A Division Method of Determining the Early-Warning Zone on an Expressway for Automated Vehicles

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1.Introduction

Traffic incidents, referred to as “all events which affect (or may affect) the capacity of the road and hinder the smooth flow of traffic” [1], can cause severe congestion in an expressway. An incident may propagate to a large area of the transportation network and result in gridlock for a network [2]. Although expressways make up only a small part of the urban transportation network, they form the backbone of most urban transportation networks. These roads carry more than a third of all vehicle travel [3]. It is important to provide a division method for early-warning zone to deal with the short-term mismatch of traffic supply and demand caused by these incidents so that travel safety and overall network throughput are increased.

Over the past two decades, advances in wireless communications, processing power, and sensing technology have been integrated into traffic management systems. In particular, automated vehicles have been prototyped with substantial advances in sensing technologies, associated pattern recognition, and control intelligence [4]. Information connectivity of connected and automated vehicles (CAVs) is not only a prerequisite to formulate a more intelligent driving scheme but also a necessary function to optimize the operation of future mixed traffic flows. CAVs can obtain the information of multiple vehicles ahead through vehicle-to-X communication technology, which will play a vital role in improving traffic condition and efficiency [5–9]. Thus, the driving environment is expected to change with the introduction of automated vehicles. Regular vehicles and automated vehicles have different driving logics. Humans have a faster reaction time compared to robots [10]. In a mixed urban traffic flow, which is composed of both regular vehicles and automated vehicles (RAVs), the study of the relationship between the length of the automated-driving early-warning zone and the capacity of the expressway plays a vital role to enhance traffic condition.

In previous studies, research on the incident warning model has been carried out from the perspective of driving behavior and incident characteristics. Researches on driving
behavior promote the development of intelligent transportation systems to decrease the traffic congestion and increase traffic capacity and travel efficiency [8, 9]. By analyzing the driving behaviors in the incident affected area, previous studies proposed that the forward incident warning model addressed the congestion [11–15]. By analyzing the characteristics and incident types of expressway collisions, a side collision and rear-end incident warning model can be developed to avoid incidents from happening [16, 17]. For frequent types of incident, safety and efficiency-based control methods can be proposed to provide a real-time warning [18].

For future RAV mixed traffic flow, scholars have carried out various studies. Ye and Yamamoto [19] provided some insights on how to eliminate the influence of incidents on overall road capacity. The results presented the optimal capacity under different CAVs rates. They showed that varying demand levels may have a positive impact on the development of the CAV controlling system. Hoogendoorn and Bovy [20] proposed a cellular automaton model under a mixed traffic flow. In their model, the typical cellular automaton is a discrete, nondeterministic rule-based asynchronous model, which discretizes time and space.

Cellular automata models are vital and universally used tools for research in the microscopic simulation of traffic heterogeneity and its stochastic nature. They have the ability to handle various types of traffic with a high computational efficiency. Cellular automaton (CA) is able to represent the different stages of traffic flow, including the metastability region. It can capture some essential features observed in realistic traffic, such as density waves and the influence of the drivers’ behavior [21, 22].

Previous studies on the incident warning model focused on the current traffic flow model, while more attention should be paid to the future mixed traffic flow conditions. With the traffic flow composed with connected and automated vehicles, the following aspects should be considered in incident warning research:

(i) The impact of length of the early incident warning area on the capacity of the expressway
(ii) The impact of the automated-driving behavior on the early incident warning area and on its capacity
(iii) The impact of the proportion of automated vehicles in RAV mixed traffic flow on the capacity

The contributions of this paper are as follows:

(i) This study establishes a codirectional two-lane cellular automaton model for the incident’s early-warning zone. It divides the early-warning zone into an accelerate lane-changing area, a decelerate lane-changing area, and a forced lane-changing area.
(ii) Based on the CA modeling, the impact of the early-warning zone length of CAVs on the capacity of an incident affecting expressway of RAV mixed traffic is also discussed.

2. Methodology

Cellular automata are important models to study traffic flow in incident affected areas, particularly in the research of the driving behavior and basic characteristics of traffic flow. These studies designed some basic rules (e.g., speed change and mandatory lane-changing) and proved its effectiveness through experiments [20–22]. Based on these basic rules, this paper establishes a cellular automaton model to reflect real traffic flow.

