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A high fidelity traffic simulation model based on cellular automata and car-following concepts

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Abstract

A high fidelity cell based traffic simulation model (CELLSIM) has been developed for simulation of high volume of traffic at the regional level. Straightforward algorithms and efficient use of computational resources make the model suitable for real time traffic simulation. The model formulation uses concepts of cellular automata (CA) and car-following (CF) models, but is more detailed than CA models and has realistic acceleration and deceleration models for vehicles. A simple dual-regime constant acceleration model has been used that requires minimal calculation compared to detailed acceleration models used in CF models. CELLSIM is simpler than most CF models; a simplified car-following logic has been developed using preferred time headway. Like CA models, integer values are used to make the model run faster. Space is discretized in small intervals and a new concept of percent space occupancy (SOC) is used to measure traffic congestion. CELLSIM performs well in congested and non-congested traffic conditions. It has been validated comprehensively at the macroscopic and microscopic levels using two sets of field data. Comparison of field data and CELLSIM for trajectories, average speed, density and volume show very close agreement. Statistical comparison of macroscopic parameters with other CF models indicates that CELLSIM performs as good as detailed CF models. Stability analyses conducted using mild and severe disturbances indicate that CELLSIM performs well under both conditions.

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Keywords: Traffic simulation; Car-following models; Cellular automata; Space occupancy; Model validation

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1. Introduction

In the past, the use of microscopic models has been limited in scope and scale of application. Applications were restricted to arterial or small networks with limited number of vehicles. With the advent of faster computers, microscopic models are now used in simulating traffic on the level of cities and freeway networks. The INTEGRATION model has been used to simulate traffic for the Salt Lake Metropolitan Area (Rakha et al., 1998). The MITSIM model (Yang, 1997) has been used to evaluate aspects of both the traffic control system and the ramp configurations of the Central Artery/Tunnel project in Boston. Similarly, AIMSUN2 have been used to simulate the Rings Roads of Barcelona (Barcelo et al., 1996). These models use various techniques to simulate high volume of traffic on large networks with shorter execution time. MITSIM supports distributed implementation. AIMSUN2 uses parallel computers to shorten the execution time. Similarly, the TRANSIMS project used CA models to simulate traffic for the city of Fortworth-Dallas using parallel computers, mostly coupled workstations (Nagel and Barrett, 1997). Traffic simulation using CA models has also been performed on vector supercomputers to simulate traffic in shortest possible time (Nagel and Schleicher, 1994).

CF models use realistic driver behavior and detailed vehicle characteristics that require higher computational resources. Models like INTRAS (FHWA, 1980), CORSIM (NETSIM & FRESIM) (Halati and Henry, 1998), CARSIM (Benekohal and Treiterer, 1988), and INTELSIM (Aycin and Benekohal, 1998, 1999) use detailed acceleration models. In NETSIM, FRESIM, CARSIM and INTELSIM, quadratic equations are solved to calculate acceleration rates. Since these programs require higher computational resources, the execution time can be longer than real time when large number of vehicles are simulated on a network. The INTEGRATION model required an execution time 2–17 times the real time depending on the number of vehicles in the system on a 200 MHz Pentium PC (Rakha et al., 1998). The number of vehicles simulated was not reported in the paper. These times are clearly not feasible for practical purposes even with the faster computers available today. The MITSIM model reported time factors ranging from 0.48 to 2.2 on an SGI Indy R4400 workstation with 200 MHz of speed (Yang, 1997; Yang and Koutsopoulos, 1996). MITSIM was able to simulate 22,000 vehicles (Yang and Koutsopoulos, 1996). Current car following models have detailed routines that require higher computational resources and longer execution time. Thus, there is a need to simulate high volume of traffic with shorter execution time using efficient algorithms on a personal computer.

On the other hand, CA models can be considered simple microscopic models that are straightforward with a logic that usually consist of a few integer operations. Because of their simplicity, they are able to perform several millions updates in a second (Nagel, 1995; Krauss, 1998). Thus, they may be used for simulating high volume of traffic over large networks. However, CA models do not have realistic driver and vehicular behavior models. Vehicles are modeled as particles having unrealistic acceleration and deceleration rates. Vehicles accelerate independently of their velocity and have speed jumps of about 27 km/h in 1 s (Nagel, 1998). Vehicles tend to change speed abruptly; they can come to a stop from a maximum speed of 135 km/h in 1 s (Nagel, 1998). Hence, they have very erratic acceleration and deceleration behavior. In STCA (Stochastic Traffic Cellular automata), space is discretized into cells of 7.5 m (24.61 ft) (Nagel, 1998). Thus, vehicle movement is restricted to a multiple of 7.5 m and this obviously is not suitable for studying real world problems since the model is too coarse. Because of these

shortcomings they cannot be used for conducting detailed traffic flow studies at the high fidelity level.

Research to improve the behavior of CA models by finer discretization of cells was carried out by Krauss et al. (1996, 1997) and more recently by Knospe et al. (2000). However, the results from Krauss' model, Fig. 3 (Krauss et al., 1996) clearly showed decelerations from the model which exceed decelerations in reality. In some cases of the Krauss' model, both acceleration and deceleration rates were set equal to constant values. Although Krauss' and Knospe's models use finer discretization, they do not provide realistic representation of a platoon of vehicles going through a disturbance.

The limitations in CF and CA models motivated the development of CELLSIM. CELLSIM presents a simplified approach to the development of a high fidelity traffic simulation model. This approach has been adapted to minimize the amount of computational resources, allowing higher volume of traffic to be simulated on a regional level. The model formulation uses concepts of CA for simplicity and speed. Like CA models, the cell based or spatial discretization approach has been adopted as well. Integer values instead of floating point numbers have been used to shorten the model's execution time. The concepts of CF models are used for realistic modeling of driver and vehicular behavior. Realistic driver behavior is achieved using preferred time headway (TP) (see Section 2). A dual-regime acceleration model is formulated which requires minimal calculation compared to detailed acceleration models used in CF models. A simple deceleration model is also used. Moreover, the model introduces a simplified car-following logic.

CELLSIM has been validated comprehensively at the macroscopic and microscopic levels using two sets of field data. Validation at the macroscopic level has been performed for average speed, density and volume. Unlike CA models, whose validation is only possible at the macroscopic level (Ponzlet, 1996), CELLSIM's results show very close agreement with the field data. Validation at the microscopic level has been conducted for trajectory and speed of individual vehicles. The microscopic results from CELLSIM also showed close agreement to the field data. Additionally, error tests and techniques from the field of econometrics have been used to evaluate the results of simulation. CELLSIM performed well when tested for stability analyses using mild and severe disturbance conditions.

Space is discretized in CELLSIM, but at a finer level than CA models. Spatial discretization is used in a unique way to calculate percent SOC, which is an improved measure of traffic congestion compared to density. The concept of SOC can be used in a variety of applications for traffic flow studies including real time control of bottleneck and incident conditions.

CELLSIM and CA models are different from the Cell Transmission model (CTM) (Daganzo, 1994) in several ways. In CTM, the highway is partitioned into small sections (cells) and vehicles move in and out of these cells over time. In CTM it is not necessary to know where the vehicles are located within the cell. Traffic flow is established as a result of the comparison between the maximum number of vehicles that can be sent by the cell upstream to those that can be received by a cell downstream. This is different from CA models where a single vehicle occupies a cell at a time compared to several vehicles occupying a section/cell of the highway in CTM. The flow in CTM is a function of the flow-density relationship, whereas the flow in CA models is dependent on the speed of vehicles and their interaction. A detailed comparison between CELLSIM, CA models and CTM, is out of the scope of this paper. For details and a complete list of references on CTM the reader is referred to Daganzo (1999).

This paper describes the concepts, background and the motivation behind the formulation of the model. The development of the car following logic, acceleration and deceleration models, the collision avoidance sequence, spatial discretization and occupancy, computational speed and the model applications are discussed in detail. The paper also discusses the various methods used in validation of the model in detail. In the end, conclusion and recommendations for future research are presented.

2. Model formulation

This section describes the formulation of car-following logic, acceleration model, deceleration model, the collision avoidance sequence and the driver's reaction time in CELLSIM.

2.1. Car following logic

In CELLSIM the car following logic is implemented when a pair of vehicles, leader and follower, are at a distance of less than or equal to 76 m (250 ft). The distance between the leader and the follower is defined as space gap and is measured from the rear bumper of the leader to the front bumper of the follower. A distance of 76 m is used because Herman and Potts observed that for separations greater than 61 m (200 ft), car following is negligible on driver's behavior (Aycin and Benekohal, 1998). Therefore, when vehicles are separated by more than 76 m (250 ft), they are considered to be free flowing. In free flow condition, vehicles accelerate to reach their desired speed and then coast. The desired speed of vehicles was calculated using a truncated normal distribution with a mean and standard deviation. Maximum speed of vehicles was assumed to be fixed in the model. Thus, final speed during acceleration is thus minimum of speed updated at every time step, desired speed of the driver, and maximum speed of the vehicle.

In car following, a follower tries to maintain a space gap equal to his/her desired space gap behind the leader. Desired space gap is defined as the product of follower's speed and preferred time headway (TP). TP is the time headway a follower prefers to maintain during steady-state car following. TP can be found from the field data by averaging the time headways of a follower at the same speeds with the leader (Aycin and Benekohal, 1998). TP can also be found from an appropriate distribution that represents reaction time of drivers.

The car-following logic depends on the desired space gap and the relative speeds of the leader and follower. Follower accelerates, decelerates or maintains speed (coast) according to Table 1. Three cases of space gap versus desired space gap are considered. The first case is when the space gap of the follower is greater than the desired space gap. When the speed of leader is greater or equal to the speed of the follower, follower accelerates to its desired speed. Follower also accelerates to its desired speed in case when the speed of leader is less than their speed and space gap is greater than three times their speed (approximately 3 s of time headway). However, it coasts when space gap is greater than twice its own speed and the available space gap is around 7.62 m (25 ft). This threshold was observed in the field data sets and is used so that the follower does not coast when the leader is coming to a stop. In other cases follower decelerates.

The second case is when space gap of the follower is equal to its desired space gap. The follower coasts when the speed of the leader is greater or equal to its own speed. It decelerates when the

Table 1
Action taken by the following vehicle

Cases	Speeds		
	$V_L^a > V_F^b$	$V_L = V_F$	$V_L < V_F$
Space gap ^c > desired space gap ^d	Accelerate	Accelerate	Space gap > $3V_F$, accelerate Space gap > $2V_F$ and space gap > 7.6 m, coast Other cases decelerate
Space gap = desired space gap	Coast	Coast	Decelerate
Space gap < desired space gap	Coast	Decelerate	Decelerate

^a V_L = speed of leader.

^b V_F = speed of follower.

^c Space gap = rear end to front end distance between leader and follower, respectively.

^d Desired space gap = speed \times TP.

leader is driving at a slower speed to avoid collision. The third case is when the available space gap is less than the desired space gap. Followers decelerate when the speed of the leader is equal or less than their speed. Followers coast when the speed of the leader is greater than their speed. This condition fits the driver behavior since the follower achieves the desired space gap when the leader is increasing the space gap when travelling at a higher speed than the follower.

