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Fuzzy Cellular Automata (FCA) model for signalized intersections

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Abstract: *At signalized intersections, the decision-making process of each individual driver is a very complex process that involves many factors. In this article, a Fuzzy Cellular Automata (FCA) model, which incorporates traditional Cellular Automata (CA) and Fuzzy Logic (FC), is developed to simulate the decision-making process and estimate the effect of driving behavior on traffic performance. Different from existing models and applications, the proposed FCA model utilizes Fuzzy Interface Systems (FIS) and membership functions to simulate the cognition system of individual drivers. Four FIS are defined for each decision-making process: car-following, lane-changing, amber-running and right-turn filtering. A field observation study is conducted to calibrate membership functions of input factors, model parameters, and to validate the proposed FCA model. Simulation experiments of a two-lane system show that the proposed FCA model is able to replicate decision-making processes and estimate the effect on overall traffic performance.*

1 INTRODUCTION

Cities around the world are looking for new answers to deal with perennial road traffic problems, such as traffic congestion and safety. In recent years, much attention is being paid to road intersections controlled by signal, as signalized intersections form one of the most common bottlenecks in the urban traffic system. This is because intersections are places where different traffic movements come into conflict.

Microscopic simulation approaches are often applied to model the complex vehicle movements at signalized intersections by simulating the individual road user's decision-making process in car-following and lane-changing operations. A number of simulators have been developed at microscopic level, such as SIDRA, VISSIM and CORSIM (Al-Ghandour et al., 2011; FHWA, 2014; PTV Vision, 2014). Several software packages, such as VISSIM, are able to model the individual road user's perception and decision-making process (PTV Vision, 2014). However, the applications of most current models and software are essentially for capacity assessment. To estimate conflicts based on microscopic simulation, a software package called SSAM was developed by Federal Highway Administration (FHWA, 2011). In essence, SSAM relies on simulation packages (such as VISSIM) which require calibrations inherent to the simulation packages. SSAM is shown to provide acceptable results for rear-end conflicts. However, it is found that SSAM tends to over-estimate the occurrences, and under-estimate the severity, of rear-end and lane-changing conflicts. SSAM is also found to over-estimate the severity of crossing conflicts (Chai and Wong, 2015).

Cellular Automata (CA) models, which are generally more computationally efficient than other microscopic simulation models, are often applied for modeling and simulating complex scenarios (Nakatani, 1993; Schreckenberg et al., 1995; Lu et al., 2011; Mallikarjuna and Rao, 2009). In CA models, roads are gridded into a series of cells. Each cell has limited space, either being occupied by a road user or not occupied. The road user's position and speed are represented in discrete values and are updated according to analyst-defined transition rules (Szeto and Jiang, 2011). CA models have several advantages for modeling vehicle movements at signalized intersections compared to other microscopic simulation models. Based on flexible transition rules, it is becoming easier to use CA models to simulate microscopic traffic behavior accurately while leveraging on parallel CA computation (Kwon, 2000; Clarridge and Salomaa, 2010; Luo et al., 2013). Moreover, with flexible transition rules, CA models allow analysts to define decision-making rules for individual vehicles. With the high computational efficiency, CA models allow analysts to simulate vehicle movements under real-time traffic conditions (Horng, 2014).

However, upon reviewing current CA models, several limitations have been identified. In conventional CA models, deterministic or stochastic, control strategies of vehicle movements are not realistic enough. In deterministic models, transition rules are inherently fixed. However, in reality, decisions vary between different drivers. In stochastic

models, probability parameters are involved to determine vehicle movements, such as amber running and acceleration or deceleration. As stochastic models entail more (random) variables, many more simulation runs are required compared to deterministic models. Moreover, conventional probability distributions alone cannot adequately represent decision-making process of each driver.

In recent years, artificial intelligent techniques are applied to improve traffic models (Adeli and Hung, 1995; Adeli and Karim, 2005; Karim and Adeli, 2002). Fuzzy logic (FL) theory can be applied to overcome the limitations of cellular automata models (Sama and Adeli, 2000ab; Placzek, 2012; Forero Mendoza et al., 2014). Compared to traditional logic with exact and fixed solution, fuzzy logic contains uncertainty and approximation which are well suited to represent human factors in driving (Boutalis et al., 2013; Chiou and Huang, 2013; Smith and Nguyen, 2007; Jahani et al., 2014). Incorporation of fuzzy control into micro-simulation is able to reduce overall cognitive dissonance in the modeling process (Dell'Orco and Mellano, 2013; Kodogiannis et al., 2013; Siddique and Adeli, 2013; Zhang and Ge, 2013). Moreover, compared to other simulation models, linguistic terms are used to describe the environment and responses (Adeli and Karim, 2000; Adeli and Jiang, 2003; Karim and Adeli, 2002; Yan and Ma, 2013ab). These linguistic terms to describe drivers' cognitions, such as perception, intention and attitude. In this way, decision-making procedure of the individual driver can be modelled in a very clear and straight-forward way (Rigatos, 2013; Rokni and Fayek, 2010).

In previous studies, fuzzy rules have been applied to describe driving behavior of vehicles (Wu et al., 2000). Drivers' behavior in the dilemma zone at signalized intersections has also been modeled by fuzzy sets (Hurwitz et al., 2012).The concept of FCA has been developed and applied to several areas such as image processing and fire spread simulations. Those models are found to be more intelligent than traditional CA models in responding to environmental changes (Mraz et al., 2000; Patel et al., 2013). However, few studies have been found to apply FCA in simulating microscopic vehicle movements and interactions (Gong and Liu, 2010). Yeldan et al. (2012) incorporated fuzzy sets into continuous CA model to simulate different vehicle movements along freeways in which fuzzy membership functions are developed in car-following and

lane-changing rules. However, as only macroscopic outputs are analyzed in that study, the impact of involving fuzzy sets into CA models is still not clear. Moreover, as most current traffic FCA models focus on speed control of vehicles, dynamic decision-making of road users such as disobeying signal control, gap acceptance, movement directions, lane usage and behavior when conflict occurs has not been well-studied so far.

This study develops a FCA model, which incorporates FL and CA to simulate vehicle movements at signalized intersections. The outline of this paper is as follows. In Section 2, Fuzzy Interface Systems (FIS) are defined to model vehicle movements. Section 3 describes calibration procedures for membership functions. Section 4 introduces FCA model development, including embedding FIS with CA model and developing the improved CA model. Model validation at macro and microscopic levels is also introduced in Section 5. In Section 6, model performance is tested by simulation experiments. The paper ends with discussions of advantages and limitations of the proposed FCA model and conclusions.

2 FUZZY INTERFACE SYSTEMS (FIS)

2.1 Forward movements

Two FIS (F_1 and F_2) are developed to determine φ_a (if accelerate) or φ_d (if decelerate) at the next time step based on inputs from the current time step (definitions of all symbols can be found in table A.1 in the appendix). For each vehicle, the acceleration φ_a depends on the following variables: current velocity (v_n) of the subject vehicle; relative velocity between leading and subject vehicle ($v_{n+1} - v_n$); front gap (g_n); distance to stop-line (DS) and signal timing (t^s). Linguistic terms used in the fuzzy sets are summarized in Table 1 (Jiang and Adeli, 2003; Adeli and Jiang, 2006; Jiang and Adeli, 2008; Sun, 2012; Aghabayk and Forouzideh, 2013). The first set of fuzzy rules (F_1) estimate the impact of leading vehicle by including the first three inputs (v_n, $v_{n+1} - v_n$, and g_n), as shown in Figure 1. Inputs related to signal control (DS and t^s) are separated as the second fuzzy set of rules. v_n is also included in F_2 as drivers do consider their current velocity when making decisions controlled by traffic signal.

The reason of developing two fuzzy set of rules is to provide different movement strategy for vehicles before and

Table 1
Fuzzy set terms in forwarding model.

