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Original Paper

Analyzing Safe Spacing Threshold of Follower Vehicle of Reaction Point based on Behavioral Driver Using Artificial Neural Networks

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Abstract

Various reasons lead to traffic oscillation, one of which is the sudden drop in the speed of the leader driver. The stop and go traffic wave along with two parameters [τ,δ] is propagated toward the upstream based on the Newell's car following model. The follower vehicle drivers respond differently to the reception wave based on their intrinsic behavior characteristics, which it leads to the deviation of the follower driver's behavior from the ideal driver's trajectory, Newell. This article is classified the follower driver's behavioral patterns based on the asymmetric behavioral theory in the deceleration phase and the hysteresis phenomenon in the acceleration phase, and different behavioral pattern of the follower vehicle driver in the NGSIM trajectory data. By fixing the parameters τ, δ, the hypothesized direction of the Newell driver is identified and the degree of deviation of the follower driver's behavior from Newell driver's path is also determined. The follower driver responds differently to the reception deceleration wave based on any behavioral pattern, which leads to secure a safe spacing and to change behavior at the behavioral change point. Then, the neural network models are developed to analyze the effective parameters at the microscopic level on the safe spacing of the follower driver at the behavioral change point based on different behavioral patterns. The analysis results show that the most effective parameters on the follower driver's safe spacing at the behavioral change point are two independent parameters of the follower vehicle driver's speed at the wave reception point and the deceleration wave leading to congestion based on the over reaction-timid behavioral pattern, and the parameter of the deceleration wave leading to congestion based on the under reaction-timid and over reaction-aggressive behavioral patterns.

Keywords: Stop–go traffic,Safe spacing,Behavioral change point,Behavioral patterns,Artificial neural networks, NGSIM data.

1. Introduction

A sudden drop in the speed of the leader vehicle results in developing stop and go traffic. These results cause negative effects such as, time delay, consumed energy and safety dangers. Different reasons, lane change maneuvers and traffic moving bottleneck, leads to growth and propagate an oscillation wave in traffic [1], [2], [3], [4], [5], [6], [7], [8], [9], [10] and [11]. Also , developed traffic oscillation results in propagating deceleration waves from downstream to upstream [7],[12]. Because of variety of features, modeling stop and go traffic results in estimating important congestion effects. But, scare of data trajectory results in making unclear in order to model time – distance diagram.

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The first theory of behavioral car following theory introduced based on two distinct curves in deceleration and acceleration phases of speed – spacing chart. According to this theory, spacing of acceleration phase bigger than deceleration phase [13]. Also, Newell considered parallel path of follower and leader vehicle and describe the same wave speed of stop and go traffic in both phases, deceleration and acceleration. But, his research couldn't explain life cycle of traffic oscillation, generation and growth wave in vehicle platoon [14]. Also, The same wave speeds were considered by Del Castillo (2001). life cycle of traffic oscillation were analyzed in congestion. Based on his researches, traffic oscillation has grown or delayed according to traffic congestion. In the other words, traffic congestion results in growing traffic oscillation if there is congested traffic [15]. Kim and Zhang considered non-parallel trajectory of vehicles. Using stable time period and assuming the time interval change stability for any driver results in calculating waves with different speeds for any phase [16]. Yeo and Skabardonis demonstrated a microscopic asymmetric theory considering the speed- spacing relationship. Five states of traffic flow considered such as, free-flow, acceleration, deceleration, coasting and stationary [17]. Transitions and that traffic equilibrium exists were determined as 2-dimensional area bordered by acceleration-curve and deceleration-curve. Based on driver behavior characteristics, their research owing to describe traffic phenomena, vehicle maneuvering error, anticipation, life cycle of stop and go traffic cases, generation, growth and dissipation. Based on this theory, follower behavior are arranged into two groups, under reaction and over reaction, in deceleration and acceleration phase. Laval and Leclercq (2010) founded that aggressive or timid driver behaviors cause the formation and propagation of stop and go traffic. Traffic oscillation properties, period and amplitude, were simulated by driver behavior and Newell car following model [18]. Because vehicles platoon behavior before and after oscillation is different, it results in identifying delay in recovering the vehicle speed. The hysteresis phenomenon in traffic oscillation are developed by delay of recovered speed and asymmetric spacing in deceleration and acceleration phase [19,20]. The asymmetric theory in deceleration and acceleration phase developed hysteresis phenomena by numerous researchers [21,22,23,24]. Laval founded that hysteresis magnitude estimation results in measurement errors and based on non-steady state conditions. Hysteresis phenomena magnitude was classified into four levels: Strong level, Weak level, Negligible level, Negative level. Also, he presented that different driver behaviors results in separate loops of flow – density plot in deceleration and acceleration phase. Timid behavior developed clockwise loop of speed – spacing plot and aggressive driver counter-clockwise loop of speed – spacing plot [25]. Chen et al, 2012 presented a behavioral car-following model that it cause to develop the formation and propagation of stop and go waves in traffic congestion. They founded that driver different behaviors of before and during oscillation cause traffic oscillation [3]. Chen et al, 2012 analyzed traffic hysteresis using behavioral car-following model. They founded that driver behavior cause different type of traffic hysteresis in traffic oscillation. But, driver position is independent experiencing traffic oscillations [26]. Mirbaha et al., 2017 classified follower behavior using two theories, behavioral asymmetric theory and hysteresis. Artificial neural networks developed and studied time of two phases, deceleration to congestion, based on behavioral patterns. they founded Increasing the spacing difference of two phases results in decreasing time of under reaction – timid behavior pattern and increasing time of overreaction – timid behavior pattern [27]. In this paper, two theories asymmetric behavior theory and hysteresis phenomena were used for determining behavioral patterns. Different microscopic parameters were identified at the microscopic level. artificial neural networks were developed to simulate the follower driver's safe spacing at the behavioral change point.