In case of acceleration from a stopped position, the follower accelerates after the leader reaches a speed in the range of 1.2–1.8 m/s (4–6 ft/s). The range depends on the space gap between the follower and the leader. When the space gap is shorter, the follower accelerates when the leader attains a higher speed, whereas when the space gap is greater, it accelerates even when the leader's speed is lower. This is carried out to provide enough room for the follower to accelerate behind the leader.

2.2. Acceleration model

A dual-regime constant acceleration model is used in CELLSIM. The dual-regime model provides several advantages compared to a single-regime model (constant acceleration model). The single-regime model gives a reasonable approximation when the vehicle is accelerating within a given gear but they are greatly in error when the vehicle is accelerating up through the gears (Searle, 1999). Additionally, when the vehicle reaches top gear the acceleration is only a small fraction of what is available at lower speeds. It is incorrect to use a single-regime model since it provides same constant acceleration rate at higher and lower speeds. The dual-regime model by using two different acceleration rates overcomes this problem to an extent by providing higher acceleration rate at lower speeds and lower acceleration rate at higher speeds. This provides realistic acceleration behavior and shows strong agreement with field data as shown in Fig. 2. However, the dual-regime model does not show change in speed for every gear change.

NETSIM, FRESIM, and CARSIM use constant acceleration models, in which the acceleration profile is in the form of a step function and this causes rate of acceleration to be discontinuous from the previous time step (Aycin and Benekohal, 1998). In the dual-regime model, acceleration rate is constant until the change in rate. The model has only one point of discontinuity when a

vehicle is accelerating i.e. when the acceleration rate changes. However, the acceleration profile is discontinuous, when a vehicle decelerates. In NETSIM, FRESIM, CARSIM and INTELSIM, the acceleration rates are quadratic roots which require solution. The acceleration rates are checked for permissible limits depending on the current speed of the vehicle. The rates are then revised if the limits are not satisfied. This requires extensive computational resources when higher volume of traffic is simulated. On the other hand, the dual-regime model provides realistic speeds with minimal calculation.

The two acceleration rates were found from the average speed profile of vehicles from the Ohio State Data (Treiterer, 1975) which are 1.1 and 0.37 m/s/s (3.6 and 1.2 ft/s/s). The dual-regime model is expressed as:

$$v = u + a_1 \times t, \quad 0 \leq v < 12.19 \text{ m/s (40 ft/s)} \quad (1)$$

and

$$v = u + a_2 \times t, \quad v \geq 12.19 \text{ m/s (40 ft/s)} \quad (2)$$

where v is the speed at the end of time step, ft/s, u the speed at the beginning of time step, ft/s, a_1 the acceleration constant 1 = 1.1 m/sec² (3.6 ft/sec²), a_2 the acceleration constant 2 = 0.37 m/sec² (1.2 ft/sec²), and t the time step (1 s).

The above equations are basic kinematic equations, which describe the laws of motion. The position of vehicle is then updated as (again a basic kinematic equation):

$$S_E = S_B + u \times t + \frac{a \times t^2}{2} \quad (3)$$

where, a is the acceleration constant (a_1 or a_2), ft/s/s, S_B the position at the beginning of time step, ft, and S_E the position at the end of time step, ft.

2.2.1. Comparison of different acceleration models

Several acceleration models were tried to fit the average speed profile of vehicles from the field data. The dual-regime model provided the closest fit to the field data. Modified Searle's model (Searle, 1999) was first used in CELLSIM, but the model required extensive calibration and is not as simple as the dual-regime model (Bham and Benekohal, 2000, 2002a,b). Other models considered were the linear-decreasing model, polynomial, two-term and three-term sinusoidal models (Akcelik and Biggs, 1987). These models are detailed, use several parameters and require extensive use of computational resources. A constant acceleration model did not fit the data well. The dual-regime model was thus formulated, as it is much easier to calculate required minimal calculation and provided the closest fit to the field data. Speed profiles from these models is presented in Fig. 2.

The speed profile from the above models was used instead of the acceleration profile, because speed shows lesser variation than acceleration rates. Speed profile was also preferred over the distance profile (position of vehicles), since speed of drivers from simulation needs to be similar to speed from the field data and if speeds are equal, similar positions will be found. In addition, speed provides a better measure of fit than position, because position of vehicles is a cumulative measure of distance travelled over time and over estimates can cancel out under estimates. Hence speed is a preferred parameter in validation of acceleration models. For more details on comparison, evaluation and validation of several acceleration models see (Bham and Benekohal, 2002a,b).

2.3. Deceleration model

Two deceleration models are used in CELLSIM; one for reducing the speed of vehicles and the other for avoiding collision. When collision avoidance (explained in Section 2.4) requirement is not governed, vehicles decelerate according to Table 1. A simple deceleration model is used in reducing the speed of vehicles. The deceleration model can reduce the speed of a vehicle and bring it to a stop or it can reduce the speed and thereby increase the desired space gap of the follower.

The deceleration rate is calculated using the speed of the leader and the follower. The speed of the leader is used so that the follower reduces its speed closer to the speed of the leader. In case of stopping, the deceleration rate allows the follower to stop behind the leader and maintain a buffer space. The deceleration rate is calculated as:

$$d_F = \frac{u_L^2 - u_F^2}{2 \times \text{sp}} \quad (4)$$

where d_F is the desired deceleration rate of follower, ft/sec², u_L the speed of the leader at beginning of time step, ft/s, u_F the speed of the follower at beginning of time step, ft/s, 'sp' space gap—buffer space (ft), space gap the distance between front end of the follower and rear end of the leader at the beginning of time step (ft), and buffer space the distance between the follower and the leader during stopped condition, ft.

Eq. (4) is basically a derived form of the basic kinematic equation:

$$2ad = v^2 - u^2 \quad (5)$$

$$\Rightarrow a = \frac{v^2 - u^2}{2 \times d} \quad (6)$$

where, a is the rate of acceleration/deceleration, d the distance traveled, v the final speed, and u the initial speed.

The allowable maximum deceleration rate is 3.05 m/s/s (10 ft/sec²) which represents normal deceleration in reality. Speed is then updated similar to Eqs. (1) and (2) and position is updated similar to Eq. (3).

2.4. Collision avoidance

The collision avoidance sequence is required in two emergency conditions to avoid collision. The first condition is when the leader brakes at a deceleration rate equal to or greater than 4.88 m/sec² (16 ft/sec²). For the collision avoidance condition to govern it is checked if the follower will be able to maintain a buffer space behind the braking leader, in case, it decelerates to a stop. This condition can be expressed as:

$$\text{space gap} + \frac{v_L^2}{2 \times d_L} - \frac{v_F^2}{2 \times d_F} \leq \text{bs} \quad (7)$$

where space gap is the distance between front end of follower and rear end of leader, ft, d_F , d_L the assumed deceleration rate of leader and follower = 16 ft/sec², and 'bs' the buffer space.

The second condition is when a follower approaches a stopped vehicle. For this condition to govern, the speed of the follower should be greater or equal to the buffer space between the follower and the stopped vehicle. If any of the above conditions govern, collision avoidance sequence is used to reduce the speed of the follower. The following equation is used to calculate the deceleration rate:

$$d_F = \frac{u_F^2}{2 \times \text{sp}} \quad (8)$$

where d_F is rounded to an integer number.

Speed and position are then updated in the same manner as explained in Section 2.2. The maximum allowable deceleration rate for followers during collision avoidance is 6.4 m/s/s (21 ft/s/s). This represents maximum deceleration rate that can be used in emergency conditions.

2.5. Reaction time

To keep CELLSIM simple, reaction time equivalent to time step (1 s) is assumed for drivers. Thus followers react in the next time step to the stimulus from the leader. This is very close to 1.21 s the mean reaction time of unalerted drivers in car following as suggested by Taoka (Aycin and Benekohal, 1998). This is also close to the average reaction time of drivers found from the field data (Ohio data) using TP. TP as explained before, can be found by averaging the time headways of a driver at the same speeds with the leader. By definition, TP is considered as the upper limit of reaction time of a driver and an assumed 80 percent of it, represents the reaction time of a driver (Aycin and Benekohal, 1998). TP for drivers in the Ohio data ranged from 1.1 to 1.9 s, 80 percent of this range is 0.88–1.52 s. The average of this latter range equals 1.2 s. Thus, 1 s of reaction time is appropriate to use as it is very close to the average reaction time of drivers found in the Ohio Data and also suggested by Taoka.

2.6. Integer numbers

Like CA models, CELLSIM uses integer values for most of its calculation. Integer values have proved to be 10–15 percent faster in runtime than floating point numbers (SPEC, 2000). Hence, they reduce the execution time of the model. Results from CELLSIM shows that even when integer values are used instead of floating point numbers, the results show close agreement to the field data.

3. Spatial discretization and occupancy

Division of space in cells provides several advantages compared to continuous space used in CF models. The concept of spatial discretization is used in CELLSIM, since it is faster to simulate using discrete values. The discreteness of the space can bear significant computational advantages because operation on integer numbers can in general be performed much more efficiently than floating point numbers (Krauss, 1998). Space in CELLSIM is discretized in cells of 1 ft (0.31 m). Unlike CA models variable vehicle length is incorporated and every unit of vehicle occupies a unit

of the highway. This finer spatial representation overcomes the shortcoming in CA models where every cell is 7.5 m in length. Validation of CELLSIM shows that realistic results are achieved using this concept without loss of accuracy.

Spatial discretization can be used for measuring SOC, a new concept which provides an improved measure of state of congestion, compared to density. In SOC length of each vehicle is incorporated rather than using average or single vehicle length for all vehicles. Vehicle length is important when longer vehicles are present in higher percentage. Trucks with longer length occupy more space and therefore contribute more towards congestion. SOC calculates the ratio of total length occupied by vehicles to the total highway length. In CELLSIM it is calculated as the ratio of number of cells occupied by all the vehicles to the total number of cells on the highway. Percent SOC is calculated as:

$$\text{SOC} = \frac{\text{No. of Cells Occupied}}{\text{Total No. of Cells}} \times 100 \text{ or } \text{SOC} = \frac{\text{Space occupied by vehicles}}{\text{Length of study section}} \quad (9)$$

SOC thus computes the percentage of highway occupied by vehicles. It incorporates length of each vehicle and presents an accurate state of traffic compared to density. On the other hand density represents number of vehicles per kilometer (mile) but when vehicles with varying lengths are occupying the highway, it is not clear how much of the highway length is occupied. Density can be calculated using percent time occupancy (TOC), which is defined as the percentage of time a point or short section of roadway is occupied by a vehicle. The relationship between density and TOC is defined as (May, 1990):

$$k = \frac{52.8}{L_D + \bar{L}_V} \text{TOC} \quad (10)$$

where k is the density (vehicles per lane-mile), \bar{L}_V the average vehicle length (ft), L_D the detection zone length (ft).

Again density is calculated using average length of vehicle. With varying vehicle lengths, density is only approximate. Hence, percent SOC presents a more accurate measure compared to density.