Current velocity (v_n)	Relative velocity ($v_{n+1} - v_n$)	Front gap (g_n)	Distance to stop-line (DS)	Signal timing (t^s)	Driver's response (φ_a, φ_d)
High	Opening fast	Far	Far	Just became green	Strong acceleration (SA)
Normal	Opening	Medium	Medium	About to become amber	Light acceleration (LA)
Slow	About zero	Close	Close	Amber	No action (NA)
	Closing			Just became red	Light deceleration (LD)
	Closing fast			About to become green	Strong deceleration (SD)

after the stop-line. Vehicles before the stop-line are controlled by both F_1 and F_2 while vehicles after the stop-line are controlled only by F_1. Suppose O_1 and O_2 are the outputs of F_1 and F_2, respectively, which means given a certain set of inputs, the fuzzy rule in F_1 will lead to decision O_1 and the fuzzy rule in F_2 will lead to O_2. Then, the final driver response O (before stop-line) is computed as $O = \min(O_1, O_2)$.

The target decisions are driver's response: strong acceleration (SA); light acceleration (LA); maintain current speed with no action (NA); light deceleration (LD); and strong deceleration (SD) (Celikoglu, 2013). Fuzzy rules are created based on common sense to describe the willingness of acceleration or deceleration of each driver, as summarized in Tables 2 to 5. In F_2, when the signal is about to turn amber or during amber phase, two drivers' responses are defined for drivers who have decided either to cross or to stop before the stop-line. The decisions (stop or cross) are computed based on a set of fuzzy rules introduced in Section 2.2.

2.2 Stopping propensity before stop-line

The observations of 6 intersection were made during weekdays (MON, TUE, and WED) at 6:00-7:00 pm during peak hour. Locations of the survey sites are described in Table A.2. In total, 86,972 vehicles (50,325 cars, 21,342 heavy vehicles and 15,305 motorcycles) were observed using automatic vehicle detection and tracking algorithms (Malinovskiy et al., 2009; Chai and Wong, 2013a). Position, velocity, neighboring traffic conditions, as well as signal phases of each tracked vehicle were recorded. Among the 6 observed intersections, No. 1 to No. 4 are used for calibration

and No. 5 and No. 6 are used for validation. Automatic vehicle tracking is applied to record vehicle trajectories and velocity profiles (Chai, 2015).

Stopping propensity of different vehicle types is simulated in the proposed CA model. Drivers approaching a signalized intersection when signal is about to turn amber or in amber phase have to decide whether to cross or to stop before the stop-line. The variables include distance to stop-line (DS) in meters, moving velocity (v_n) in km/h, and time to the onset of red phase (t^r) in seconds. Stopping probabilities are modeled by a binary logistic regression (Hurwitz et al., 2012):

$$p_s^n(stop) = \left(1 + e^{-\beta_n}\right)^{-1} \qquad (1)$$

where p_s^n is the stopping probability of the nth vehicle, β_n is a linear combination of the three input factors, as: $\beta_n = a + b_1 * DS_n + b_2 * v_n + b_3 * t_n^r$. As the three inputs are fuzzy memberships, the above equation is calibrated based on field observations at 4 intersections as the following equations.

$$p_s^n(car) = [1 + \exp\{-(-1.02 + 0.129DS_n - 0.54v_n - 0.23t_n^r)\}]^{-1} \qquad (2)$$

$$p_s^n(heavy\ vehicle) = [1 + \exp\{-(-2.61 + 0.17DS_n - 0.31v_n - 0.27t_n^r)\}]^{-1} \qquad (3)$$

$$p_s^n(motorcycle) = [1 + \exp\{-(2.59 + 0.08DS_n - 0.72v_n - 0.18t_n^r)\}]^{-1} \qquad (4)$$

2.3 Lane-changing movements

At signalized intersections, vehicles change lanes very often along the approach and departure lanes. Two types of lane-changing are observed: Type (I) is to change to (straight-through or turning) approaching lanes at the corresponding to desired departure direction; Type (II) is to move to a more convenient lane (with shorter queue or being less congested). In the proposed lane-changing fuzzy model (F_3), input factors include current velocity (v_n), front gap (current lane) (g_n), front gap (target lane) (g_n^t), rear gap (target lane) ($g_n^{t,rear}$), rear vehicle velocity (current lane) ($v_n^{t,rear}$). To model Type (I) lane-changing, an additional input, distance to stop-line (DS), is involved (Sun and Kondyli, 2010). That is, with the same velocity and gaps, if the subject vehicle is closer to the stop-line, the probability of making Type (I) lane-changing will be higher.

2.4 Gap acceptance of right-turn filtering

In Singapore, which is a left-hand driving country, most signalized intersections are controlled with permissive right-turn signal control. During straight-through green phase, the right-turn vehicle needs to wait for appropriate gaps in opposing straight-through traffic stream to make a right-turn (Wang and Abdel-Aty, 2007). There is a risk of collision if the right-turn vehicle moved without enough gaps or when
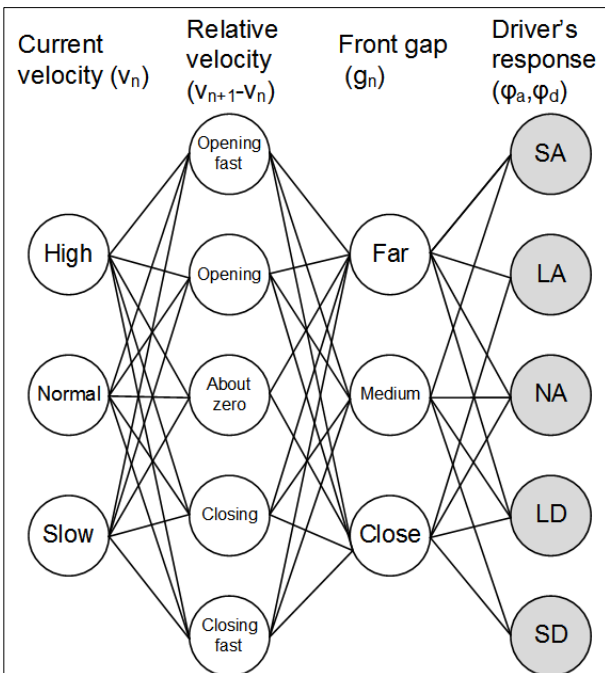

Figure 1 Structure of F_1 (Car-following)

Table 2
1st set of fuzzy rules (F_1).

	Current velocity (v_n)	Relative velocity ($v_{n+1} - v_n$)	Front gap (g_n)	Driver's response (φ_a, φ_d)
1	Slow	Opening fast	Far	SA
2	Slow	Opening fast	Medium	SA
3	Slow	Opening fast	Close	LA
4	Slow	Opening	Far	SA
…	…	…	…	…
42	High	Closing	Close	SD
43	High	Closing fast	Far	LD
44	High	Closing fast	Medium	SD
45	High	Closing fast	Close	SD

Table 3
2nd set of fuzzy rules (F_2).

	Current velocity (v_n)	Distance to stop-line (DS)	Signal timing (t^s)	Driver's response (φ_a, φ_d)
1	Slow	Far	Just became green	SA
2	Slow	Far	About to become amber	SA/NA
3	Slow	Far	Amber	SA/LD
4	Slow	Far	Just became red	LA
…	…	…	…	…
42	Fast	Close	About to become amber	NA/SD
43	Fast	Close	Amber	NA/SD
44	Fast	Close	Just became red	SD
45	Fast	Close	About to become green	LD

Table 4
3rd set of fuzzy rules (F_3).

	Current velocity (v_n)	Front gap (current lane)	Front gap (target lane)	Rear gap (target lane)	Rear velocity (target lane)	Driver's response)
1	High	Far	Far	Far	High	No
2	High	Far	Far	Far	Normal	No
3	High	Far	Far	Far	Slow	No
…	…	…	…			…
74	Fast	Close	Far	Far	Medium	Yes
75	Fast	Close	Far	Far	Slow	Yes
…	…	…	…			…
243	Slow	Close	Close	Close	Slow	Yes

Table 5
4th set of fuzzy rules (F_4).

