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Analyzing Microscopic Behavioral between Two Phases of Follower and Leader in Traffic Oscillation with Developing Artificial Neural Networks

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Abstract

A Sudden speed drop in the leader vehicle of vehicle platoon results in propagating the deceleration wave from downstream towards the upstream flow. Points of wave propagation of the leader vehicle towards the follower vehicle identification are done based on Newell's theory in trajectory data. Deceleration wave propagates based on two parameters, time and space, τ- δ. A follower driver performs different behavioural reactions that they result in deviating follower driver from Newell's trajectory. In this paper, follower driver behaviour was identified based on two theories. The asymmetric microscopic driving behaviour theory and traffic hysteresis were used during the deceleration and acceleration phases, respectively. The data trajectories were classified into different traffic phases. Driver's parameters were identified at the microscopic level. Since the follower driver had the nonlinear behaviour, artificial neural networks were developed. They were able to analysis and identify effective parameters of dependent variable between deceleration phases leading to congestion phase, based on the behavioural patterns. Analysis results present effective parameters based on any behavioural patterns. Spacing difference of two phases, deceleration and congestion phases, was the most effective parameter of both two behavioural patterns, under reaction – timid and over reaction – timid. Increasing the spacing difference of two phases results in decreasing (increasing) time based on under reaction – timid (over reaction – timid).

Keywords: Stop–Go Traffic; Behavioural Patterns; Time between Two Phases; Deceleration Phase; Congestion Phase; Artificial Neural Networks.

1. Introduction

Stop and go traffic is frequently observed in congested freeway, unfortunately our understanding of traffic oscillation is not enough. When vehicle platoon enters the traffic oscillation, a follower driver presents different reactions in F service. When a leader vehicle develops sudden speed drop, it results in propagating deceleration wave in vehicle platoon. Stop – go traffic develops negative effects such as: travel delay, wasted energy and safety risks. Different reasons, lane change maneuvers and traffic moving bottleneck, leads to form and propagate an oscillation wave in traffic [1-10]. Stop – go waves grow or disappear in vehicle platoon based on vehicle models or lane change maneuvers [11] and [12]. Various behavioral characteristics of stop – go traffic result in the necessity of identifying and understanding congestion traffic. There is a need to the trajectory data in order to estimate different effects of traffic. Newell proposed the first theory of follower different behavior based on separating speed – spacing of deceleration and acceleration phases. Based on Newell's theory, spacing of acceleration phase is more than deceleration phase [13]. Also, Newell

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described stop-and-go traffic waves considering the parallel trajectories of leader and follower vehicles. Based on his theory, he used the same wave speeds of stop-and-go traffic for both deceleration and acceleration phases.

Because a leader vehicle changes its speed from V to V', wave speed propagates from downstream to the upstream. The wave speed is calculated by d^i/τ^i , based on Newell's theory [14]. Castillo analyzed the life cycle of stop and go traffic in congestion based on the same vehicle trajectory and stop – go wave speed. His researches present traffic oscillation based on growth and disappearing congestion in vehicle platoon [15]. Kim and Zhang calculated waves based on unequal speeds for acceleration and deceleration phases. Data trajectories were considered unparalleled. Also, time gap was considered completely stochastic for any driver [16]. Yeo and Skabardonis offered a microscopic asymmetric theory based on the speed- spacing relationship. In this theory, acceleration and deceleration curves were obtained by joining their starting points. Traffic condition is divided into 5 states: free-flow, acceleration, deceleration, coasting and stationary [17].

Behavioral asymmetric theory is able to describe different phase transitions of deceleration and acceleration phases. Also, this theory can explain traffic phenomena, vehicle maneuvering error, anticipation, life cycle of stop and go traffic cases, generation, growth and dissipation based on driver behavior characteristics. Laval and Leclercq classified behavioral pattern based on aggressive or timid driver. Research results identified traffic oscillation properties. They simulate properties such as, period and amplitude, based on the driver behavior and Newell's car following model [18]. Comparing vehicle platoon behavior before and after oscillation leads to identify delays in recovering the speed of the vehicle. This condition of delay results in the occurrence of the hysteresis phenomenon in stop and go traffic and asymmetric spacing in deceleration and acceleration phases [19, 20]. Asymmetric behavioral theory cannot completely analyze the hysteresis phenomena during acceleration and deceleration phases [21-24]. Treiterer and Myer studied vehicle platoon behavior for entering and exiting oscillation. They used the trajectory data from aerial photographs. Their research led to a quantitative relationship between speed average, density and flow rate and density. When a vehicle platoon enters traffic oscillation, conditions of before and after traffic oscillation did not restore immediately. This situation results in forming hysteresis loops [25].

Zhang formulated the hysteresis in traffic flow as a mathematical model to explain the transition between different traffic flows based on the driver behavior. According to Figure 2, the speed-density curve was divided into three traffic phases; namely, relaxation phase in acceleration pattern, prediction phase in deceleration pattern, prediction- relaxation balanced phase in strong equilibrium. Figure 2. demonstrates an increase in driver concentration on acceleration pattern, and also a reduction in driver concentration in the deceleration phase [20]. Zhang and Kim (2005) proposed a new car-following theory. In this theory, they presented a new value of headway that it was as a function of gap distance, and traffic phase, including acceleration, deceleration and coasting condition [26]. Laval findings show that hysteresis magnitude estimation bases Edie's observations. In invariable density, He classified hysteresis phenomena into four levels: Strong, Weak, Negligible, and Negative level. Also, his research presents that different driver behaviors result in forming different loops of flow – density diagram during deceleration and acceleration phases. Two patterns, timid and aggressive maneuver, were presented. Timid maneuver is formed by a clockwise loop of speed – spacing plot and aggressive maneuver is developed by a counter-clockwise loop of speed – spacing plot [27].

Ahan considered the kinematic wave model with variable wave speed. This condition results in analyzing the evolution of speed-spacing relationships as vehicles exit from stop-and-go oscillations. Their results presented that hysteresis magnitude takes place less frequently and in smaller amplitude than previously thought [28]. Chen presented the behavioral asymmetric theory. This model is able to reproduce the spontaneous formation and ensuing propagation of stop and go waves in traffic oscillation. The statistical results of their model revealed that traffic oscillation depends on driver behavior. Also, a correlation between driver behavior before and during oscillation is considered [3]. Chen analyzed traffic hysteresis based on a behavioral car-following model. The results presented that type of traffic hysteresis is dependent on driver behavior. They found that type of traffic hysteresis is dependent on driver behavior when experiencing traffic oscillations, but driver behavior is independent of its position along the oscillation. Also, their investigations revealed development in different stages of oscillation, grown and fully-developed, depending on the different patterns of hysteresis and driver behavior characteristics [29].

Orfanou developed artificial neural network models to identify, analyze hysteresis characteristics based on classifying phenomena behavioral perspectives, aggressive and timid, at the microscopic level. They founded that changes in the two parameters, spacing and acceleration at the end of the phenomenon, are the most critical determinants [30]. Abdi and Salehikalam analyzed the time between two phases, entering the stop and congestion phases. Driver behavior is studied based on different phases of follower driver at the microscopic level. They founded that increasing deceleration wave leading to congestion results in decreasing the time between two phases based on timid-over reaction pattern. Also, increasing deceleration wave caused to increase the time between two phases based on timid – under reaction and constant over reaction – timid [31]. Han Peng et al., proposed a new car following model in order to calculate the delay time of car motion and kinematic wave speed in traffic congestion based on the driver behavior, aggressive and timid. His numerical simulation indicated that aggressive follower behavior resulted in improving traffic flow because of making rapid response to the velocity variation of leader driver [32]. Han Peng et al., presented a new anticipation optimal velocity model by considering the anticipation effect and starting and stopping follower movement in a single line for car following theory. Numerical simulation showed that negative speed and headway may disappear owing to anticipation effects [33].