Comparison of density and SOC is presented in Fig. 1. Fig. 1a shows density and Fig. 1b shows SOC for different combination of vehicle lengths. Fixed number of vehicles was simulated in both cases. As observed in Fig. 1b, percent SOC provides a better feel for the state of traffic compared to density. Density, for example, varies around 38 to 83 vehicles/mile when length of all vehicles is 50 ft. It varies again from 33 to 63 vehicles/mile when half the vehicles are 50 ft and half of them are 118 ft in length. This shows that variation in density is small in uncongested conditions i.e. around 35 vehicles/mile even when occupancy of the highway changes due to different length of vehicles. This also shows that density varies more near congested conditions compared to uncongested conditions when different length of vehicles is used. On the other hand, SOC varies from 30% to 66% for all 50 ft vehicles, whereas it varies from 40 to 75 percent. SOC shows variation in both congested and uncongested conditions of traffic. Thus SOC provides a better feel for the state of traffic in both conditions of traffic. It is an improved measure because it incorporates length of every vehicle compared to average length of vehicle used in density. Moreover, measuring density for different length of vehicles requires separate plot charts for trucks and passenger vehicles. This is not required for SOC since it incorporates different length of vehicles in a single plot.

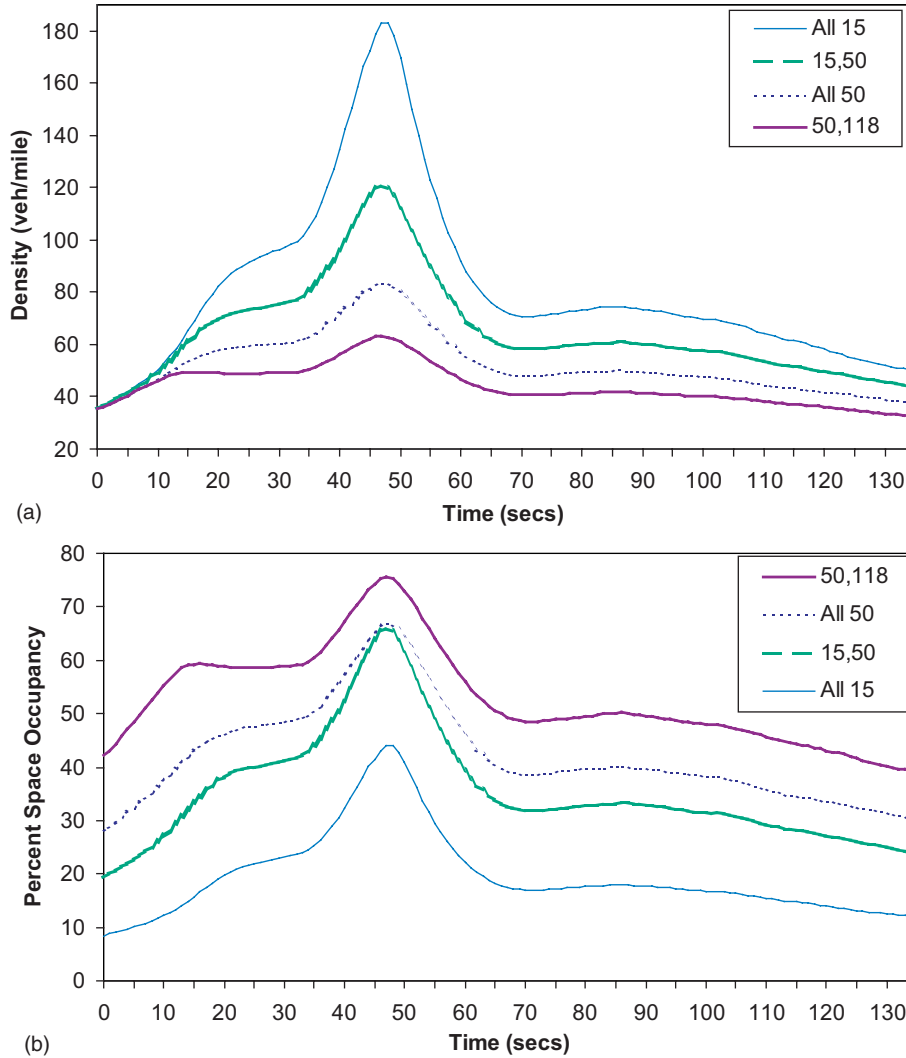


Fig. 1. (a) Platoon density (top) and (b) percent platoon space occupancy (bottom) versus time, plotted for different vehicle lengths.

Comparison of SOC and TOC is out of the scope of this paper. Length of vehicles used for comparing density and percent SOC are 4.57 m (15 ft, passenger car), 15 m (50 ft, WB-40), and 36 m (118 ft, WB-114) in length. A combination of these vehicles is used in Fig. 1.

4. Model validation

Validation of CELLSIM is performed at microscopic and macroscopic levels using the procedure suggested by Benekohal (1989). The procedure has been used for validation of other

microscopic traffic simulation models (see e.g., Benekohal and Treiterer, 1988; Aycin and Benekohal, 1998). Additionally, validation techniques used in evaluation of prediction models of econometrics are also in the paper. Thus, a comprehensive methodology is adopted for validation of CELLSIM.

For microscopic validation, both speed and position of individual vehicles computed from CELLSIM, are compared to the field data sets. For macroscopic validation, average speed, density, and volume from CELLSIM are compared to corresponding values from the field data. Statistical analysis of macroscopic parameters is performed and the results of statistical analysis from CELLSIM are compared to the results from NETSIM, FRESIM, CARSIM and INTEL-SIM using the same platoon data. The three fundamental relationships of traffic flow obtained from CELLSIM and field data are also compared. Moreover, stability analyses have also been performed to evaluate the behavior of vehicles in the model undergoing typical and emergency deceleration.

4.1. Field data sets

Two sets of field data are used in validation of CELLSIM: the Ohio State University Data (Ohio Data) (Treiterer, 1975) and the data collected by the FHWA (Smith, 1985). The Ohio Data, is unique since speed and position of 13 vehicles in a platoon is captured for 130 s. This amount of information is not captured in other data sets. The number of vehicles captured in FHWA data set is 4 and the data is available for only 40 s. Both the data sets provide speed and position for all vehicles at 1 s interval. For Ohio Data, the position and speed of a vehicle is estimated to be accurate within ± 0.15 m (0.5 ft) and ± 1.6 km/h (1 mph) respectively. The Ohio Data used is for platoon 123 that traveled on one lane of I-70 near Columbus, Ohio. The FHWA data was collected at Mulholland Drive in Los Angeles, California, and the section was 409 m (1341 ft) long with a 3% upgrade. The FHWA data is accurate within 0.9–1.5 m (3–5 ft). The freeway had five lanes and data from the left most lane is used. Both data sets comprise of passenger vehicles only.

The data sets are relatively old and vehicular acceleration, deceleration and size have changed over the years. However, a model that can simulate the traffic flow characteristics in Ohio and FHWA data will also be able to simulate traffic flow characteristics of today's vehicle. Collection of newer data set for the development and validation of a simulation model requires extensive resources that were out of the scope of this research.

4.2. Model parameters

A model requires input to its parameters, which can be either assigned randomly from a distribution or obtained from the field data. However, in order to make meaningful comparison with the field data, input parameters must be obtained from the same data set, only then the simulation model will be able to replicate characteristics of drivers of the field data and meaningful comparison can be made between the results of the simulation model and field data. If the inputs are provided from a different data set, then behavior of drivers in simulation will not match the behavior of drivers in the field data, then a meaningful comparison would not be made.

To validate the results of CELLSIM with the field data, drivers in CELLSIM must have similar characteristics to the Ohio and FHWA data sets. Only then a valid comparison can be made

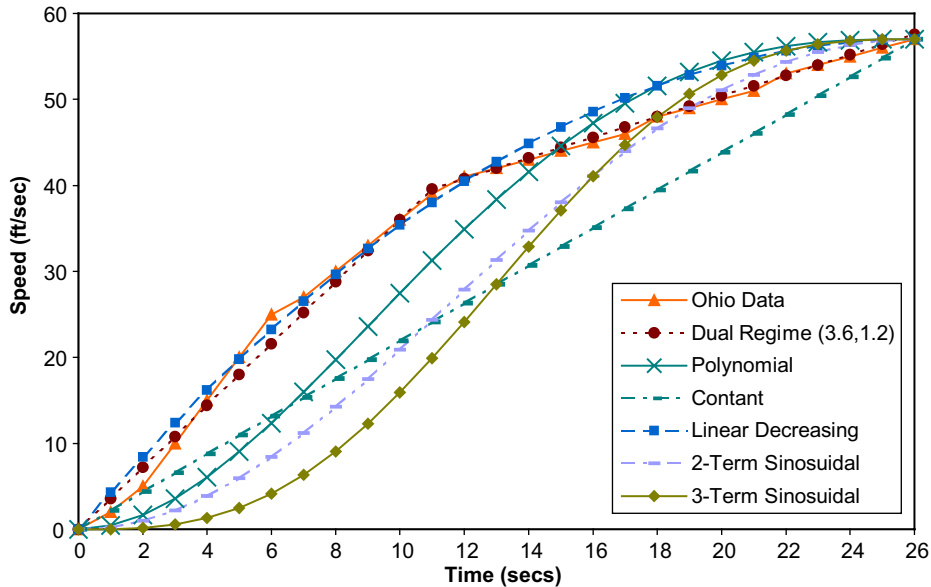


Fig. 2. Comparison of speed profiles for different acceleration models.

between the results of CELLSIM and data sets. Data sets were used to obtain input parameters for the model i.e. the acceleration constants (a_1 and a_2), TP (preferred time headway), and the buffer space (bs). TP and bs are specific for each driver and is thus obtained from the data sets.

To calculate the acceleration rates for the dual-regime model, speed profile of each vehicle during acceleration was plotted. Average speed for every time second was then computed to find an average speed profile. The best fit to the speed profile provided the acceleration rates for the dual-regime model. The average speed profile and the dual regime model for the Ohio Data are presented in Fig. 2. The acceleration rates calculated for the FHWA Data are 1.25 m/sec^2 (4.1 ft/sec^2) and 1.13 m/sec^2 (3.7 ft/sec^2). Maximum speed of vehicles used in CELLSIM is 29 m/s (95 ft/s) since none of the vehicles in the data sets exceeded this value.

4.3. Microscopic validation

Microscopic validation requires the comparison of individual vehicle trajectories and speeds from simulation versus field data (Benekohal, 1989). Fig. 3 shows the speed of every third vehicle in the platoon for the Ohio Data. The speeds from simulation do not tend to closely match with their corresponding values in the field data. This is acceptable as long as the differences are not large. Fig. 3 also shows the stop and go condition of traffic. The leader stops first and then the followers. Followers come to a stop one by one. The leader after remaining stopped for several seconds, accelerates and the followers accelerate behind their leaders. The simulation model is able to replicate this queue formation and stop and go condition similar to the real world data.