2.1. CA Models for Manual Driving Condition. To demonstrate the methodology of information acquisition on manual driven vehicles, the author simplifies the hypothesis to different driving behaviors [22]. This study is modeled on four different behaviors:

(i) During manual driving, a psychological safe distance is subconsciously required. When the distance is less than a safe distance, the vehicle will decelerate. When the distance is greater than a safe distance, acceleration will be considered.
(ii) Drivers can only perceive the distance from the vehicle in front and the nearest proceeding vehicle in adjacent lanes. They cannot rely on the speed perception of other vehicles to determine their driving behavior.
(iii) When there is an incident ahead, the driver can only perceive its occurrence if the incident appears in his or her visual range.
(iv) In normal driving condition, manual driving seeks for less travel time.

Simulated roads are divided into cells grids, with a Von Neumann neighborhood and a constant homogeneous boundary. In cellular automata, the Von Neumann neighborhood comprises the four cells orthogonally surrounding a central cell on a two-dimensional square lattice. The length of the road consists of three cell chains, which, respectively, represent the entrance area \( L_1 \), the early-warning area \( L_2 \), and the incident affected area \( L_3 \), as shown in Figure 1. In a typical single-lane Nagel–Schreckenberg (NaSch) model and its extensions, one CA cell represents a car and its surroundings [23].

The typical cellular automaton is a discrete, nondeterministic rule-based asynchronous model, which discretizes time and space. Through low computational complexity, the model can be used to model a large number of vehicles [20]. Each lane is divided into single cells (the road in this model consists of two lanes). The individual cells are adjacent to each other; i.e., the vehicle can be moved from one cell to the next placed on the front, right, or left side of the cell, which contains the front of the vehicle [24]. The vehicle speed is defined as the moving forward cell
number in a time step. In the developed CA model, vehicles are distributed in CA cells. Each cellular grid has two states at any time $t$, which are either empty or occupied. Each cell can only be occupied by one vehicle at a time [25]. The cell size is established on the basis of the vehicle length and the width of the lane.

The vehicle speed is expressed as the number of road cells that the vehicle can travel in one second. In this study, the vehicle speed range is between 0 and 2 cells. According to the theory of calculating safe distance introduced by Chen and Meng [23], the safe distance is set as the length of 1, where $d_a$ is the general acceleration of the vehicle, which is 1 cell, while $d_m$ denotes the general deceleration of the vehicle, which is 1 cell.

Equations (1)–(3) define the expression of the distance of the vehicles from cell $i$ in lane $j$ to the nearest vehicle in driving $d(i,j)$, $d(i,j)$, and $d(i,j)$:

$$d(i,j) = \text{pos}_{i+1,j} - \text{pos}_{i,j},$$

$$d(i,j) = \text{pos}_{i+1,j} - \text{pos}_{i,j},$$

$$d(i,j) = \text{pos}_{i+1,j} - \text{pos}_{i,j}. (3)$$

All definitions and notations used in the model formulation are summarized in the following:

- $i$: the number of the cell in which the given vehicle is found
- $j$: the number of the lane of the road. In this model, $j \in \{1, 2\}$
- $V_{(i,j)}$: the speed of vehicle from cell $i$ in lane $j$ (the velocity of the vehicle $i$ at time $t$ is given in cells per unit time)
- $d(i,j)$: the distance of the vehicle from cell $i$ in lane $j$ to the preceding vehicle in the same lane
- $d(i,j)$: the distance of the vehicle from cell $i$ in lane $j$ to the nearest vehicle in the left adjacent lane
- $d(i,j)$: the distance of the vehicle from cell $i$ in lane $j$ to the nearest vehicle on the right adjacent lane
- plaza: the status of the cell being occupied with one vehicle
- pos: the spatial position of the cell
- VType: the type of the vehicle
- $D_{safe}$: the safe distance between the vehicles with a minimum length of one cell (the value is 1)
- $P_{slow}$: the slowing down random probability.