Zheng et al., developed a neural network model in order to investigate the relation between the relative speed and acceleration. Their simulation results presented that model performance of instantaneous delay is better than fixed reaction delay. Also, considering the instantaneous delay in vehicles platoon resulted in occurring more collisions with fixed reaction delay. This illustration showed the necessity of considering the instantaneous delay in order to avoid collision between the follower and leader vehicles [34]. Mohsen Poor Arab Moghadam et al., presented a car-following model that developed a combination of an Adaptive Nero-Fuzzy Inference System (ANFIS) and a Classification And Regression Tree (CART). It simulated the reaction time of follower behavior of each driver-vehicle-unit (DVU). Their results were compared with Ozaki's reaction time [35].

Han et al., presented a stochastic traffic breakdown model in order to study the microscopic mechanisms to macroscopic features of stochastic breakdown. They followed Newell theory and their results resulted in introducing two elements of breakdown, trigger and propagation upstream. Their results of probability model showed that the breakdown probability: (i) because of increasing the flow and merging spacing, (ii) owing to decreasing merging speed, and most importantly, (iii) due to increasing the deviation in headway distribution [36]. In this paper, behavioral patterns of follower are identified based on two theories, asymmetric behavior theory and hysteresis phenomena. Then, the time between two phases, deceleration wave reception and congestion, analyzed based on behavioral patterns in deceleration and acceleration phases at the microscopic level. Traffic phases are identified in traffic oscillation based on asymmetric theory. Microscopic parameters are determined at the microscopic level. Then, in order to distinguish effective parameters of time between two phases, the artificial neural network develops because of the follower complex behavior.

2. Research Methodology

Based on behavioral car following models, driver behavior in traffic oscillation was classified based on two theories, asymmetric theory and hysteresis phenomena. Trajectory data was divided into phases, deceleration, stop, congestion, and acceleration. When follower acceleration was continually less than -1and leaded to congestion, deceleration phase start determined for two follower and leader vehicles based on behavioral asymmetric theory. Propagation and receive points of deceleration waves are determined based on Newell theory. It resulted in determining space parameter, d. Newell trajectory identified using space parameter in starting deceleration phase leading to congestion. Determining follower behavioral from observed data to Newell resulted in four different behavioral patterns in deceleration phase, over reaction, under reaction, over constant reaction, and under constant reaction. Also, in acceleration phase, there were two behavioral patterns, aggressive and timid, using hysteresis phenomena. An overview of the research was presented in Figure 1. to provide better and more straightforward understanding of the methodology. Then, any part was explained and calculated separately.

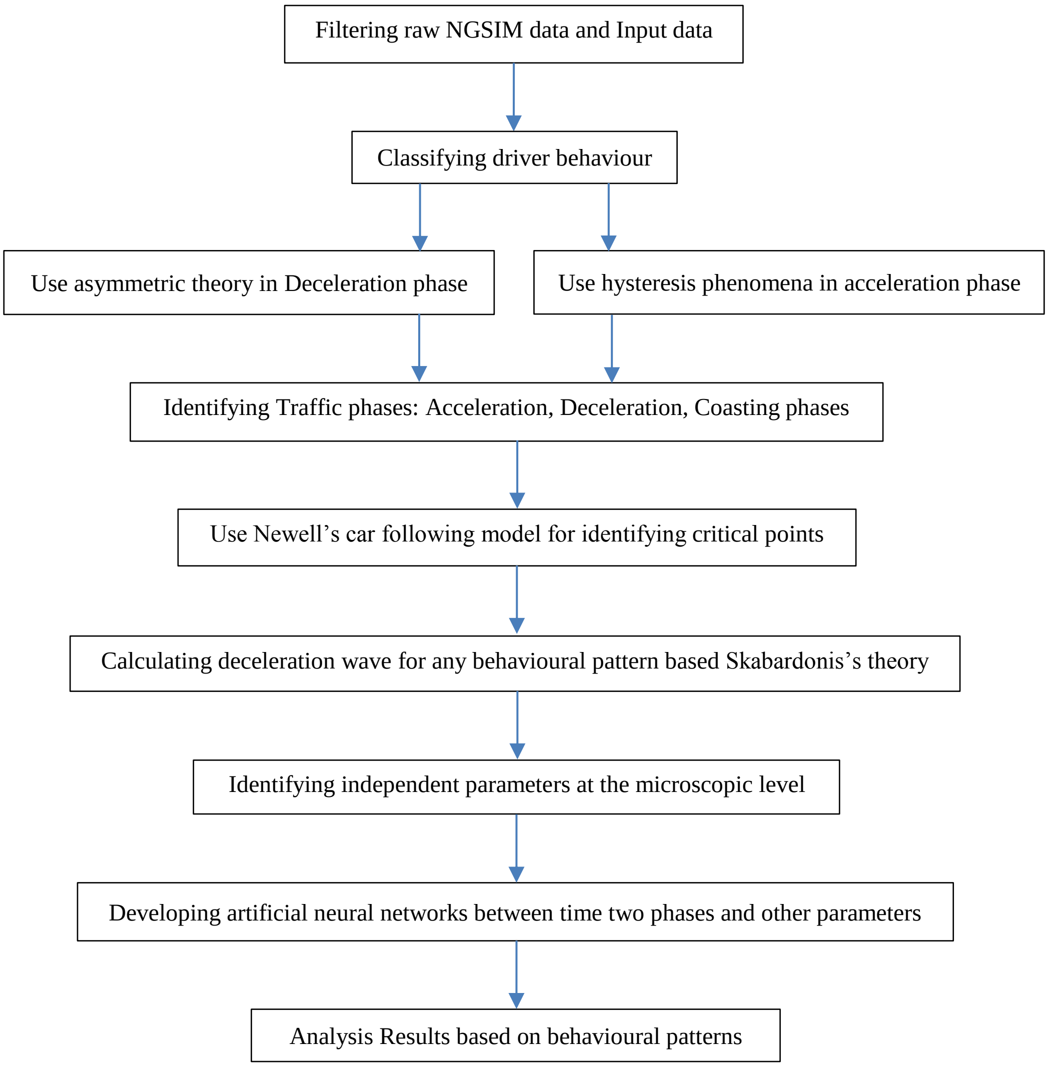

Figure 1. Flowchart of research methodology

2.1. Phasing Trajectory

According to Figure 2, follower trajectory is classified into three phases: deceleration wave diffusion, entering stop phase and congestion phase. Deceleration phase start leading to congestion is identified based on deceleration value. If follower and leader deceleration value are smaller than -1, it results in exiting coasting phase and vehicle speed starts speed drop owing to zero speed. According to Figure 3, vehicle acceleration may increase, but increasing acceleration is in deceleration phase, deceleration value always is smaller -1 value. In other hand, safe spacing isn't enough in deceleration phase and follower vehicle can't exit from deceleration phase and leading to zero speed in this methodology.

W_1: Deceleration wave leading to congestion
W_2: Stop wave
W_3: Congestion wave
T: Time between two phases, deceleration and congestion phases