Fig. 4 shows the trajectory of vehicles for the 13 vehicles from CELLSIM and the Ohio data. From the figure it is evident that the positions of vehicles from CELLSIM and field data show

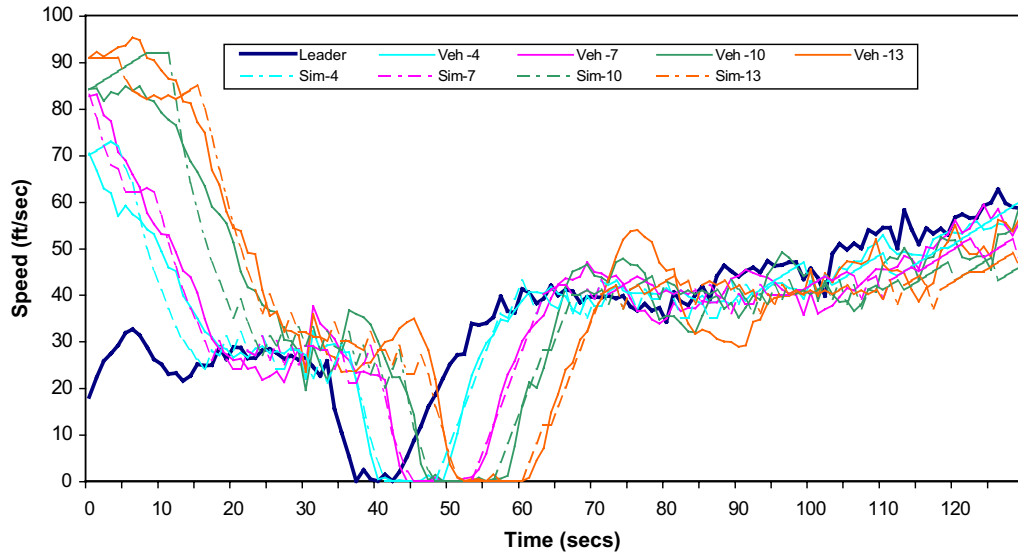


Fig. 3. Comparison of speed profiles for vehicles 4, 7, 10 and 13 from CELLSIM (Sim) versus Ohio data (Veh) (continuous lines present Ohio data, dot-dashed lines present results of CELLSIM). Bold line represents leader.

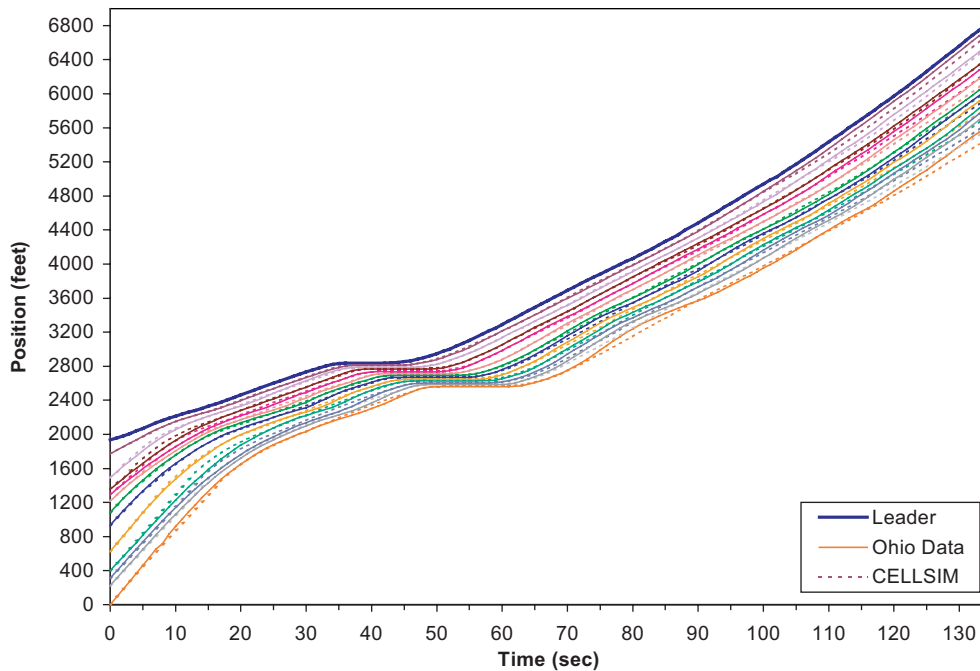


Fig. 4. CELLSIM versus Ohio data, trajectory plots for 13 vehicles.

close agreement for every time second. Results of microscopic validation using the FHWA data is presented in Fig. 5. Again the results match closely. For Ohio and FHWA data sets, the closeness

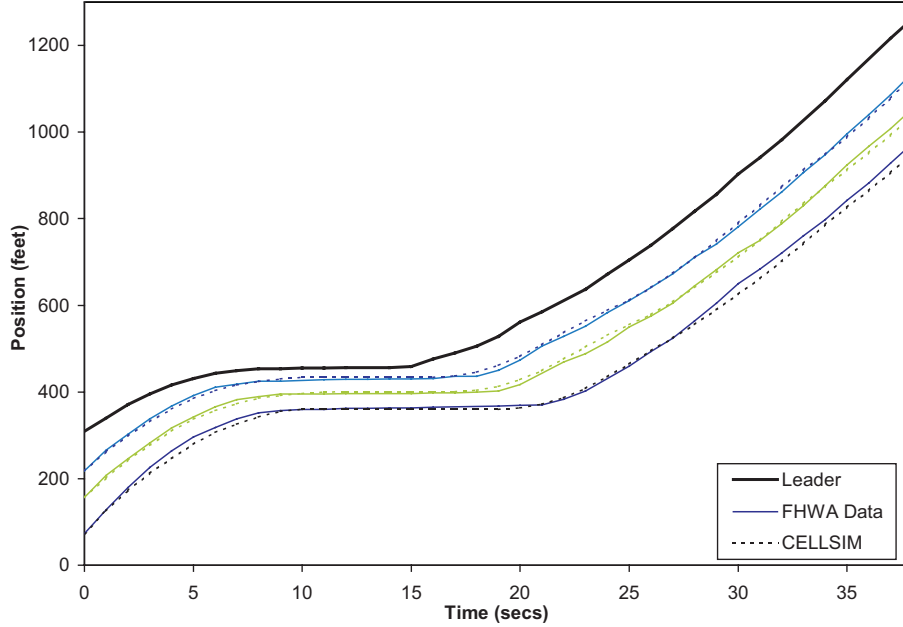


Fig. 5. CELLSIM versus FHWA data, trajectory plots for four vehicles.

of results from CELLSIM and the field data clearly indicates the validity of the model at the microscopic level. No abnormalities or unexpected behavior is found in these results. To support the claims of visual inspection, error tests were also performed. These tests are discussed in Section 4.3.1.

4.3.1. Error tests

Error tests are conducted since they do not impose any restriction or require assumptions about the data set. Most statistical tests require assumptions of normality and the data to be mutually independent. This is not the case with the data sets here. The distribution of data is not normal and the simulation and field data are not independent. Vehicles in simulation start with the same speed and position as in the field data. Speed and position of vehicles are also dependent on their preceding values. In addition, the leader is the same in data sets as well as simulation. Hence the data sets cannot be assumed to be mutually independent. Because of the above reasons, error tests were found to be better suited for comparison of simulation results and the field data.

Error tests are used to quantitatively measure the closeness of fit of results from simulation compared to the field data. The result is considered to be perfect, if values from simulation and field data are identical. The root mean square (RMS) error test is one test, which compares quantitatively the simulation results from field data. It is expressed as:

$$\text{RMS Error} = \sqrt{\frac{1}{N} \sum_{n=1}^N (y_n^s - y_n^0)^2} \quad (11)$$

where y_n^s is the value from simulation at time n , y_n^0 the corresponding observed value (from field data), and N the number of observations (130 for Ohio data).

The RMS error measures the deviation of the simulated value from the observed value. The magnitude of error can be evaluated only by comparing it with the average size of the variable in question. Another test that does not require comparison with the average size of variable is the RMS percent error. It is defined as:

$$\text{RMS Percent Error} = \sqrt{\frac{1}{N} \sum_{n=1}^N \left(\frac{y_n^s - y_n^0}{y_n^0} \times 100 \right)^2} \quad (12)$$

The RMS percent error values tend to be large when smaller values are compared with larger differences. Similarly, it tends to be large when observed values are very small. Another error test is the mean percent error, which is defined as:

$$\text{Mean Percent Error} = \frac{1}{N} \sum_{n=1}^N \left(\frac{y_n^s - y_n^0}{y_n^0} \times 100 \right) \quad (13)$$

Mean percent error provides the deviation of simulated values from the observed values as a percent, which provides a good quantitative measure of deviation. But the problem with percent errors is that they are close to zero if large positive errors cancel out large negative errors (Pindyck and Rubinfeld, 1998). To avoid this problem both positive and negative percent errors are also calculated and used in the analysis as they are clearly present if the model is underestimating or overestimating compared to the observed values. Mean absolute errors can also be calculated to avoid the problem of positive and negative errors canceling out but important information is lost when only magnitude of errors is known. RMS errors are used more often as they tend to penalize large individual errors more heavily (Pindyck and Rubinfeld, 1998). However, low RMS errors are only one desirable measure of close fit to field data.

Another statistic used in econometrics is Theil's inequality coefficient, which is defined as (Pindyck and Rubinfeld, 1998):

$$U = \frac{\sqrt{\frac{1}{N} \sum_{n=1}^N (y_n^s - y_n^0)^2}}{\sqrt{\frac{1}{N} \sum_{n=1}^N (y_n^s)^2} + \sqrt{\frac{1}{N} \sum_{n=1}^N (y_n^0)^2}} \quad (14)$$

The numerator of U is the RMS error and the scaling of the denominator is such that U always falls between 0 and 1. If $U = 0$, i.e. $y_n^s = y_n^0$ for all n , then there is perfect fit. If $U = 1$, the performance of the model is as bad as it can possibly be. Hence the Theil's inequality coefficient measures the RMS error in relative terms. Theil's inequality coefficient can be decomposed into smaller errors, which provides a useful means of breaking up the total error. These smaller errors represent specific type of errors in the model. The decomposition is as follows (Pindyck and Rubinfeld, 1998):

$$\frac{1}{N} \sum_{n=1}^N (y_n^s - y_n^0)^2 = (\mu_s - \mu_o)^2 + (\sigma_s - \sigma_o)^2 + 2(1 - \rho)\sigma_s\sigma_o \quad (15)$$

where μ_s and μ_o are the means, and σ_s and σ_o are the standard deviations of simulated and observed values, respectively. ρ is the correlation coefficient and can be calculated as:

$$\rho = \frac{(1/N) \sum (y_n^s - \mu_s)(y_n^0 - \mu_o)}{\sigma_s \sigma_o} \quad (16)$$

The first term on the right hand side of Eq. (15) is zero, if the average change from simulation coincides with the average change in observed values. Errors in this term are called errors in central tendency (Theil, 1966). The second term is zero, if the standard deviations are equal. Errors due to the second term are termed errors due to unequal variation (Theil, 1966). The third term is zero, if the correlation coefficient is 1; or if the covariance of simulated and observed values changes ($\rho\sigma_s\sigma_o$) and takes its maximum value, viz., the product of the two standard deviations ($\sigma_s\sigma_o$) (Theil, 1966). Errors in the third term are termed errors due to incomplete covariation. A convenient way to handle the decomposition is to divide each of the three terms by their sum. This leads to (Pindyck and Rubinfeld, 1998):

$$U^M = \frac{(\mu_s - \mu_o)^2}{(1/N) \sum (y_n^s - y_n^0)^2} \quad (17)$$

$$U^S = \frac{(\sigma_s - \sigma_o)^2}{(1/N) \sum (y_n^s - y_n^0)^2} \quad (18)$$

and

$$U^C = \frac{2(1 - \rho)\sigma_s\sigma_o}{(1/N) \sum (y_n^s - y_n^0)^2} \quad (19)$$

The proportions U^M , U^S and U^C are called the bias, the variance and the covariance proportions of U , respectively. They are useful as a means of breaking down the simulation error into its characteristic sources. U^M is an indication of systematic error, since it measures the extent to which the average values of the simulated and actual ones deviate from each other. A large value of U^M , would mean that a systematic bias is present and the model needs to be revised. U^S indicates the ability of the model to replicate the degree of variability in the variable of interest. If U^S is large, it means that the actual series has fluctuated considerably while the simulated series shows little fluctuation, or vice versa. This would again indicate that the model should be revised. U^C measures unsystematic error, i.e. it represents the remaining error after deviations from average values have been accounted for. Since it is unreasonable to expect simulation results to be perfectly correlated with the actual outcome, this component of error is less worrisome than the other two. For any value of $U > 0$, the ideal distribution over the three sources is $U^M = 0$, $U^S = 0$, and $U^C = 1$ (Pindyck and Rubinfeld, 1998).

