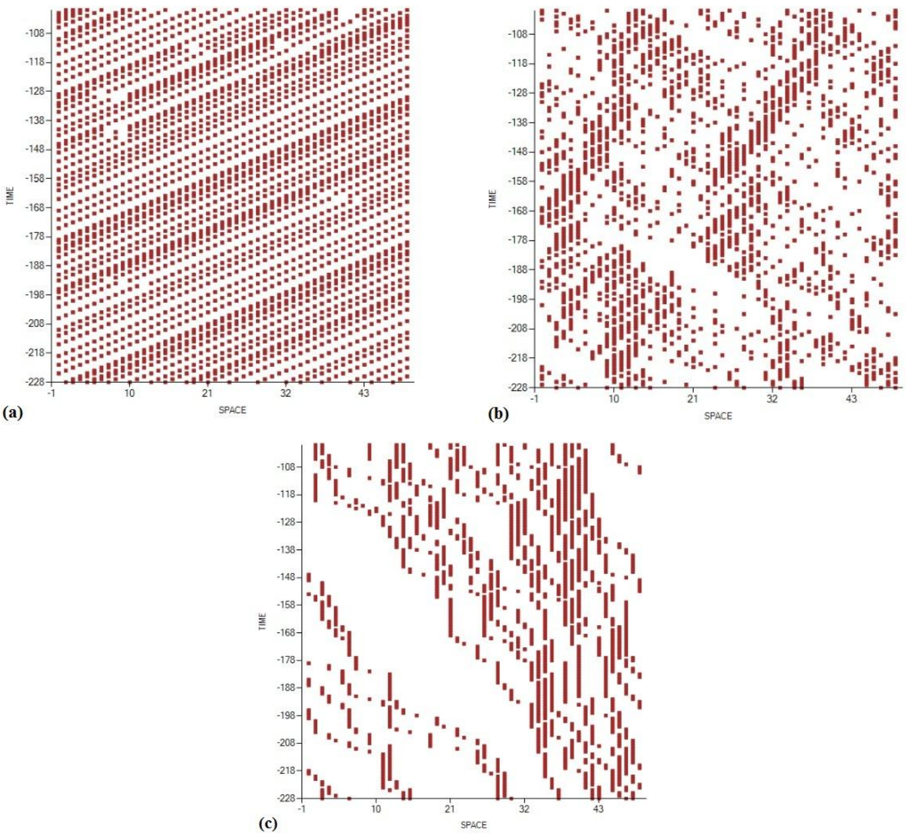

Figure 3-9. Space-time diagram for density ρ = 0.50 and P_b = 0 (a), P_b = 0.3 (b), and P_b = 0.7 (c); with lane-changing maneuvers.

The comparative graph shows that for the traffic density ρ < 0.75, the lane-changing maneuvers have given a good impact to reduce the congestion level. However, in all spontaneous-braking parameter value condition, the result shows that there is no significant impact that is contributed by lane-changing maneuver.

3.4 Discussion

In this work, we simulate the braking behavior of the driver and present the new Cellular Automata model for describing this characteristic. The original NaSch model has been modified to accommodate the parameter of spontaneous-braking probability. This spontaneous-braking probability rule captures the natural of braking behavior due to human behavior. This simulation shows that the traffic congestion can be caused by the braking behavior of drivers. Moreover, we also evaluate the effect of lane-changing to reduce the congestion that is caused by the parameter of spontaneous-braking probability.

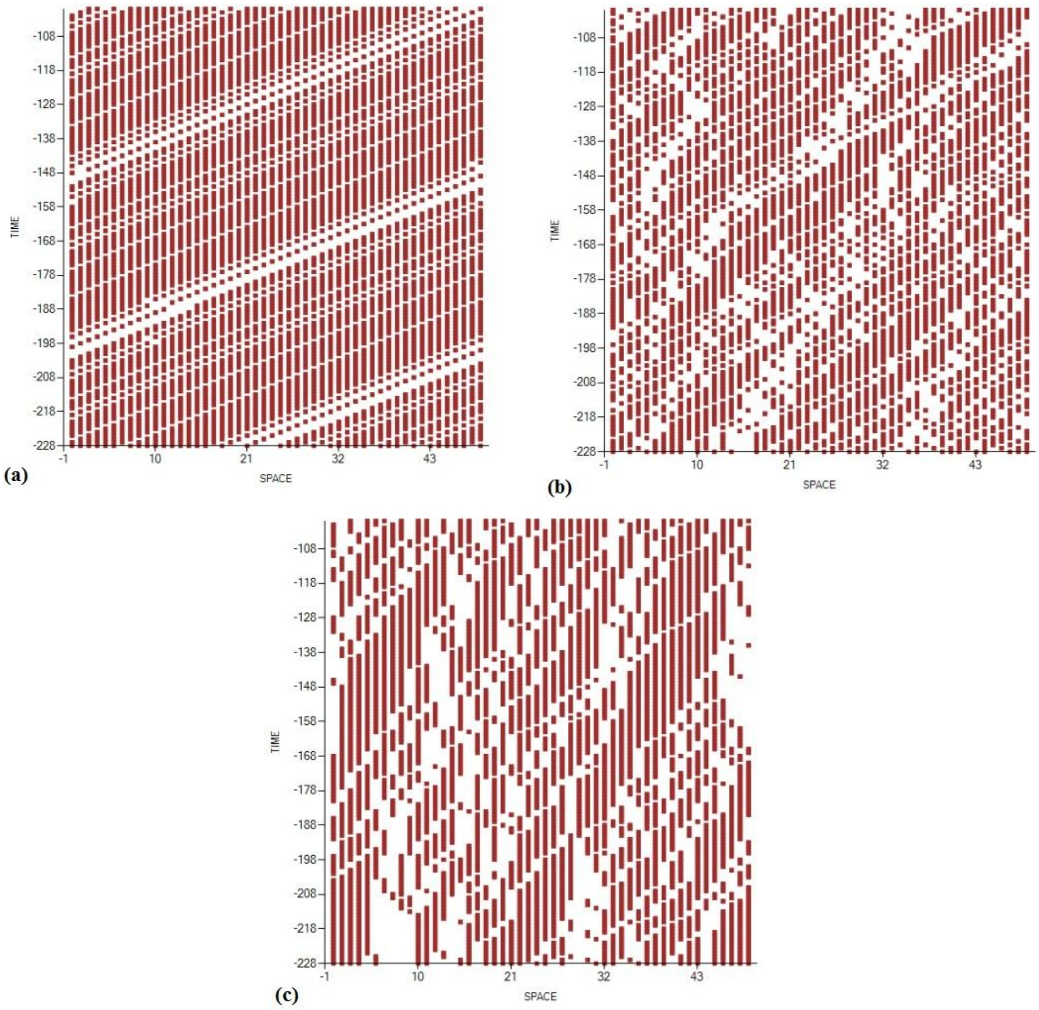

Figure 3-10. Space-time diagram for density $\rho = 0.75$ and $P_b = 0$ (a), $P_b = 0.3$ (b), and $P_b = 0.7$ (c); with lane-changing maneuvers.

CHAPTER 4.
EFFECT OF DRIVER SCOPE AWARENESS FOR THE LANE CHANGING MANEUVERS

This research investigated the effect of drivers' visibility and their perception (e.g., to estimate the speed and arrival time of another vehicle) on the lane changing maneuver. The term of scope awareness was used to describe the visibility required by the driver to make a perception about road condition and the speed of vehicle that exist in that road. A computer simulation model was conducted to show this driver awareness behavior. This studying attempt to precisely catching the lane changing behavior and illustrate the scope awareness parameter that reflects driver behavior. This research proposes a simple cellular automata model for studying driver visibility effects of lane changing maneuver and driver perception of estimated speed. Different values of scope awareness were examined to capture its effect on the traffic flow. Simulation results show the ability of this model to capture the important features of lane changing maneuver and revealed the appearance of the short-thin solid line jam and the wide solid line jam in the traffic flow as the consequences of lane changing maneuver.

Contents

4.1 Overview

The simulation model that can express the real traffic condition becomes the most important aspect in the field of traffic analysis and modeling. Study of traffic flow tries to capture and analyze the movement of individual vehicles between two points and the interactions between them. Traffic systems are characterized by a number of entities and features that make them hard to capture, analyze, control, and modify. The real traffic systems are formed by a combination of human interaction, that is interaction between driver entities, and human-environment interaction, such as driver interaction with the vehicle, with traffic information, and with the physical road condition. Studies about traffic and transportation have shown that driver behavior is one of the main contributors to some traffic event or phenomena. Our recent simulation study about the traffic flow showed that the traffic congestion can be influenced not only by the road capacity condition, but also by the driver behavior[44].

The other studies also found the strong relationship between the driver' speed behavior and accidents[48][49][50][51]. Safe driving is a very important element for all the people on the road at any given time. Study of traffic accidents shows that human factors are a sole or a primary contributory factor in road traffic accidents[52]. There are two separate components that affect human factors in driving, driving skills and driving style[53]. Driving style has a direct relationship to the individual driving behavior. The U.S. Department of Transportation recently reported that driver behavior leading to lane-change crashes and near-crashes[54]. In some countries, the reckless driving behaviors such as sudden-stop by public-buses, tailgating, or vehicles which changing lane too quickly also could give an impact to the traffic flow. The lane changing maneuver is one of the phenomena in the highway. A Lane changing is defined as a driving maneuver that moves a vehicle laterally from one lane into another where both lanes have the same direction of travel. Lane changing maneuvers are occasionally performed in order to avoid hazards, obstacles, vehicle collision, or pass through the slow vehicle ahead. Changing lanes requires high attention and visual demand compared to normal highway of freeway driving due to the need to continually monitor areas around the subject vehicle[46]. However, in the real traffic situations there are some reckless drivers that changing lanes at the moment they signal or who make last minutes decision on the road. Frequent lane changing in roadway could affect traffic flow and even lead to accidents. The lane changing behaviors can be vary depend on the characteristic of the driver[55]. Some crashes accidents typically referred to as Look-But-Fail-To-See errors because drivers involved in these accidents frequently report that they failed to notice the conflicting vehicle in spite of looking in the appropriate direction, commonly occur when drivers change lanes[56]. This mean the driver typically use their perception in order to estimate the speed and the arrival time of the other vehicles before making a maneuver, e.g., lane changing maneuver. A psychology study has shown the accuracy level of this perception may contribute to both failures to detect the collision and to judge the crash risk (e.g., time-to-contact). From a certain distance, a short fixation may be enough to identify an approaching vehicle. Duration of gaze interpreted as the amount of time devoted to processing a stimulus, longer and shorter gazes reflect difficult and simple processing, respectively. Inaccuracy of the gazes duration are likely to reflect a failure to process these stimuli[57].