2. Methodology

in order to provide better understanding of the methodology, figure 1 presents an overview of the research.

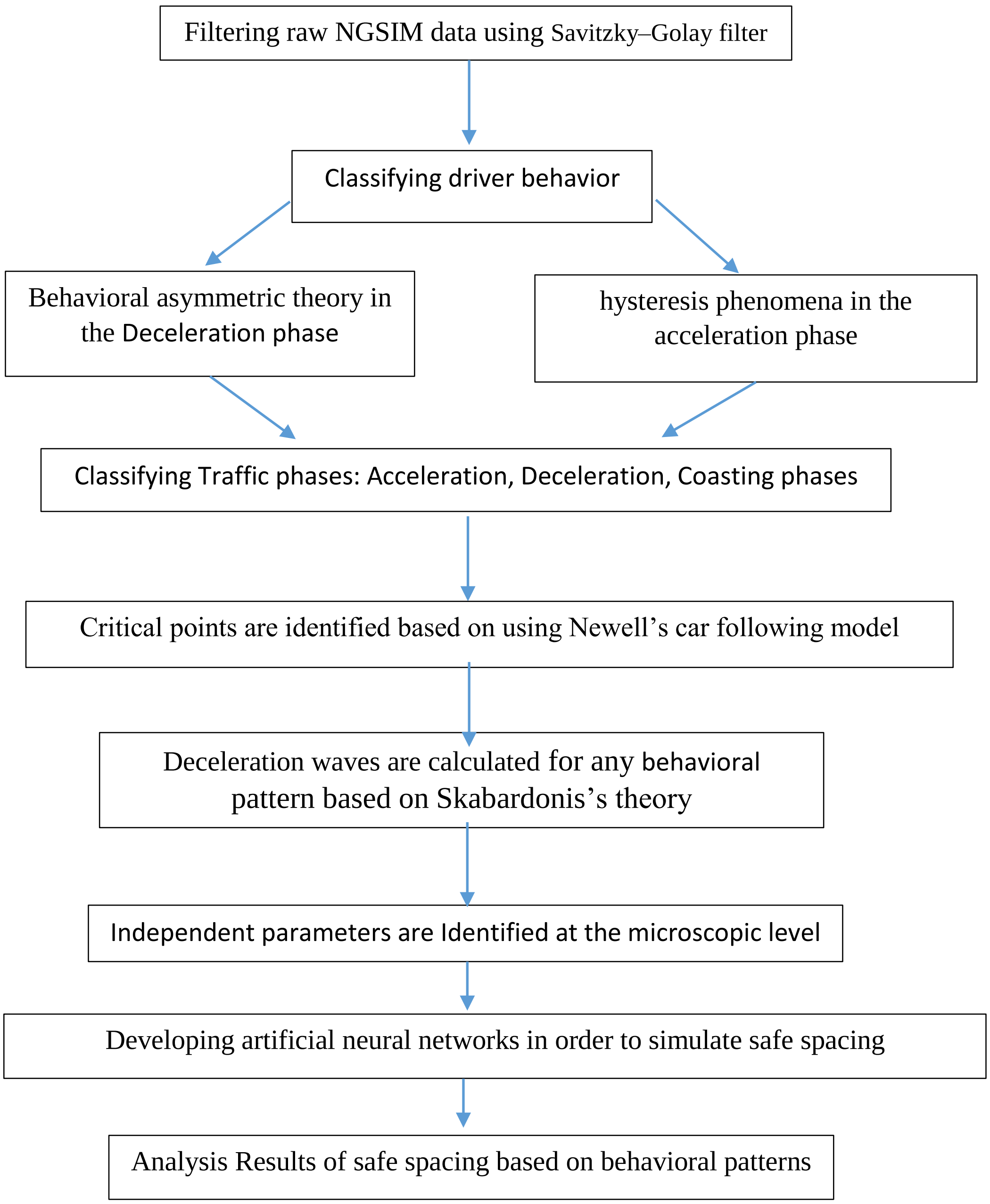


Figure1. Flowchart of research methodology

2.1 Driver Behavior Classification

In this research, NGSIM data are classified into four behavioral patterns in deceleration phase and two behavioral patterns in acceleration phase. Using the performance errors of the follower driver in the deceleration phase, follower behavioral patterns were divided such as, under reaction, under constant reaction, over reaction, and over constant reaction. Using on the hysteresis phenomenon in the acceleration phase, two patterns, aggressive and timid drivers, were identified. The statistical results of the analysis of 544 vehicle platoons of NGSIM were presented in table 1, based on the categories of drivers' behaviors. Because available data of behavioral patterns was scare, only three drivers' behaviors: over reaction-timid, over constant reaction-timid, and under reaction-timid were studied.

Table1. Statistical results of examining 544 vehicle platoons of NGSIM

In deceleration phase		In acceleration phase	
		Aggressive	Timid
Over Reaction	295	63	232
Under Reaction	129	19	110
Over Constant Reaction	90	6	84
Under Constant Reaction	30	14	16
Platoon total	544		

2.2 Introducing Follower Vehicle's Behavior Diversion

According to figure 2, when follower vehicle receives a deceleration wave in a traffic oscillation, follower deviates from Newell trajectory based on different behavioral patterns. Then, follower tends to Newell's trajectory in the behavior diversion point. Parameters and points of follower are identified at the microscopic level based on the received deceleration wave.