	Current velocity (v_n)	Opposing velocity	Opposing gap	Driver's response
1	High	Far	Far	Yes
2	High	Far	Medium	Yes
3	High	Far	Close	No
…	…	…	…	…

the opposing straight-through vehicle(s) travelled too fast. Therefore, a set of fuzzy rules (F_4) is developed for right-turn vehicles to decide whether to stop or to move according to velocity and position of subject and opposing vehicles. Input factors are current velocity (v_n), velocity of the opposing vehicle (v_n^o), and gap provided by opposing straight flow (g_n^o).

3 MEMBERSHIP FUNCTIONS

In this study, membership functions of input factors are derived based on field observations. Firstly, it is assumed that membership functions are triangular and trapezoidal for better computational efficiency (Groeger, 2002; Yeldan et al.,

2012). According to field observation, the 85th percentile of maximum acceleration and deceleration rates are $4m/s^2$ and $-3m/s^2$ with mean acceleration and deceleration rates being $2m/s^2$ and $-2.5m/s^2$. As five linguistic terms are used to describe driver responses in F_1 and F_2 (car-following), as in Table 1, applied membership function is derived as Figure 2a. μ is the membership degree with different values of output factors. Driver responses in F_3 (lane-changing) and F_4 (right-turn filtering) are 0-1 decisions.

Membership functions of input factors for each fuzzy set are derived according to observed vehicle movements, membership functions of driver responses, and defined fuzzy rules. It is assumed that driver responses can be achieved using input factors and defined fuzzy rules. In this study, fuzzy rules and sets are defined to describe driving behavior. Moreover, relationship between input factors and driver

(a) Driver response classified in 3 groups

(b) Frequencies of front gap with deceleration decision

(c) Frequencies of front gap with no action decision

(d) Frequencies of front gap with acceleration decision

(e) Membership functions of front gap

(f) Driver response classified in 5 groups

(g) Membership functions of relative velocity

*SD: Strong Deceleration
LD: Light Deceleration
NA: No Action
LA: Light Acceleration
SA: Strong Acceleration

Figure 2 Structure of F_1 (Car-following)

responses can be obtained from field observation. As average perception-response time (PRT) at signalized intersections is set as 1s in this study, driver response at each time shall be determined by traffic and signal conditions 1s earlier. Using back-stepping technique, membership functions of input factors are derived. Detailed calibration processes are described in following example.

The methodology to calibrate membership functions of each input consists of three steps, as shown in Figure 2. First, vehicle decisions are classified into several groups based on the number of linguistic terms of the input factor. For example, in F_1, front gap is described in three linguistic terms (Close, Medium, Far). Driver responses (velocity change) are also classified in three groups (Deceleration, No action, Acceleration). If the acceleration rate is larger than $2.5m/s^2$, the driver decides to accelerate while if deceleration rate is smaller than $-1.5m/s^2$, the driver decides to decelerate. Otherwise, it is assumed that no obvious action is made by the driver. Observed movement characteristics (front gap and acceleration/deceleration rates after 1s) are also classified in three groups. As average and maximum acceleration and deceleration rates are known from field observations, membership function of velocity change can be plotted as shown in Figure 2a. Assume the other factor (relative velocity) follows a normal distribution. When front gap is Close, velocity change will be deceleration. Therefore, according to membership functions and fuzzy rules, driver decision can be classified in three ranges, as shown in Figure 2a. Figures 2b to 2d shows the relationship between relative gap and frequencies of making each decision. Membership function of this factor is then calibrated as Figure 2e. Other input factors are calibrated using a similar method. Another example is to calibrate membership functions of relative velocity, which is described in five linguistic terms. Driver response in acceleration and declaration is classified into five groups, as shown in Figure 2f. According to field observation, membership function is calibrated as Figure 2g.

Fuzzy memberships of F_3 and F_4 are also calibrated based on similar approach. Driver responses (lane change and filtering) are also classified in two groups (Yes and No). Histograms of corresponding input factors of the two groups are therefore used to derive two membership functions for the most safe and hazardous situations. The median membership function is then derived as the submission of all membership functions for any input value is 1.

4 FCA MODEL DEVELOPMENT

4.1 CA model embedded with FIS

In the proposed FCA model, fuzzy sets introduced in Section 2 are embedded with CA model by using the Fuzzy Logic Toolbox of Matlab (Mamdani fuzzy interface). By using the 'Evafis' function in Matlab, response of each driver at each time step will be computed according to dynamic traffic flow and signal timing. The output response will be
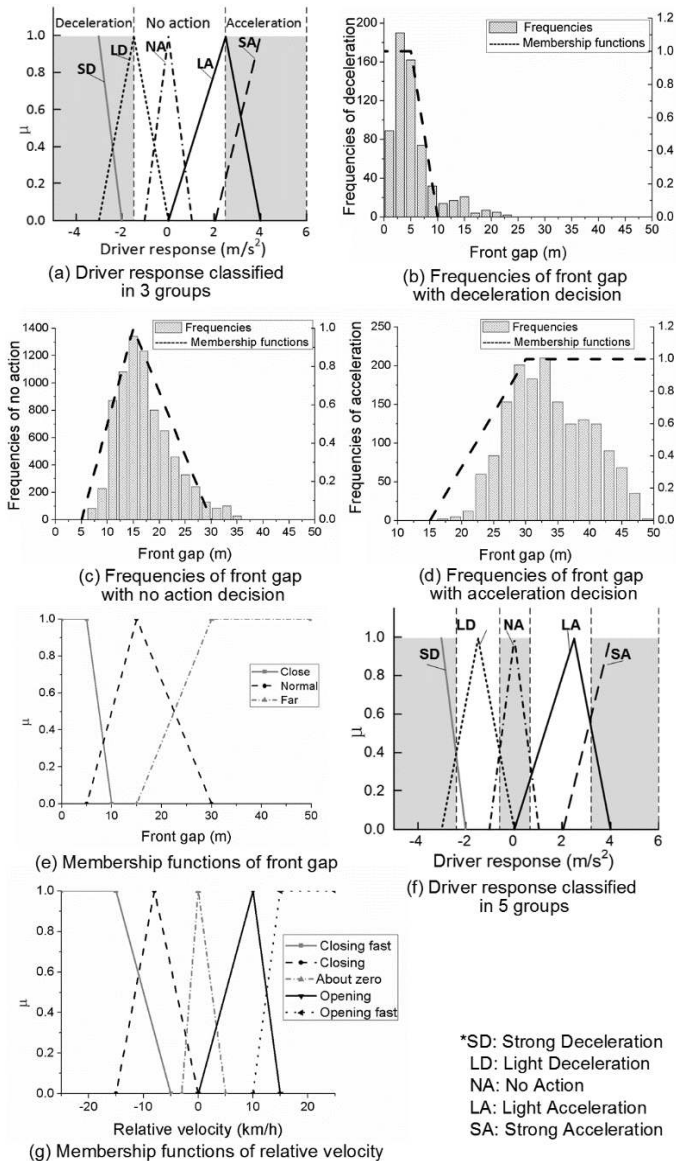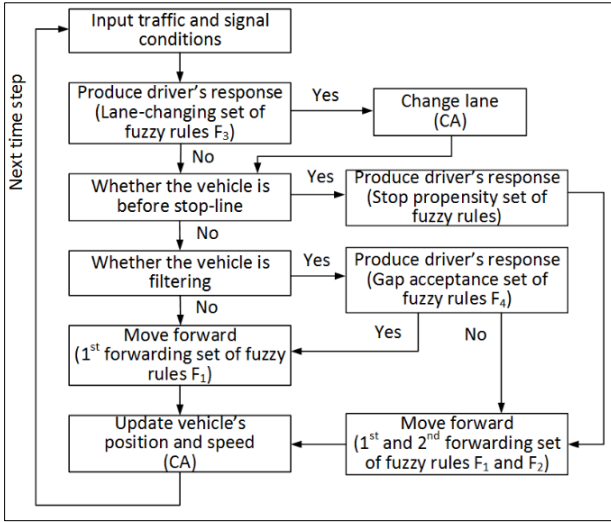
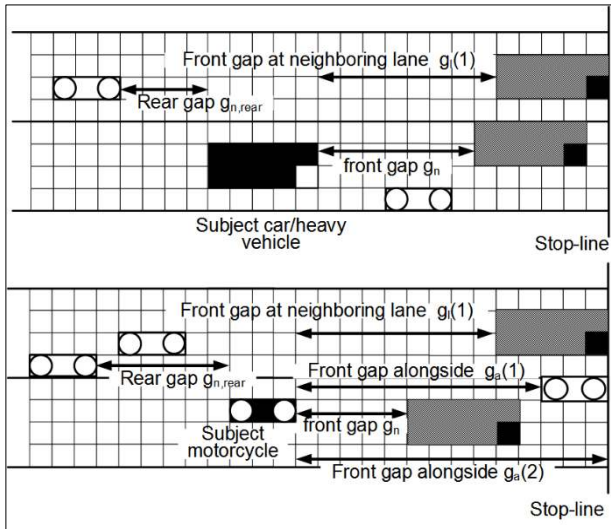**Figure 3** Structure of the proposed FCA model

Figure 4 Front and rear gaps of different subject vehicle types

used to provide vehicle velocity and position at the next time-step, as shown in Figure 3. Centroid defuzzification method is used.