This research was interested to investigate the effect of drivers' visibility and their perception (e.g., to estimate the speed and arrival time of another vehicle) on the lane changing maneuver. In the real traffic situations, this parameter of scope awareness has a strong relationship with human perception in order to make a lane changing maneuver decisions. One purpose of this study was to examine how different driver visibility and scope awareness might affect traffic flow. We consider that the driver decision to make a lane changing is influenced by the condition of both its current and target lane. The estimation about the gap with ahead and backward vehicle in target lane, includes their speed, will affect the human perception to make a safety lane changing. This chapter introduces one of the driver behavior parameter; that is scope awareness parameter. The term of scope awareness was used to describe the visibility required by the driver to make a perception of road condition and the speed of vehicle that exist in that road. Since there are various types of driving skill and style of the drivers that exist in the roadway then the value of scope awareness probabilities could be vary. This studying attempt to precisely catching the lane changing behavior and illustrate the scope awareness parameter that reflects driver behavior. A computer simulation model was conducted to show this scope awareness behavior. In this simulation model, the scope awareness parameter reflected as the length of the road at the adjacent lane that is considered as safely area by the subject driver before making a lane changing.

The Cellular Automata model of Nagel and Schreckenberg[24] was improved to better capture the effect of scope awareness that reflect drivers' behavior when making a lane changing. This NaSch model has been modified to describe more realistic movement of individual vehicle when make a lane changing maneuver. Moreover, the recent study of spontaneous braking behavior[44] has been enhanced through the investigation of its relationship with the driver's scope awareness behavior.

4.2 Related Research Works

Due to the rapid development of computer technology then research about traffic simulation and modeling has increasingly grown. Computer simulation in traffic model has developed from a research tool of experts to a widely used technology for practitioners and researchers in the research, planning, demonstration, and development of traffic systems. The increasing of computational speed and power make the scope of research of traffic simulation have been growing. Since the early 1950's, the research simulation have evolved from local road analysis into more complex systems where several type of parameters are integrated in one system. The research about traffic modeling can be divided into two categories: microscopic model and macroscopic model. Microscopic model described traffic behavior as resulting from discrete interaction between vehicles as entities. This microscopic model range from simple analytical models to more detailed analytical models. While the macroscopic models concern to describe the aggregate traffic behavior phenomena by considering the fundamental relationships between vehicles speed, flow, and density.

Most microscopic models (e.g., the car-following model) use the assumption that all the vehicles have a uniform driving behavior. These microscopic models use deterministic approach and, therefore difficult to capture inherent stochastic nature of real traffic. On the other hand, a major limitation of macroscopic models is their aggregate nature. The macroscopic models concern the traffic flow as continuous system, then these models cannot capture the discrete dynamic aspects that arise from vehicles interaction[4].

On the other side, the interaction between vehicles has strong relationship with the driver behavior. Some research studies have shown that the driver behavior play an important role for the traffic events. One cause of those traffic events is due to the observations and reactions of drivers are governed by human perception and not by technology based sensor and monitoring systems. The emotional aspect of the driver contributes to the many situations in traffic such as car crashes and congestion[5]. Another study also shown that the driver behavior is a fundamental factor and a key source of complexity in predicting traffic network states unfolding over time[6].

In real traffic, most highways consist two or more lanes. Regarding this road condition, there are a few analytical models for multi-lane traffic. Nagatani was one of the first researchers that introduced a CA model for two lane traffic[42]. His model used deterministic approach and the maximum velocity $v_{max} = 1$. Then, building on Nagatani's model, Rickert et.al.[43], considered a model with $v_{max} \geq 1$. Rickert proposed a symmetric rule set where the vehicle changes lanes if the following criteria are fulfilled:

$$gap(i) < l \qquad \textit{Eq. 4-1}$$

$$gap_0(i) > l_0 \qquad \textit{Eq. 4-2}$$

$$gap_{0,back}(i) > l_{0,back} \qquad \textit{Eq. 4-3}$$

Meanwhile, Nagel et.al.[7] also discussed two lane traffic and lane changing rules based on a cellular automata model. Furthermore, we enhanced the original NaSch model by introduced the spontaneous braking parameter as a driver behavior that periodically affect the traffic flow and lane changing decision[44]. However, these models have not considered about drivers' visibility and speed estimation of the vehicles within the monitoring area which may have important influence on human' hazard perception and lane changing decision.

4.3 Model Description

This proposed model uses two-lane highway with unidirectional traffic character in periodic boundaries condition. Two-lane model is necessary in order to accommodate the lane changing behavior in the real traffic condition. A one-dimensional chain of L cells of length 7.5 m represents each lane. This value is considered as the length of vehicle plus the distance between vehicles in a stopped position. Each time-step has been setup to $\mathrm{t} = 1\,\mathrm{s}$ and $x = 7.5\mathrm{m}$, then corresponding to speed increments of $\mathrm{v} = \mathrm{x}/\mathrm{t} = 27\ \mathrm{km/h}$. Therefore, a vehicle's speed in this simulation model has a minimum value $v_{\min}$ = 0 km/h and maximum value $v_{\max}$ = 135 km/h, corresponded to the value of real traffic condition. A one-lane loop consists of 100 cells. There are just two possibility states of each cell. Each cell can only be empty or containing by just one vehicle. The speed of each vehicle is integer value between $v = 0,1,\ldots,v_{max}$. In this model, all vehicles are considered as homogeneous then have the same maximum speed $v_{max} = 5$. The speed value number corresponds to the number of cell that the vehicle proceeds at one time step. The state of a road cell at the next time step, form t to $t+1$ is dependent on the states of the direct frontal neighborhood cell of the vehicle and the core cell itself of the vehicle.

Rickert et al.[43], among others, have discussed about criteria of safety by introduced the parameters which decide how far the vehicle looks ahead on current lane, looks ahead on desired lane, and looks back on desired lane. Those criteria have to be fulfilled before a vehicle makes a lane changing. However, in real traffic condition, these criteria of safety rules by Rickert are not sufficient to describe driver's behaviors in highway traffic. This paper introduces a new additional parameter to accommodate the driver behavior when making a lane changing. In addition to considering the gap of cell between vehicles, we also consider about the speed parameter of the other vehicles that situated in the desired lane. This research discusses in more detail the parameter of scope awareness Sa that reflects the various characters of drivers. This scope awareness parameter takes into account the dynamic characteristic of the drivers while decide to make a lane changing. Here, the smaller Sa value reflects the degree of driver aggressiveness and awareness. Figure 4-1 describes the scope awareness definition from the perspective of vehicle-1.

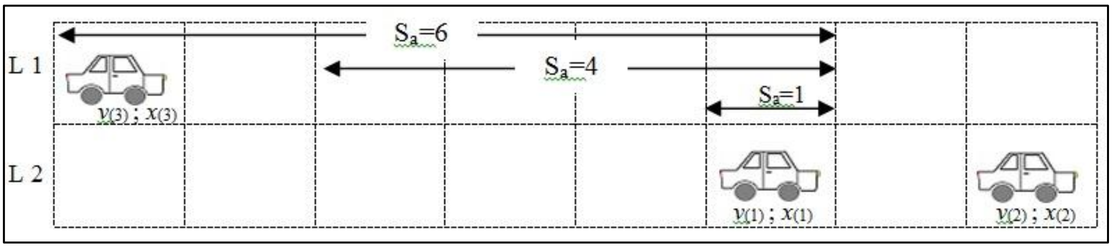

Figure 4-1. Schematic definition diagram of scope awareness Sa from the perspective of vehicle (1) in its current speed and position v(1); x(1).

The updating rule for lane changing maneuver is done according to a set of rules. The set of rules of the lane changing maneuver is analogous as the liquid movement. Compare to the lane changing model of Nagel and Rickert[43], there are two basic differences rules in our model. The first one, as the result of traffic conditions ahead of subject driver (Eq. 4-4), the subject vehicle would consider changing its lane not only due to the comparison value between number of gap and condition which decide how far the vehicle look ahead in current lane (Eq. 4-1), but also depending on the current speed of the subject vehicle that can be vary based on traffic situation. Another difference is the scope awareness value (Sa). The subject vehicle would consider the velocity of every vehicle that situated along its scope awareness area then decide whether possible or not to change the lane (Eq. 4-8).

At the beginning of each iteration, the subject driver checks whether a lane changing is desirable or not. The subject driver looks ahead to check if the existing gap in the current lane can accommodate his current speed. If not, then due to the randomness number of percentage ratio, the subject driver decides whether he will maintain or decelerate the vehicle speed due to the existing gap number or change his lane. When the subject driver chooses to change lanes, then he looks sideways at the other lane to check whether the cell next to the subject vehicle is empty and the forward gap on the other lane is equal or longer than his current lane. If one cell is unoccupied or free-cell then its state is 0. Moreover, the subject driver also looks back at the other lane to check road condition. In the real traffic situation, a subject driver also has to look back on the other lane in order to estimate the velocity of the following vehicle to avoid a collision. Eq. 4-8 accommodates the driver behavior that estimate the velocity of vehicle at the moment before making a lane changing.

As mentioned before, this paper uses the parameter of scope awareness Sa which decide how far the coverage area on the desired lane that is considered as the scope of awareness by the driver. If there is another vehicle within the area of scope awareness then the subject driver estimates the speed of the vehicle in order to avoid collision during the lane changing maneuver. The subject driver will make a lane changing maneuver if the speed of the vehicle that located within the area of scope awareness is less than the existing gap. The lane changing rules can be summarized as follows:

$$gap_{same} < v_{current} \qquad \textit{Eq. 4-4}$$

$$cell_{next} = 0 \qquad \textit{Eq. 4-5}$$

$$rand() < p_{change} \qquad \textit{Eq. 4-6}$$

$$gap_{target} > gap_{same} \qquad \textit{Eq. 4-7}$$

$$v_{vehicle,back} \leq gap_{back} \ ; \ X(vehicle_{back}) \in Sa \qquad \textit{Eq. 4-8}$$

The lane changing rules are applied to vehicle that change from right lane to left lane and conversely. Vehicle is only move sideways and it does not advance. Once all the lane changing maneuvers are made then the updating rules from a single lane model are applied independently to each lane. Figure 4-2 shows the schematic diagram of lane changing operation. In this Figure 4-2, the subject vehicle $v_{(1)}$; $x_{(1)}$ is assumed that have current speed $v_1^t = 3$ cells per time step and the parameter of scope awareness S_a = 4 cells.

In order to avoid the introduction of any unrealistic artifacts in the simulation then this proposed model uses Eq. 4-7 to express the more realistic lane changing decision. According to Eq. 4-7, the driver must consider that the forward gap in the desired lane is more than the gap in the current lane. This consideration is important because this proposed model uses the different desired velocities into the vehicles.

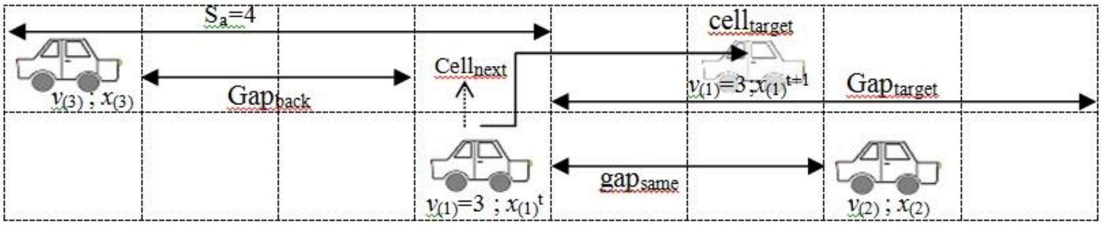

Figure 4-2. Schematic diagram of a lane changing operation.