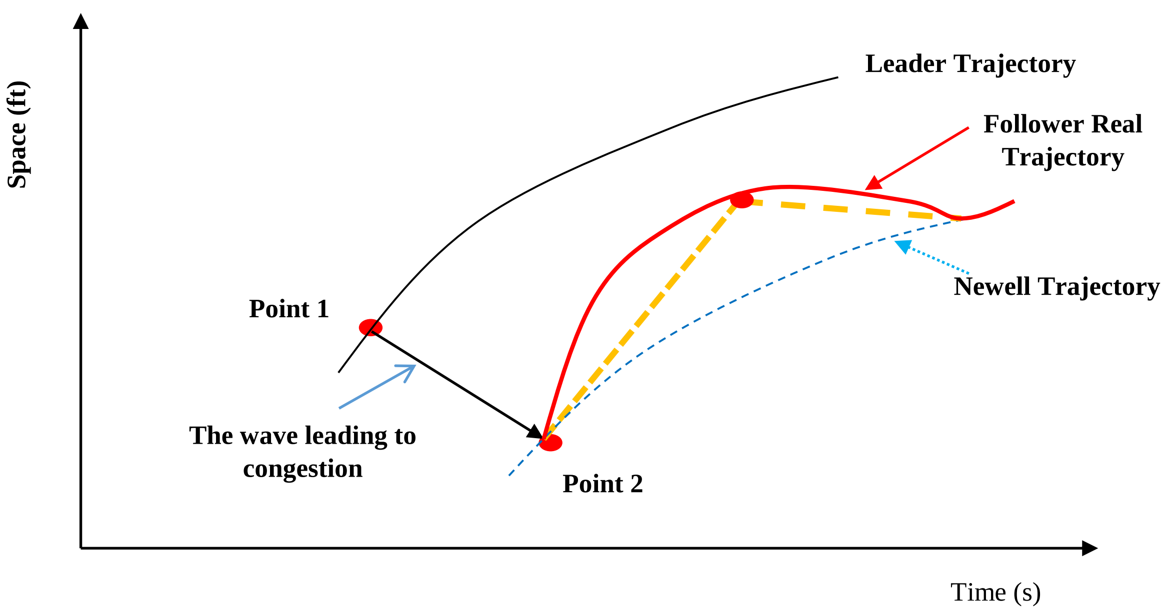


Figure 2. identifying behavior diversion point

2.3 Calculating deceleration wave

Aim of any car following models describe following trajectory and position of vehicle in t time to leader vehicle. If leader vehicle, n-1, moves with constant speed, the follower vehicle will also continue his/her movement with constant speed, v [14]. Spacing of two vehicles, follower and leader, may change, but if freeway is homogeneous and all vehicles are considered one type, spacing may considers constant, S_n, and change for different vehicles. Based on Newell's car following model, if the leader vehicle speed changes from V to $\boldsymbol{V'}$, a deceleration wave propagates with proportion to space ($\boldsymbol{d^i}$) and time ($\boldsymbol{\tau^i}$) parameters ($\frac{\boldsymbol{d^i}}{\boldsymbol{\tau^i}}$) from the downstream to the upstream of traffic in traffic oscillation. Based on skabardonis's theory, if following conditions are established for any vehicle, deceleration wave value calculates based on two parameters, $\boldsymbol{\tau}$ and d [17].

$$t_{k\ point}^{follower} > t_{k\ point}^{Leader}$$
$$Y_{k\ \mathrm{point}}^{follower} < Y_{k\ \mathrm{point}}^{leader}$$

2.4 Introducing the Parameters

In this paper, time of receiving deceleration wave is identified in stop and go traffic based on Newell's car following model and asymmetric behavioral theory. Behavior diversion point of follower and safe spacing is determined for any behavioral pattern. Three independent parameters of follower are determined such as, W(DCC): the deceleration wave leading to congestion, V_{f2}: the follower speed of receiving deceleration wave, S_R: the follower spacing in reaction point, S_{f2}: the follower spacing of received deceleration wave.

2.5 Developing artificial neural networks

Because there are the complicity of the driver's behavior and many parameters and errors, artificial neural networks are developed in order to model human driver's behavior. Artificial neural networks were widely used for simulating traffic problems. Intelligent algorithms, artificial neural networks, can solve nonlinear problems in a black-box style. Zheng et al., Khodayari et al., Xiaoliang, Hongefi and Panwai have used artificial neural network model to simulate real traffic, based on traffic data [28, 29, 30, 31, 32]. Artificial neural networks are computational models that are characterized by a large parametric and flexible structure and inspired by neurological studies. An artificial neural network is composed of the arbitrary number of neurons that associate the inputs set with the outputs [33]. According to Table 2, multilayer perceptron structures was presented in artificial network. In this paper, multilayer perceptron networks were used based on the feed-forwards networks and the error back-propagation learning rule. The artificial neural network model consists of four layers, an input layer, two hidden layers, and an output layer. Any layer include neurons that get information from previous layers and then transfer them to the next layers. The number of neurons in the layers is determined by estimating and error in order to reach the ideal conditions. According to table 2, neural network structure was presented Tansig function was considered at the neural network stimulus. The static-based neural network training methodology is the consideration of weights for all variables, except for fixed input variables after training the neural network. Trajectory data was classified three parts, training (70%), Cross – validation (15 %), testing (15%) [34].