4.2 Cell space

A smaller cell size of 0.9 m by 0.9 m square is chosen to simulate mixed traffic flow in the proposed FCA model. Lane width is taken as 3.6 m therefore a lane is constituted by 4 rows of cells. According to physical sizes of different vehicle types, a car occupies 5×2 cells, a heavy vehicle occupies 13×3 cells, while a motorcycle takes 3×1 cells. A leading cell (highlighted as the black cells in Figure 4) is defined for each vehicle to represent its exact position. Definition of front and rear gaps for subject vehicle is shown in Figure 4. If subject vehicle is a motorcycle, two additional gaps (front gap alongside for both sides) are computed to

allow motorcycles to move laterally within the same lane. The leading cell of each turning vehicle can only occupy cells of the turning path.

In this study, a cross-intersection with typical geometric design is simulated. Each intersection approach contains four lanes, one exclusive left-turn storage lane, two exclusive straight-through lanes, and an exclusive right-turn storage lane.

4.3 Key features in the proposed FCA model
(i) Multiple cell states

In this model, three movements are pre-assigned to each vehicle to represent straight-through, left-turn and right-turn vehicles. For the simulation, each cell (exclude the boundary cells representing road boundaries) could be in one of five possible types of states, including being occupied by straight-through /right-turn or left-turn vehicle, not occupied, or cannot be occupied due to minimum gap clearance.

(ii) Minimum Gap Clearance

Minimum gap clearance in the proposed model includes front and lateral gap. According to the observation study (introduced in Section 2) of over 450 stand-still vehicles at 4 different intersection approaches, the minimum gap in front of cars and heavy vehicles is around 2.5m. Minimum gap between motorcycles is around 1m. Therefore, rear-end gap clearance is set as 3 cells (2.7m) for cars and heavy vehicles and 1 cell (0.9m) for motorcycles. Along-side gap clearance is not applied at approach and departure lanes and defined as 1 cell (0.9m) at intersection-box. In certain conditions, target cell is defined as cannot be occupied due to minimum gap clearance.

(iii) Start-up lost time and right-turn waiting area

With a sample of 50 platoons of vehicles, average start-up lost times of the first three vehicles are 1.50s, 1.08s, 0.85s. In the improved CA model, start-up lost time is added by postponing the start of the first 2 vehicles each for 1 time step (of 1s). Right-turn waiting areas are widely used in Singapore and are also featured in the studied approach. Right-turn vehicles can move forward and wait in the waiting area during the full green phase. Vehicles moving to waiting area have to stay clear of opposite straight-through vehicles.

4.4 Modified NaSch model for forwarding movements

The forwarding rules in this study are modified based on a multi-lane NaSch model (Schreckenberg et al., 1995; Rickert et al., 1996). Suppose, x_n and v_n denote the position in forwarding x direction and velocity of the leading cell, respectively, of the nth vehicle. Then, $d_n = x_{n+1} - x_n$ is the space headway in between the nth vehicle and the $(n+1)^{th}$ vehicle in front of it at time t. Front gap is therefore defined as $g_n = d_n - b - g_t$, where b is number of cells occupied by front vehicle in forwarding direction and g_t is the applied gap tolerance. At each time step t→t+Δt, the arrangement of each vehicle is updated in parallel according to the following rules; in all instances, v_n is rounded to integer value.

Rule 1: Acceleration.

If $v_n < v_{max}$, the velocity of the nth vehicle is increased by φ_a (computed from F_1 and F_2 as introduced in Section 2), but v_n remains unaltered if $v_n = v_{max}$ (subject to Rule 3), i.e.

$$v_n \rightarrow \min(v_n + \varphi_a \times \Delta t, v_{max}) \qquad (5)$$

Rule 2: Deceleration (due to other vehicles).

At green or amber phase:

If $g_n/\Delta t \leq v_n$, which means if subject vehicle continues moving, it will 'over-run' the front car at next time step. Therefore, the velocity will be reduced by φ_d to $\frac{g_n}{\Delta t} - \varphi_d \times \Delta t$;

At red phase: Assume DS is the distance between vehicle and stop-line.

If $\min(g_n, DS)/\Delta t \leq v_n$, which means if subject vehicle continues moving, it will 'over-run' the front car or stop-line at next time step, the velocity of the nth vehicle is reduced to

$$v_n \rightarrow \min\left(v_n, \frac{g_n}{\Delta t}, \frac{DS}{\Delta t}\right) - \varphi_d \times \Delta t \qquad (6)$$

Rule 3: Randomization.

If $v_n > 0$, the velocity of the nth vehicle is decreased randomly by $v_r = 1$ with probability p_r but v_n does not change if $v_n = 0$, whereby p_r is selected as 0.2 according to field observation (Chai, 2015).

$$v_n \rightarrow \max((v_n - v_r), 0) \text{ with probability } p_r \qquad (7)$$

Rule 4: Vehicle movement.

Each vehicle is moved forward according to its new velocity determined in Steps 1-3, i.e.,

$$x_n \rightarrow x_n + v_n \times \Delta t \qquad (8)$$

5 MODEL VALIDATION

As introduced in Section 2.2 the proposed FCA model is validated by comparison with observed traffic data at two signalized intersections (Sites No. 5 and No. 6) on both macroscopic and microscopic levels.

5.1 Average travel time

To investigate the model validity, a simulation using observed vehicle characteristics including traffic density and arrival distribution is performed for the two sites (Sites No. 5 and No. 6). After 20 signal cycles, average travel time from observation and simulation are shown in Table 6 (Chai, 2015). A total number of 390 vehicles are observed and simulated. Travel time is clocked from 150m to stop-line until 150m after entering departure lane, using vehicle front

bumper as reference point. The results show very good agreement. Therefore, CA model is confirmed to be able to replicate the realistic signalized intersection traffic at the macroscopic level.

5.2 Trajectories

Simulated vehicle trajectories are compared against field data from Site No. 6 (Jurong Town Hall Road and Jurong East Ave 1). In order to generate the same initial headway distribution, observed arrival distribution and initial vehicle density are used to generate vehicles in the simulation. After the onset of signal cycle, a total of 307 vehicles (163 cars, 65 heavy vehicles and 79 motorcycles) captured from field observations along four approach lanes are generated in the simulation with arrival time and velocity at the instant the vehicle enters the cell space. Figure 5 shows examples of
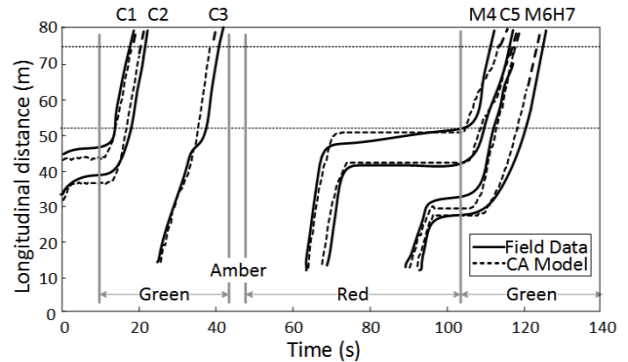
(a) (Lane 2, C: Car, H: Heavy vehicle; M: Motorcycle)
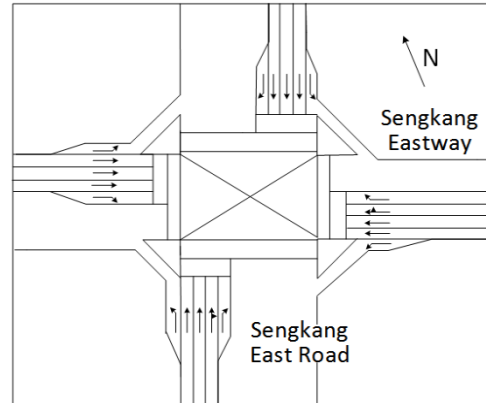
(b) Intersection layout of survey site