2.1.1. The Car-Following Model. With a periodic boundary condition, all vehicles travel in the same direction. This flow is shown in Figure 1. The status of the vehicle forward (in the next iteration) is related to the speed the vehicle moves and results in either increased or reduced speed. This effect is a consequence of the road condition ahead of the vehicle. In each step, the iteration rules of the cells are updated from $t$ to $t+1$, which is carried out in three separate areas, normal driving area, incident sensing area, incident driving area, and nonincident driving area. Three areas are listed as follows.

(1) In Normal Driving Area. The acceleration of the current lane 1 is set as the first condition, and the acceleration of the adjacent lane 2 is set as the second condition. Three rules applied to the current area are as follows:

Acceleration rule: when the relative distance of the vehicle in front (the distance between the lag vehicle and the preceding vehicle) is greater than the length of one cell, that is, $d_{(i,j)}(t) > 1$, then the vehicle $i$ will accelerate in accordance with the following rule: $v_{(i,j)}(t+1) \longrightarrow \min(v_{(i,j)}(t)+1, 2)$.

Deceleration rule:

If the relative distance of the vehicle in front is less than or equal to the length of one cell, that is, $d_{(i,j)}(t) \leq 1$, and the relative distance to the nearest vehicle on the neighboring adjacent lane is less than or equal to the length of one cell, that is, $d_{(i,j)}(t)(d_{(i,j)}(t)) \leq 1$, then the vehicle $i$ will decelerate in accordance with the rule: $v_{(i,j)}(t+1) \longrightarrow \max(v_{(i,j)}(t)-1, 0)$.

Random slowing down rule: the speed of the vehicle $i$ may decrease by one unit with a probability, that is, $P_{slow}$. $P_{slow}$ is accounted in the condition that the speed decreases due to the influence of various uncertain factors, such as pedestrian obstructions and distractions. This rule reflects the situation of speed reduction in relation to an incident other than approaching the vehicle, listed as follows: $v_{(i,j)}(t+1) \longrightarrow \max(v_{(i,j)}(t)-1, 0)$.
(2) In Incident Sensing Area. It is suggested that drivers, for safety concerns, will behave more carefully in this area. At incident point, if \( a_{i,j+1} = 1 \), then vehicle \( i \) will be stopped. The driver may make a decision to change lanes. The rule applied is as follows: \( v_{i,j}(t) = 0 \).

(3) In Incident Driving Area and Nonincident Driving Area. Three rules applied to the current area are as follows:

- Low speed rule: if \( d_{i,j}(t) > 1 \), then \( v_{i,j}(t) = 1 \).
- Deceleration rule: if \( d_{i,j}(t) \leq 1 \), then \( v_{i,j}(t + 1) \rightarrow \max(v_{i,j}(t) - 1, 0) \).
- Random slowing down rule: the speed of the vehicle may be reduced because of the condition of roads or the actions of other drivers. This rule reflects the situation of speed reduction in relation to an incident other than approaching the vehicle in accordance with the following rule: \( v_{i,j}(t + 1) \rightarrow \max(v_{i,j}(t) - 1, 0) \).

2.1.2. The Lane-Changing Model. Generally speaking, a lane-changing (LC) process can be divided into two stages. The first stage is regarded as LC decisions, in which a driver is mentally motivated to change lanes based on the surrounding traffic. The second stage, which is called as LC implementation, is the physical process that a vehicle moves from the current lane to the target lane [26]. In this paper, the LC model is carried out in two separate areas, normal driving area and incident sensing area. Two areas are listed as follows.

(1) In Normal Driving Area. If a driver is not traveling at the desired speed and the adjacent lane speed is acceptable, then the vehicle changes lanes.

When \( d_{i,j}(t) \leq 1 \), if \( d_{i,j}(t) > 1 \) (the acceleration condition), \( a_{i,j+1}(t) = 0 \) and \( a_{i-1,j+1}(t) = 0 \) (the safety condition), then vehicle \( i \) changes lanes to the left and accelerates in accordance with the following rule: \( v_{i,j}(t + 1) \rightarrow \min(v_{i,j}(t) + 1, 2) \).