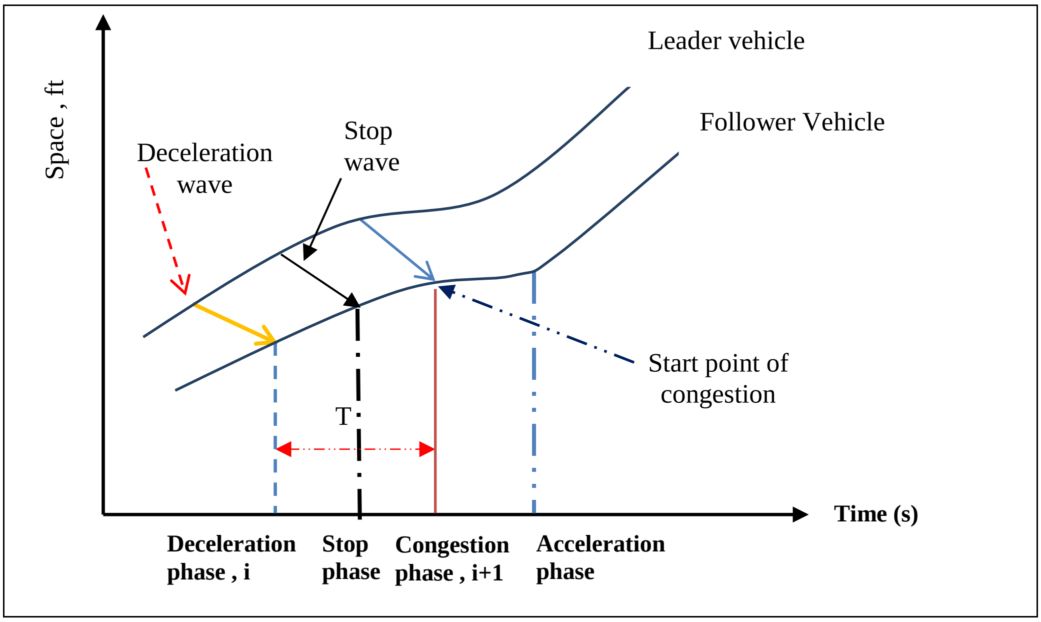

Figure 2. Phasing trajectory of follower and leader vehicle

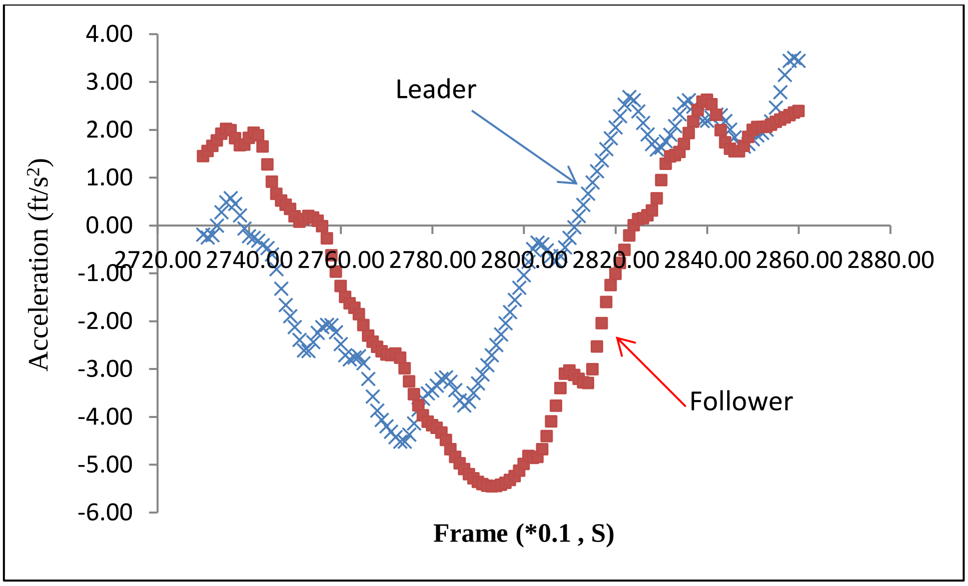

Figure 3. Acceleration – time diagram of follower vehicle (propagating deceleration wave to exit from stop phase) based on NGSIM data

2.2. Newell's Car Following Model

The purpose of each car following model explains depends of follower trajectory and position in time to leader vehicle. If leader vehicle moves with constant speed, follower vehicle behaves from leader vehicle, constant speed, v, According to Figure 4 [14]. Spacing of follower and leader vehicles can change in time. But, if freeways are considered homogeneous and traffic is one type, spacing is constant in value, S_n. In Newell's model, when leader vehicle changes speed from V to V', deceleration wave transfers speed , d^i/τ^i , from downstream to upstream that results in acceleration and deceleration according Figure 5. In this model, space and time parameters, τ^i and d^i, are constant from independent speed. This result develops linear relation between speed and spacing, $s^i=d^i+\tau^i v$. The first, behavior change points are identified based on Newell's theory. Then, two parameters, τ – d, are calculated. While following conditions are established, wave speed is calculated based on Skabardonis's theory according to one and two equations [37].

$$t_{k\ point}^{follower} > t_{k\ point}^{Leader} \tag{1}$$

$$Y_{k\ \text{point}}^{follower} < Y_{k\ \text{point}}^{leader} \tag{2}$$

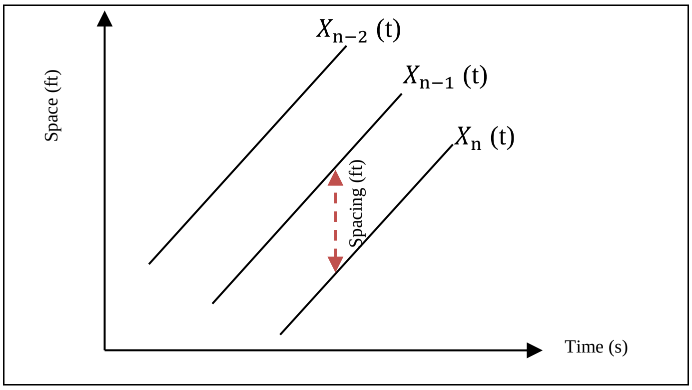

Figure 4. Vehicle trajectory with constant speed [14]

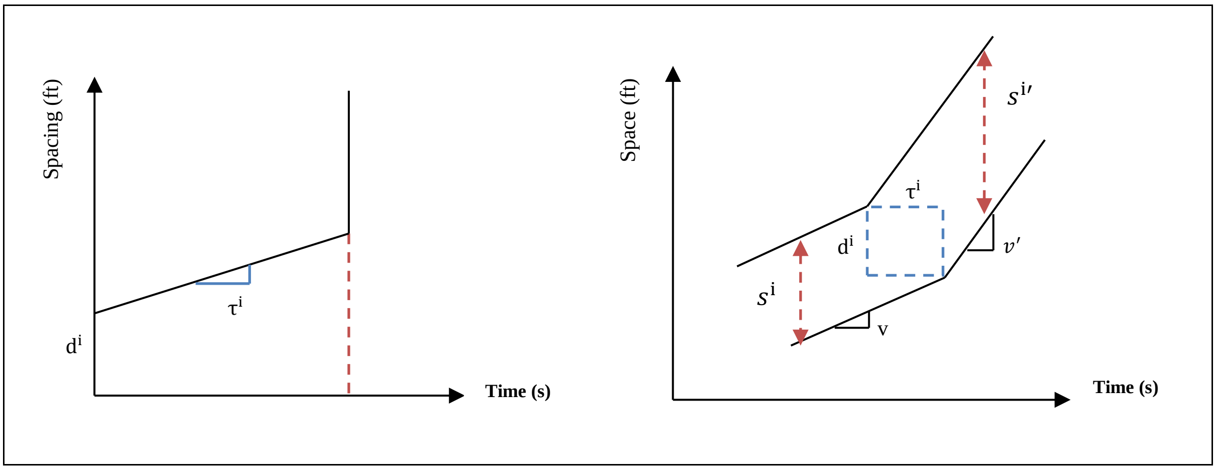

Figure 5. Linear relation of spacing – speed [14]

2.3. Driver's Behavioral Patterns in Traffic Oscillation

Driver's behavioral analysis was done by extensive analysis of vehicle trajectories at the level microscopic. Drivers present that driver's complex behavioral results in driver's different responses in traffic, maneuvering errors, and driver different behavior. Start point of deceleration phase leading to congestion for a follower and leader vehicle is determined based on Newell's theory. When the leader vehicle change his speed, the follower vehicle follow his leader and drop his speed. Follower and leader trajectory are followed in acceleration – time diagram. According to Figure 6, when the follower vehicle receives deceleration wave, the follower deviates from Newell trajectory. Based on the behavioral asymmetric theory, this behavioral change was resulted in developing four behavioral patterns were determined in deceleration phase, under reaction, over reaction, under reaction / overreaction constant up, according to Figure 7. According to Figure 7a, a follower driver follows under reaction pattern if the follower driver has done lower speed drop in the deceleration phase based on the behavioral asymmetric theory. If follower driver has more speed drop in the deceleration phase, behavioral pattern of driver results in over reaction, according to Figure 7b. Both other patterns, over constant reaction, and under constant reaction are similar to over-reaction and under-reaction. But, there is a difference. When the follower driver receives deceleration wave leading to congestion to a leaving wave of stop, the follower has constant reaction and does not tend to Newell's driver [17].