Table 2. Structural Characteristics of the Neural Network Model

Parameter	value
Input space:	W(DCC): the deceleration wave leading to congestion V_{f2}: the follower speed of receiving deceleration wave S_{f2}: the follower spacing of received deceleration wave.
Architecture	Tansig S_R: the follower spacing in reaction point
Learning rule	Back - propagation

3. Data

The FHWA has developed Vehicle trajectory data of two freeway sites, Interstate 80 (I-80) and US highway 101 (US-101) as the Next Generation Simulation (NGSIM) program. NGSIM data was detailed data sets of the vehicle class, space, vehicle class, vehicle velocity and acceleration, lane identification, leader and follower vehicle, spacing and headway every one-tenth of a second. Trajectory data sets were derived from 5000 vehicles of I-80 freeway that 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 that were gathered 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 [35 , 36].

4. Result Analysis

4.1 Neural Network Performance Evaluation

According to Table 3, the perceptron performance evaluation of the neural network shows that the correlation coefficient between observed and predicted data is based on each different behavioral pattern is different and it is presented associated with each variable.

Table 3. Statistical Evaluation of the Neural Network Performance

	Under reaction - Timid	Over reaction - Timid	Over reaction - Aggressive
MSE	0.053	0.058	0.057
MAE	0.130	0.131	0.129
Percent Correct	94 %	90 %	91 %

4.2 The Follower Vehicle Safe Spacing at the Behavioral Change Point

4.2.1 Over reaction-timid Driver

As shown in Fig.3, the sensitivity analysis results of the trajectory data obtained from three parameters at the microscopic level indicate that the most effective parameters on the follower driver safe spacing at the behavioral change point are the follower vehicle speed at deceleration wave reception and the deceleration wave.

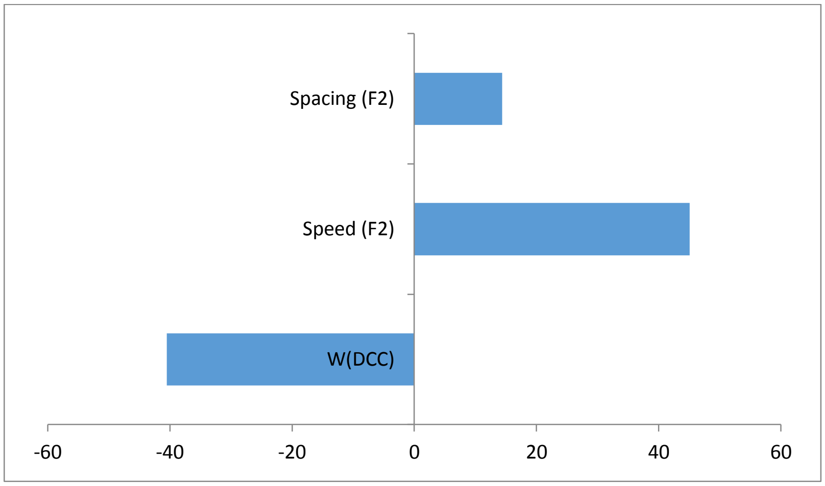


Figure 3. The Sensitivity Analysis of the Independent Variables at the Microscopic Level Based on the Behavioral Pattern of Overreaction- timid

4.2.1.1 The Neural Network Pattern of the Effective Parameter at the Microscopic Level

As shown in Fig.4, accelerating the follower vehicle speed at the deceleration wave reception leads to a decrease in the follower vehicle safe spacing at the behavioral change point. Increasing the follower vehicle speed leads to a smoother flow of traffic. The follower driver based on the overreaction- timid behavioral pattern has secured the safe spacing at the higher speeds. When the follower vehicle receives the deceleration wave, it attempts to drop speed less and to secure a low safe spacing at the behavioral change point. But at lower speeds, the flow of traffic is less. When the follower driver receives the deceleration wave, s/he forced to lower more speed and to increase a more safe spacing at the behavioral change point.

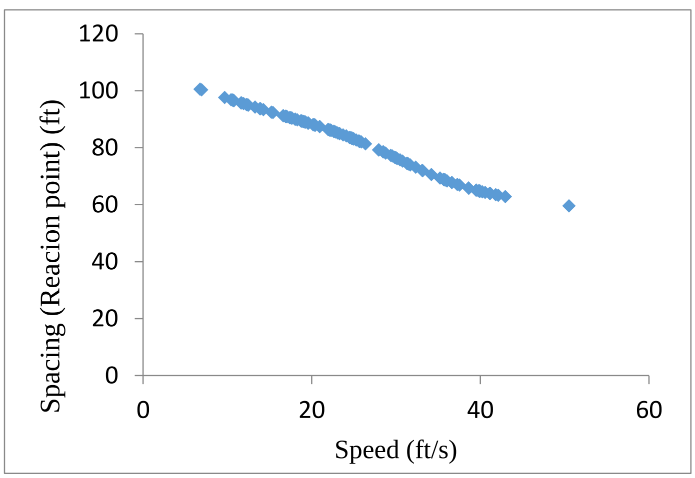


Figure 4. The Neural Network Pattern of the Spacing at the Behavioral Change Point Based on the Follower Vehicle Speed at the Deceleration Wave Reception

As shown in Fig.5, increasing the follower vehicle spacing at deceleration wave reception leads to an increase in the follower vehicle spacing at the behavioral change point. When the follower driver at less spacing receives the deceleration wave, the follower driver, due to the lack of maneuverability, in order to increase the safe spacing, his/her behavior deviates toward the ideal driver behavior at the behavioral change point with a less spacing. However, the follower driver with over reaction has the ability to increase more the safe spacing as the spacing level at deceleration wave reception increases. Consequently, s/he increases his/her safe spacing on the path based on his/her behavioral pattern in order to continue his tendency and keeping his behavior based on his/her behavioral pattern, which leads to an increase in safe spacing and a faster drop in speed at the behavioral change point.

