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# Microscopic Modeling of Driver Behavior Based on Modifying Field Theory for Work Zone Application

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# Microscopic Modeling of Driver Behavior Based on Modifying Field Theory for Work Zone Application

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# DEDICATION

To my family, my professors, my coworkers, and my swim team.

# ACKNOWLEDGMENTS

To the professors and advisors, who not only taught me technical material but instilled true inspiration: I cannot thank you enough.  You've given me the tools for success and motivated me to use them.  Your knowledge of technical material, patience with students, and passion for teaching are all qualities I aspire to emulate and integrate throughout my career.

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# ABSTRACT

MICROSCOPIC MODELING OF DRIVER BEHAVIOR BASED ON MODIFYING
FIELD THEORY FOR WORK ZONE APPLICATION

FEBRUARY 2015

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Because many freeways in the U.S. and abroad are being reconstructed or
rehabilitated, it becomes increasingly important to plan and design freeway work zones
with the utmost in safety and efficiency. Central to the effective design of work zones is
being able to understand how drivers behave as they approach and enter a work zone
area.  While simple and complex microscopic models have been used over the years to
analyze driver behavior, most models were not designed for application in work zones
and thus do not capture the interdependencies between lane-changing and car-following
vehicle movements along with the drivers' cognitive and physical characteristics.

With the use of psychology's field theory, this dissertation develops a framework
for creating vector-based, explanatory, deterministic microscopic models, to enhance our
understanding of driver behavior in work zones and better aid freeway planners and
designers.  In field theory, an agent (i.e. the driver) views a field (i.e. the area surrounding
the vehicle) filled with stimuli and perceives forces associated with each stimuli once

these stimuli are internalized.  Based on this theory, the new modeling framework, Modified Field Theory (MFT), is designed to directly incorporate drivers' perceptions to roadway stimuli along with vehicle movements for drivers of different cognitive and physical abilities. From this framework, specific microscopic models, such as a simple freeway work zone car following model, can be created.

It is postulated that models derived from this framework would more accurately reflect the driver decision-making process, naturally modeling the effects of external stimuli such as innovative geometric configurations, lane closures, and technology applications such as variable message boards.

A simple freeway work zone car following model was created using the MFT framework.  Two MFT car-following agents were created and calibrated.  The second agent (Agent 2) followed the first agent (Agent 1) through a one-lane segment of freeway.  Car-following data for Agent 2 was plotted on a graph of relative speed vs. distance to the lead vehicle, showing car-following behavior.

Car-following behavior for Agent 2 was validated against Federal Highway Administration (FHWA) Turner Fairbank Highway Research Center (TFHRC) Living Laboratory data for simple freeway work zone car-following (Driver 15).   The car-following behavior of Agent 2 replicated the "spiraling" trend observed in Driver 15. Unlike other models (such as Wiedemann), this model does not 'force' these trends to occur; these trends occur naturally, as a result of the perception-reaction time delay and the nature of the forces involved.  Additionally, unusual car following trends reported for Driver 15 were replicated in Modified Field Theory when conditions surrounding each event were synthetically recreated.

Results demonstrated that the Modified Field Theory framework can successfully replicate the process by which a driver scans the driving environment and reacts to their surroundings. Microscopic models can successfully be created using this framework. Results demonstrated that models created from this framework naturally recreate behavioral trends observed in empirical data, and that these models are capable of replicating driving behavior in unusual scenarios, such as the car following behavior of a subject vehicle when the lead vehicle has a strong sudden acceleration event.

Before this model can be applied to work zones, other calibration and validation efforts are required.

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# CHAPTER 1

# INTRODUCTION

The Interstate System is comprised of approximately 210,000 lane-miles of pavement, has more than 55,000 bridges, and tens of thousands of other significant structural elements [1]. As many of these elements are reaching 40 to 50 years of age, bridges and other structures will require substantial rehabilitation, and within the next 20 to 30 years, many will require complete replacement [1]. Many of our freeways are approaching middle age and require repair, which means more work zones can be expected in the near future [2]. Work zone activity has already been increasing over the past few years, and the number of work zones is projected to increase [2].

Work zones can create delays. In 2007, there were an estimated 4.2 billion hours of delay, 10% of which were caused by work zones [3]. Delays along the freeway caused by work zones accounted for nearly 24% of the total non-recurring delays [3]. According to the 2011 Urban Mobility Report, even when roadway construction occurs during the off-peak, it has the potential to increase traffic congestion [4]. Work zones have been identified as a major contributor to the off-peak delays experienced in urban areas, which averaged 11 hours of delay per non-peak traveler in 2010 [4, end of Table 4].