Once the lane changing maneuvers are made to all possibility vehicles then the updating rules from a single lane model are applied independently to each lane. Together with a set of lane changing rules, the road state can be obtained by applying the following rules to all by parallel updated:

Acceleration :

$$v_i \rightarrow min(v_i + 1, v_{max}) \qquad \textit{Eq. 4-9}$$

Deceleration :

$$v_i \rightarrow min(v_i, gap_{same(i)}) \qquad \textit{Eq. 4-10}$$

Driving :

$$x_i \rightarrow x_i + v_i \qquad \textit{Eq. 4-11}$$

4.4 Simulation Result – Analysis and Discussion

The simulation starts with an initial configuration of *N* vehicles, with fixed distributions of positions on both lanes. This simulation uses the same initial velocity for all vehicle $v_{min} = 0$ and the maximum vehicle speed has been set to $v_{max} = 5$ cell/time-step. The velocity corresponds to the number of cells that a vehicle advances in one iteration. Many simulations performed with different density ρ. The density ρ can be defined as number of vehicles *N* along the highway over number of cells on the highway *L*. This traffic model uses close (periodic) boundary conditions. This means that during one simulation, the total number of vehicles on the highway cannot change. Vehicles go from left to right. If a vehicle arrives on the right boundary then it moves to the left boundary. Since this model assumes symmetry character of the both lanes then the traffic flow characteristics on both lanes are identical.

4.4.1 Traffic Flow

In order to examine the effect of scope awareness on the traffic flow then the model was simulated over 1000 iterations on 10^2 cells in 2-dimensional lane, for all possibility density level. The flow indicates the number of number of moving vehicles per unit of time. Along with the study of this proposed model, this paper also conducted a comparison study for the case of traffic without using scope awareness parameter. Results from the simulation are summarized in Figure 4-3. After 1000 time step, when the system reaches a stationary velocity state then the flow was computed. The whole process then repeated over 50 times for both each density level and each scope awareness value to make statistics and the flow-density diagram was obtained.

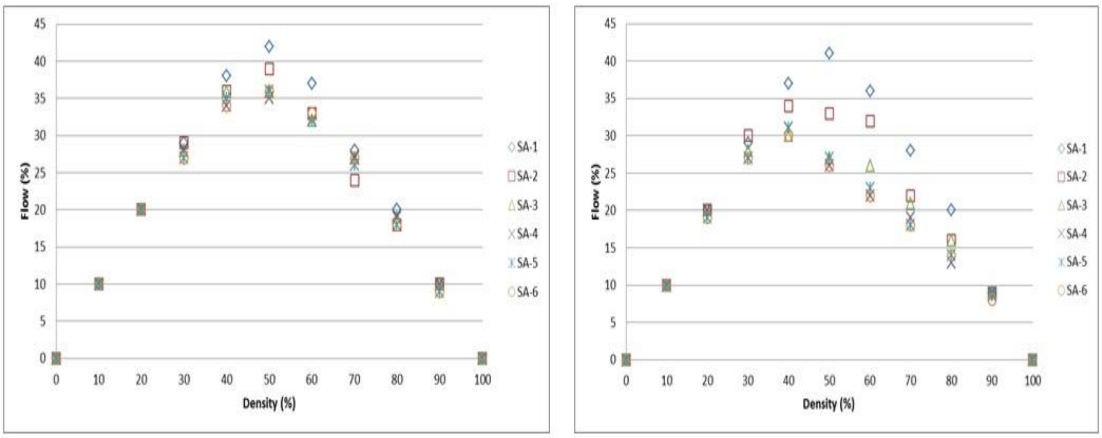

Figure 4-3. The average flow-density diagram of the proposed model (left) is compared to a two-lane traffic system without using scope awareness parameter (right).

A number of interesting observations can be made:

- The proposed model reproduces a recognizable diagram of flow towards density relationship. Flow is linearly increasing together with the increases in density level. A maximum flow level is achieved at density level ρ=0.5

for each value of S_a. After reaches the critical point of flow at ρ=0.5, the flow at each level of S_a becomes linearly decreasing in density. In other words, the laminar flow turn into back travelling start-stop waves after density level ρ=0.5. Another thing that also interest is in the scope awareness value Sa=3, Sa=4, and Sa=5, this simulation produced almost the same flow level at all density levels. Scope awareness value Sa=1 reached the highest number of flow. This may happen because in the Sa=1, the driver can be described as the most aggressive driver, who makes a lane changing maneuver with only consider the empty area beside him. This behavior also confirms the result on Figure 4-4 that compared the number of lane changing for each value of scope awareness.

- Compared to the model without scope awareness consideration (Figure 4-3-right diagram), the usage of S_a parameter produced a better flow of vehicles, especially above density ρ=0.4. This Sa parameter maintained the traffic to keep flowing by carefully calculate the appropriate time to make a lane changing decision, thus the lane changing maneuver does not disturb the traffic in the target lane.
- Since the parameter of scope awareness has a strong relationship with the lane changing decision then Figure 4-4 shown the ratio of lane changing number over density. The results of each S_a value are not surprising. If the distance of scope awareness becomes longer then the lane changing number becomes lower. However, the surprise thing is the behavior of the lane changing variance. For each changes of S_a value into the higher one, the critical point of maximum lane changing decreases almost half than before. The critical point of maximum lane changing for each S_a value is same at ρ=0.2, except for S_a=5 at ρ=0.3. This is due to the fact that the chances of the vehicles to change the lane become fewer caused by density increases.

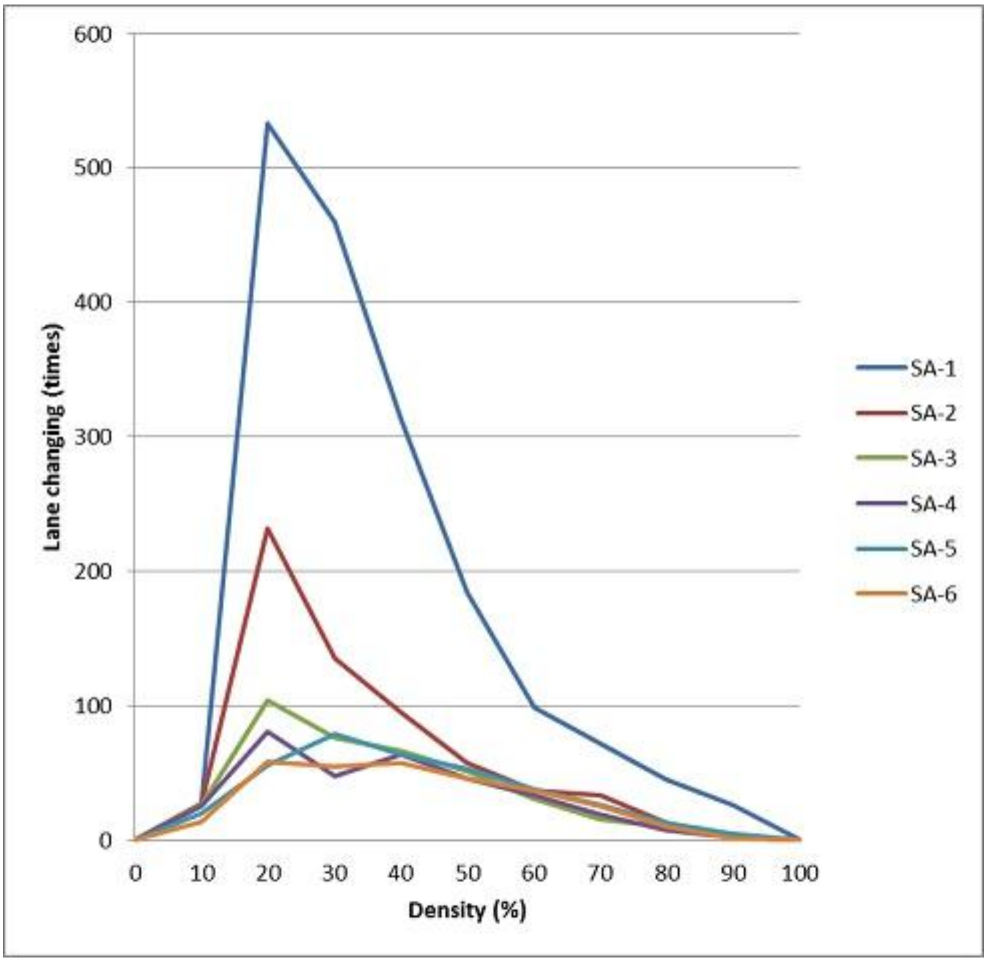

Figure 4-4. The ratio of lane changing number over density.

4.4.2 Space Time Diagram

In order to explore more clearly the effect of scope awareness on the traffic flow then the space-time diagram was reproduced. The space-time diagram represents the location of the vehicles at the certain time. This research conducted the space-time diagram for density $\rho = 0.25$, $\rho = 0.5$, and $\rho = 0.75$. These three values of density assumed as the light traffic, moderate traffic, and heavy traffic in the real traffic condition, respectively. Figure 4-5, Figure 4-6, and Figure 4-7 show the result for each density at the all values of scope awareness. To make the comparison fairly then this simulation used initial fixed distributions of positions of the vehicles. The horizontal axis represents space and the vertical axis represents the time. Vehicles go from left to right (space axis) and from top to bottom (time axis).

In the light traffic condition ρ=0.25 (Figure 4-5), it can be seen that the increases of scope awareness distance affect the vehicles flow. Free flow phase showed in Sa=1 diagram (Figure 4-5-a), which are drawn as light area and have a more shallow negative inclination. However, when the Sa value was increased then some solid area starting appear. This solid area with steep positive inclination reflects the traffic jam. One can observed from Figure 4-5, there are many regions that show the high frequency of short vehicle life lines appearing and disappearing that indicate the great number of lane changing at this traffic density ρ=0.25. Once the scope awareness increases then this frequency of short vehicle life lines become smaller than before (Figure 4-5-f).