When \( d_{i,j}(t) \leq 1 \), if \( d_{i,j}(t) > 1 \) (the acceleration condition), \( a_{i,j+1}(t) = 0 \) and \( a_{i-1,j+1}(t) = 0 \) (the safety condition), then vehicle \( i \) changes lanes to the right and accelerates in accordance with the following rule: \( v_{i,j}(t + 1) \rightarrow \min(v_{i,j}(t) + 1, 2) \).

(2) In Incident Sensing Area. Since vehicle cannot travel to the incident lane, it only allowed to change to the non-incident lanes. If \( a_{i,j+1}(t) = 1 \), then vehicle \( i \) changes lanes to the right in accordance with the following rule: \( v_{i,j}(t + 1) = 0 \).

2.2. Models under the RAV Mixed Traffic Environment of Manual Driving and Automatic Driving Condition. After being informed of the incident ahead, vehicles tend to implement different driving rules from this early incident warning. In the case of a two-lane reduction caused by expressway traffic incidents, the capacity of expressway will decrease. In this study, it is suggested that, in the early-warning area \( (L_2) \), the motivation of an automated vehicles in the incident lane to change lanes will increase enormously. Therefore, development of the driving rules will be modified for more lane-changing.

Based on all the above rules, the early-warning zone will be divided into an accelerate lane-changing area \( (L_{2A}) \), a decelerate lane-changing area \( (L_{2B}) \), and a forced lane-changing area \( (L_{2C}) \). Three specific areas are shown in Figure 2. This analysis will show the expressway capacity changed under various combinations of three areas.

2.2.1. Basic Hypothesis. The information connectivity and the pursuit of driving efficiency are the main characteristics of CAVs. These two characteristics are of positive significance for the stable operation of traffic flow and the reduction of fuel consumption and travel time [4, 27, 29, 30]. Based on the application of future connected and automated vehicle (CAV) techniques along with the consideration of its characteristics, the proposed model is based on four different driving behaviors:

(i) Automated driving obtains abundant real-time traffic information, such as the position and velocity of front and rear vehicles on the current lane and adjacent lanes.

(ii) The connected and automated vehicles can transmit road information in real time.

(iii) Automated driving receives its instructions from an operating system. Thus, random slowing down rules will not be considered.

(iv) Automated driving vehicle aims for traveling efficiency. Therefore, automated-driving seeks for less travel time. In normal driving, the current lane will be prioritized. Yet, lane-changing decisions will be considered, when the acceleration conditions are not satisfied.

2.2.2. Instructions of Parameters. Compared to the manual driving vehicles, CAV embodies more abundant parameters on cell status. Therefore, in the developing model, the following notation will be used:

\[ v_d: \] the relative velocity to the proceeding vehicle, given in cells per unit time

\[ v_l: \] the relative velocity to the nearest proceeding vehicle on the left adjacent lane

\[ v_r: \] the relative velocity to the nearest proceeding vehicle on the right adjacent lane

Equations (4) through (6) express the velocities of the vehicles from cell \( i \) on lane \( j \) to the nearest vehicle in driving \( v_{d_{i,j}}, v_{l_{i,j}}, \) and \( v_{r_{i,j}} \):

\[ v_{d_{i,j}} = v_{(i+1,j)} - v_{(i,j)}, \]  
\[ v_{l_{i,j}} = v_{(i+1,j-1)} - v_{(i,j)}, \]  
\[ v_{r_{i,j}} = v_{(i+1,j+1)} - v_{(i,j)}. \]
2.2.3. The Car-Following Model under the Normal State.

With the periodic boundary condition, all vehicles travel in the same direction. This condition is shown in Figure 2. The status of the vehicle forward (in the next iteration) is related to the speed that the vehicle moves. The results either increased or reduced speed, which is a consequence of the situation on the road ahead of the vehicle.

In each time step \( t \rightarrow t + 1 \), the vehicle, in accordance with the rules of NaSch model and its extension, updates its cell status, with measurements such as velocity and position. The NaSch model is used in this study because it reflects the basic characteristics of traffic flow, and it is more convenient to determine the maximum vehicle length and vehicle speed in a mixed traffic environment [23]. This procedure is carried out in accordance with the following conditions.