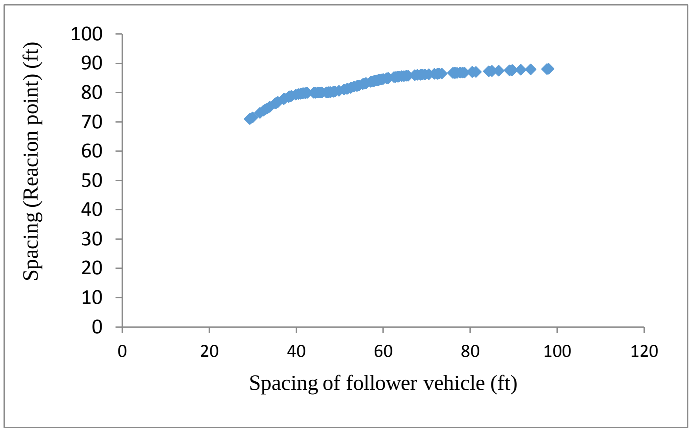


Figure 5. The Neural Network Pattern of the Spacing at the Behavioral Change Point Based on the Follower Vehicle Spacing at the Deceleration Wave Reception

According to Fig.6, the increase in the negative value of the deceleration wave speed in the values less than -8ft/s will decrease and then increase the safe spacing at the behavioral change point, and in the positive values of the acceleration wave, the coasting phase leads to an increase and then a decrease in safe spacing at the behavioral change point. When the follower driver based on the over reaction- timid behavioral pattern receives the negative deceleration wave with more intensity, the follower driver will tend to drop speed more rapidly, which leads to an increase in safe spacing at the behavioral change point. By reducing the negative value of the deceleration wave less than 8ft/s, the impact of the wave on the follower vehicle will be reduced, which result in the follower driver neglecting the accelerating wave effect. Moreover, the follower driver based on the overreaction behavioral patter continues neglect at the positive values of the deceleration wave, which lead to the driver's tendency to move at a constant speed and the lack of an appropriate drop in speed at the deceleration wave reception. The neglect of the follower driver leads to the reduction of the safe spacing on the path toward the congestion phase and a more rapid drop in speed and an increase in the safe spacing. A further deceleration on the path will result in an increase in the safe spacing at the behavioral change point into the ideal driver.

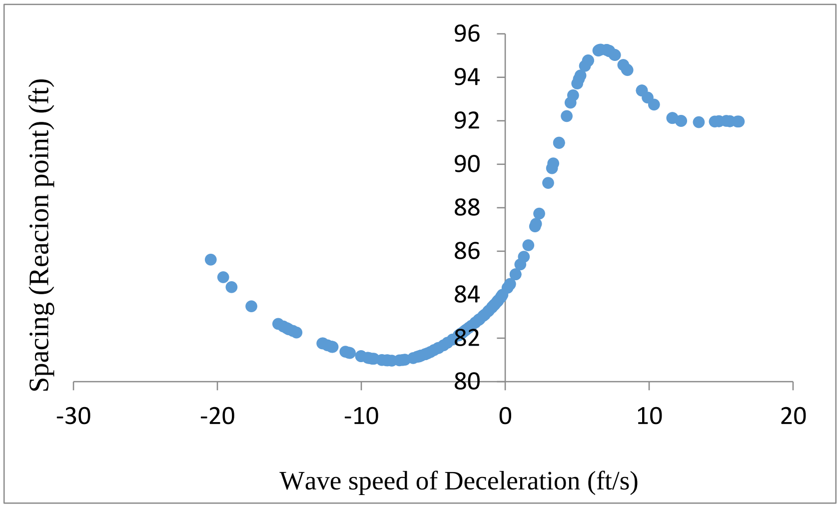


Figure 6. The Neural Network Model of the Spacing at the Behavioral Change Point Based on the Acceleration Wave Speed

4.2.2 The Under reaction- timid Driver

According to Fig.7, the results of the sensitivity analysis of the trajectory data obtained from three parameters at the microscopic level indicate that the deceleration wave parameter is the most effective parameter on the level of follower safe spacing at the behavioral change point.

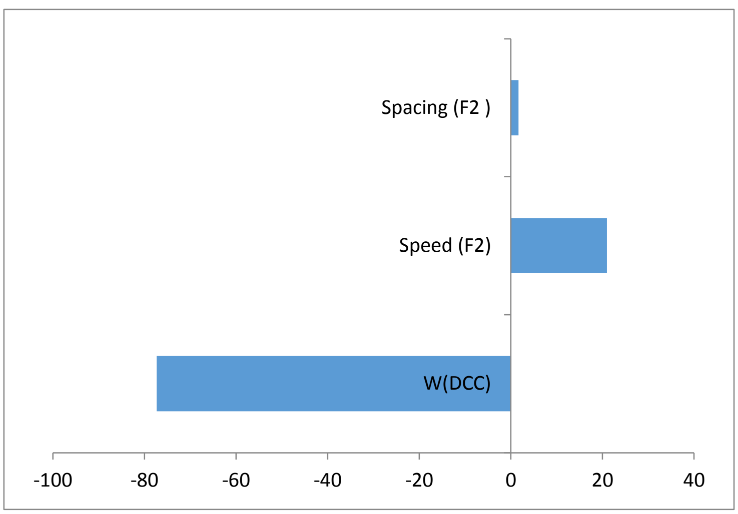
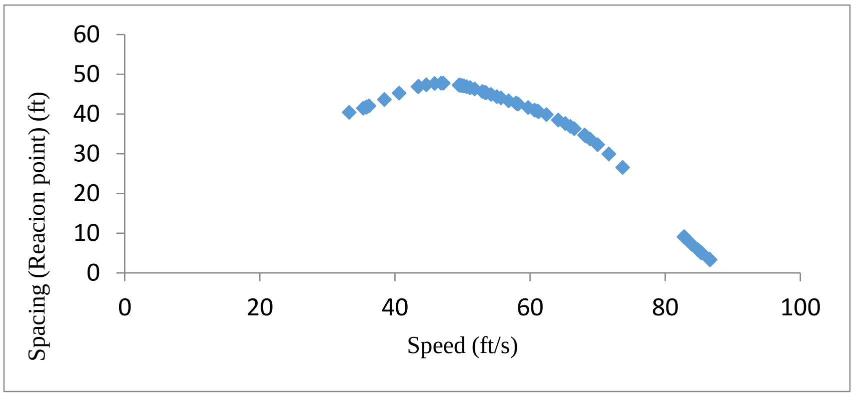