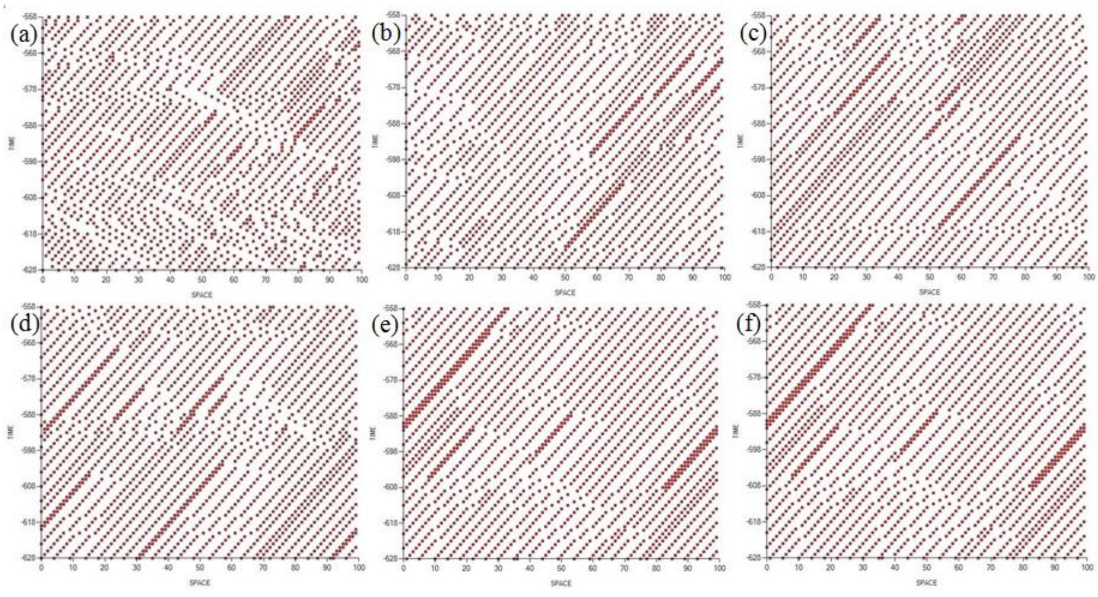

Figure 4-5. Space-time diagram for light traffic condition (density ρ = 25%). Lane changing probability 100%. (a) for Scope awareness Sa=1 ; (b) for Scope awareness Sa=2 ; (c) for Scope awareness Sa=3 ; (d) for Scope awareness Sa=4 ; (e) for Scope awareness Sa=5 ; (f) for Scope awareness Sa=6.

In the moderate traffic ρ=0.5 (Figure 4-6), the phenomena that showed in the Figure 4-5 also appear in this density. The diagram of Sa=1 (Figure 4-6-a) shows the appearance of slight traffic jam distributed in the whole simulation area. In this density level, a solid moving jam appears since Sa=2 (Figure 4-6-b). Along with a wide solid line, there are also some short-thin solid lines appear in the diagram of Sa=2. While in the diagram of Sa=6 (Figure 4-6-f), some of these short-thin solid lines disappeared. Refer to the Figure 4-4, at the certain density value, once the S_a value was increased then the number of lane changing decreased. One can be observed that the short-thin solid line caused by the lane changing maneuver of another vehicle from adjacent lane, which resulted the subject vehicle has to make a spontaneous braking in order to avoid collision. As the result of this spontaneous braking causing another following vehicles has to adjust or decrease their speed with the vehicle ahead. This phenomenon produces a short traffic jam. On the other hand, the wide solid line appeared as a result of deceleration into the minimum speed of the vehicle as the consequence of the reduced opportunities for lane changing maneuver.

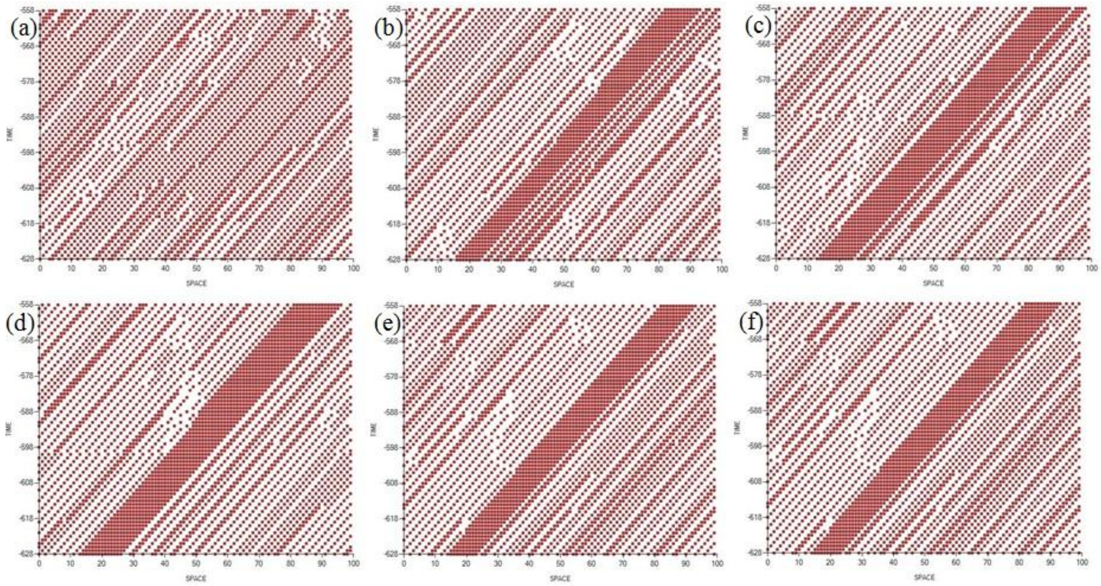

Figure 4-6. Space-time diagram for moderate traffic condition (density $\rho = 50\%$). Lane changing probability 100%. (a) for Scope awareness SA=1 ; (b) for Scope awareness SA=2 ; (c) for Scope awareness SA=3 ; (d) for Scope awareness SA=4 ; (e) for Scope awareness SA=5 ; (f) for Scope awareness SA=6.

However, in the heavy traffic condition (Figure 4-7), this model showed that the differences value of scope awareness did not affect the traffic condition. In this traffic condition, the opportunity to make a lane changing is very small. This result imply that in the heavy traffic condition, the driver characters that related to lane changing style have no influence to the traffic condition.

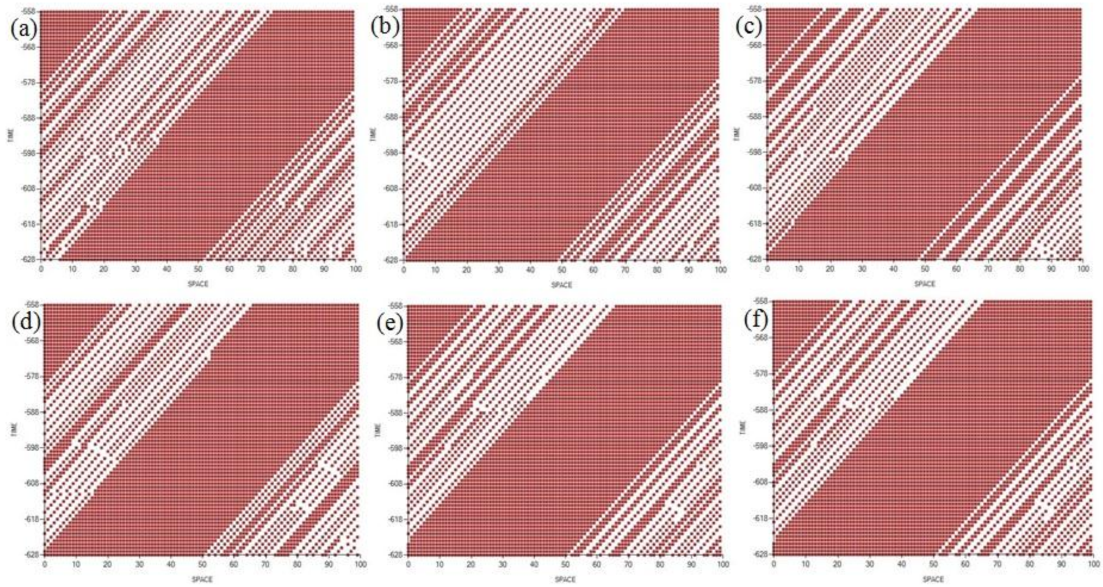

Figure 4-7. Space-time diagram for heavy traffic condition (density ρ = 75%). Lane changing probability 100%. (a) for Scope awareness SA=1 ; (b) for Scope awareness SA=2 ; (c) for Scope awareness SA=3 ; (d) for Scope awareness SA=4 ; (e) for Scope awareness SA=5 ; (f) for Scope awareness SA=6.

4.4.3 Lane Changing and Spontaneous Braking

The analysis of space-time diagram shown by Figure 4-5, Figure 4-6, and Figure 4-7, revealed an effect of spontaneous braking that appears in the traffic flow. Therefore, to complete the analysis of this paper then we computed the number of spontaneous braking that arise during the simulation. In this simulation, we defined the spontaneous braking as the braking action by the vehicle as influenced by lane changing maneuver of another vehicle. Once the vehicle has done a lane changing and occupied a certain cell that is previously targeted by another vehicle in the current lane then a spontaneous braking will be counted.

Table 4-1 and Table 4-2 present the ratio of spontaneous braking number over lane changing by using scope awareness parameter and without using the scope awareness parameter, respectively. The “0” (zero) value explain that the spontaneous braking did not happen, although the lane changing maneuver still occur in this certain traffic condition. The description of “N/A” means that the lane changing maneuver did not occur at all in this traffic condition.

Table 4-1. Percentage ratio of spontaneous braking over lane changing by using scope awareness parameter

DENSITY (%)	SA-1 (%)	SA-2 (%)	SA-3 (%)	SA-4 (%)	SA-5(%)	SA-6 (%)
10	56	40	23	24	20	0
20	82	74	63	38	18	3
30	81	60	12	0	0	0
40	82	35	3	0	0	0
50	92	11	0	0	0	0
60	83	8	0	0	0	0
70	85	9	0	0	0	0
80	80	0	0	0	0	0
90	88	0	0	0	0	0

Table 4-2. Percentage ratio of spontaneous braking over lane changing without using scope awareness parameter (without vehicle speed estimation)

DENSITY (%)	SA-1 (%)	SA-2 (%)	SA-3 (%)	SA-4 (%)	SA-5 (%)	SA-6 (%)
10	53	45	36	48	13	0
20	82	83	80	63	17	6
30	71	64	55	9	0	0
40	74	63	6	0	0	N/A
50	85	33	0	0	N/A	N/A
60	89	14	0	N/A	N/A	N/A
70	91	20	0	N/A	N/A	N/A
80	100	0	0	N/A	N/A	N/A
90	100	N/A	N/A	N/A	N/A	N/A

4.4.4 Vehicle Speed Estimation Error

As mentioned before, the scope awareness parameter in this proposed model has a strong relationship with the capability to estimate the vehicle speed within the certain scope awareness value. In this section, we explored what occurs when we change the value of speed estimation error. The higher value of the speed estimation error means the higher chance of the driver to make an inaccuracy perception that may contribute to both wrong decision to make a lane changing and failures to detect the collision.

Figure 4-8 shows the effect of speed estimation error to the lane changing (left) and to the spontaneous braking action (right) in the light traffic ρ=0.25, moderate traffic ρ=0.5, and heavy traffic ρ=0.75, whereas Figure 4-9 illustrates the ratio of spontaneous braking over lane changing for the case S_a=6.