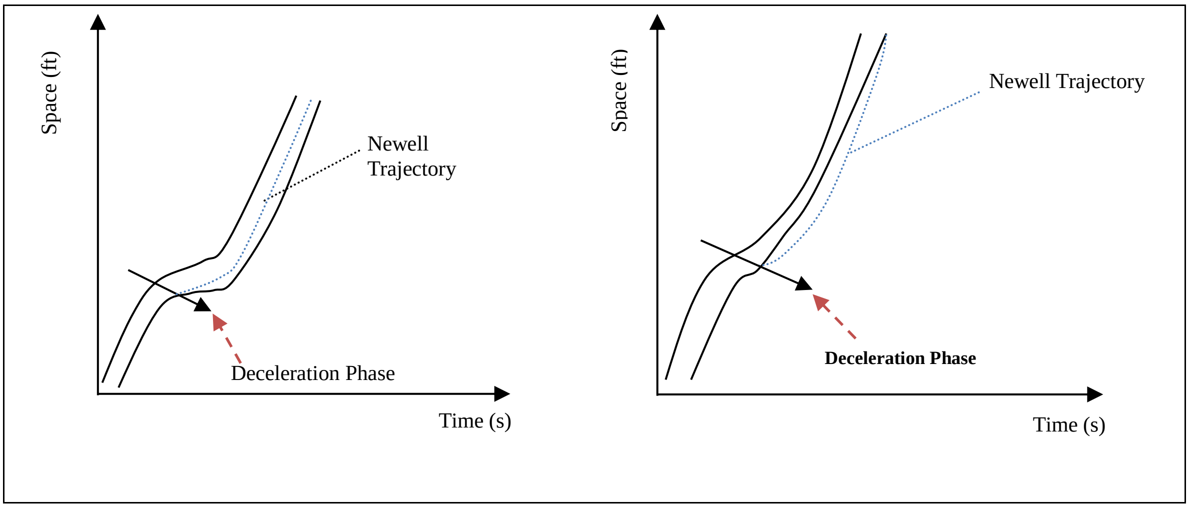

Figure 6b. Aggressive driver **Figure 6a. Timid driver**

Figure 6. Driver behavioural patterns of acceleration phase at the microscopic level [19]

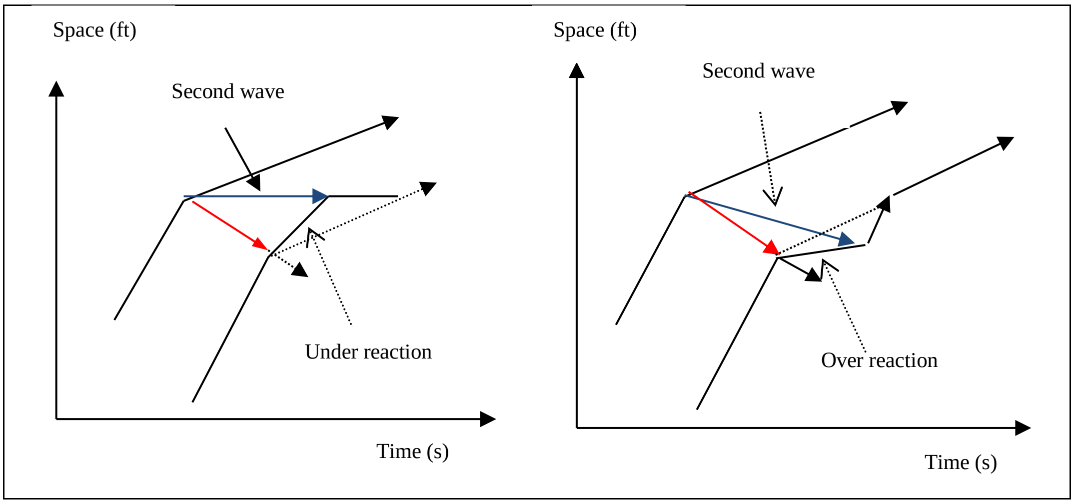

Figure 7a. Under reaction **Figure 7b. Over reaction**

Figure 7. Under and Over reaction behavioural pattern of deceleration phase [17]

When the follower exits from traffic oscillation, the driver presents timid (aggressive) patterns, based on phenomena hysteresis. If the follower do later (faster) reaction to leader and follower trajectory put in under (above) Newell's trajectory in space – time diagram, timid (aggressive) pattern is presented according to Figure 8a and 8b respectively. On the other words, if wave propagates with more (fewer) speed and sooner (later) reaction during acceleration phase, driver follows behavioural results in aggressive (timid) at the level microscopic developing counter clockwise (clockwise) circles in spacing – speed [19].

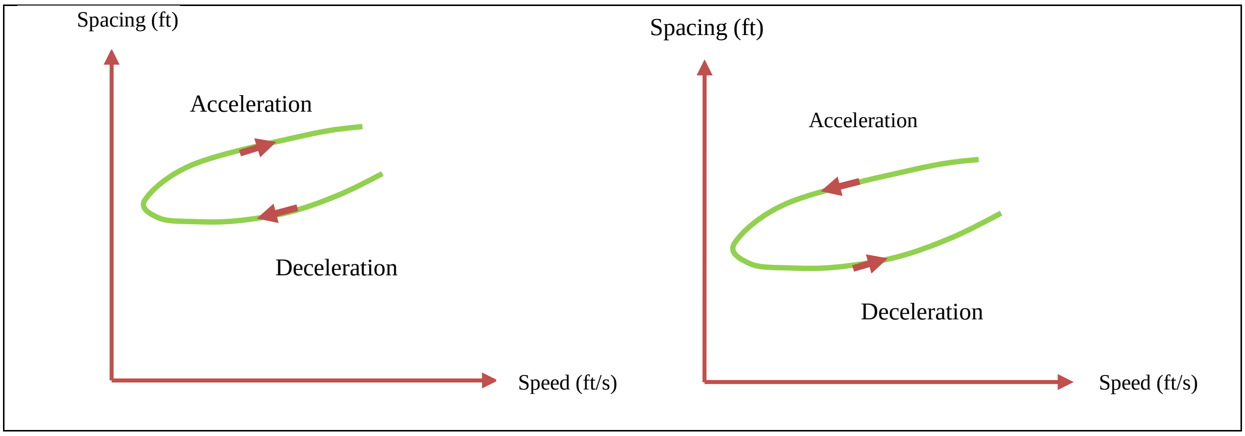

Figure 8b. Timid driver **Figure 8a. Aggressive driver**

Figure 8. Driver behavioural patterns of acceleration phases at the microscopic level based on hysteresis [19]

2.4. Introducing the Parameters

When the follower receives deceleration wave, follower driver reacts different responses that results in different properties of behavioural change point. In this paper, artificial neural networks were developed for determining effects the effect of independent variables on the dependent variable, the time between two phases, based on the follower behavioural patterns in deceleration and acceleration phases. Eight parameters at the microscopic level are considered including of S_{L1}, S_{F1}, S_{L2}, S_{F2}, $\Delta S(L) = S(L2) - S(L1)$, $\Delta S(F) = S(F2) - S(F1)$, $\Delta S(F2: i, i+1) = S(F2, i+1) - S(F2, i)$, $\Delta V(F2: i, i+1) = V(F2, i) - V(F2, i+1)$. The mentioned parameters were defined as follows:

- The leader vehicle spacing at the wave propagation point, S_{l1}
- The leader vehicle spacing at the wave reception point, S_{l2}
- The follower vehicle spacing at the wave propagation point, S_{f1}
- The follower vehicle spacing at the wave reception point, S_{f2}
- The spacing difference of leader vehicle between wave propagation and receive points, $\Delta S_l = S_{l2} - S_{l1}$
- The difference of the follower vehicle between wave propagation and reception points, $\Delta S = S_{f2} - S_{f1}$
- The difference of follower vehicle between two phases, deceleration and congestion phases, $\Delta S(F2: i, i+1) = S(F2, i+1) - S(F2, i)$.
- The speed difference of follower vehicle between two phases, deceleration and congestion phases, $\Delta V(F2: i, i+1) = V(F2, i) - V(F2, i+1)$.