Figure 7. The Sensitivity Analysis of the Independent Variables at the Microscopic Level Based on the Overreaction- timid Behavioral Pattern

4.2.2.1 The Neural Network Patterns of the Effective Parameters at the Microscopic Level

As shown in Fig. 8, at a speed of less than 50ft/s, accelerating the follower vehicle at the deceleration wave reception leads to an increase and after the 50ft / s, it leads to a decrease in the follower spacing at the behavioral change point. In other words, in the values greater than 50ft/s due to the smoothness of the traffic flow, the maneuverability of the driver with under reaction increases and the driver can drive in a less safe spacing. When the follower driver receives the deceleration wave at higher speeds, s/he does not pay attention to the effect of the deceleration wave, so that, he is forced to secure a safe spacing at the behavioral change point. However, at lower speeds, due to the reduced maneuverability of the follower driver in order to drive at a safe spacing, s/he is forced to follow the deceleration wave and try to drop the speed and then increase safe spacing at the behavioral change point.

Figure 8. The Neural Network Pattern of the Safe Spacing at the Behavioral Change Point Based on the Follower



Vehicle Speed at the Deceleration Wave Reception

As shown in Fig. 9, increasing the safe spacing at the wave reception leads to an increase in the safe spacing to 40ft, and then to a decrease in its amount at the behavioral change point. Results indicate that the follower driver based on the under reaction behavioral pattern in the values less than 40ft, increasing the follower spacing at the wave reception leads to an increase in the driver maneuverability and ignoring the received deceleration wave and also a decrease in the safe spacing on the path. The spaces more than 40ft are the enough safe spacing for driver with under reaction to drive in a safe spacing, which leads to a lower drop in speed and a decrease in spacing at the behavioral change point.

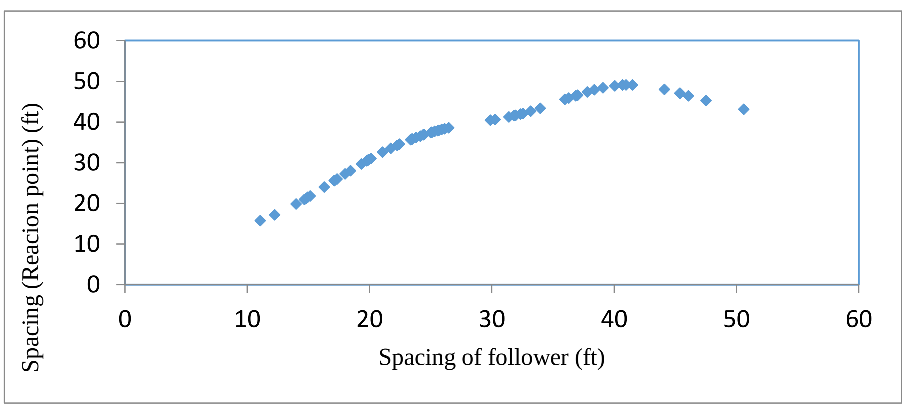


Figure 9. The Neural Network Pattern of the Spacing at the Behavioral Change Point Based on the Follower Vehicle Spacing at the Deceleration Wave Reception

As shown in Fig. 10, an increase in the negative value of the deceleration wave leads to oscillatory changes in the driver safe spacing at the behavioral change point. This oscillatory behavior of the driver with under reaction reflects the more complexity of the under reaction behavioral pattern due to the high maneuverability of driving in a low safe spacing.

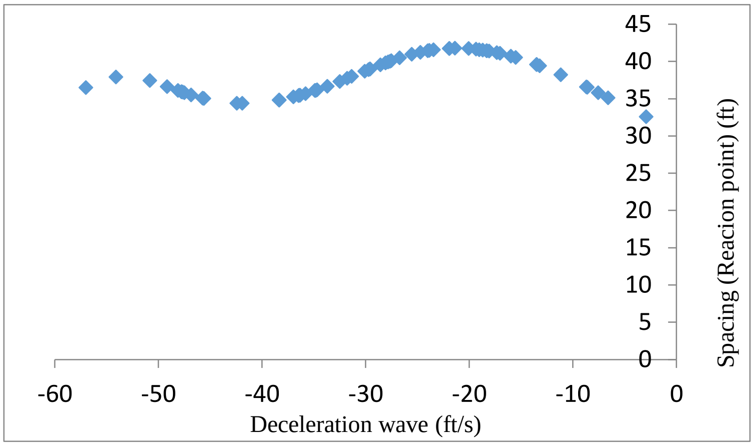


Figure 10. The Neural Network Pattern of Spacing at the Behavioral Change Point Based on the Acceleration Wave Speed

4.2.3 The Overreaction-aggressive Driver

According to Fig.11, the results of the sensitivity analysis of the trajectory data obtained from three parameters at the microscopic level indicate that the deceleration wave parameter is the most effective parameter on the level of follower safe spacing at the behavioral change point.