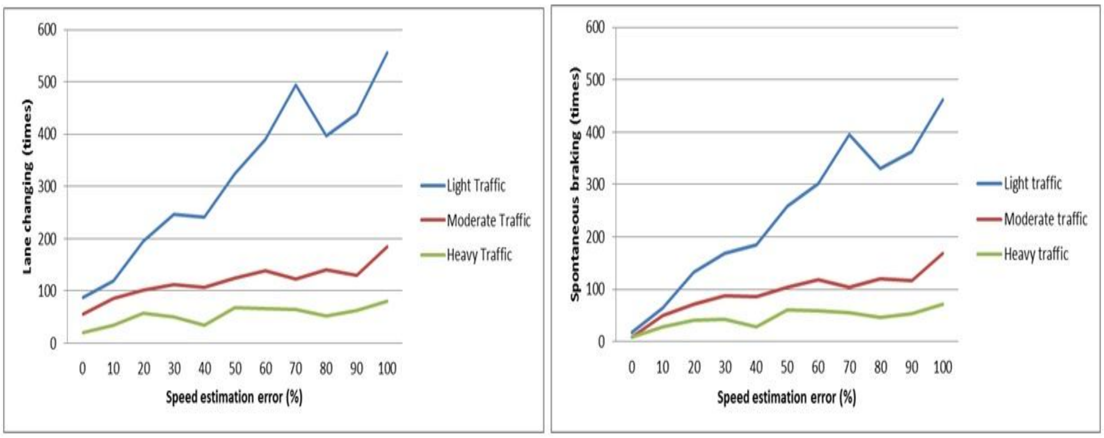

Figure 4-8. Effect of speed estimation error to the lane changing maneuver (left) and to the spontaneous braking number (right). Both diagrams was simulated for the case S_a=6.

In order to examine more clearly the effect of speed estimation error on the traffic flow then the space-time diagram was reproduced. The space time diagram of light traffic, moderate traffic, and heavy traffic are shown by Figure 4-10, Figure 4-11, and Figure 4-12, respectively.

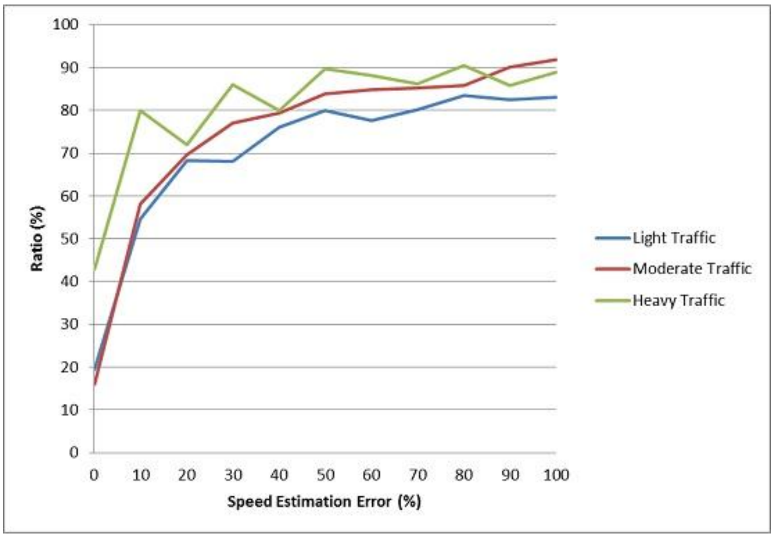

Figure 4-9. Ratio of spontaneous braking over lane changing number for the case of S_a=6.

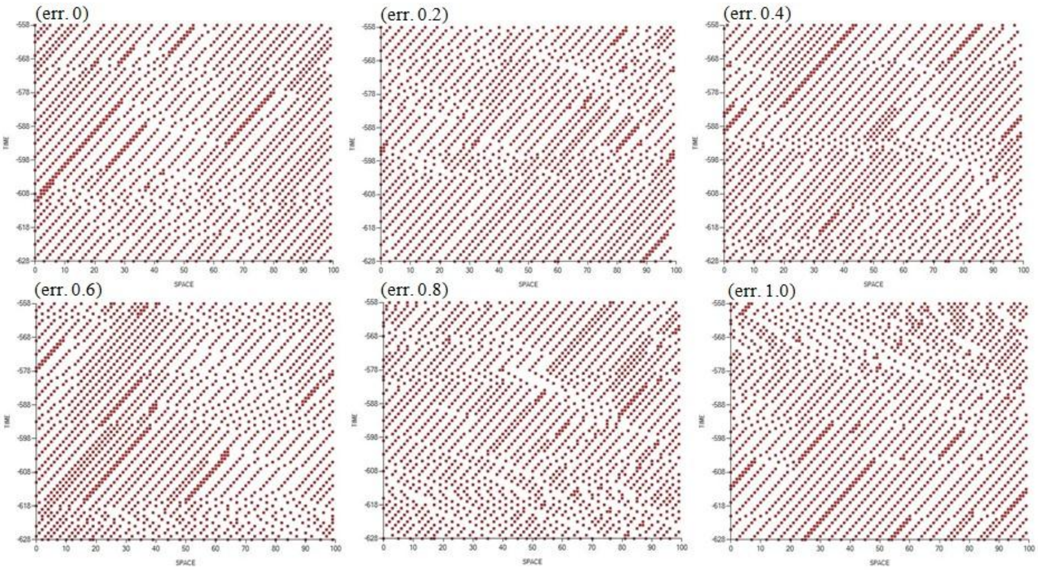

Figure 4-10. Vehicle speed estimation error for light traffic.

The phenomena of short-thin solid lines and wide solid lines also appear in these values of traffic density. The appearance of short-thin solid lines and the disappearance of wide solid line confirmed the conclusion that the short-thin solid line caused by the lane changing maneuver of another vehicle from adjacent lane so the subject vehicle has to make a spontaneous braking in order to avoid collision, and the wide solid line appeared as a result of deceleration into the minimum speed of the vehicle as the consequence of the reduced opportunities for lane changing maneuver.

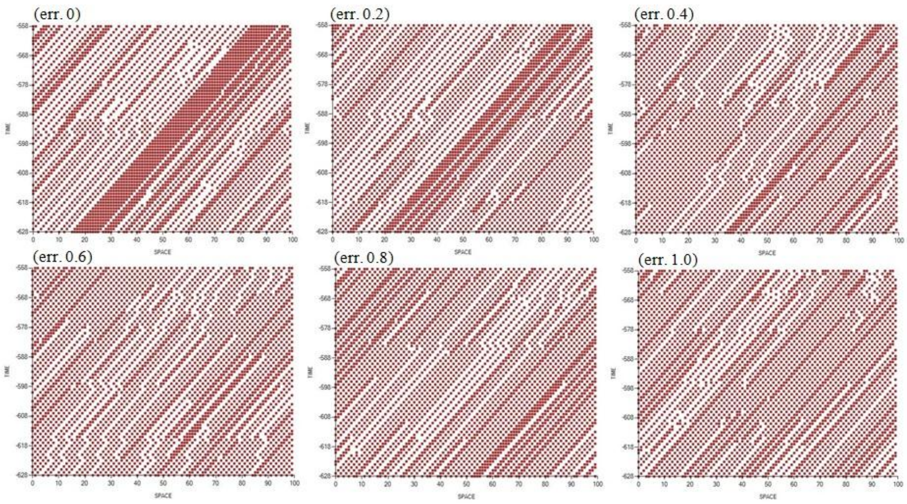

Figure 4-11. Vehicle speed estimation error for moderate traffic.

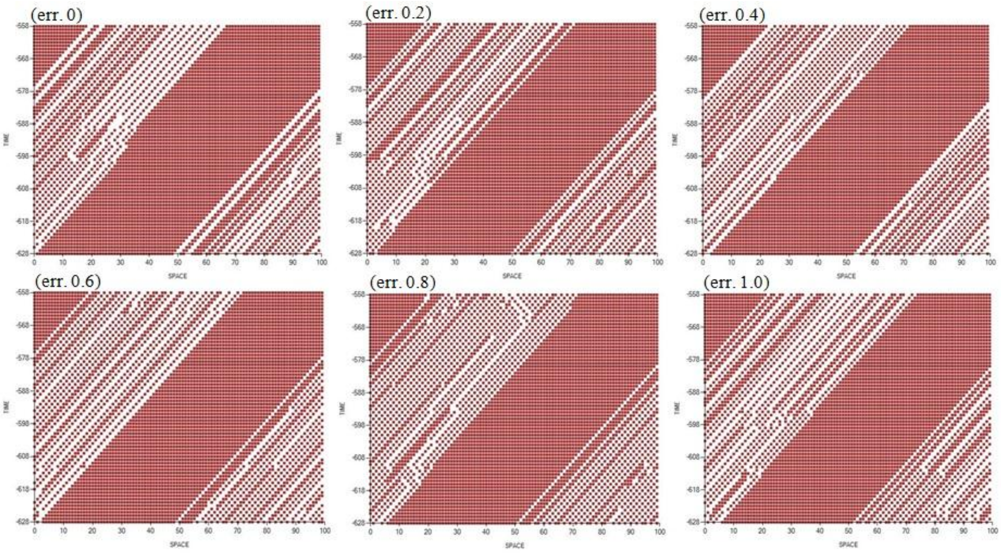

Figure 4-12. Vehicle speed estimation error for heavy traffic.

4.5 Discussion

This research has presented a simple model of the traffic cellular automata to describe a driver behavior in a two lane highway model. The term of scope awareness introduced to reflect the visibility required by the driver to make a perception of a road condition and the speed of vehicle that exist within the certain area of the road before making a lane changing maneuver. The relation between flow-density and space-time has been investigated in order to examine the effect of scope awareness parameter in the traffic flow. Some conclusions can be observed from this study:

- This model describes the realistic traffic situation, in particular capture the situation when driver make a lane changing maneuver. Compared to the conventional approach, the usage of scope awareness model approach produce a better flow of vehicles.
- The various value of the scope awareness may represent the characteristic and the experience level of the drivers. The increases of the scope awareness value means the driver become more aware to estimate the road condition in order to make a lane changing maneuver.

- This proposed model has revealed the phenomena of the short-thin solid line jam and the wide solid line jam in the traffic flow. This study found that the short-thin solid line caused by the lane changing maneuver of another vehicle from adjacent lane which resulted the subject vehicle has to make a spontaneous braking in order to avoid collision. As the result of this spontaneous braking causing another following vehicles has to adjust or decrease their speed with the vehicle ahead. This phenomenon then produces a short queue of vehicles. On the other hand, a wide solid line appeared as a result of deceleration into the minimum speed of the vehicle as the consequence of the reduced opportunities to make a lane changing maneuver.
- This simulation results showed that lane changing maneuvers with taking into account another vehicle speed could reduce the level of traffic congestion. However, in the heavy traffic (high dense) situation, the opportunity to make a lane changing is small, so that the congestion will always exist.

By taking into consideration the scope awareness parameter, the traffic cellular automata model proposed here can reflect certain characteristics of lane changing maneuver in the real traffic situation. This simulation result can serve as a reference for transportation planning, evaluation, and control. Moreover, this result will pave the way for accurate simulation of a more complex traffic system. Based on the result of this paper, the effect of road shape towards the vehicle deceleration will be studied hereafter.

CHAPTER 5.
VALIDITY OF SPONTANEOUS BRAKING AND LANE CHANGING WITH SCOPE OF AWARENESS BY USING MEASURED TRAFFIC FLOW

This chapter presents the validation method and its evaluation of the spontaneous braking and lane changing with scope awareness parameter. By using the real traffic flow data, the traffic cellular automaton model that accommodate these two driver behaviors, e.g., spontaneous braking and driver scope awareness has been compared and evaluated. The real traffic flow data have been observed via video-recording captured from real traffic situation. The validation results shown that by accommodate spontaneous braking and scope awareness parameters, this model can produced traffic flow's accuracy value 83.9% compared to the real traffic flow data.