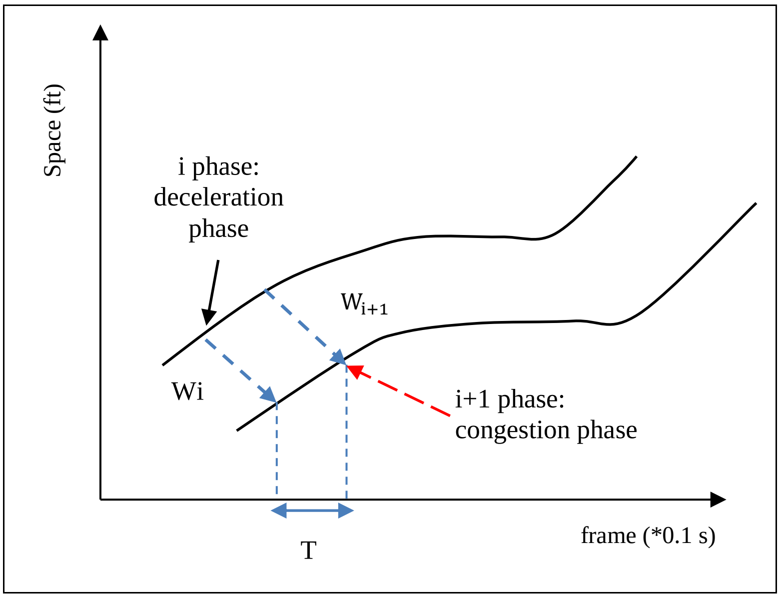

Figure 9. Introducing parameters at the microscopic level in oscillation

2.5. The Artificial Neural Networks

The car following models were classified into two categories: the first models were based on mathematical and the second models were based on inputs – outputs. In the mathematical models, follower vehicle behaviour was presented by mathematical equations. Inputs and outputs were calculated and measured based on the real data, in the artificial neural network models. The follower nonlinear behaviour was resulted using intelligent algorithms, artificial neural networks. Zheng et al., Khodayari et al., Xiaoliang, Hongefi and Panwai have used the neural network model to identify the delay instant reaction in the following vehicle models [38-42].

2.6. Developing Artificial Neural Networks

There are many parameters and errors of data and the raw trajectory data and not important to illustrate target function, that is why behavioural patterns were developed based on the neural networks (NNs) to identify and analyse effective parameters of stop and go traffic at a microscopic level, which affect the behaviour diversion. The different parameters effect was identified the time between two phases based on the behavioural patterns using artificial neural network. Neural networks were computational models consisting of large parameter space and adaptable structure. They were inspired by the structure and functional aspects of biological neural networks [43]. Neural networks were constructed based on learning the various functions with actual, discontinuous and vector values. They were created based on connecting several processors, which relate the input groups to the output through the artificial neurons. Using a connectionist approach to computation, a neural network is developed by an interconnected group of artificial neurons with activation functions and processes information. Neurons relate input and output groups. According to table 1, the Multi-Layer Perceptron (MLP) that was used belongs to the feed-forward neural networks, which were usually trained via the error back-propagation learning rule, in this paper [44]. Neural networks were modelled based on four layers, one output layer and two hidden layers. Each one of these layers was considered the inputs and forwarding them to the next layer. Some neurons of hidden layers adjust according to the error correction rule. Performing MLP as a universal approximate function will result in their advantage over the more complex structures of ANNs. When the activation function of MLP was correctly selected, it can be directly related to an equivalent statistical model [45]. In this paper, Tansig function is selected as an activation function of MLP. The training ANNs methodology is based on fixing the weights for all variables except for the weight of the variable (input vector). And also, the data are divided into three following parts: training (70%), Cross – validation (15 %), testing (15%)

Table 1. Structural, learning specifications of the proposed MLP

Parameter	value
Inputs	The leader vehicle Spacing at the wave propagation point, S_{l1}
	The follower vehicle Spacing at the wave propagation point, S_{f1}
	The leader vehicle Spacing at the wave reception point, S_{l2}
	The follower vehicle Spacing at the wave reception point, S_{f2}
	The difference in the leader vehicle spacing between wave propagation and receive points, $\Delta S_l = S_{l2} - S_{l1}$
	The difference in the follower vehicle spacing between wave propagation and receive points, $\Delta S = S_{f2} - S_{f1}$
	The difference in the follower vehicle spacing between two phases, deceleration and congestion phases, $\Delta S(F2: i,i+1)=S(F2,i+1)-S(F2,i)$
	The difference in speed of follower vehicle between two phases, deceleration and congestion phases, $\Delta V(F2: i,i+1)=V(F2,i)-V(F2,i+1)$
Outputs	Time between two phases
Architecture	Tansig
Learning Structure	Back - propagation

2.7. Sensitivity Analysis of the Time between Two Phases

This paper has used Crystal Ball software since it can define sensitivity analysis between dependent and independent variables. An artificial neural network of Matlab software was linked to the Crystal Ball software. Crystal Ball software used neural network model and determined parameter effects between independent and dependent variables.

3. NGSIM Data

Vehicle trajectory data for the present study are collected from two freeway sites, Interstate 80 (I-80) and US highway 101 (US-101), that are part of the Next Generation Simulation (NGSIM) program. It consists of vehicle and frame of identification number, space, vehicle class, vehicle velocity and acceleration, lane identification, leader and following vehicle, spacing and headway every one-tenth of a second. I-80 (Us-101) freeway is 1650 (2100) ft long with six lanes, including a High Occupancy Vehicle (HOV) lane. The trajectories with more than 5000 vehicles of I-80 freeway were collected for a 45-min period (4:00–4:15 p.m. and 5:00–5:30 p.m.) and vehicle trajectories of US-101 freeway were collected for a 45-min period (7:50–8:35 a.m.). Both freeways traffic conditions during the study period represent transient to congested states with frequent stop and-go oscillations. Using the Savitzky – Golay filter method makes smooth the raw trajectory data of NGSIM provided by camera for vehicle positions every 0.1 s. According to Table 2, results of classifying behavioral patterns are presented based on behavioral theories [46, 47].

Table 2. Behavioural classified results of follower vehicle

	The number of pairs of deceleration phase patterns	Aggressive	Timid
Over reaction	295	63	232
Under reaction	129	19	110
Over constant reaction	90	6	84
Under constant reaction	30	14	16

4. Analysis Results

4.1. Neural Network Performance Evaluation

Performance evaluation of neural network perceptron was presented according Table 3. The results indicate that there is a correlation coefficient between the observed and anticipated data based on different behavioural patterns.

Table 3. Statistical evaluation measures of the MLP of percent correct

	Under reaction - Timid	Over reaction - Timid
MSE	0.04	0.051
MAE	0.11	0.13
Percent Correct	0.93 %	0.92

4.2. Over Reaction–Timid

Frequency chart was presented in Figure 10. Based on over reaction-timid behavioural pattern Results showed that time of between two phases were 50-80 frame (5-8s). In other words, when follower received deceleration wave, follower may drive 5-8 second in traffic oscillation then driver enter traffic congestion. According to Figure 11, the results of the sensitivity analysis of the time between two phases indicate that $SF2$, ΔS(F i,i+1)= S(F2,i+1)-S(F2,i), Δ(V)=v(F2,i) parameters are the most effective at the microscopic level based on timid – over reaction.