Figure 5 Trajectories and intersection layout (Site No. 5)

Table 6
Comparison of traffic delay (s) from CA simulation and field data

	Site No. 5			Site No. 6		
	Cars	*Heavy vehicles*	*Motorcycles*	*Cars*	*Heavy vehicles*	*Motorcycles*
Field data	97.48	101.87	74.39	109.85	122.37	92.53
CA simulation	94.3	103.98	76.63	115.61	118.63	95.38
Error	3.4%	−2.0%	−2.9%	−5.0%	3.2%	−3.0%

comparison between trajectories (longitudinal distance) from CA model and field data in Lane 2.

An error assessment for each pair of vehicle positions at each time step is also done for a sample of 114 vehicles. The root Mean Square Error (RMSE) and Mean Percentage Error (MPE) are relatively small and the deviations (around 5%) between the simulation and field data are acceptable which
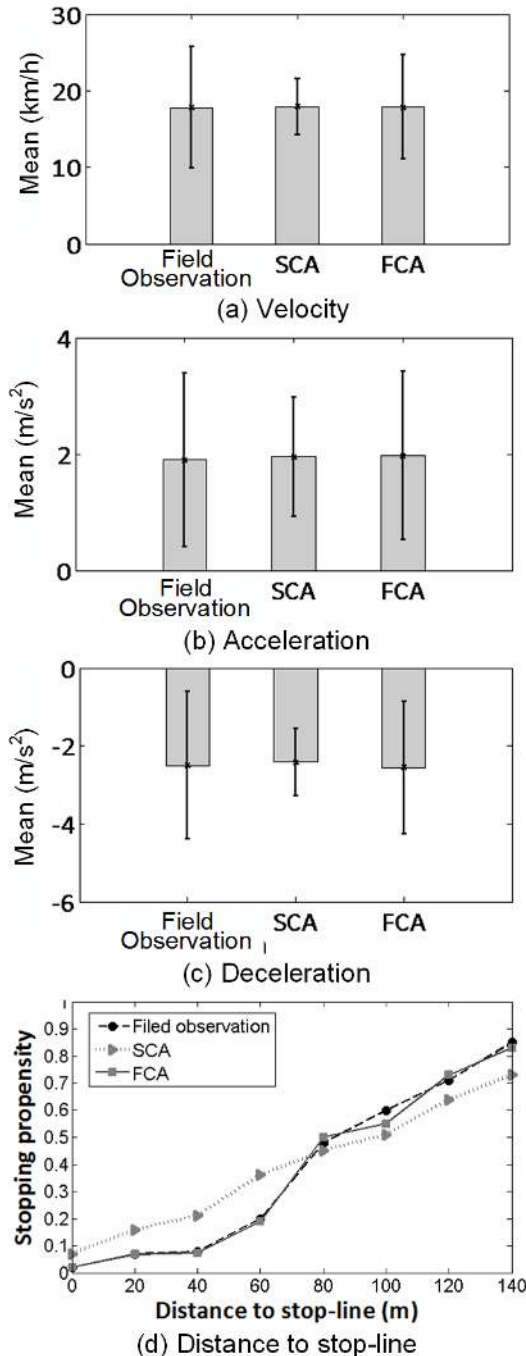

Figure 6 Comparison between FCA model, SCA model and field observation

present evidence that the CA model can well describe traffic dynamics at the microscopic level.

5.3 Comparison between FCA and CA models

To further validate the proposed FCA model, distributions of several movement characteristics are compared for simulation from FCA, stochastic CA (SCA) model and field observation, as shown in Figure 6 (Chai, 2015). Velocity and acceleration rates shown in these two figures are based on a 3-term moving average (Chai, 2015). FCA model and observation profiles are in close agreement.

6 SIMULATION EXPERIMENT

Microscopic simulation experiments of car-following and lane-changing are conducted to test the proposed vehicle control logic in this study. Two straight-through lanes at the intersection approach, as shown in Figure 7, are selected for this experiment. With the geometric layout of the case intersection as shown in Figure 7, Lanes 2 and 3 are selected for the experiment. The system length is 360m (400 cells) including 150m before stop-line and 210m after the stop-line. In this two-lane system, each straight-through vehicle can choose whether to change to the other lane before or after stop-line. To evaluate microscopic car-following and lane-changing movement, a subject vehicle is assigned which arrives at the start point of intersection approach (150m before stop-line) at 12s into the onset green phase. Therefore, if the subject vehicle is moving forward with an average speed higher than 30km/h, it is able to cross the stop-line before the onset of amber.

Car-following and lane-changing are affected by traffic condition as well as signal control. Therefore, four factors are involved in the experiment: (1) Traffic volume in the subject lane, vol_s, (2) traffic volume along neighboring lane, vol_n, (3) signal phase, and (4) being before or after the stop-line. A total of 32 simulation scenarios are conducted, with different traffic volumes for each straight-through lane varying from 100 pcu/h (passenger car unit per hour; saturation degree=0.24) to 400pcu/h (saturation degree =0.96). In Scenarios 1-16, only the subject vehicle is allowed to make lane-changing while all other vehicles are forbidden to change lane. In Scenarios 17-32, all simulated vehicles are free to make lane-changing.
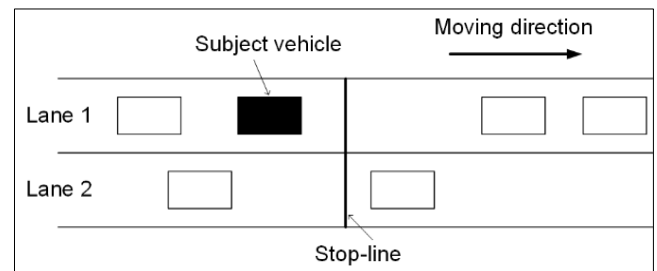

Figure 7 Studied two-lane system

To determine input number of vehicles for each vehicle type, vehicle composition is applied as Car: Heavy vehicle: Motorcycle=3:1:1 according to field observation. Passenger Car Equivalent (PCE) values calibrated in Singapore are used for converting turning (Kok and How 1992) and straight-through vehicles (Pang and Meng 1990). Signal cycle is 100s, green time assigned for each movement direction is 30s for straight through green phase (with permissive right-turn) and 15s for exclusive right-turn green phase. The simulation runs for 30 signal cycles, approximately 1 hour. Simulation outputs are calculated according to average results of 5 runs as suggested by Zheng et al. (2012).

To access the numerical simulation outputs, 5 evaluation measurements are selected as: (1) travel time, t^t, (2) time and position of the 1st actual lane-changing, t_c, p_c, (3) average willingness of lane-changing before change lane, $\bar{w}_c$ (4) frequency of lane-changing at each lane $\bar{f}_c^1$, $\bar{f}_c^2$ and (5) frequency of lane-changing per vehicle during green and amber-red signal phase $\bar{f}_c^g$, $\bar{f}_c^{ar}$. Among them, measurements 1-3 are for the subject vehicle, while 4-5 are average performance for overall traffic flow.