(1) In Entrance Area (L1). The acceleration of the current lane 1 is set as the first condition and the acceleration of the adjacent lane 2 as the second condition. The two rules applied, acceleration and deceleration rules, are as follows:

Acceleration rule:

When \( d_{i,j} > v_{i,j} (t) \), vehicle \( i \) on lane \( j \) will accelerate in accordance with the following rule: \( v_{i,j} (t + 1) \rightarrow \min (v_{i,j} (t + 1), 2) \).
When \( d_{i,j} \leq v_{i,j} (t) \) and \( vd_{i,j} (t) > 0 \), vehicle \( i \) on lane \( j \) will accelerate in accordance with the following rule: \( v_{i,j} (t + 1) \rightarrow \min (v_{i,j} (t + 1), 2) \).

Deceleration rule: the lane conversion is complete before the speed update. When \( d_{i,j} (t) \leq v_{i,j} (t) \) and \( vd_{i,j} (t) \leq 0 \), the adjacent lane does not obtain the acceleration condition for lane change, vehicle \( i \) on lane \( j \) will decelerate in accordance with the following rule: \( v_{i,j} (t + 1) \rightarrow \min (v_{i,j} (t), 2) \).
If for the left adjacent lane, any of the following conditions are not satisfied, \( d_{i,j} (t) \leq v_{i,j} (t), v_{i,j} (t) < 0, \) plaiz\(a_{i,j-1} = 0, \) plaiz\(a_{j-1,i} = 0 \), then the acceleration condition of lane change cannot be obtained. When changing lanes to the right, the right lane follows the same rules.

(2) In Incident Affected Area (L3). Acceleration and deceleration rules applied are as follows:

Acceleration rule:

When \( d_{i,j} (t) > v_{i,j} (t) \), then vehicle \( i \) on lane \( j \) will accelerate in accordance with the following rule: \( v_{i,j} (t + 1) \rightarrow \min (v_{i,j} (t + 1), 2) \).

When \( d_{i,j} (t) \leq v_{i,j} (t) \) and \( vd_{i,j} (t) > 0 \), vehicle \( i \) on lane \( j \) will accelerate in accordance with the following rule: \( v_{i,j} (t + 1) \rightarrow \min (v_{i,j} (t + 1), 2) \).

Deceleration rule: when \( d_{i,j} \leq v_{i,j} (t) \) and \( vd_{i,j} (t) \leq 0 \), vehicle \( i \) on lane \( j \) will decelerate in accordance with the following rule: \( v_{i,j} (t + 1) \rightarrow \max (v_{i,j} (t) - 1 , 0) \).

2.2.4. The Car-Following Model in the Early-Warning Area

(1) On Nonincident Lane. The acceleration of the current lane 1 is set as the first condition. Acceleration and deceleration rules applied are as follows:

Acceleration rule:

When \( d_{i,j} (t) > v_{i,j} (t) \), then vehicle \( i \) on lane \( j \) will accelerate in accordance with the following rule: \( v_{i,j} (t + 1) \rightarrow \min (v_{i,j} (t + 1), 2) \).
When \( d_{i,j} (t) \leq v_{i,j} (t) \) and \( vd_{i,j} (t) > 0 \), then vehicle \( i \) on lane \( j \) will accelerate in accordance with the following rule: \( v_{i,j} (t + 1) \rightarrow \min (v_{i,j} (t + 1), 2) \).

Deceleration rule: when \( d_{i,j} \leq v_{i,j} (t) \) and \( vd_{i,j} (t) \leq 0 \), then vehicle \( i \) on lane \( j \) will decelerate in accordance with the following rule: \( v_{i,j} (t + 1) \rightarrow \max (v_{i,j} (t) - 1 , 0) \).

(2) On Incident Lane (L2A). It follows the same longitudinal driving rules as nonincident lanes.