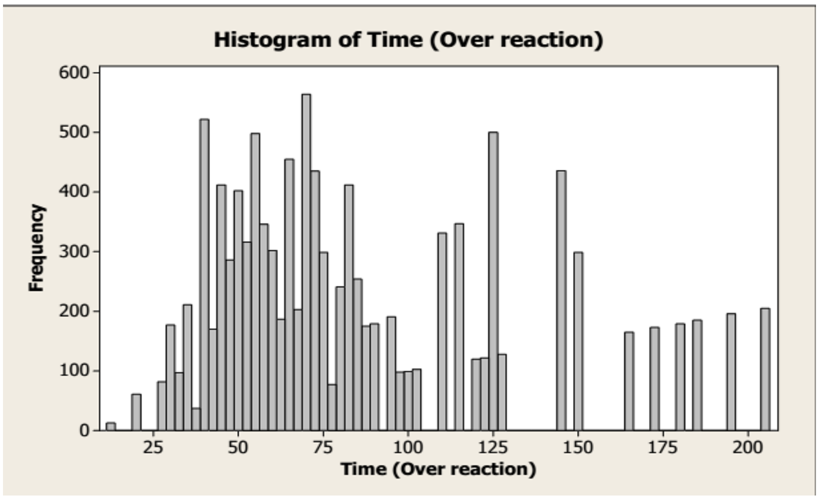

Figure 10. Frequency chart of time between two phases based on Over reaction – timid

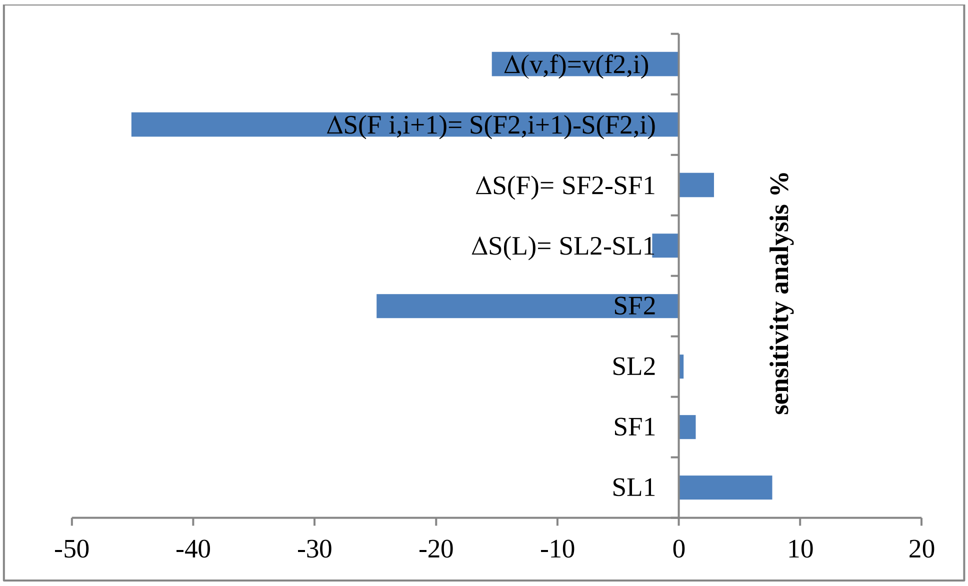

Figure 11. Results of the Sensitivity Analysis of Artificial Neural Network for all Inputs based on Over Reaction-Timid Driver

4.2.1. Spacing Difference of Follower Vehicle between Two Phases

Increasing the spacing difference of the follower between two phases results in increasing the time between two phases according to Figure 12. When spacing is increased, the follower feels more safe spacing. In this condition, the follower driver is able to move with more maneuverability. This driving situation leads to increase the time between two phases.

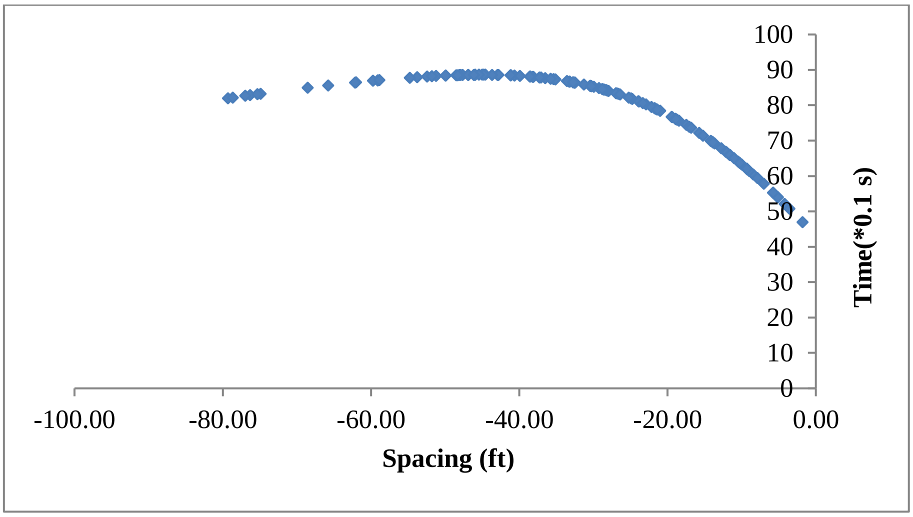

Figure 12. The artificial neural network diagram of the spacing difference between two phases

4.2.2. Spacing Difference of the Follower Vehicle between Wave Propagation and Reception Points

According to Figure 13, The spacing difference of follower divides time changes into two parts, ΔS(F)> < 0, based on the driver behavioural patterns. For condition of ΔS(F)>0, spacing of reception point is bigger than spacing of wave propagation point. The follower driver trend to drive with more safe spacing based on over reaction in deceleration wave. This act results in increasing the speed drop and decreasing the time between two phases. For the value of ΔS(F)<0, spacing of wave propagation point is larger than wave reception point. This condition leads to decrease the reaction time, faster the reaction, and increase more speed drop and safe spacing.

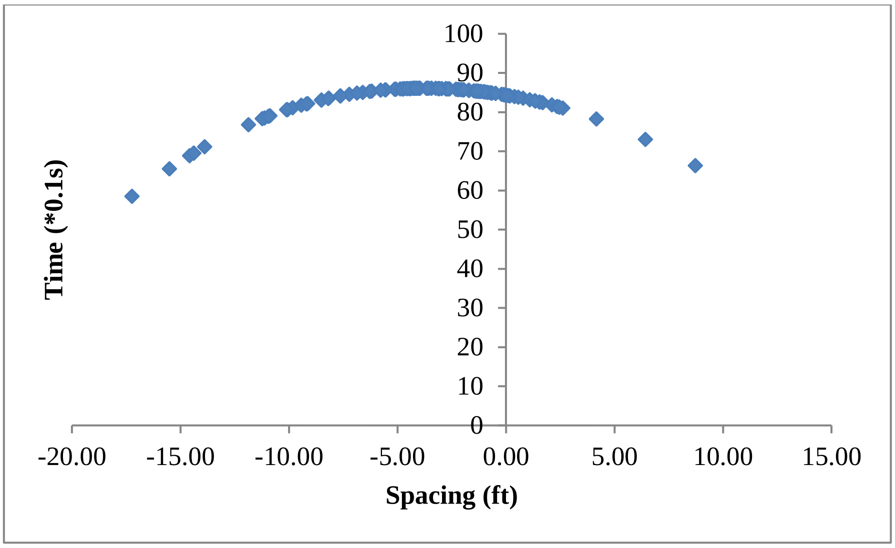

Figure 13. The artificial neural network diagram of the spacing difference between wave propagation and reception points

4.2.3. The Follower Vehicle Spacing at the Wave Reception Point

According to Figure 14, increasing the follower spacing at the reception point will result in decreasing the time between two phases. The follower driver with over - reaction pattern tend to drive in a safer spacing. This condition causes to keep enough safe spacing in traffic oscillation. In order to develop enough safe spacing, the follower driver reacts more severely. That results in decreasing the stop time between two phases. In other hand, the follower nature of the over- reaction pattern need to drive in a safer spacing that results in more severe reaction, decreasing the time between two phases.

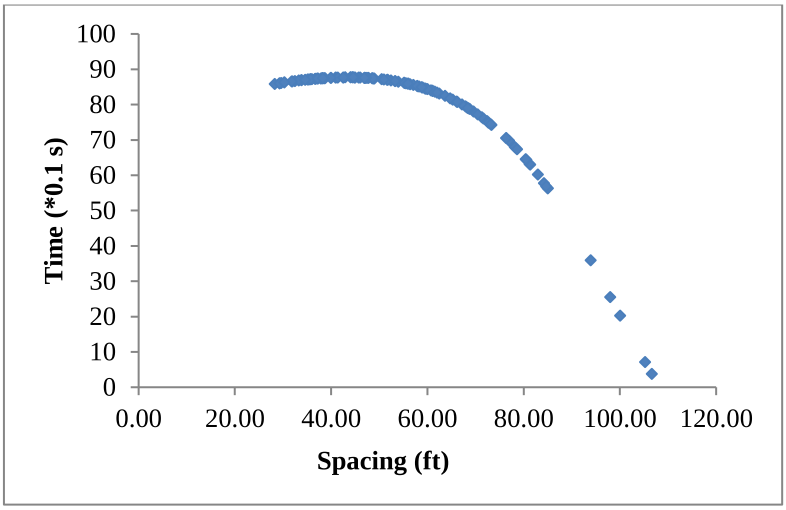

Figure 14. The artificial neural network diagram of the follower spacing at the wave receive point

4.2.4. The Speed Difference of the Follower Vehicle between Two Phases

The speed difference between two phases results in decreasing the time between two phases in Figure 15. It leads to flow traffic and increase safe spacing in traffic oscillation. Because of over - reaction follower nature, the follower vehicle drives in large spacing. That condition results in increasing the safe spacing.