Contents

5.1 Overview

Validation is one of the important processes in the field of simulation and modeling. The validation process is concerned with determining whether the conceptual simulation model is an accurate representation of the system under study. However, the validation process cannot be defined to result a perfect model, since the perfect one would be the real system itself [58]. Naturally, any model is the simplification of the real world. On the other hand, simulation uses a model to develop conclusion providing insight on the behavior of the real world elements being studied. In the field of computer simulation, this term enhanced as the uses of computer programming to capture the real world situation. The origin of computer simulation and modeling is in the desire to forecast future behavior due to current phenomena. In the discipline of traffic engineering and transportation planning, computer simulation and modeling is needed because it can study models of traffic and its phenomena for analytical or numerical treatment, can be used for experimental studies to describe detail evolution of the system over time, and produce the picture of current reality, as well as future estimation.

On the other words, the increasing trend of traffic congestion in most cities becomes the important issue in transportation system. Since travel demand increases at a rate often greater than the addition of road capacity, the situation will continue to deteriorate unless better traffic management strategies are implemented. To coup this problem, traffic simulation models are becoming as one of the important tool for traffic control. These simulation models is needed to asses, generate scenarios, optimize control, and estimate the future behavior of the system at the operational level. Through simulation the overall picture of traffic system can be pictured as well as the ability to assess current problems and the possible solutions immediately. Simulation and model can be a good tool to show some characteristics of complex traffic system, e.g., stable and unstable states, deterministic, chaotic or even stochastic behavior with phase transitions, fractal dimension and self-organized criticality. However, since the advance of technologies and application of transportation system in urban network and road way were not envisioned when many simulation models were developed, the existing models may not be directly applicable to such of this road system [59].

This chapter evaluates the simulation model that accommodates the driver behavior rules of spontaneous braking probability and lane changing scope awareness, by compare their simulation results to the real traffic data.

5.2 Validation Method

Validation is used to determine the real world system being studied is accurately represented by the simulation model. Referring to ISO standard, the following steps in validation are listed [60]:

1. Component testing: checking of software subcomponent (the model)
2. Functional validation: checking of model capabilities and inherent assumptions.

3. Qualitative verification: comparison of predicted traffic behavior with informed expectations.
4. Quantitative verification: comparison of model predictions with reliable experimental data.

The first two of these items are usually based on simple test cases and do not require empirical data. The third is based on comparison with observation, and the last on comparison with quantitative and experiment data.

Often, the test has to be done in several times to obtain the best result of validity. By a thorough analysis of the simulation's output data then the best result would be taken. If the model's output data closely represents the expected values for the system's real-world data, then validity is more likely.

When a model has been developed for an existing system, a validity test becomes a statistical comparison. Data collected from the situation of real system can be used as theoretical comparator [61]. However, when the system does not yet exist, validity becomes harder to prove. In many cases, validity cannot be definitely proven until some point in the future when the system being modeled has been deployed and running.

5.3 Real Data Gathering

Empirical data is used in validation of simulation results. The data used in this validation is based on video analysis. The usual approach towards data recording is observation and counting. The analysis is done manually, i.e., there was no automatic device that extracted the information from video. The evaluation of the data presented below is based on the following assumptions and methods. Since we interest to evaluate the effect of spontaneous braking behavior in the traffic flow then their number through video recording have been counted.

A field observation using micro scenario where the actual traffic condition were captured by a 30 minutes video recorded. The parameter that was counted is traffic flow and the number of spontaneous braking. The actual data were taken from two-lane urban roadway with a length approximately 500m. The video camera was placed on the pedestrian bridge. Figure 5-1 shows the observation location. Among the location, there are two traffic signal at the end of lane, then to distinguish between the normal braking and the spontaneous braking of vehicle, we use an assumption. For the vehicle that stop due to traffic signal would be categorized as normal braking, other than that would be categorized as spontaneous braking. Figure xxx presents show the example images captured from video data.

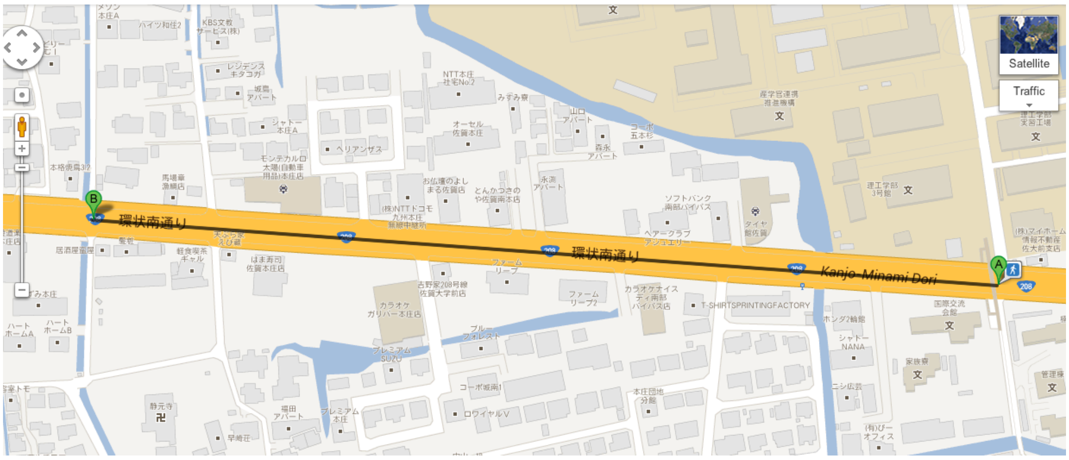

Figure 5-1. The location of observation

Through the video recording, the number of traffic flow and spontaneous braking has been counted for each of the recorded video data. The observation data were taken from 16 different real urban road traffic video data. These data were taken in the morning and afternoon as being assumed as peak traffic time. Figure 5-3 and Figure 5-4 show the example images of spontaneous braking type that captured from video data. The red rectangles show the examples of spontaneous braking type that had been counted.

Figure 5-2. Example image captured from real condition

Figure 5-3. The example-1 of spontaneous braking type captured from video data

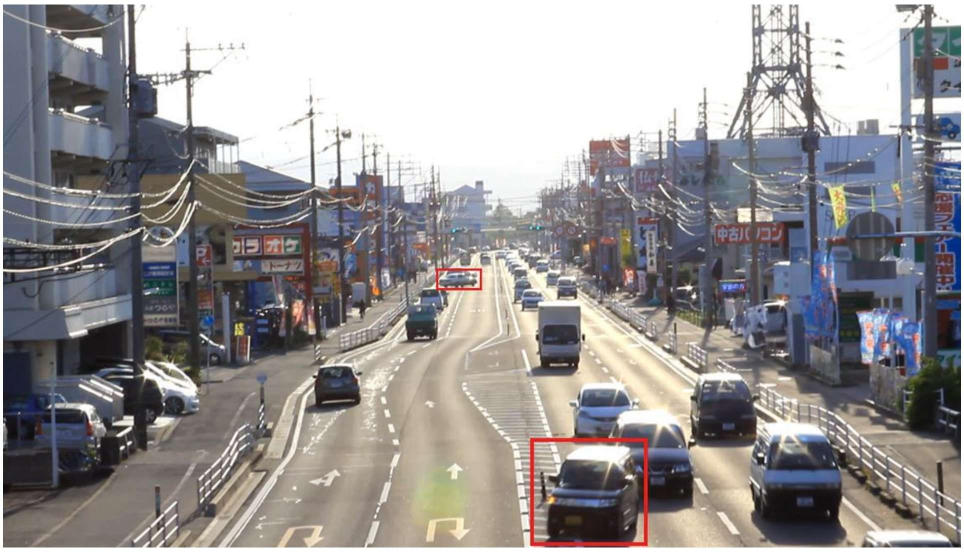

Figure 5-4. The example-2 of spontaneous braking type captured from video data

Since we interest to evaluate the accurate value of the propose model to reproduce real traffic flow condition then the numbers of traffic parameters provided by video recording, i.e., spontaneous braking events, flow number, cars density value, and average speed of the cars, have been evaluated. Table 5-1 shows the average density values of the observation results. In traffic data analysis, there are three related types of data: speed, flow, and density. Speed *v* (km/hr) is defined as the distance covered per unit time. Since the speed of every vehicle is almost impossible to track on the roadway, therefore, in practice, average speed is based on the sampling of vehicles over a period of time or area and is calculated and used in formulae. Some sensing systems can directly measure it. Flow q is the rate in which vehicles arrive at a particular point on a roadway and described in terms of vehicles per hour (cars/hr). Traffic sensing systems usually record the traffic volume, which is the actual number of vehicles to arrive during a sampling period (e.g., 30 seconds). Thus, volume can be converted to a flow rate by multiplying the recorded volume by the number of sampling periods in an hour. Density k is defined as the number of vehicles per unit area of the roadway. The density value is described in terms of vehicle per unit area (cars/km). By measure flow and speed, the density is calculated by dividing the flow rate by the speed.

Table 5-1. The average values of the observation results.

AVG. SPEED (km/hr)	DENSITY (cars/km)	DENSITY (%/km)	SP. Braking (%)	Real Data FLOW (cars/hr)
50	18.28	7	4	914
50	20.18	8	4	1009
40	24.3	9	4	972
40	25.8	10	5	1032
40	28.75	11	3	1150

Since the real traffic data was recorded in 30 minutes video then based on this traffic flow counter, then we estimated the traffic flow for 1 hour. The average speed of vehicles was obtained by field experiment, e.g., driving a car along the observation area then calculated the average speed among such area. Once the flow q and speed values v were obtained then the density value k in the observation area was calculated by using the equation:

$$k = \frac{q\ (cars/hr)}{v\ \ (km/hr)} \qquad \textit{Eq. 5-1}$$

In the traffic cellular automaton model, most of the typical models use a consideration that one cell of the simulation model equal to the 7.5m length of the real system. This value is considered as the length of vehicle plus the distance between vehicles in a stopped position. Referring to this assumption then for 1 km road length there must be 133 vehicles that equal to maximum density among the road lane. Table 5-1 shows the summarized data. Data from the sequences video that have same density value have been calculated and retrieved their average value.

5.4 Comparison and Analysis

In this observation, we evaluated the number of traffic parameters provided by video recording, i.e., spontaneous braking events, flow number, cars density value, and average speed of the cars. There were several types of vehicle exist in this observation, e.g., motorbike, bus, passenger car, and bicycle. However, in the data analyzing, we just considered for the car types, include truck and bus. After those traffic parameters had been calculated then through the simulation model those real traffic data has been compared. We compared the number of traffic flow resulting from real traffic data and the proposed model. This evaluation used spontaneous braking number and density level from real traffic data. By using those parameters as input value, we obtained the traffic flow results of simulation model.

The comparison result of traffic flow is shown by Figure 5-5. Referring to the video observation, in the simulation model we used the probability of lane changing 0.1. In this evaluation, we also compared the traffic flow result by using Nagel-Schreckenberg model [24]. The comparison result shows the model that accommodates spontaneous braking and driver scope awareness produced the better result of traffic flow rather than the original Nagel-Schreckenberg model [24]. The accuracy values between real data flow and our model are presented in Table 5-2, as well as Nagel-Schreckenberg model.