(3) On Incident Lane (L2B). Changing lanes to nonincident lane is set as the first condition. The uniform velocity rule and slowing down rule applied are as follows:

Uniform velocity rule: when vehicle \( i \) obtains the acceleration condition of lane change, \( dr_{i,j} (t) > v_{i,j} (t) \), or obtains both, \( dr_{i,j} (t) \leq v_{i,j} (t) \) and \( vr_{i,j} (t) > 0 \). Yet, when \( plaiz\(a_{i,j+1} = 1 \) and \( plaiz\(a_{i-1,j+1} = 1 \) (the safe condition), then \( v_{i,j} (t + 1) = v_{i,j} (t) \).
Slowing down rule: when vehicle \( i \) does not obtain the acceleration condition to change lanes \( (dr_{i,j} (t) \leq v_{i,j} (t) \) and \( vr_{i,j} (t) \leq 0) \), then vehicle \( i \) will decelerate in accordance with the following rule: \( v_{i,j} (t + 1) \rightarrow \max (v_{i,j} (t) - 1 , 0) \).

(4) On Incident Lane (L2C). Changing lanes to a nonincident lane is set as the first condition. Meanwhile, due to the fact that this section is close to the incident scene, a stricter lane-changing condition will be adopted.
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2.2.5. The Lane-Changing Model under the Normal State.

For the normal lane-changing model, the dissatisfaction of the current lane on the acceleration condition is set as the first condition. The adjacent lane on the acceleration condition for lane change is set as the second condition. The adjacent lane on the safe condition for lane change is set as the third condition. Based on all the above conditions, normal lane-changing rules are set in the following two manners:

1. When \( d_{i,j}(t) \leq v_{i,j}(t) \) and \( vd_{i,j}(t) \leq 0 \), if the next three conditions can be satisfied at the same time \((dl_{i,j}(t) > v_{i,j}(t))\), then vehicle \( i \) changes lanes to the left and \( v_{i,j}(t + 1) \rightarrow \min(v_{i,j}(t) + 1, 2) \).

2. When \( d_{i,j}(t) \leq v_{i,j}(t) \) and \( d_{i,j}(t) \leq v_{i,j}(t) \) and \( \max(v_{i,j}(t) + 1, 2) \) can be satisfied at the same time, then vehicle \( i \) changes lanes to the left and \( v_{i,j}(t + 1) \rightarrow \min(v_{i,j}(t) + 1, 2) \).

3. When changing lanes to the right, the right lane follows the same rules.

2.2.6. The Lane-Changing Model in the Early-Warning Area.

Lane-changing decision in the early-warning area is to avoid or eliminate congestion. Therefore, changing lanes to the nonincident lane is set as the first condition. Considering the fact that CAV on the nonincident lane will not change to the incident lane, the lane-changing model in the early-warning area is only meaningful to CAVs on the incident lane.

In the \( L_{2A} \) area (accelerate zone), the current road section is far from the incident affected area; therefore, vehicle \( i \) on the incident lane seeks for the acceleration of lane change. When simultaneously obtaining three conditions \((dr_{i,j}(t) > v_{i,j}(t))\), then vehicle \( i \) changes lanes to the right and \( v_{i,j}(t + 1) \rightarrow \min(v_{i,j}(t) + 1, 2) \).

When \( dr_{i,j}(t) > v_{i,j}(t) \), simultaneously obtaining three conditions \((vr_{i,j}(t) > 0, plaza_{i,j}(t) = 0, plaza_{i,j-1}(t) = 0)\), then vehicle \( i \) changes lanes to the right and \( v_{i,j}(t + 1) \rightarrow \min(v_{i,j}(t) + 1, 2) \).

In the \( L_{2B} \) area (decelerate zone), compared to the accelerate zone, the distance of decelerate zone to the incident affected area is decreasing. Therefore, the motivation of drivers to change lanes in either uniform velocity or deceleration is stronger. When vehicle \( i \) obtains the lane-changing condition in the \( L_{2A} \) area, then vehicle \( i \) changes lanes to the right and \( v_{i,j}(t + 1) \rightarrow \min(v_{i,j}(t) + 1, 2) \).

When vehicle \( i \) does not obtain the lane-changing condition in the \( L_{2A} \) area, lane changing can still be achieved under the uniform velocity rule and slowing down rule, listed as follows:

1. **Uniform Velocity Rule.** When \( dr_{i,j}(t) = v_{i,j}(t) \) and \( vr_{i,j}(t) < 0 \), then vehicle \( i \) changes lanes to the right. It will maintain the original velocity, that is, \( v_{i,j}(t + 1) = v_{i,j}(t) \).