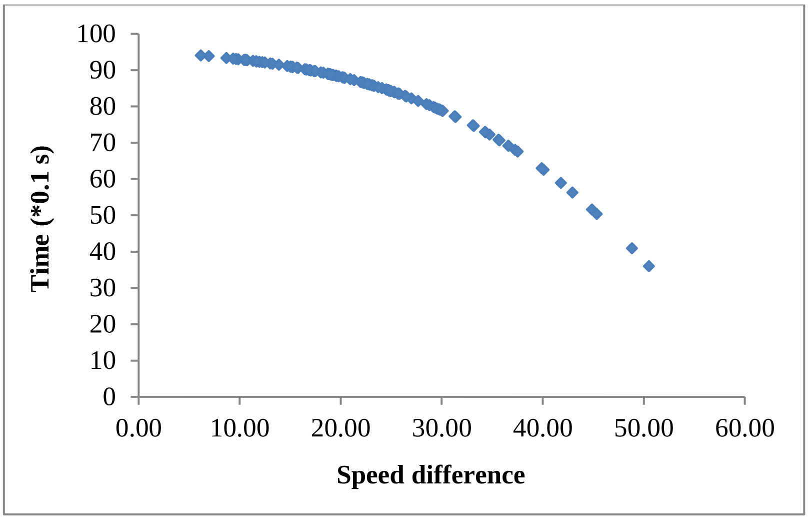

Figure 15. The artificial neural network diagram of the speed difference between two phases

4.3. Under Reaction-Timid

Frequency of under reaction- timid behavioural pattern is presented in Figure 16. Results show that driver tend to drive in 30-50 frame (3-5 s) for entering traffic congestion. In order word, no considering enough safe spacing results in entering traffic congestion. According to Figure 17, the sensitivity analysis of the time between two phases is based on the behavioural pattern and parameters at the microscopic level. The effective parameters of the time between two phases are, ΔS(F)= SF2-SF1 ,and ΔS(F i,i+1)= S(F2,i+1)-S(F2,i).

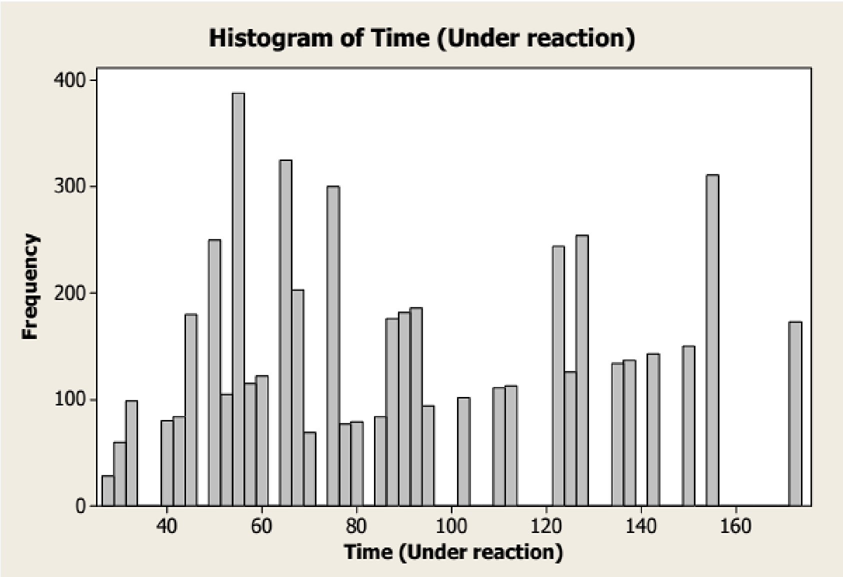

Figure 16. Frequency chart of time between two phases based on Under reaction- timid

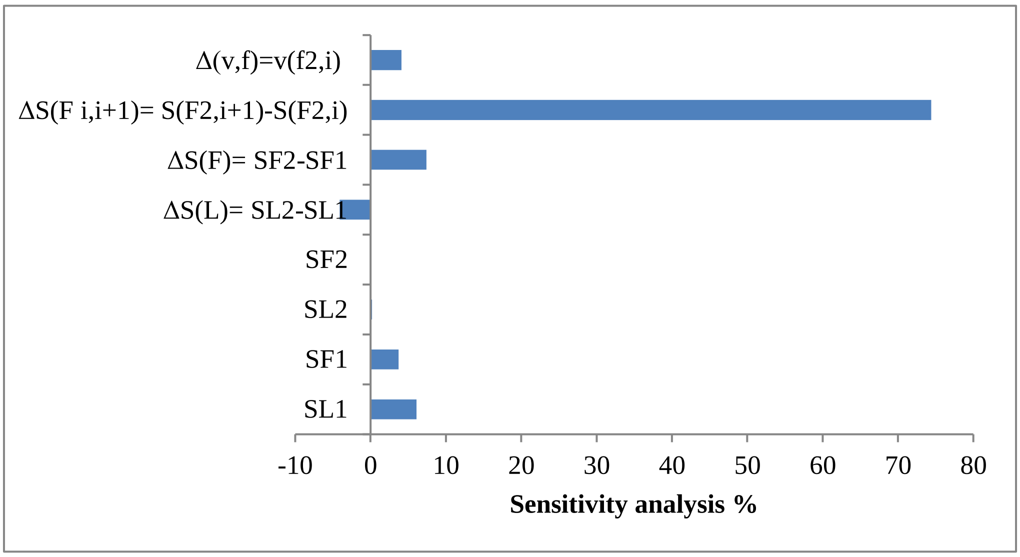

Figure 17. The sensitivity analysis of parameters based on the under reaction-timid

4.3.1. The Follower Spacing Difference Between Two Phases

According to Figure 18, increasing the spacing will lead to decrease the time between two phases. Increasing safe spacing results in increasing maneuverability of follower based on under reaction behavioural pattern. Increasing maneuverability results in decreasing safe spacing in traffic oscillation and disregarding the received deceleration wave. In this condition, the follower has to severe reactions, decreasing the reaction time, for developing enough safe spacing in traffic oscillation.

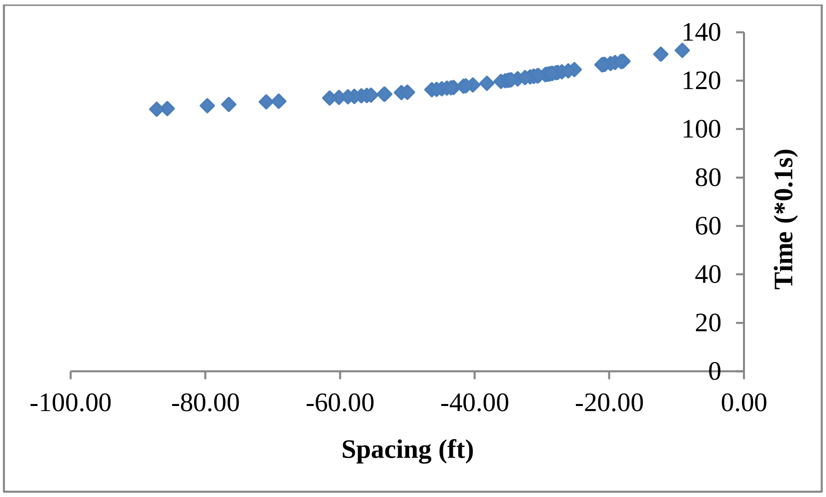

Figure 18 Artificial neural network diagram of follower spacing difference between two phases

4.3.2. The Spacing Difference of the Follower Vehicle Between Wave Propagation and Receive Points

Increasing the follower spacing difference between two points will result in increasing the time between two phases, according to Figure 19. The follower maneuverability increases between two phases based on under reaction pattern when spacing difference in platoon increases. Based on increasing maneuverability, follower vehicle is able to drive in not enough spacing of traffic oscillation. This situation develops trend to be later reaction, more time.