4.3.2. Analysis of results

The above tests were performed for the position and speed of individual vehicles from simulation versus the field data for every time second. Ohio Data was used for this comparison as the data is more reliable and provides a bigger data set with more vehicles and longer duration, compared to the FHWA data. These tests were also performed for the macroscopic parameters and the results are described in Section 4.4. Tables 2 and 3 presents results of tests for position and speed of individual vehicles, respectively. The test for the leader is not conducted since it is the exact same in field and in simulation.

Table 2

Error tests for position of vehicles (Ohio data)

Vehicle number	Mean (%) positive error	Mean (%) negative error	Mean (%) error	RMS (%) error	RMS error	Theil's inequality coefficient
2	0.20	−0.71	−0.24	0.63	35.75	0.0044
3	0.37	−0.45	−0.07	0.57	24.52	0.0031
4	0.80	−0.36	0.05	0.86	20.82	0.0027
5	0.99	−0.54	0.03	1.02	34.57	0.0046
6	0.64	−0.54	−0.01	0.82	30.64	0.0041
7	0.31	−0.57	−0.24	0.59	23.08	0.0032
8	0.31	−0.72	−0.43	0.77	30.80	0.0043
9	0.55	−0.81	−0.33	0.92	42.05	0.0060
10	1.44	−0.95	0.18	1.84	48.82	0.0071
11	1.55	−1.29	−0.21	1.77	57.88	0.0086
12	0.87	−1.33	−0.38	1.42	54.82	0.0082
13	0.58	−1.50	−0.73	1.63	45.34	0.0070
Average	0.72	−0.81	−0.20	1.07	37.42	0.0053

Table 3

Error tests for speed of vehicles (Ohio data)

Vehicle number	Mean (%) positive error	Mean (%) negative error	Mean (%) error	RMS (%) error	RMS error	Theil's inequality coefficient
2	10.81	−13.56	−2.42	20.70	3.19	0.0411
3	12.67	−12.81	−1.51	17.67	4.20	0.0522
4	10.05	−12.06	−2.47	18.04	4.17	0.0518
5	12.90	−12.77	−2.96	19.23	4.44	0.0556
6	13.58	−13.63	−1.36	21.17	4.63	0.0579
7	17.30	−12.97	−1.75	23.53	4.33	0.0534
8	21.78	−13.95	−0.78	34.89	4.71	0.0569
9	23.61	−12.82	−0.92	26.99	5.01	0.0569
10	36.71	−15.93	5.13	72.35	6.22	0.0689
11	17.31	−16.03	−5.71	24.83	5.68	0.0628
12	17.60	−15.97	−4.03	24.39	5.87	0.0643
13	27.19	−13.77	1.69	34.81	6.11	0.0648
Average	18.46	−13.86	−1.42	28.22	4.88	0.0572

The results show that the simulation results closely match the field data for both the position and speed of individual vehicles. The mean percent errors for position of all vehicles are less than 0.5 percent. Negative values for mean error indicate underestimation and positive values overestimation and nine out of thirteen vehicles showed underestimates in mean percent errors, which means that they traveled slightly less than the actual vehicles. The mean positive and negative errors are less than 2 percent with the average value being less than 1 percent. The RMS percent error is also less than 2 percent. All of the errors are hence very small. These results clearly

indicate quantitatively that the difference in position of each vehicle in simulation versus field data is not more than 2 percent. The RMS error and the Theil's inequality can be used for comparison. Vehicles 9–13 show slightly larger values for the RMS error and the Theil's inequality coefficient compared to other vehicles. One of the reasons could be that they follow a simulated leader rather than a leader from the field data and the error gets larger as they get farther away from the original leader. Another reason could be error in one of the input parameters. However, the Theil's coefficient is very close to zero and the RMS error not large enough to indicate problems in the model.

For analysis of speed, speed of individual vehicles from field data was rounded to integer values for comparison with results from simulation. This was done since the value of speed in simulation might be equal to the corresponding value of speed in the field data, but since integer values are used in the model it is different. This difference would show an error in the model during the tests although it is an error due to rounding. The result of analysis of speed is presented in Table 3. The mean percent error for speed of all vehicles is less than 6 percent. The value of mean error is negative for most of the vehicles except vehicles 10 and 13. However, these errors are small considering relative difference in speed from simulation and field data for every second can be large. The mean positive error is less than 25 percent for nine vehicles. Only vehicles ten and thirteen have positive errors higher than that. The average of mean positive error is less than 19 percent. The negative errors are less than 16 percent for all vehicles with an average value of 14 percent. The average RMS percent error is equal to 28 percent. Vehicle ten has the maximum RMS percent error of 72 percent. This error can be large especially at lower speeds where differences can be large. The difference in speeds between simulation and field data divided by a small quantity and then multiplied by one hundred and squared (Eq. 12) can produce high error values. Hence, the RMS percent error should be used for comparison rather merely pointing an error in the model. For further investigation of vehicle ten the RMS error and Theil's inequality can be checked. Both RMS error and the Theil's inequality are low for vehicle ten, which indicates the results are valid. However, the RMS error and the Theil's inequality comparatively are slightly higher, which suggests that improvement in simulation of vehicle ten can be made to simulate the actual conditions more closely. This also suggests that the error tests in combination can be used for indicating problems in individual behavior of vehicles. The RMS error and Theil's inequality for the rest of the vehicles are all very small. These results show quantitatively that the difference in speed of each vehicle from CELLSIM versus field data for every second are small and acceptable.

Tests for U^M , U^S , and U^C for individual vehicles were not needed, since large errors or problems were not found. In addition, these tests are not recommended for microscopic validation since such detailed evaluation of each vehicle is not needed. However, thorough evaluation of errors for macroscopic parameters should be performed and this is discussed in detail in Section 4.4.

4.4. Macroscopic validation

In macroscopic validation, the overall performance of the platoon in the simulation model is compared with the data sets. The following comparisons were suggested between simulation results and field data for macroscopic validation (Benekohal, 1989):

1. Comparison of flow parameters over time,
2. Statistical analysis, and
3. Comparison of fundamental relationships of traffic flow.

Results from statistical analysis of macroscopic parameters from CELLSIM were compared to other known models for the same platoon data. This was carried out to evaluate how well the model performs, compared to other more detailed models. In addition to the above comparison, the following tests were also carried out:

4. Error tests, and
5. Stability analysis.

The error tests are carried out to quantitatively determine the accuracy of results from simulation. Stability analysis checks the overall behavior of the simulation model during normal and emergency deceleration conditions. Details are discussed in the following sections:

4.4.1. Comparison of flow parameters

The flow parameters used for comparison are: average speed, density and volume. These parameters were computed from CELLSIM and the field data sets for 1 s intervals. Figs. 6 and 7 show the plots between these parameters and time for both the data sets. The figures show the disturbance experienced by the platoons. In the Ohio Data, since speed of all 13 vehicles have been averaged for every time second zero platoon speed is not observed despite the fact that all vehicles were stopped for several seconds. The plot shows an average minimum value. For the FHWA Data average speed of vehicles shows that they come to a complete stop. From Figs. 6 and 7, it is clear that average speed computed from CELLSIM closely matches the speed from Ohio and the FHWA data sets. However, the simulation data does not show as much variation as the field data sets.

The density and volume plots are also presented in Figs. 6 and 7. Density is calculated as:

$$k = 5280 \times \left[\frac{N - 1}{s_{\text{first}} - s_{\text{last}}} \right] \quad (20)$$

where k is the density in vehicles per mile, N the number of vehicles in platoon, s_{first} , s_{last} the position (front ends) of the first (platoon leader) and the last vehicle in the platoon at a point in time, ft.

The denominator of Eq. (20) represents the distance from the front end of the first vehicle (platoon leader) to the last vehicle in the platoon. $N - 1$ headways exist between N vehicles and are considered in the equation. Figs. 6 and 7 show the fluctuation in density for the Ohio and the FHWA data for the total simulation time. The density increases and reaches jam density when the vehicles come to a stop. The density plot between CELLSIM and the Ohio Data show very good agreement. For the FHWA data the results from CELLSIM are also reasonably close.

For volume, the results from CELLSIM and the data sets also show good agreement; however, the results are not as close as for average speed and density. Volume does not show as close an agreement as density and average speed since it is computed as product of speed and density. The figures confirm visually that the simulation results are in agreement with the field data sets.