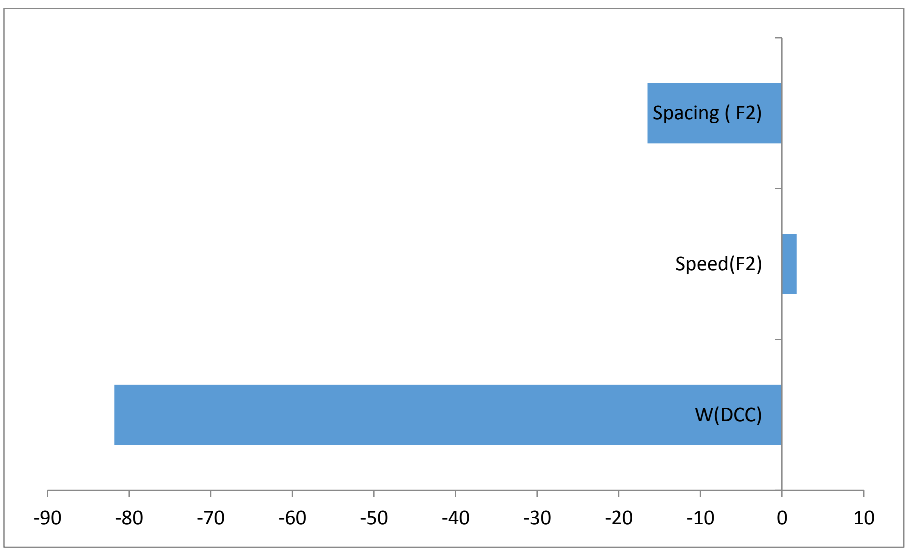


Figure 11. The Sensitivity Analysis of the Independent Variables at the Microscopic Level Based on the Overreaction-aggressive Behavioral Pattern

4.2.3.1 The Neural Network Patterns of the Effective Parameters at the Microscopic Level

As shown in Fig. 12, increasing the follower vehicle speed at the deceleration wave reception leads to a decrease in the follower vehicle spacing at the behavioral change point. The neural network pattern of the follower driver based on the overreaction-aggressive behavioral pattern is similar to the behavioral logic and pattern of the follower driver with the overreaction- timid.

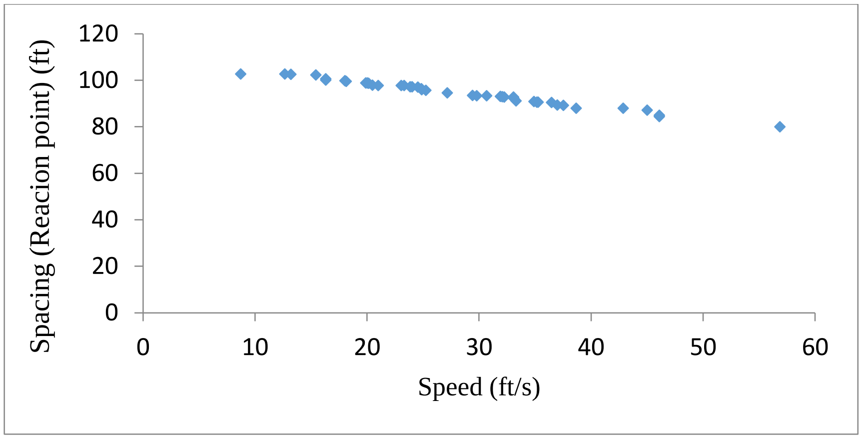


Figure 12. The Neural Network Pattern of Spacing at the Behavioral Change Point Based on the Speed of the Vehicle at the Deceleration Wave Reception

According to Fig.13, increasing the follower spacing in a space less than 80ft leads to an increase in the follower spacing at the behavioral change point and it decreases after 80ft in the values less than 80ft, increasing the follower safe spacing at the deceleration wave reception leads to increase the driver's maneuverability in order to secure a safer spacing and more drop in speed. But in the values greater than 80ft, the follower driver tends to behave aggressively, his/her behavioral pattern, due to the high increase in the safe spacing. In other words, due to the adequacy of the safe spacing in the deceleration phase in high spacing, the driver decelerates less to enter the acceleration phase faster.

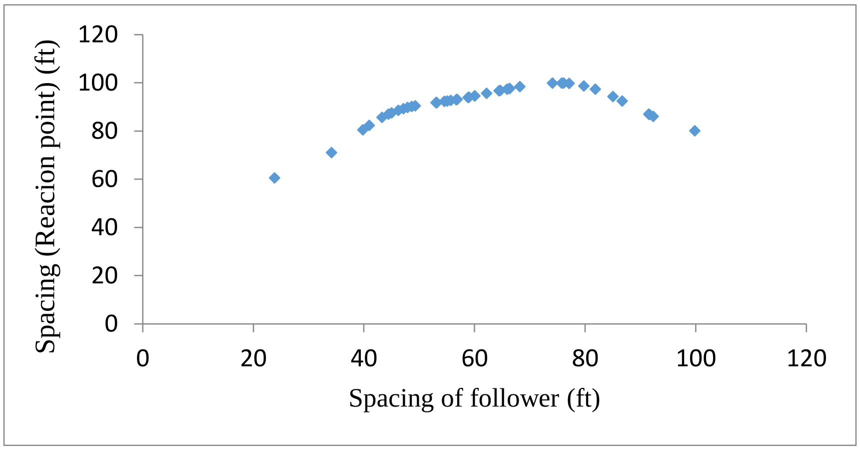


Figure 13. The Neural Network Pattern of Spacing at the Behavioral Change Point Based on the Follower Vehicle Spacing at the Deceleration Wave Reception