Simulation results are summarized in Figures 8 and 9. When lane-changing is permitted for subject vehicle only, lane-changing behavior of the subject vehicle is observed in 9 scenarios, as the 9 symbols plotted in Figures 8b and 9c. (vol_s, vol_n) of the 9 scenarios are shown in different x-value and symbol type. However, when lane-changing is permitted in all scenarios, lane-changing of subject vehicle is only observed in 4 out of 16 scenarios, when $(vol_s, vol_n) = (300,100)$; $(300, 200)$; $(400, 100)$; $(400,200)$ pcu/h. Times and positions of lane-changings among the four scenarios show that bigger difference in traffic volumes between subject and neighboring lanes will result in earlier lane-changing. Moreover, when all vehicles are able to change lane, traffic volumes are balanced between the two lanes.

Overall, the simulation results of Figures 8 and 9 indicate that the proposed FCA model is able to simulate vehicle responses under various traffic conditions and microscopic car-following and lane-changing behavior of vehicles. In addition, several conclusions can be observed according to the simulation results.

1) From Figures 8 and 9, whether free lane-changing is allowed or not, travel time of subject vehicle (in lane 1) is affected by traffic volume in both subject lane and neighboring lane. However, it is found that when all simulated vehicles are allowed to change lane, the impact of traffic volume on the neighboring lane is higher.

According to Figure 9, if lane-changing is allowed, more lane-changings are observed from lanes with higher traffic volume to the lane with lower traffic volume. The two-lane system is found to be able to self-organize itself to achieve a more balanced condition through lane-changing, when all vehicles are free to change lane.

(a) Travel time, t^t

(b) Time of the 1st actual lane-changing, t_c

(c) Position of the 1st actual lane-changing, p_c

(d) Average willingness of lane-changing before change lane, w_c

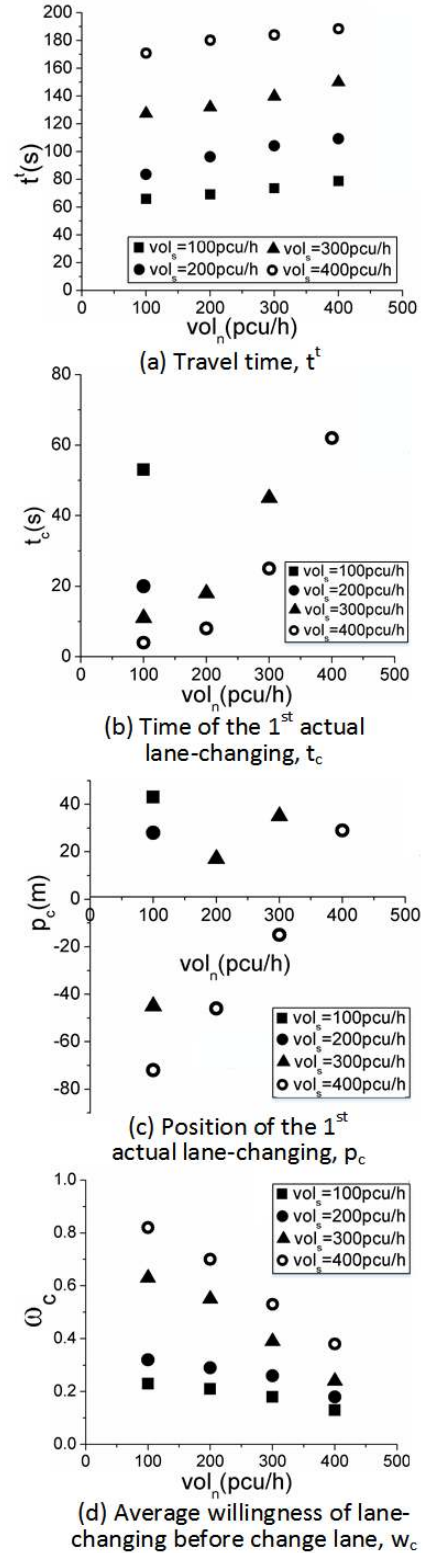**Figure 8** Numerical results under various traffic conditions (Scenarios 1-16: lane-changing permitted for subject vehicle only)

(a) Travel time, t^t

(b) Average willingness of lane-changing before change lane ω_c

(c) Frequency of lane-changing in lane 1, $\bar{f}_c^1$

(d) frequency of lane-changing in lane 2, $\bar{f}_c^2$

(e) Frequency of lane-changing per vehicle during green, $\bar{f}_c^g$

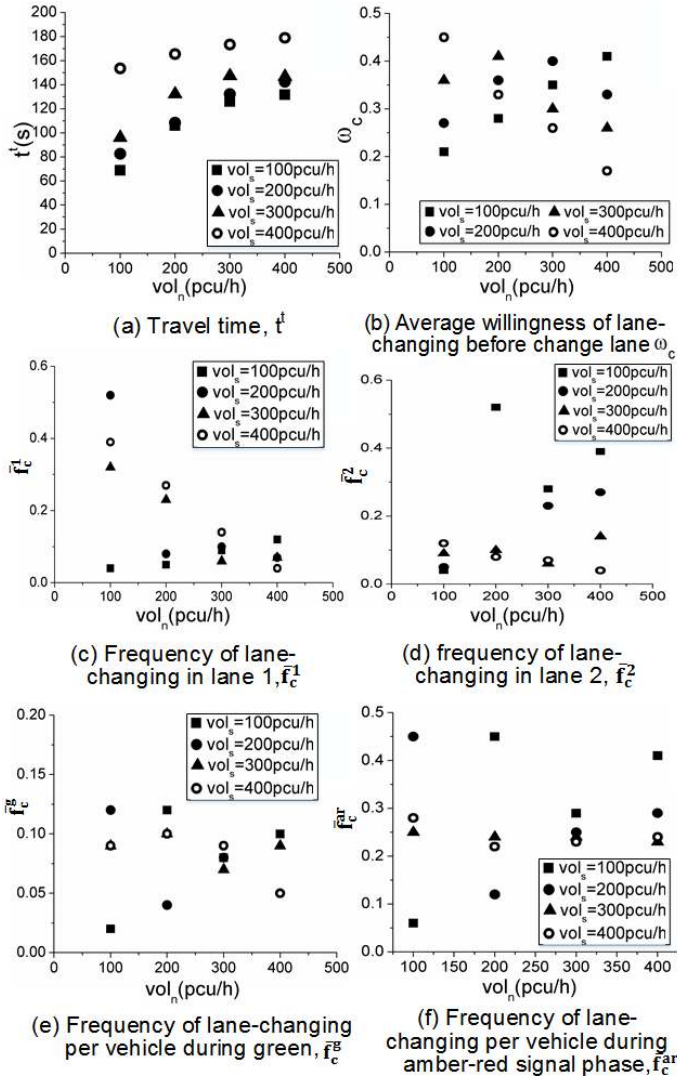(f) Frequency of lane-changing per vehicle during amber-red signal phase, $\bar{f}_c^{ar}$

Figure 9 Numerical results under various traffic conditions (Scenarios 17-32: free lane-changing)

2) In Figure 9, lane-changing frequencies before the stop-line during green signal phase are found to be much fewer than during amber and red signal phases, especially in scenarios with higher traffic volume. This phenomenon has two causes: First, most vehicles which change lane before stop-line is to enter a shorter queue. Therefore, most lane-changing occurrences are during amber and red phase. Second, vehicles usually travel with higher velocity during green phase which deters lane-changing.

7 CONCLUSIONS

It is without doubt that the approach of combining Fuzzy Logic and Cellular Automata is able to involve decision-making and cognitions of individual driver in microscopic simulation. In this study, an improved FCA model is developed by applying FIS and membership functions to generate drivers' responses that are embedded into the CA model. Four different fuzzy sets are designed to simulate driver's response to signal timing changes, surrounding vehicles in front and rear along the same lane, neighboring lane and from opposing approach during filtering. The fuzzy sets are embedded in CA model to simulate mixed traffic flow at signalized intersections.

The membership functions and more variables in the proposed FCA model may reduce the overall computational efficiency compared to the CA models without fuzzy logic. However, with improvements involving decision-making process, the FCA model is able to model decision-making of each driver and estimate dynamic driver's responses. Simulation results of case study demonstrated that this approach is able to assess lane-changing and right-turn filtering behavior. Moreover, compared to most existing software, CA models have high computational efficiency. The proposed FCA model can also be embedded in CA models for application in safety assessment (Chai and Wong, 2015).The loss in accuracy by discretization is not tackled in this research, hence the issue of (improvement/loss) of accuracy is not covered in this paper, but it is certainly a worthy research aspect in its own right.