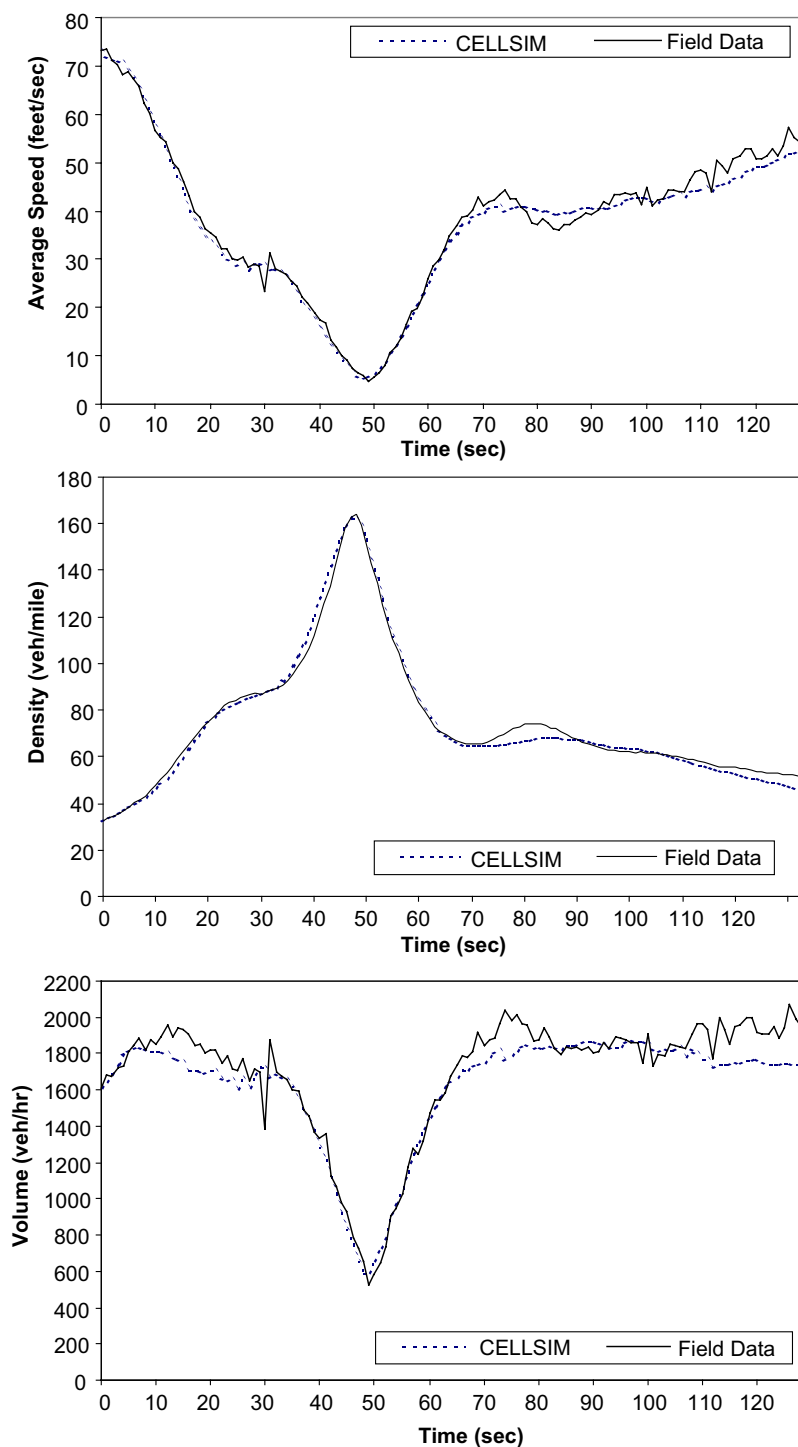


Fig. 6. CELLSIM versus field data (Ohio data) average speed, density and volume versus time plots.

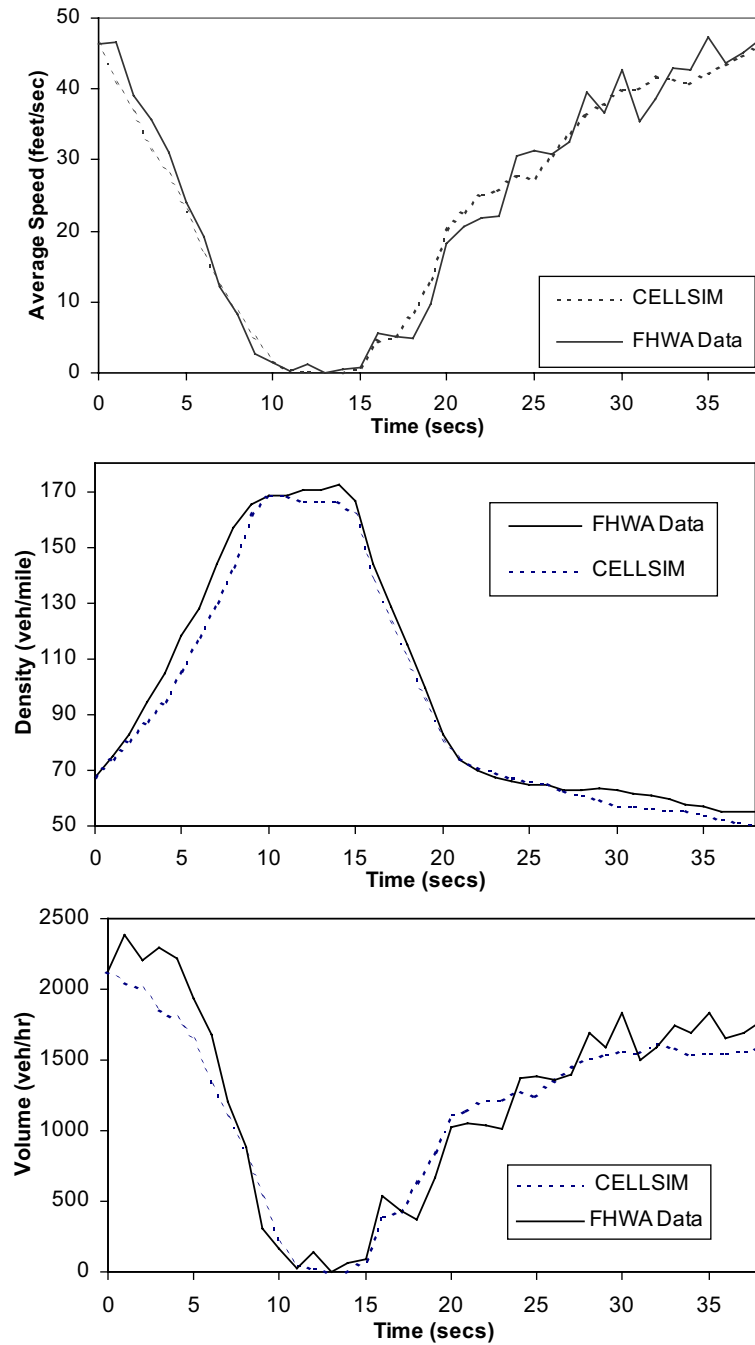


Fig. 7. CELLSIM versus FHWA data, average speed, density and volume versus time plots.

Statistical analyses and error tests of macroscopic parameters were also carried out to support the visual claim. These tests are discussed in the following sections.

4.4.2. Statistical analysis of flow parameters

Linear regression analyses were used to compare average speed, density and volume computed from CELLSIM with those from the field data. The aim is to find how well the field data can be explained by simulation or vice versa. The regression equation used, is of the form:

$$Y = B0 + B1 \cdot X \quad (21)$$

where Y is the speed, density or volume from simulation, X the speed, density or volume from field data, and $B0$, $B1$ the regression variables.

Table 4 presents the summary of results from regression analyses. For both data sets, density shows the highest R^2 i.e. 0.992. The R^2 for speed is also in the range of 0.98. Since volume is the product of speed and density, values of R^2 are less than density and speed. The slope of the regression line ($B1$) and the y -intercept ($B0$) are close to one and zero, respectively, both for speed and density. The regression analysis indicates a strong agreement between the results of CELLSIM and both the field data sets. CELLSIM is able to replicate two completely different sets of field data, collected at different sites involving different vehicle and driver characteristics. The high R^2 values and closeness of slope to one and intercept to zero indicates that CELLSIM's result are very close to the values computed from the field data sets.

To compare the statistical results of CELLSIM with other CF models, R^2 values of average speed and density are compared for the same platoon of the Ohio data. This is presented in Section 4.4.3.

4.4.3. Comparison of regression analysis with other car-following models

Table 5 shows results of regression analysis (R^2) of macroscopic parameters for various car-following models when validated using platoon 123 of the Ohio Data. The models in Table 5 were validated using the same methodology used in CELLSIM. CELLSIM compares well with sophisticated models like INTELSIM which incorporates different reaction times of each driver in detail. The reaction times used in INTELSIM are also flexible because of the model's shorter simulation time step. However, the results are almost identical. This shows that even with the simplicity in modeling and the round off errors due to the use of integer numbers it compares well

Table 4
Results of regression, CELLSIM versus Ohio and FHWA data

Macroscopic parameter	$B0$	$B1$	$SE(B0)^a$	$SE(B0)^a$	SE^b	R^2
<i>Ohio data</i>						
Average speed	0.115	0.974	0.432	0.010	1.867	0.986
Density	−4.715	1.049	0.735	0.008	3.066	0.992
Volume	183.609	0.863	42.482	0.022	96.264	0.921
<i>FHWA data</i>						
Average speed	1.028	0.944	0.676	0.023	2.357	0.979
Density	−0.643	0.969	2.217	0.014	4.952	0.992
Volume	159.743	0.859	64.292	0.030	202.387	0.958

^a Standard error for regression variables.

^b Standard error for the macroscopic parameter.

Table 5

Comparison of R^2 from car-following models for platoon 123 of Ohio data

Macroscopic parameter	INTELSIM ^a	CARSIM ^b	CARSIM ^c	NETSIM ^a	INTRAS ^c	FRESIM ^c
Average speed	0.985	0.984	0.97	0.96	0.97	0.96
Density	0.994	0.989	0.93	0.95	0.97	0.96
Volume	0.923	0.844	0.77	0.48	0.85	0.82

^a From reference Aycin and Benekohal (1998).^b From reference Benekohal and Treiterer (1988).^c From reference Aycin and Benekohal (1999).

with models that are much more detailed. Results from CARSIM, NETSIM, FRESIM, and INTRAS presented are average of five runs. The results from CELLSIM show better performance when compared with average values from these models.

4.4.4. Comparison of fundamental relationships of traffic flow

Further validation is performed by comparing the three fundamental relationships of traffic flow from Ohio Data versus CELLSIM. Volume versus density, average speed versus density, and volume for every second of time are plotted. The plots are presented in Fig. 8. The values of average speed, density, and volume are used from Fig. 6. The only difference is that they are plotted against each other rather than time. Results from CELLSIM again closely match the field data. This indicates that CELLSIM is able to reproduce the fundamental diagrams of traffic found in the real world with great accuracy. However, the simulated data is devoid of transience as observed in the field data. This shows that real world drivers tend to be influenced by several factors that cannot be incorporated in a simulation model (Aycin and Benekohal, 1998).

The fundamental diagrams also show the hysteresis effect created due to the stop and go condition. The arrows in Fig. 8 indicate the platoon approaching and leaving the disturbance. CELLSIM is able to replicate this effect, clearly showing that the model can be used for studying traffic phenomenon. Other traffic phenomenon can also be studied in greater detail since higher number of vehicles can be simulated microscopically.

4.4.5. Error tests

The error tests discussed previously were also used to test the macroscopic parameters of average speed, density, and volume. The results are presented in Table 6. Density shows the closest fit to the field data, followed by speed and volume. The error in speed tends to be larger than position, as observed in microscopic validation. However, the mean percent error for all parameters including the mean negative and positive errors are all less than 6 percent. Hence no unexpected errors are present. The RMS percent errors are also small. The RMS error for volume is high as a number but for evaluation it should be compared with its average value. But comparison with average value is not necessary in the presence of Theil's inequality coefficient and the three proportions which are presented in Table 7. Theil's coefficient is minimal for the three parameters clearly indicating that no problems exist in the model.