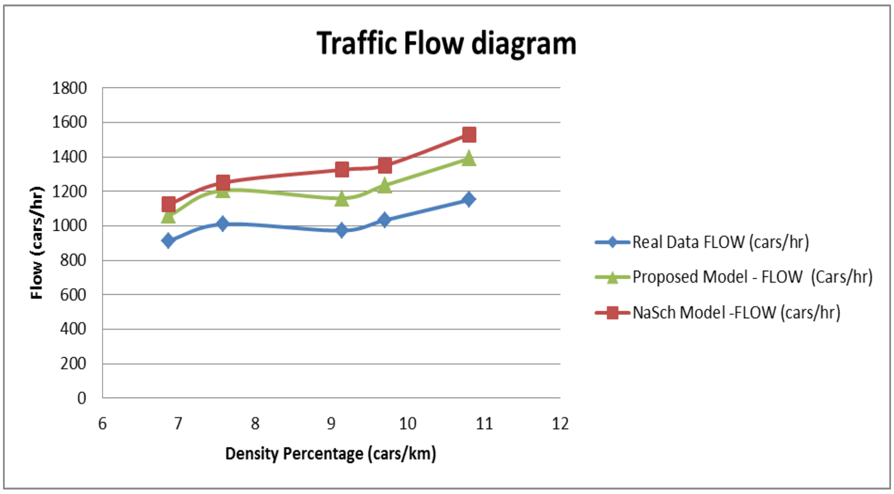

Figure 5-5. Comparison results of real data vs proposed model vs NaSch model.

Table 5-2. Traffic flow acurration values

Data Source	Accuration (%)
Real Data	100
NaSch Model	75.9
Proposed Model	83.9

It can be seen from the comparison results (Figure 5-5), there is a discrepancy between real data and simulation results. The simulation model produced .25 higher cars flow than real traffic flow. Therefore, in this work, we also tried to compare the real traffic data flow to various values of spontaneous braking probability and scope awareness. Figure 5-6 presents the scatter graph of comparison between real data flow and several spontaneous braking probability values. While Figure 5-7 presents the comparison result between real traffic flow data and several value of driver scope awareness parameter, i.e., scope awareness 3 cells and scope awareness 6 cells, respectively.

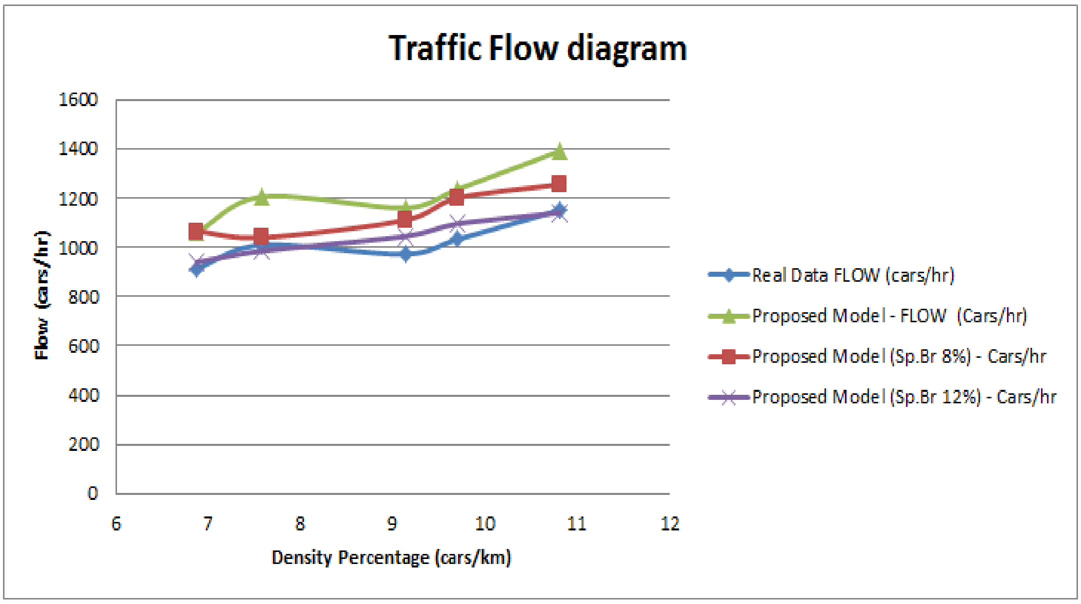

Figure 5-6. Comparison of real data to several spontaneous braking values.

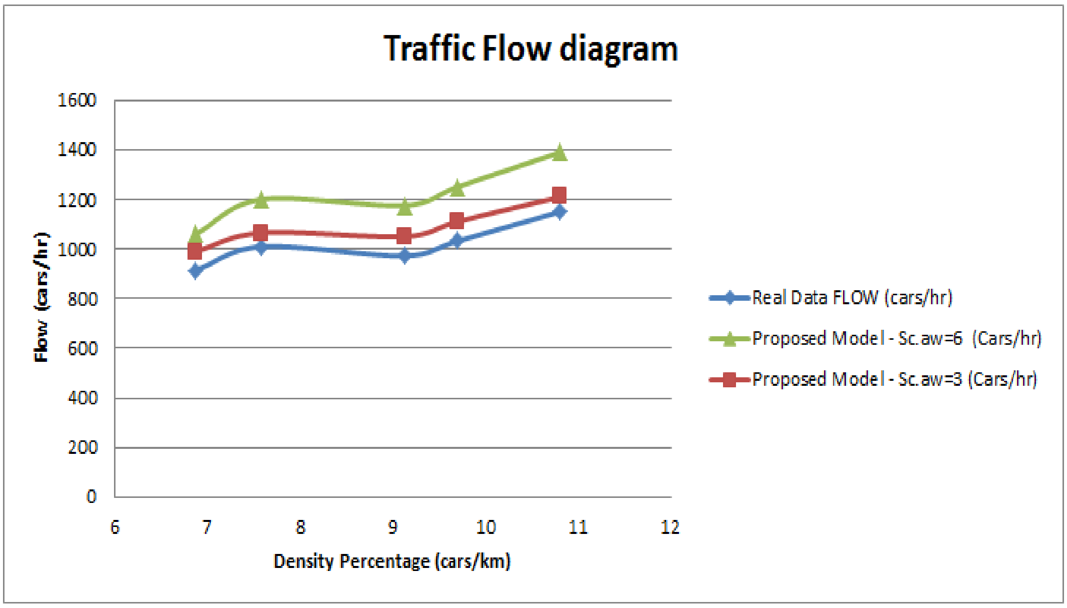

Figure 5-7. Comparison of real data to several Scope Awareness values

5.4.1 Traffic Flow and Average Speed Estimation

In addition, this paper also evaluated and made estimation for traffic flow and average speed on every density values. Referring to the Figure 5-6, it can be seen that by using spontaneous braking probability value = 0.12 , the simulation can produces a similar flow behavior to the real traffic flow data. Thus, in order to predict the future traffic behavior, the simulation model used spontaneous braking probability = 0.12 . Figure 5-8 and Figure 5-9 present the traffic flow and speed estimation for all density values, respectively. The horizontal axis represents the percentage of car's density levels on the roadway-length. While vertical axis in Figure 5-8 represents the percentage of the cars that can move at one time step in simulation. In Figure 5-9, the vertical axis describes the maximum speed that can be reached by the car at the specific density level.

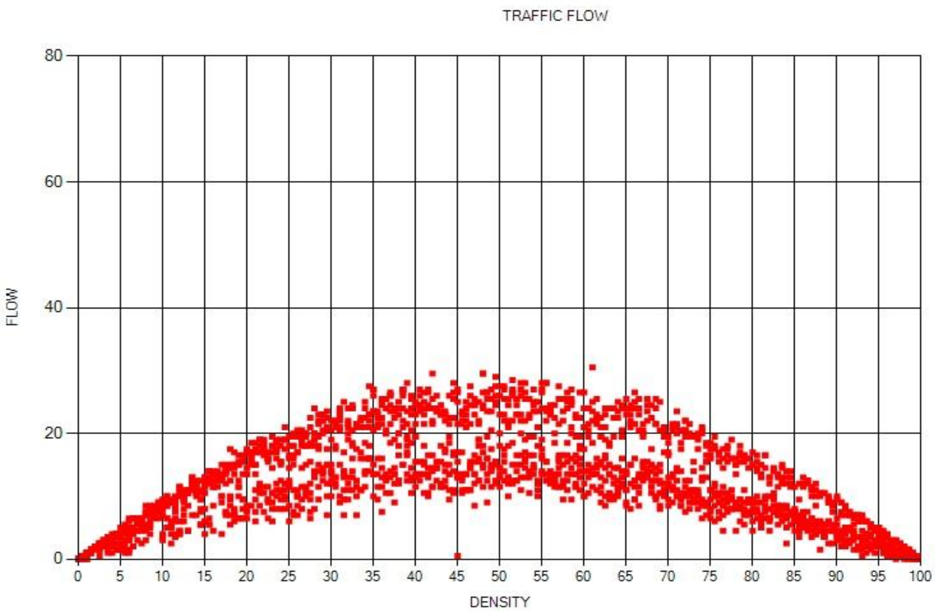

Figure 5-8. Traffic flow estimation for all density values.

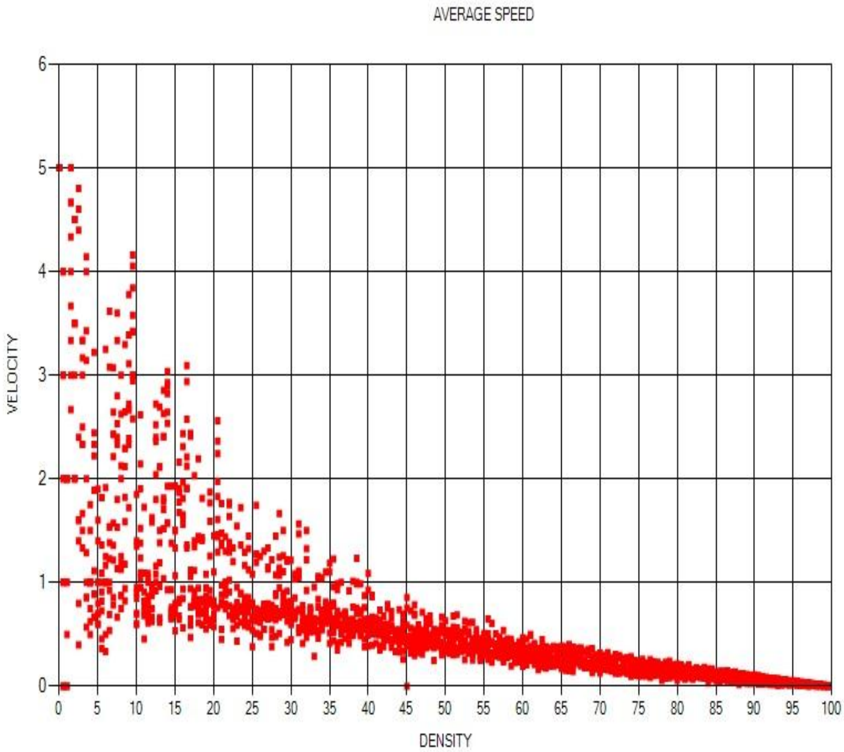

Figure 5-9. Average speed estimation for all density values.