2. **Slowing Down Rule.** When \( dr_{i,j}(t) > v_{i,j}(t) \), then vehicle \( i \) changes lanes to the right and \( v_{i,j}(t + 1) \rightarrow \min(v_{i,j}(t) + 1, 2) \).

In the \( L_{2C} \) area, due to an incident ahead, forced lane changing should be used to avoid the road blockage. This condition is to satisfy \( plaza_{i,j}(t) = 0 \), then vehicle \( i \) changes lanes to the right and \( v_{i,j}(t + 1) \rightarrow 0 \).

For CAV, the selection of the driving behavior is based on sufficient parameters of cell status.

In the entrance area, the distance between the vehicle \( i \) and the velocity of vehicle \( i \) is set as the first condition. The relative velocity to the proceeding vehicle is set as the second condition. This measurement is used to determine whether the car that is being followed is accelerating or decelerating.

The distance between the vehicle \( i \) and the nearest proceeding vehicle in an adjacent lane and the velocity of vehicle \( i \) are set as the first lane-changing condition. The relative velocity to the nearest proceeding vehicle in an adjacent lane is set as the second condition. The distance between vehicle \( i \) and the nearest lag vehicle in the adjacent lane is compared to the safe distance to determine whether it is safe to change lanes.

In the accelerate zone (accelerate to change lanes), vehicles should follow the same driving rules of the entrance area and expect that vehicles in the nonincident lane are not allowed to change lanes to the incident lane.

In the decelerate zone (decelerate to change lanes), vehicles should follow the same car-following rules of the entrance area and expect that vehicles in the nonincident lane are not allowed to change lanes to the incident lane. Additionally, lane-changing behavior for deceleration and maintaining a uniform velocity is accepted on the incident lane.

In the forced zone (forced to change lanes), vehicles on the nonincident lane follow the slowing down car-following rule. On the incident affected lanes, lane-changing motivation is generated particularly when safety conditions are considered. In the incident affected area, vehicles should follow the normal car-following rule, not considering the random slowing down rules.


3. Simulation Modeling and Analysis

3.1. Simulation Description. Based on the initial stimulation conditions, codirectional two-lane cellular automata models of RAV mixed traffic flows have been created to study the impact of the early-warning area on road capacity. The program is developed using MATLAB.

Attempts have been made to study how the temporary lane reduction caused by radical traffic incidents affect the capacity of an expressway under the environment of both manual and automatic driving vehicles. This study proposes the concept of an early-warning area based on information intersection of CAV. Taking into account the distance from the incident affected area and the detailed variation of drivers’ behavior, the early-warning area is divided into 3 parts, an accelerate lane-changing area \( L_{2A} \), a decelerate lane-changing area \( L_{2B} \), and a forced lane-changing area \( L_{2C} \). This stimulation aims to find how the length of automated-driving early-warning zone affects the capacity of an expressway.

First, by broadening the respective length and range of each road segment, the variation can be defined. The length range of \( L_{2A} \), \( L_{2B} \), and \( L_{2C} \) varies from 10 to 110 (cell). The length of a single cell is set to 7.5 m, and a one-time step corresponds to about 1 s in real time [28]. The fluctuation is set to be 10 (cell). To avoid any contingency, randomly generated seeds are added to each length condition. The average value is used to further examine road section capacity. In accordance with the trend, the length range is narrowed to determine the separate length of \( L_{2A} \), \( L_{2B} \), and \( L_{2C} \) and the total length of early-warning area. This is done to determine the optimal capacity. Based on the optimal length, research will be conducted on the impact of the CAV penetration on the road capacity.

3.2. Simulation Setup. Based on the proposed model, initial configurations are employed in the simulations:

(i) All vehicles are homogeneously distributed on the road.

(ii) All vehicles are distributed in a mega jam, using periodic boundary conditions. Each simulation has a duration for 1 hour and contains 3600 steps. The simulation uses the following parameters (see Table 1).