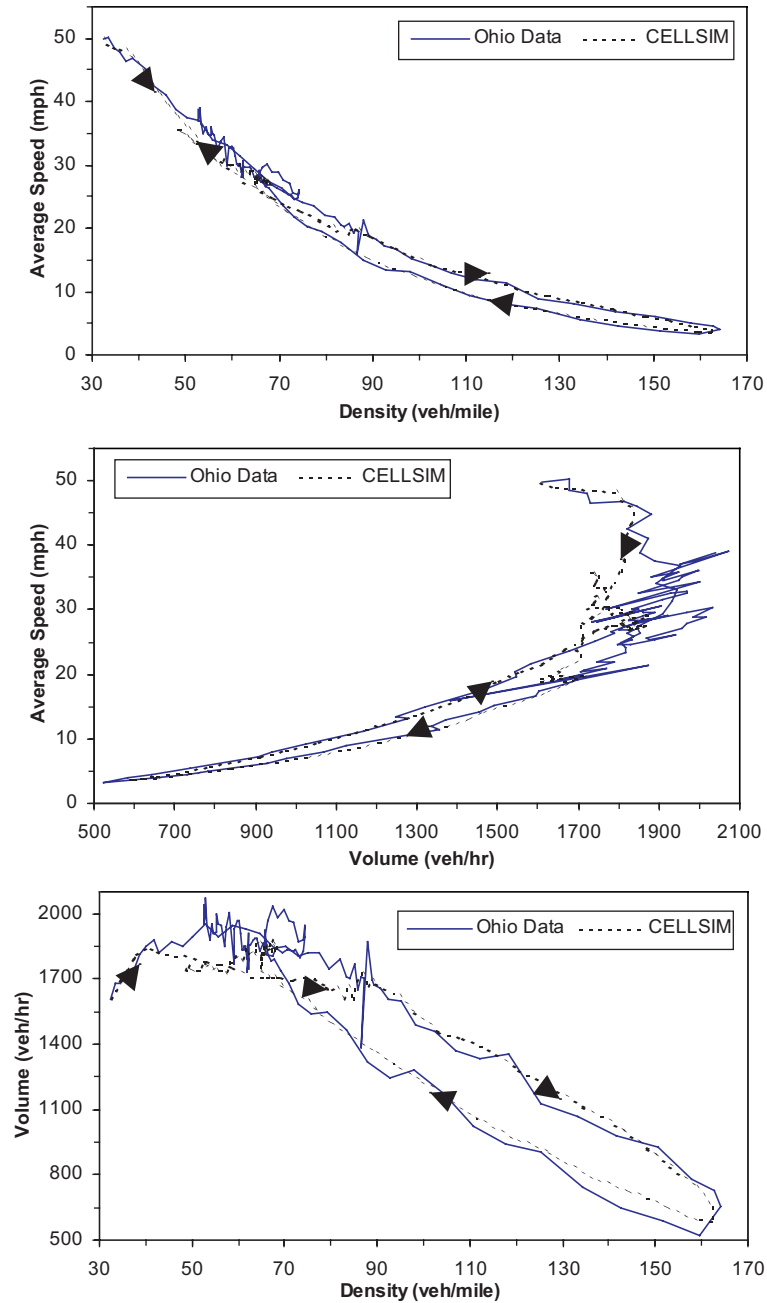


Fig. 8. Fundamental diagrams of traffic flow, comparison between Ohio data and CELLSIM.

The total error and its breakup indicated in Eq. (15), and the values of U^M , U^S and U^C are presented in Table 7. For the macroscopic parameters, the error due to incomplete covariation

Table 6
Results of error tests for Ohio data

Macroscopic parameters/ error tests	Mean (%) positive error	Mean (%) negative error	Mean (%) error	RMS (%) error	RMS error	Theil's inequality coefficient
Average speed	4.93	−5.12	−2.30	6.15	2.19	0.0267
Density	2.40	−3.64	−1.41	4.19	3.08	0.0193
Volume	−5.96	−3.39	3.69	6.93	122.03	0.0361

Table 7
Breakup of total error for macroscopic parameters

Macroscopic parameter/ errors	Total error $1/N \sum (y_n^s - y_n^0)^2$	Central tendency $(\mu_s - \mu_o)^2$	Unequal variation $(\sigma_s - \sigma_o)^2$	Incomplete covariation $2(1 - \rho)\sigma_s\sigma_o$	Bias pro- portion U^M	Variance proportion U^S	Covariance proportion U^C
Average speed	4.81	0.95	0.15	3.71	0.198	0.031	0.771
Density	9.50	0.34	2.27	6.89	0.036	0.239	0.725
Volume	14891.59	4541.99	1377.85	8971.75	0.305	0.093	0.602

(third term of Eq. (15)) is the largest source of error. This error is also indicated by U^C the covariance proportion. U^C measures unsystematic error and since it is unreasonable to expect simulation results to be perfectly correlated with actual outcomes, this component of error is less worrisome than U^M and U^S . The error in central tendency is the second largest error for both speed and volume. This error is also indicated by U^M . U^M for speed is not troubling and does not indicate that a systematic error is present. This is also the case for volume. However, the errors in volume are a result of the errors in speed and density. Thus, the errors in volume should not be considered troubling on its own. For density the error in central tendency is the least of the three errors indicating a close fit to the field data. The error for density in unequal variation indicates that the results from simulation fluctuated slightly higher than the field data and is not troubling as well. Overall, the error tests prove that the macroscopic parameters for average speed, density and volume from simulation closely match the Ohio data.

4.4.6. Stability analysis

Stability analysis is performed to check the stability and validity of the car-following model in traffic disturbance. Two disturbances; (a) mild disturbance (normal deceleration) and (b) severe disturbance (emergency deceleration) were introduced and the behavior of the vehicles were observed for unrealistic acceleration, deceleration or abnormalities, in CELLSIM. Ten vehicles with identical characteristics were used in the analysis and their behavior was observed from the plots of speed and space gap. Vehicles at start were separated with a time headway (time separation between rear bumper of the leader and front bumper of the follower) of 1 s.

For the mild disturbance, the leader decelerates at a rate of 1.83 m/s/s (6 ft/s/s) from a speed of 27.4 m/s (90 ft/s) to 9.14 m/s (30 ft/s). This represents typical deceleration in normal driving. The leader maintains its speed of 9.14 m/s for 5 s before accelerating back to its original speed. The

leader uses an acceleration rate of 1.22 m/sec^2 (4 ft/sec^2). Followers go through the same disturbance, behind the leader. This mild disturbance in the platoon is presented in Fig. 9. Speed and space gap of every third vehicle is plotted in Fig. 9a and b, respectively.

In Fig. 9a and b, it is observed that the speed and space gap profile of followers during deceleration and acceleration remains stable. However, transience can be seen in the speeds of the followers when they try to stabilize their speeds and desired space gap behind the leader. This occurs when the leader maintains its reduced speed of 9.14 m/s (30 ft/s) for 5 s. Followers try to achieve their desired space gap behind the leader. But this is not possible since the leader accelerates back to its normal speed. Because of the disturbance the acceleration of vehicles can be checked for unusual rates of acceleration and abnormal behavior. However, no unusual acceleration rates were found. Due to the deceleration of the leader, no collision or excessive decel-

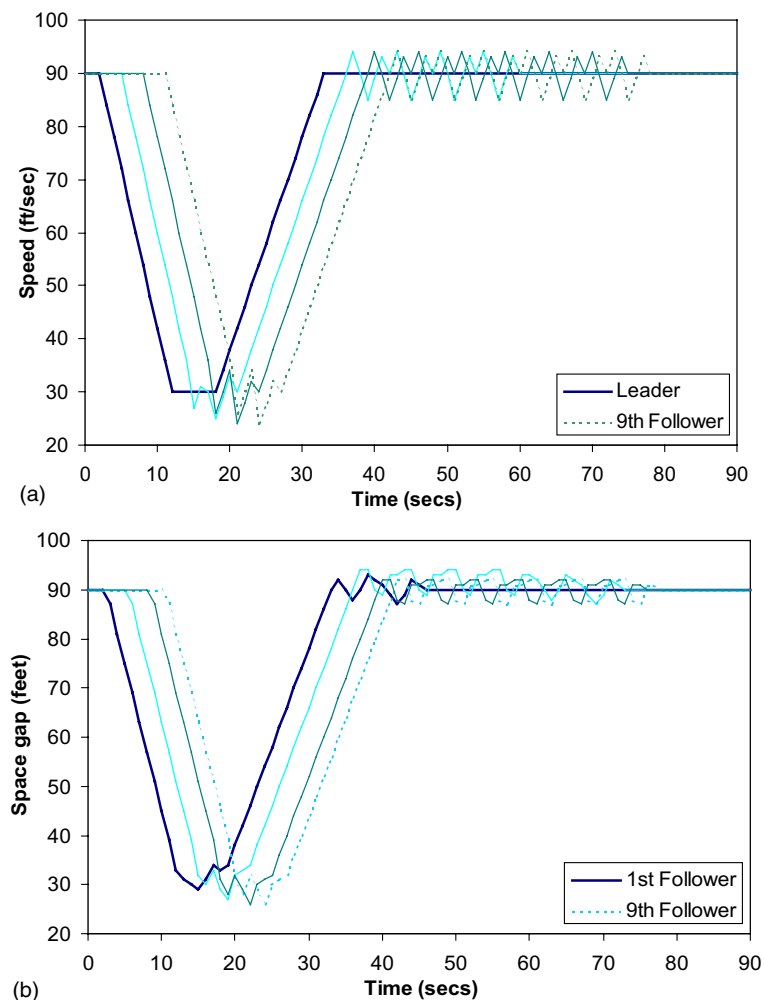


Fig. 9. (a) Stability analysis: speed versus time for mild disturbance scenario (top) and (b) stability analysis: space gap versus time for mild disturbance scenario (bottom).

eration rates were found either. This checks the stability and the behavior of vehicles in the model. An unstable model will show unexpected behavior of followers either going into the disturbance or coming out of it. The abnormalities will show up as limited or excessive deceleration or acceleration in the behavior of the following vehicles. The dampening effect in speed of followers is also present as they try to reach the steady state condition after the disturbance. Around the 80th time step all vehicles have reached their steady state and no transience in speed is observed. Similarly, the space gap between vehicles shows the transience in reaching the steady state but no abnormal space gap is observed for any vehicle.

In the severe disturbance scenario, the platoon goes through two disturbances. First the leader comes to a stop using an emergency deceleration rate of 6.4 m/sec^2 (21 ft/sec^2) from a speed of 25.6 m/s (84 ft/s). The leader remains stopped for several seconds before accelerating to a speed of 11 m/s (36 ft/s). The leader then again decelerates to a stop. The rate of deceleration used in this second disturbance is 5.5 m/s/s (18 ft/sec^2). The followers are forced to follow the leader and go through this stop and go condition. They avoid collision by trying to stop behind the leader and maintain a buffer space. This rigorously tested the collision avoidance sequence and the stability of the model. In both disturbances no collisions occurred. However, because of the nature of the severity of the test, the buffer space was reduced to zero. Plot of speed of every 3rd vehicle and their space gap for the severe disturbance case is presented in Fig. 10a and b, respectively. It is clear from the figures that no excessive acceleration or unrealistic deceleration occurred in any vehicle. None of the follower's deceleration rate exceeded the maximum allowable deceleration rate of 6.4 m/sec^2 (21 ft/sec^2). Every follower closely followed its leader. The severe disturbance scenario tested the stability of CELLSIM and confirms that the model is able to handle severe case of disturbance in a platoon. It also tests the working of the collision avoidance sequence.