CHAPTER 6.
CONCLUSIONS

This thesis simulates the spontaneous braking behavior of the driver and introduces the new Cellular Automata model for describing this characteristic. This research has presented a simple model of the traffic cellular automata to describe a driver behavior in a two lane highway model. Moreover, the effect of driver scope awareness in lane changing maneuver also has been investigated. The traffic cellular automata model has been modified to accommodate the parameter of spontaneous-braking probability and scope of awareness.

The spontaneous-braking probability rule captures the natural of braking behavior due to driver characteristic. This simulation shows that in the specific density value, the traffic congestion can be caused by the spontaneous braking behavior of drivers. We also evaluate the effect of lane-changing to reduce the congestion that is caused by the parameter of spontaneous-braking probability. This thesis investigated the effect of drivers' visibility and their perception (e.g., to estimate the speed and arrival time of another vehicle) on the lane changing maneuver. Driver scope awareness parameter was introduced to reflect the characteristic of drivers.

The term of scope awareness introduced to reflect the visibility required by the driver to make a perception of a road condition and the speed of vehicle that exist within the certain area of the road before making a lane changing maneuver. The relation between flow-density and space-time has been investigated in order to examine the effect of scope awareness parameter in the traffic flow. By taking into consideration the scope awareness parameter, the traffic cellular automata model proposed here can reflect certain characteristics of lane changing maneuver in the real traffic situation.

A validation of spontaneous braking and scope awareness model using measured real traffic flow has been introduced. The real traffic data support the simulation model in particular for spontaneous braking and driver scope awareness behavior. This validation shows that the traffic cellular automaton model that accommodate the probability of spontaneous braking and scope awareness have given more accurate description about traffic flow situation.

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APPENDIX-A.
TRAFFIC DATA MEASUREMENT METHODS

The purpose of this appendix is to provide a brief overview for the traffic data measurement methods. This section presents a description of traditional and emerging methods. The term of traffic measurement here refers to a traffic count that is a count of traffic along a particular road, either done electronically or by people counting by the side of the road. Generally, traffic count technologies can be split into two categories[62]: the intrusive and non-intrusive methods. The intrusive methods basically consist of a data recorder and a sensor placing on or in the road. While non-intrusive methods are based on remote observations.

A.1 Intrusive technologies

The intrusive methods basically consist of a data recorder and a sensor placing on or in the road. The most important ones are briefly described as follow:

- **Inductive detector loops (IDL)** (Figure A-1(3)): this type of technique consisting of coated wire coils buried in grooves cut in the road surface, sealed over with bituminous filler. A cable buried with the loop sends data to a roadside processing unit. The zone of detection for inductive loop sensors depends on the cut shape of the loop slots. The zones depending on the overall sensitivity of system not correspond precisely to the slot dimensions. IDLs are a cheap and mature technology. They are installed on both major roads and within urban areas, forming the backbone detector network for most traffic control systems. This type of detector is a very cheap technology. However, the weaknesses are the loop easy damaged by utility and street maintenance activities or penetration of water, IDLs with low sensitivity fail to detect vehicles with speed below a certain threshold, and miscount vehicles with complex or unusual chassis configurations, or vehicles with relatively low metal content (e.g. motorcycles), and some radio interference occurs between loops in close proximity with each other.

- **Pneumatic road tubes** (Figure A-1(2)): this method uses a rubber tubes that are placed across the road lanes that uses pressure changes to record the number of axle movements in a counter placed on the side of the road. This pressure changes are produced when a vehicle’s tires pass over the tube. The pressure pulse closes an air switch, producing an electrical signal that is transmitted to a counter or analysis software. The main drawback of this technology is that it has limited lane coverage and its efficiency is subject to weather, temperature and traffic conditions. This system may also not be efficient in measuring low speed flows or when the vehicle volumes are high. While the advantages of toad tube sensors are quick installation for permanent and temporary recording of data and low power usage. Road tube sensors are usually low cost and simple to maintain. Sensor manufacturers often supply software packages to assist with data analysis.
- **Piezoelectric sensors**: the sensors are placed in a groove along roadway surface of the lane(s) monitored. The principle is to convert mechanical energy into electrical energy. Indeed, mechanical deformation of the piezoelectric material modifies the surface charge density of the material so that a potential difference appears between the electrodes. The amplitude and frequency of the signal is directly proportional to the degree of deformation. This system can be used to measure weight and speed.
- **Magnetic loops (**Figure A-1(1)**)**: it is the most conventional technology used to collect traffic data. The loops are embedded in roadways in a square formation that generates a magnetic field. The information is then transmitted to a counting device placed on the side of the road. This has a generally short life expectancy because it can be damaged by heavy vehicles, but is not affected by bad weather conditions. This technology has been widely deployed in Europe (and elsewhere) over the last decades. However, the implementation and maintenance costs can be expensive.

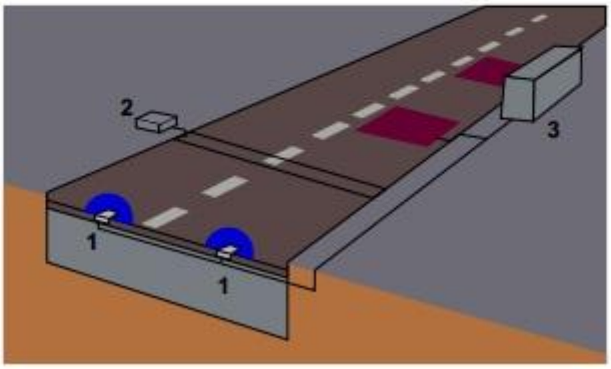

Figure A-1 Typical intrusive detector configurations [62]. *(1) Magnetic loops; (2) Pneumatic road tubes; (3) Inductive detector loops*

A.2 Non-Intrusive technologies

Non-intrusive methods are based on remote observations. Non-intrusive techniques include manual counts, video data collection, passive or active infrared detectors, microwave radar detectors, ultrasonic detectors, passive acoustic detectors, laser detectors and aerial photography. All these technologies represent emergent fields that are expanding rapidly with continuing advances in signal processing[63]. At present time such technologies are used to provide supplemental information for selected locations or for specific applications (e.g., queue detection at traffic signals). Most non-intrusive systems are operationally and somewhat visually similar, consisting of small electronics unit mounted in a weatherproof housing placed in various locations (Figure A-2).

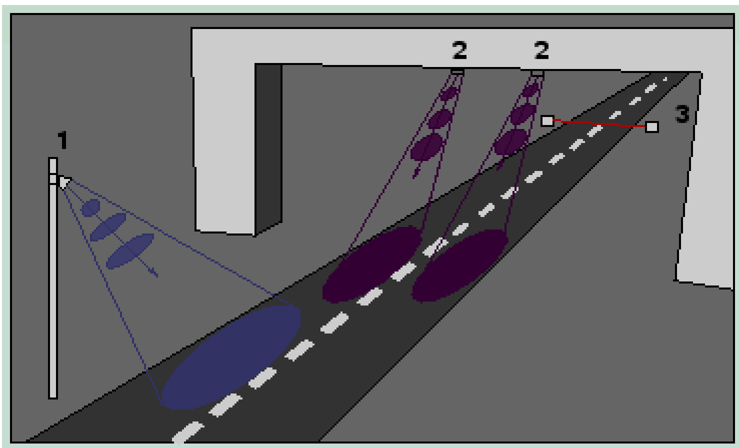

Figure A-2 Typical non-intrusive technology configurations [63]. *(1) Roadside; (2) Bridge underside; (3) Cross-fire*

The examples of this kind of technique are briefly described hereafter [64]:

- **Manual counts**: it is the most traditional method. In this case trained observers gather traffic data that cannot be efficiently obtained through automated counts e.g. vehicle occupancy rate, pedestrians and vehicle classifications. The most common equipments used are tally sheet, mechanical count boards and electronic count board systems.
- **Passive and active infra-red**: the presence, speed and type of vehicles are detected based on the infrared energy radiating from the detection area. The main drawbacks are the performance during bad weather, and limited lane coverage.
- **Passive magnetic**: magnetic sensors are fixed under or on top of the roadbed. They count the number of vehicles, their type and speed. However, in operating conditions the sensors have difficulty differentiating between closely spaced vehicles.
- **Microwave radar**: this technology can detect moving vehicles and speed (Doppler radar). It records count data, speed and simple vehicle classification and is not affected by weather conditions.
- **Ultrasonic and passive acoustic**: these devices emit sound waves to detect vehicles by measuring the time for the signal to return to the device. The ultrasonic sensors are placed over the lane and can be affected by temperature or bad weather. The passive acoustic devices are placed alongside the road and can collect vehicle counts, speed and classification data. They can also be affected by bad weather conditions (e.g. low temperatures, snow).
- **Video image detection**: video cameras record vehicle numbers, type and speed by means of different video techniques e.g. trip line and tracking. The system can be sensitive to meteorological conditions.

A.3 The Floating Car Data (*FCD*)

Beside the intrusive and non-intrusive technologies, then the next order automated traffic data technology is floating car data (FCD). FCD is an alternative or rather complement source of high quality data to existing technologies. They will help improve safety, efficiency and reliability of the transportation system. They are becoming crucial in the development of new Intelligent Transportation Systems (ITS). The principle of FCD is to collect real-time traffic data by locating the vehicle via mobile phones or GPS over the entire road network. This basically means that every vehicle is equipped with mobile phone or GPS which acts as a sensor for the road network. Data such as car location, speed and direction of travel are sent anonymously to a central processing center. After being collected and extracted, useful information (e.g. status of traffic, alternative routes) can be redistributed to the drivers on the road.

Basically, there are two main types of FCD, namely GPS and cellular-based systems[64]:

- GPS-based FCD: using this technique, the vehicle location precision is relatively high, typically less than 30m. Generally, traffic data obtained from private vehicles or trucks are more suitable for motorways and rural areas. Currently, GPS probe data are widely used as a source of real-time information by many service providers but it suffers from a limited number of vehicles equipped and high equipment costs compared to floating cellular data.
- FCD based on cellular phones: The mobile phone positioning is regularly transmitted to the network usually by means of triangulation or by other techniques (e.g. handover) and then travel times and further data can be estimated over a series of road segments before being converted into useful information by traffic center. This approach is particularly well adapted to deliver relatively accurate information in urban areas (where traffic data are most needed) due to the lower distance between antennas. Contrary to stationary traffic detectors and GPS-based systems, no special device/hardware is necessary in cars and no specific infrastructure is to be built along the road. It is therefore less expensive than conventional detectors and offers larger coverage capabilities. Traffic data are obtained continuously instead of isolated point data. It is faster to set up, easier to install, and needs less maintenance. Note however that sophisticated algorithms are required to extract and treat high-quality data before sending

them back to end-users. Even if the location precision is generally low (typically 300m), this weakness is partially compensated by the large number of devices. Note that more accurate data should be obtained from the UMTS technology (3G).