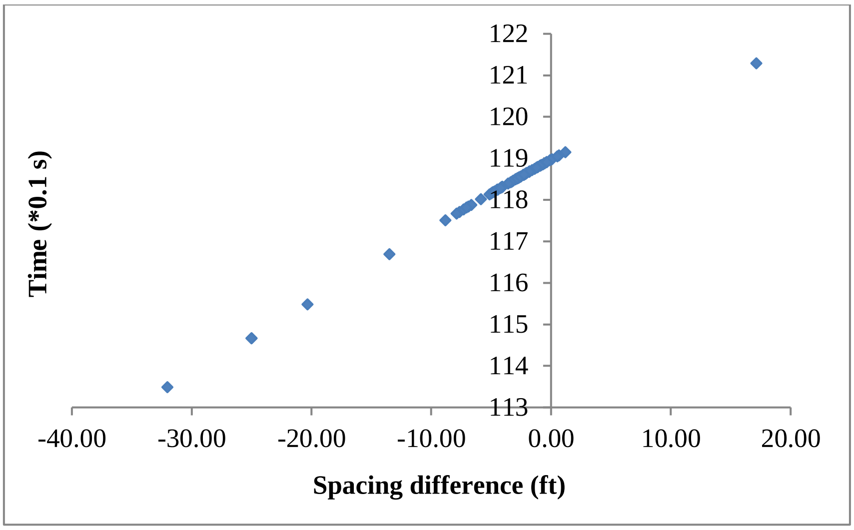

Figure 19. Artificial neural network diagram of follower spacing difference wave propagation and reception points

4.3.3. The Follower Vehicle Spacing at the Wave Reception Point

According to Figure 20, results in decreasing the time of two phases. Based on increasing spacing, the follower is able to be more maneuverability based on the behavioural pattern of receive wave reception point. This action results in disregarding follower for supplying safe spacing in traffic oscillation. The follower disinclination of speed drop results in faster response, decreasing time, to develop the safe spacing between two phases.

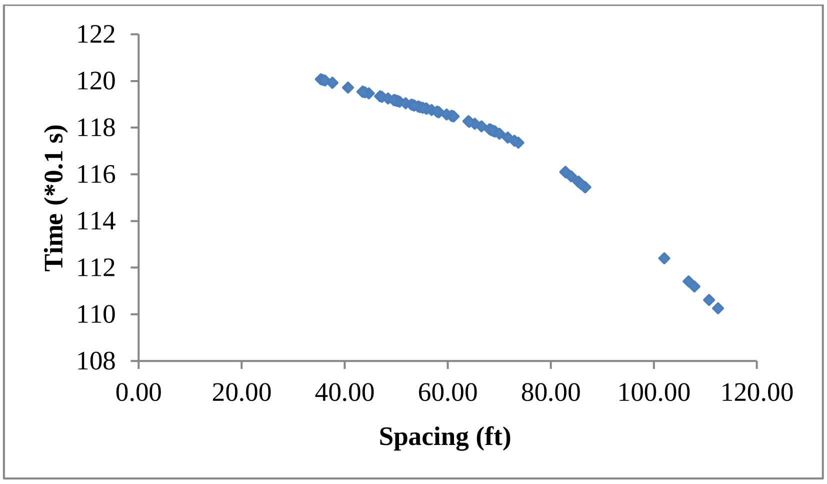

Figure 20. The artificial neural network diagram of follower spacing at the reception points

4.3.4 The Speed Difference of Follower Vehicle between Two Phases, Deceleration and Congestion Phases

According to Figure 21, time parameter is classified into two parts. If the value of independent parameter, speed, is smaller than 25 (ft/s), time parameter is decreased and if speed is higher than 25 (ft/s), the time parameter is increased. The follower maneuverability is decreased when the speed difference of the follower vehicle is smaller than 25 (ft/s). This condition results in following Newell's pattern. In other hand, faster reaction causes to decrease the time between two phases. When the speed difference of the follower vehicle is greater than 25 (ft /s), increasing the speed of two phases results in flowing traffic and increasing follower maneuverability based on under reaction behaviour. Increasing the maneuverability in traffic oscillation develops more ability for driving in small safe spacing, latter response of two phases.

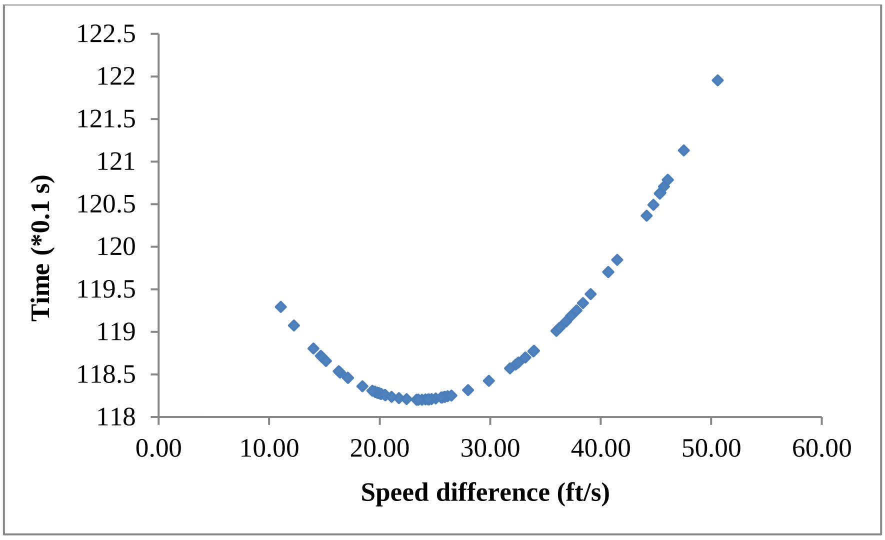

Figure 21. The artificial neural network diagram of follower speed difference between two phases

5. Conclusion

Stop – go Traffic frequently is observed in freeway traffic flow, which results in traffic oscillation. The follower vehicle drivers react to stop – go wave propagation from downstream to the upstream. Driver's different reactions result in developing different behavioural patterns and deviating to Newell's driver. In this paper, the follower different behavioural patterns are identified based on the asymmetric theory and hysteresis phenomena, respectively, during the deceleration and acceleration phases by using NGSIM data. In order to determinate deceleration wave parameters, Newell's car following model is used to identify diffusion and propagation wave points. Then, artificial neural networks are developed to analyse effective parameters at the microscopic level between two deceleration and congestion phases. Analytical results of two phases indicate that the spacing difference of the follower vehicle between two phases, deceleration and congestion, is an effective parameter of time based on any two behavioural patterns, under and over reaction pattern. Artificial neural networks results determine that increasing spacing difference of the follower vehicle between two phases will result in increasing the follower maneuverability based on under reaction pattern. Since, the follower driver has no considering propagated wave and no disregarding speed drop; this condition causes to reduce excessive safe spacing in traffic oscillation. The follower driver performs faster responses, reducing the time between the two phases, because of developing safe spacing. Based on over reaction - timid pattern, artificial neural network model presents that increasing spacing difference of the follower vehicle between two phase results in intensifying the time between two phases. The ability of the follower vehicle with over - reaction pattern to develop more maneuverability and enough safe spacing of two phases leads to increase the time and lower the speed drop. Table 4 shows the independent parameters results in the dependent parameter.

Table 4. Summary of the results

Behavioral pattern	Most effective parameter	Effective value %	Parameter behavior	Behavior reason
Under reaction - timid	Decreasing time of two phases	74.4 %	Spacing difference of two phases	decreasing safe spacing
Over reaction - timid	Increasing time of two phases	45.1 %	Spacing difference of two phases	Increasing safe spacing

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