The mild disturbance case is similar to the stability analysis performed in (Aycin and Benekohal, 2001) but the severe disturbance case is much more rigorous than the severe disturbance described in the reference. The severe disturbance described in (Aycin and Benekohal, 2001) used a deceleration rate of 4.88 m/s/s (16 ft/sec^2) compared to 6.4 m/s/s (21 ft/sec^2) used in this paper for the first disturbance. The second deceleration rate is also more severe 5.5 m/s/s (18 ft/s/s) compared to 1.5 m/s/s (5 ft/sec^2). These severe disturbances rigorously tested the stability of vehicles in a platoon in CELLSIM.

5. Computational speed

CELLSIM is implemented in *Mathematica*® (Wolfram Research, Inc.) and being a powerful and an interpreted language is slower to implement compared to compiled languages such as C and C++ or Fortran (Wagner, 1996). However, the simulation code has been kept as efficient as possible to rival the speed of other programming languages. The implementation of CELLSIM does not impose restriction on the length of the highway nor the number of vehicles simulated. However, the execution time depends heavily on the number of vehicles present in the system and it increases with the increase in their number.

To test the computational performance of the model, vehicles ranging from 500 to 2500 with increments of 500 vehicles were simulated for 1800 s. A highway with a single lane was simulated comprising of an entrance and an exit. Vehicles were fed at every second from an entrance at the

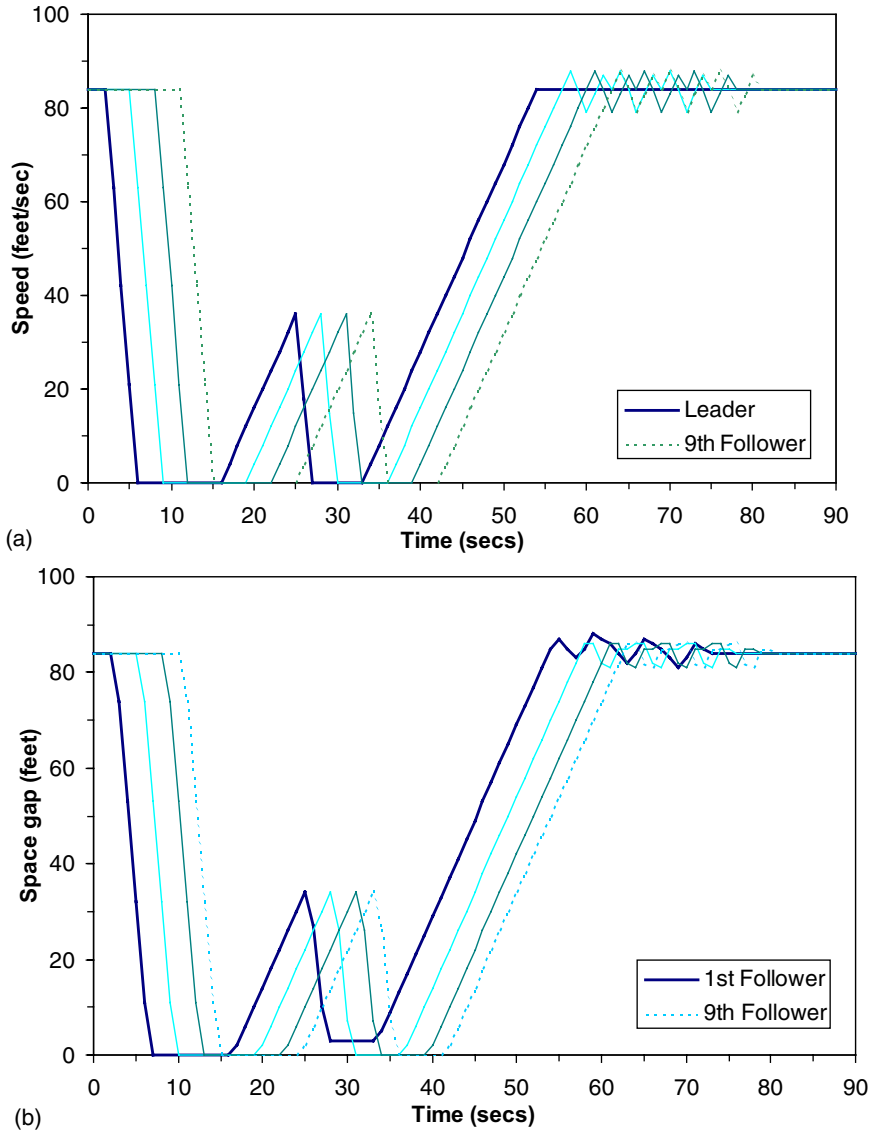


Fig. 10. (a) Stability analysis: speed versus time for severe disturbance scenario and (b) stability analysis: space gap versus time for severe disturbance scenario.

start of the section and vehicles were allowed to exit from the end of the section. The entering vehicles were checked for availability of space equal to four car lengths. This was done to ensure maneuverability of the entering vehicle and to check if other vehicles do not block the entrance. Initially, the vehicles were spaced out to have a density equal to LOS of C i.e. 24 vehicles per mile (HCM, 1994). The length of the section was thus a function of the number of vehicles at the start of simulation, which ranged from 32 to 161 km (20–100 miles) depending on the number of vehicles simulated. Extensive data e.g. speed, space gap and position of every vehicle was available

Table 8
Execution times for CELLSIM and STCA

CELLSIM				STCA			
No. of vehicles		Time (s)		No. of vehicles		Time (s)	
Average	Total	Simulation	Execution	Average	Total	Simulation	Execution
467	1223	1800	421.15	560	1253	1800	133.93
955	1781	1800	849.50	1160	1750	1800	285.01
1455	2281	1800	1312.61	1716	2300	1800	403.89
1955	2781	1800	1784.19	2214	2762	1800	531.69
2455	3281	1800	2244.03	2768	3283	1800	664.79

for every second of simulation time. The results of average number of vehicles in the system, total number of vehicles processed, simulation time, and the execution time are presented in Table 8. The average number of vehicles in the system was calculated as follows:

$$\bar{N} = \frac{\sum_{t=1}^T N\hat{t}}{T} \quad (22)$$

where, \bar{N} is the average number of vehicles in the system, N the number of vehicles in the system at every time second, and T the simulation time, seconds.

The total number of vehicles processed is the sum of vehicles at the start of simulation and the number of vehicles that exited from the end of the highway. The simulation time denotes the number of time steps in simulation and the execution time indicates the time taken by CELLSIM to complete the task of simulation from the required number of time steps. Time step of 1 s was used in simulation.

CELLSIM was able to simulate a total of around 2300 vehicles in shorter than real time. For 2800 vehicles, the execution time was close to the simulation time. As the total number of vehicles increased more than 3000, the execution time increased to more than the simulation time. The execution time is a function of the number of vehicles in the system and it increases with the increase in the number of vehicles. The execution times were computed on a Dell Dimension XPS Intel Pentium II Processor, with a processor speed of 400 MHz and 128 MB of RAM. With the processor speed now drastically improved (currently around 2.0 GHz), the execution times would also show a dramatic decrease. This will lead to a much higher number of vehicles being simulated in real time. This makes CELLSIM all the more appealing in simulating a highway network in real time.

To evaluate the computational performance of CELLSIM, its execution time was compared with a CA model. Stochastic Traffic Cellular Automata (STCA) (Nagel, 1998), was programmed in *Mathematica*[®] and its execution times were observed which are presented in Table 8. The simulation conditions remained the same as described previously for CELLSIM. Generally CA models are faster than car-following simulation models, because of their coarseness and simplicity. This is also evident from the results in Table 8. The number of vehicles simulated in real time with STCA is much higher compared to CELLSIM. However, direct comparison of execution times of CELLSIM with STCA is misleading, since STCA is much coarser than CELLSIM. The results from CELLSIM are realistic and can be validated using field data. However, this

is not the case with STCA. CA models can only be validated at the macroscopic level (Ponzlet, 1996). A particle in STCA moves in multiples of 7.5 meters (25 ft), whereas vehicles in CELLSIM, moves in multiples of 0.3 m (1 ft). STCA has speed jumps of 27 km/h (17 mph, 7.5 m/s) in 1 s, and it can come to a stop from a maximum speed of 135 km/h, a deceleration rate of 37.5 m/s/s (123 ft/s/s). This is not the case in CELLSIM and vehicles accelerate and decelerate realistically. The maximum deceleration rate in emergency conditions is 6.4 m/s/s (21 ft/s/s) and the maximum acceleration is also realistic. Thus, a direct comparison of execution times of CELLSIM with other CA models should not be made. However, it is anticipated that the execution time of CELLSIM is shorter than most CF models found in the literature, if these programs are coded in the same programming language, run on the same computer with exactly the same level of detail. However, comparison of execution times between CELLSIM and other models would be misleading, since each model has its own characteristics. The level of detail in each model is also different. Furthermore, each model is developed for a specific purpose. Thus it is not appropriate to compare execution times of different models and therefore, comparison of execution time of CELLSIM with existing CF models was not performed.

In the future, CELLSIM is planned to simulate the entire Illinois Interstate highway network. There are also plans for testing CELLSIM on parallel computers.

6. Conclusions and recommendations

A high fidelity traffic simulation model (CELLSIM) is developed for simulation of high volume of traffic on a state or regional level. Straightforward algorithms and efficient use of computational resources makes the model suitable for real time traffic simulation. The model is formulated using concepts of cellular automata (CA) and car-following (CF) models but is more detailed than CA models and simpler than CF models. Current CA models were found to be unrealistic for traffic flow studies and CF models too detailed to simulate a large network with high volume of traffic in real time on a personal computer. Results of comparison of macroscopic parameters of CELLSIM with current CF models showed that even with the simplicity in modeling, CELLSIM compared well with these models.

CELLSIM was validated both microscopically and macroscopically in detail using two sets of field data. Graphical, statistical analyses and several error tests were conducted to test the validity of the model. From the validation results, it can be inferred that CELLSIM can simulate congested and uncongested conditions of traffic realistically. It is also able to simulate the hysteresis effect as observed in real world traffic data. Moreover, the model performed satisfactorily in a most severe stability test.

Spatial discretization in CELLSIM is used to calculate percent space occupancy (SOC), which provides an improved measure of congestion compared to density. Length of each vehicle is considered against average length of vehicles used in the analysis. SOC can be used in real time traffic control for bottlenecks and traffic incident conditions. Traffic jams can be studied using CELLSIM in detail, since higher number of vehicles can be simulated microscopically. The lane changing logic of the model has been developed using the same car-following features of the model (Bham and Benekohal, 2002c).

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