According to Fig. 14, reducing the negative value of the deceleration wave speed to a positive value of 10ft/s, coasting phase, leads to decrease the safe spacing at the behavioral change point. The over reaction driver in the deceleration phase act based on his/her behavioral pattern and tends to drive in the deceleration phase with a high safe spacing. Reducing the deceleration wave intensity leads to reduce the impact of deceleration on the follower vehicle driver. Whatever the negative wave is smaller, the drop in speed of the follower vehicle will be lower. Reducing the impact of the wave on the follower vehicle will continue to a positive value of 10ft/s.

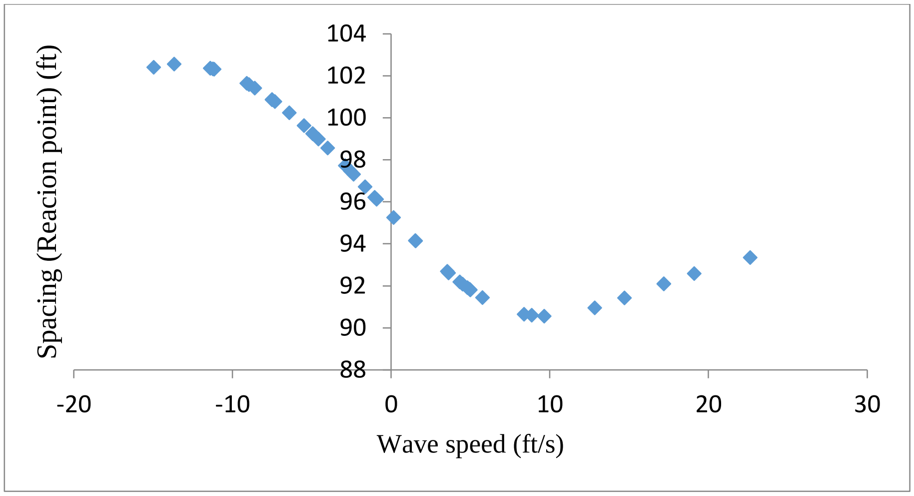


Figure 14. The Neural Network Pattern of Spacing at the Behavioral Change Point Based on the Deceleration Wave Speed

5. Conclusion

Stop and go traffic, which is often seen on freeways, leads to traffic oscillation. The follower vehicles drivers in the vehicle platoon react differently to the stop and go traffic propagated from the downstream due to their inherent behavior, which leads to the formation of the different behavioral pattern and deviation from the ideal driver behavior. This study has identified the behavioral pattern of the follower vehicle driver based on the asymmetric behavioral theory in the deceleration phase and the hysteresis phenomenon in the acceleration phase, and also it has calculated the parameters of the last stop and go wave leading to congestion, which propagated toward the upstream, based on the Newell's car following model. Then, models of the neural network pattern are created to analyze the effective parameters, at the microscopic level, on the follower vehicle spacing at the behavioral change point than the ideal driver. According to Table 4, the results of analyzing the follower safe spacing at the microscopic level at the behavioral change point show that based on the behavioral pattern of the overreaction- timid, the results of the trajectory data sensitivity analysis indicate that two parameters of the follower vehicle speed at deceleration and acceleration wave reception are the most effective parameters on the value of the follower safe spacing at the behavioral change point. Increasing the speed of the follower driver at the deceleration wave reception leads to reduce the follower vehicle safe spacing at the behavioral change point. Also, increasing the negative value of the deceleration wave speed in the values less than -8ft/s leads to decrease and then increase the safe spacing at the behavioral change point and in the positive values of the deceleration wave, coasting phase, it leads to increase and then decrease the safe spacing at the behavioral change point. Based on the behavioral patterns of under reaction- timid and over reaction-aggressive, the results of the trajectory data sensitivity analysis of three parameters at the microscopic level indicate that deceleration wave is the most effective parameter on the value of the follower safe spacing at the behavioral change point. Based on the behavioral pattern of under reaction- timid, increasing the negative value of the deceleration wave leads to the oscillatory changes in the driver safe spacing at the behavioral change point. But, based on the overreaction-aggressive, increasing the follower vehicle speed at the deceleration wave reception leads to reduce the follower vehicle safe spacing at the behavioral change point.

Table 4. The Stop Time Leading to Congestion

Behavioral pattern	The most effective parameter	Parameter behavior	The reason for the behavior of the parameter
Over reaction- timid	1.The follower vehicle speed at the deceleration wave reception 2.deceleration wave	1.Reduction of the follower vehicle safe spacing at the behavioral change point 2.decreasing and then increasing the safe spacing at the behavioral change point in the values less than -8ft/s	1.Smoothness of the traffic flow 2.Wave tendency to decelerate more in the negative values and the lower impact on the wave on the follower vehicle in the positive values, which leads to the follower driver neglecting the impact of the deceleration wave
Under reaction- timid	Deceleration wave	Oscillatory changes in the driver safe spacing at the behavioral change point	An indication of the more complexity of the under-reaction behavioral pattern in the low safe spacing
Over reaction- timid	Deceleration wave	Decreasing and then increasing the safe spacing at the behavioral change point in the values less than -10ft/s	Tendency to drive in the deceleration phase with high safe spacing

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