The emphasis in the present paper is that fuzzy logic contains linguistic terms which can be applied to model cognitions of drivers in their decision-making process. Involving fuzzy logic allows us to model driving behavior from human cognitions and attendant decision making. From the case study, impacts of intersection design and traffic factors on the microscopic driver behavior are estimated realistically. Apart from the intersection layout tested in this study, the FCA model can also be applied to estimate driver behavior in various intersection layouts, signal sequences and traffic conditions, and this shall be of great value in intersection design.

The proposed FCA model has great potential to be applied in several aspects. It shall help researchers and authorities to estimate driver's responses under various traffic conditions. As the design of signalized intersection entails combination of control strategies under dynamic traffic demand, such micro-simulation model provides a user-friendly tool to estimate microscopic vehicle behavior, and hence the impacts of the particular design. Moreover, more improvements can be made to refine and extend the applications of the proposed FCA model in future work. First, the effect of interaction between vehicles and pedestrians can be modelled by creating a heterogeneous FCA model involving both vehicles and pedestrians. Moreover, driving behavior is affected by individual characteristics, such as age, gender, which can be taken into account. Furthermore, some drivers are more risk-averse/affine compared to others. Their attitudes affect their decisions, such as stop/go decision and reaction of neighboring vehicles. By calibrating membership functions and weight factors, the FCA model can thus further improve simulation of heterogeneous drivers' behavior.

ACKNOWLEDGMENTS

APPENDIX

See Tables A.1 and A.2.

REFERENCES

Adeli, H. and Hung, S.L., (1995), Machine Learning - Neural Networks, Genetic Algorithms, and Fuzzy Systems, John Wiley and Sons, New York.

Adeli, H. and Karim, A., (2000), Fuzzy-Wavelet RBFNN Model for freeway incident detection. *Journal of Transportation Engineering,* **126** (6), 464-471.

Adeli, H. & Karim, A., (2005), Wavelets in Intelligent Transportation Systems. *John Wiley and Sons*, New York.

Adeli, H. & Jiang, X. (2003), Neuro-fuzzy logic model for freeway work zone capacity estimation. *Journal of Transportation Engineering*, **129** (5), 484-493.

Adeli, H. and Jiang, X. (2006), Dynamic fuzzy wavelet neural network model for structural system identification, *Journal of Structural Engineering*, **132**(1), 102-111.

Aghabayk, K. & Forouzideh, N. (2013), Exploring a local linear model tree approach to car-following. *Computer-Aided Civil and Infrastructure Engineering,* **28**, 581-593.

Al-Ghandour, M. N., Rasdorf, W. J., Williams, B. M. and Schroeder, B. J. (2011), Analysis of single-lane roundabout slip lanes using SIDRA. *Proceedings of the First Transportation and Development Congress*, 1235-1244.

Boutalis, Y., and Christodoulou, M., and Theodoridis, D. (2013), Indirect adaptive control of nonlinear systems based on bilinear neuro-fuzzy approximation. *International Journal of Neural Systems*, **23** (5), 1350022.

Celikoglu, H.B. (2013), An approach to dynamic classification of traffic flow patterns. *Computer-Aided Civil and Infrastructure Engineering*, **28**, 273-288.

Chai, C. & Wong, Y. D. (2013a), Traffic performance of shared lanes at signalized intersections based on cellular automata modeling. *Journal of Advanced Transportation (In press)*.

Chai, C. & Wong, Y. D. (2013b), Automatic vehicle classification and tracking method for vehicle movements at signalized intersections. *IEEE Intelligent Vehicles Symposium (IV)*, 624-629.

Chai, C. (2015), Modelling and simulation of vehicle movements at signalised junctions. PhD Thesis, Nanyang Technological University.

Chai, C. & Wong, Y. D., (2015), Comparison of two simulation approaches to safety assessment: Cellular Automata and SSAM. *Journal of Transportation Engineering*. **141**(6), 05015002.

Chiou, Y. C. & Huang, Y. F. (2013), Stepwise genetic fuzzy logic signal control under mixed traffic conditions. *Journal of Advanced Transportation*, **47**(1), 43-60.

Clarridge, A. & Salomaa, K. (2010), Analysis of a cellular automaton model for car traffic with a slow-to-stop rule. *Theoretical Computer Science*, **411**(38–39): 3507-3515.

Dell'Orco, M. & Mellano, M. (2013), A new user-oriented index, based on a fuzzy inference system, for quality evaluation of rural roads. *Computer-Aided Civil and Infrastructure Engineering,* **28**, 635-647.

Federal Highway Administration (FHWA) (2011). "SSAM 2.1.6 release notes."<http://www.fhwa.dot.gov/ downloads/research/safety/ssam/ssam2_1_6_release_not es.cfm> (accessed on 28.11.14)

Federal Highway Administration (FHWA), CORSIM. <http://ops.fhwa.dot.gov/trafficanalysistools/ corsim.htm> (accessed on 28.11.14)

Forero Mendoza, L., Vellasco, M., Figueiredo, K. (2014). Intelligent multiagent coordination based on reinforcement hierarchical neuro-fuzzy models, *International Journal of Neural Systems*, **24**(8), 1450031

Gong, Y. G. Lin, L. (2010), A fuzzy cellular automaton model based on NaSch model. *2nd International Conference on Signal Processing Systems (ICSPS)*.

Groeger, J. A. (2002). Trafficking in cognition: applying cognitive psychology to driving. *Transportation Research Part F*, **5**, 235-248.

Gundaliya, P. J., Mathew, T. V. & Dhingra, S. L. (2008), Heterogeneous traffic flow modelling for an arterial using grid based approach. *Journal of Advanced Transportation*, **42**(2), 467-491.

Hurwitz, D. S. Wang, H. Z. & Knodler, M. A. Jr. (2012), Fuzzy sets to describe driver behavior in the dilemma zone of high-speed signalized intersections. *Transportation Research Part F*, **15**(2), 132-143.

Jahani, E., Muhanna, R.L., Shayanfar, M.A. & Barkhordari, M.A. (2014), Reliability assessment with fuzzy random variables using interval Monte Carlo simulation. *Computer-Aided Civil and Infrastructure Engineering*, **29**, 208-220.

Jiang, X. and Adeli, H. (2003). Fuzzy clustering Approach for accurate embedding dimension identification in chaotic time series, *Integrated Computer-Aided Engineering*, **10**(3), 287-302.

Jiang, X. and Adeli, H. (2008), Dynamic fuzzy wavelet neuroemulator for nonlinear control of irregular highrise building structures, *International Journal for Numerical Methods in Engineering*, **74**(7), 1045-1066.

Horng G.J., (2014), Using Cellular Automata for Parking Recommendations in Smart Environments. PLoS ONE 9(8): e105973. doi:10.1371/journal.pone.0105973

Karim, A. and Adeli, H., (2002), Comparison of the Fuzzy – Wavelet RBFNN Freeway Incident Detection Model with the California Algorithm, *Journal of Transportation Engineering, ASCE*, 128 (1), 221-30.

Karim, A. and Adeli, H., (2003), Incident Detection Algorithm Using Wavelet Energy Representation of Traffic Patterns, *Journal of Transportation Engineering, ASCE,*. **128** (3), 2.

Kodogiannis, V.S., Amina, M., and Petrounias, I. (2013), A clustering-based fuzzy-wavelet neural network model for Short-term Load Forecasting, *International Journal of Neural Systems*, **23**(5), 1350024

Kok, Q. T. & How, H. Y. (1992), Turning lane capacity at signalised intersections. *B.Eng. Research Report*, Nanyang Technological University, Singapore.

Kwon, E. Choi, B. & Park, H. (2000), Distributed simulation of freeway traffic flow using personal computers. *Computer-Aided Civil and Infrastructure Engineering*, **15**, 167-175.