3.3. Model Simulation and Analysis. Increasing the length of early-warning area \( L_2 \) corresponds to a higher road capacity. In addition, the capacity of incident affected expressway is at a maximum when the length of the early-warning zone is between 450 and 600 m. This area is shown in the box which is drawn in Figure 3. Using the same length of the early-warning area, the road capacity varies distinctively, indicating that the ratio of the length of the road section \( L_{2A} \), \( L_{2B} \), and \( L_{2C} \) to \( L_2 \) plays a decisive role to the capacity in the process. In the case that the \( L_{2A} \) to \( L_2 \) length ratio on capacity where \( L_2 \) is 600 m, it has been found that a higher length proportion \( L_{2A} \) accounts for in the same length of \( L_2 \). This will lead to a greater improvement in the capacity of the corresponding road section, as illustrated in Figure 4.

Table 1: Parameter matrix of the stimulation.

| Parameter | Value |
|-----------|-------|
| Number of lanes \( B \) | 2 |
| Average arrival rate of entering vehicles \( V_a \) | 0.3 |
| Percentage/proportion of automated vehicles \( \rho \) | 0.5 |
| Probability of random slowing down of automated driving \( P_{slow} \) | 0.3 |
| Visual range of manual driving \( L_1 \) (m) | 75 |
| Length of the entrance area \( L_1 \) (m) | 375 |
| Total length range of \( L_2 \) (m) | [135, 2475] |
| Length of the incident affected area \( L_3 \) (m) | 150 |
| Length variation of \( L_4 \) (m) | 75 |
| Length range of \( L_{2A} \) (m) | [75, 825] |
| Length range of \( L_{2B} \) (m) | [75, 825] |
| Length range of \( L_{2C} \) (m) | [75, 825] |

After the confirmation of this trend, the range can be lowered down as the variation decreases. To obtain a more detailed optimal length range, length of \( L_{2A} \), \( L_{2B} \), and \( L_{2C} \) can be reduced.

Then, input parameter values with refined cell length are shown in Table 2.

The parameters shown in Table 2 lead to the following results which are shown in Figure 5.

Compared to the initial simulation, Figure 5 shows that the impact of the incident on road capacity is high when the length range of the early-warning area is reduced. This result indicates that the enhancement will be achieved for both vehicles. Furthermore, the capacity of the expressway
In this case, the proportion of accelerate zone, decelerate zone, and forced zone to the length of the early-warning area are created. When incidents (collision, construction, obstacles, etc.) occur, the proposed division method can be applied to ensure the maximum expressway capacity of the affected area. Simulations have been developed to use those rules. By analyzing the results of these simulations, the optimal total and divided length of the early-warning zone have been found.

The key findings of this study are as follows:

(i) The cellular automata approach has been performed to RAV mixed traffic flow research. Traffic flow can be stimulated, and its corresponding phenomenon can be studied, such as the traffic flow congestion and dissipation ahead of the affected area.

(ii) By analyzing these simulations, broader approaches on information acquisition play a vital and meaningful role on maintaining the vehicle traffic flow. In the case of a two-lane reduction caused by an incident, the capacity of the expressway is the highest when the length of early-warning zone is 450–600 m.

(iii) In this case, the proportion of accelerate zone, decelerate zone, and forced zone to the length of the early-warning zone is, respectively, 75%, 10%, and 15%. In addition, this simulation shows that the capacity will rise with the increase in automated driving.
This work takes one step towards promoting the study of mixed traffic flow. It is of practical relevance for various applications in the early-warning zone of real city traffic capacity. The CA model proposed in this article and the simulation program may be helpful in increasing road capacity and understanding some types of traffic behavior.

However, this study is only applied to the length of early-warning zone in the case of temporary two-lane reduction caused by a road traffic incident occupying one lane. This study provides several future research directions. First, this study should be extended to conditions with more sophisticated driving rules and traffic incidents. For example, more lanes could be used, changes in the probability of lane-changing could be added to manual driving rules, and additional environmental parameters could be added. Second, the proposed cellular automata model can be improved by using the field data to optimize the iteration rules and parameters. Through more accurate simulation, the optimal ratio of division for early-warning zone can be made more practical in engineering.

Data Availability
All the data used to support the findings of this study are included within the article.

Conflicts of Interest
The authors declare that they have no conflicts of interest.

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