Lu, W. L., Hua, W. Y., Li, P. & Wang, Y. (2011), Research on cellular automaton model for evacuation under passenger station. *International Conference on Electronics, Communications and Control (ICECC)*, 4465-4468

Luo, Y., Jia, B., Liu, J., Lam, W. H. K., Li, X. & Gao, Z. (2013), Modeling the interactions between car and bicycle in heterogeneous traffic. *Journal of Advanced Transportation (In press)*.

Malinovskiy, Y., Zheng, J. Y. & Wang, Y. H. (2009), Model-free video detection and tracking of pedestrians and bicyclists. *Computer-Aided Civil and Infrastructure Engineering*, **24**, 157-168.

Mallikarjuna, C. & Rao, K. R. (2009), Cellular Automata model for heterogeneous traffic. *Journal of Advanced Transportation*, **43**(3): 321-345.

Mraz, M., Zimic, N., Lapanja, I. & Bajec, I. (2000), Fuzzy cellular automata: from theory to applications. *12th IEEE International Conference on Tools with Artificial Intelligence*.

Nagatani, T. (1993). Jamming transition in the traffic-flow model with two-level crossings. *Physical Review E*, **48**(5): 3290.

Pang, W., & Meng, Y. S. (1990), A study of traffic saturation flow at signalised intersections. *B.Eng. Research Report*, Nanyang Technological University, Singapore.

Patel, D. K. & More, S. A. (2013), Edge detection technique by fuzzy logic and Cellular Learning Automata using fuzzy image processing. *International Conference on Computer Communication and Informatics (ICCCI)*.

Placzek, B. (2012). Fuzzy cellular model of signal controlled traffic stream. Online resource in Cornell University Library. http://arxiv.org/abs/1112.4631.

Public Transport Victoria (PTV), PTV Vision: Integration and Innovation. <http://www.ptvgroup.com/en/traffic-software/traffic-simulation/> (accessed on 28.11.14).

Rickert, M., Nagel, K., Schreckenberg, M., & Latour, A. (1996). Two lane traffic simulations using cellular automata. *Physica A: Statistical Mechanics and its Applications*, **231**(4), 534-550.

Rigatos, G. (2013), Adaptive fuzzy control for differentially flat MIMO nonlinear dynamical systems, I*ntegrated Computer-Aided Engineering*, **20**(2), 111-126.

Rokni S. and Fayek, A.R. (2010), A Multi-Criteria Optimization Framework for Industrial Shop Scheduling Using Fuzzy Set Theory. *Integrated Computer-Aided Engineering*, **17**(3), 175-196.

Sarma, K. and Adeli, H. (2000a). Fuzzy genetic algorithm for optimization of steel structures, *Journal of Structural Engineering*, **126**(5), 596-604.

Sarma, K. and Adeli, H. (2000b), Fuzzy discrete multicriteria cost optimization of steel structures, *Journal of Structural Engineering*, **126**(11), 1339-1347

Schreckenberg, M., Schadschneider, A., Nagel, K., & Ito, N. (1995). Discrete stochastic models for traffic flow. *Physical Review E*, **51**(4), 2939.

Siddique, N. and Adeli, H. (2013). Computational Intelligence - Synergies of Fuzzy Logic, Neural Networks and Evolutionary Computing, Wiley, West Sussex, United Kingdom.

Smith, J.F. and Nguyen, T.H. (2007), Autonomous and cooperative robotic behavior based on fuzzy logic and genetic programming. *Integrated Computer-Aided Engineering*, **14**(2), 141-159.

Sun, D. J. & Elefteriadou, L. (2010), Modeling vehicle interactions during lane-changing behavior on arterial streets. *Computer-Aided Civil and Infrastructure Engineering*, **25**, 557-571.

Sun, D. J. & Elefteriadou, L. (2012), Lane-changing behavior on urban streets: an "in-vehicle" field experiment-based study. *Computer-Aided Civil and Infrastructure Engineering*, **27**, 525-542.

Szeto, W.Y. & Jiang, Y. (2011), A cell-based model for multi-class doubly stochastic dynamic traffic assignment. *Computer-Aided Civil and Infrastructure Engineering*, **26**, 595-611.

Wang, X. & Abdel-Aty, M. (2007), Right-angle crash occurrence at signalized intersections. *Transportation Research Record*, **2019**, 156-168.

Wu, J.P., Brackstone, M. & McDonald, M. (2000), Fuzzy sets and systems for a motorway microscopic simulation model. *Fuzzy Sets and Systems*, **116**, 65-76.

Yan, L. and Ma, Z. (2013a), Conceptual design of object-oriented databases for fuzzy engineering information modeling, *Integrated Computer-Aided Engineering*, **20**(2), 183-197.

Yan, L. and Ma, Z. (2013b), Extending engineering data model for web-based fuzzy information modeling, *Integrated Computer-Aided Engineering*, **20**(4), 407-420.

Yeldan, Ö., Colorni, A., Luè, A. & Rodaro, E. (2012), A stochastic continuous cellular automata traffic model with a multi-agent fuzzy system. *Procedia - Social and Behavioral Sciences*, **54**, 1350-1359.

Zhang, Y. & Ge, H. (2013), Freeway travel time prediction using Takagi–Sugeno– Kang Fuzzy Neural Network.

Computer-Aided Civil and Infrastructure Engineering, **28**, 594-603.

Zheng, J., Suzuki, K. & Fujita, M. (2012), Modelling a vehicle's speed fluctuation with a cellular automata model. *WIT Transactions on the Built Environment*, **128**, 371-382.

Table A.1 Notation table

Notation	Description
β_n	Linear combination of the three input factors to compute stopping probability
d_n	Space headway of the nth vehicle
DS	Distance to stop-line
F_1	1st Fuzzy set for forwarding movement affected by front vehicle
F_2	2nd Fuzzy set for forwarding movement affected by signal timing
F_3	Lane-changing fuzzy set
F_4	Right-turn filtering fuzzy set
$\bar{f}_c^1, \bar{f}_c^2$	Frequency of lane-changing per vehicle at each lane
$\bar{f}_c^g, \bar{f}_c^{ar}$	Frequency of lane-changing per vehicle during green and amber-red phase
$\overline{g_o}$	Average available gap in the opposing vehicle stream before filtering
$g_a(i)$	The ith front gap alongside
$g_l(i)$	Front gap in the ith neighboring lane
g_n^l, g_n^r	Lateral gap on relative left and right side of the nth vehicle
g_n	Front gap of the nth vehicle
g_n^t	Front gap in target lane of the nth vehicle
$g_n^{t,rear}$	Rear gap in target lane of the nth vehicle
g_t	Gap tolerance
O	Driver response before stop-line ($O = \min(O_1, O_2)$)
O_1	Output of F1
O_2	Output of F2
p_c	Position of the 1st actual lane-changing
p_r	Probability of random deceleration
p_s	Probability of vehicle to stop at onset of amber
t	Number of time step ($\Delta t = 1s$)
t_c	Time of the 1st actual lane-changing
t^r	Time to the onset of red phase
$\bar{t}_{rt}$	Average travel time of right-turn vehicles
t^s	Signal timing
t^t	Travel time
μ	Membership degree with different values of input and output factors
vol_s	Traffic volume in the subject lane
vol_n	Traffic volume along neighboring lane
v_{max}	Maximum velocity of vehicle
v_n	Velocity of the nth vehicle
$v_n^{t,rear}$	Rear velocity in current lane of the nth vehicle
v_r	Random deceleration rate (1cell/s2)
$\bar{w}_c$	Average willingness of lane-changing
x_n	Forwarding position of the nth vehicle
φ_a, φ_d	Acceleration/ deceleration rates

Table A.2 Locations of observation study

Intersection	Location
No. 1	Woodlands Ave 2 and Woodlands Ave 5
No. 2	Woodlands Ave 2, Woodlands Ave 5, and Woodlands Ave 9
No. 3	Jalan Bahar and Jurong West Ave 5
No. 4	Choa Chu Kang Ave 1 and Choa Chu Kang Way
No. 5	Sengkang East Road and Seng kang East Way
No. 6	Jurong Town Hall Road and Jurong East Ave 1