Traffic models have been developed that can predict the impacts of a work zone on a roadway, therefore allowing engineers to reduce the total impact which work zones have on congestion [5], [6]. Both microscopic and macroscopic models have been used to predict the queues, delays, and travel times created by the introduction of a work zone within a degree of accuracy, giving planners the foresight to design and schedule a work zone that will reduce the total delay [5], [7].

Microscopic models have been used to evaluate and predict roadway conditions in work zones [8]. Microscopic models feature the calculation and prediction of the state of individual vehicles in continuous or discrete time-space and offer detailed descriptions of both road and traffic characteristics (acceleration lanes, merging, lane-changing, etc.) that are critical to work zone traffic modeling [9]. By modeling the individual reactions of each vehicle, microscopic models provide a more accurate look as to how work zone related issues, such as lane closure, impact merging behaviors and possible merging difficulties of each vehicle [8]. If an accurate microscopic model is used, the aggregate delays experienced by each vehicle in association with these merging difficulties could provide a more precise delay time, and could give engineers more insight about what causes (and how to minimize) these delays [8]. The impacts of a work zone on an existing roadway, or the impacts of an element introduced into a work zone, such as Automated Workzone Information Systems (AWIS), can be more accurately and precisely examined using accurate microscopic models, and total delays attributed to work zones can be reduced [10].

According to AASHTO, applying Intelligent Transportation Systems (ITS) is part of the solution to our capacity needs [1]. Intelligent Transportation Systems (ITS) have been used in some cases as an attempt to alleviate some of the congestion caused by work zones [10]. Systems such as Automated Workzone Information Systems (AWIS) have seen some success when implemented. An AWIS case study in California yielded a 50% reduction in maximum average peak delay [11]. Existing microscopic models are incapable of accurately modeling ITS applications and other developing roadway technologies without first making significant alterations to model algorithms [10], [12]. Existing microscopic models cannot predict the impacts of ITS applications, such as AWIS, on the driver behavior of an individual vehicle, nor can they predict the subsequent reductions in delay [10], [12].

Other work zone design elements, in addition to ITS technologies, play an important role in the functionality of a work zone. For example, proper signage and advanced warnings are crucial to ensuring vehicles move smoothly and safely away from the work zone and workers [13]. To ensure accurate microscopic modeling it is important that the impacts of new design elements, such as alternative signage strategies and pavement markings, can be easily and accurately incorporated into a modeled as they are developed.

In order to minimize the impacts of work zone queues, it is important to develop a microscopic work zone model that has the ability to accurately model each individual vehicle's reaction to work zone elements such as lane closure, incorporate ITS

implementations (both current and future), and include the effects of other design elements, such as chevrons and signage. Despite the importance of having a microscopic work zone model that is capable of modeling each driver's individual reaction to each stimulus, a model with these capabilities currently does not exist.

# CHAPTER 2

# LITERATURE REVIEW

There are four parts to this literature review, and conclusions were drawn according to the findings of each part. Briefly, the material investigated in this literature review and their associated conclusions are listed below:

*Section 2.1* is a review of current microscopic models that revealed how current microscopic models can be inaccurate. There are gaps in current microscopic models that limit their abilities to accurately model discrete differences between driver populations. Additionally, individually modeling different vehicle movements can cause inconsistencies in the vehicle movements for an individual vehicle. Finally, vehicle movements are predicted using algorithms based on statistical representations of observations made about vehicles, rather than predicting vehicle movements by assessing the impacts of local stimuli on each driver. For reasons including those described above, there are voids in current microscopic models that may cause them to be inaccurate.

*Section 2.2* contains human factors studies about various populations of driver. From this section, it was concluded that different populations of drivers behave differently. In addition, the presence of roadway stimuli such as signage or a pedestrian can elicit varying responses for different populations of driver.

*Section 2.3* defines the "spiral" trend witnessed when plotting empirically collected

naturalistic normal car following data, and discusses Wiedemann's car

following model which attempts to mimic this spiral. This section also

identifies a dataset useful for validating the car following behaviors of a new

microscopic model.

*Section 2.4* explains field theory, a psychological framework developed by Kurt

Lewin. It is hypothesized that field theory could be adopted and modified to

create a microscopic driving model. This model could potentially show the

influence of roadway stimuli on a driver.

## 2.1 Microscopic Traffic Models

Two major types of traffic flow model continue to dominate the field:

macroscopic models and microscopic models. Macroscopic models simulate traffic flow

by taking into account the cumulative traffic stream characteristics (such as speed, flow,

and density) and modeling the stream as a whole [14]. Microscopic models are the

dynamic and stochastic modeling of individual vehicle movements within a system of

transportation facilities. Both models can be (and have been) used to predict roadway

and vehicle conditions, such as delay, speed, density, etc. The main difference between

the two types of models is that microscopic models model vehicles on a per vehicle basis,

simulating the movements and choices each vehicle makes, whereas macroscopic models

simulate the traffic stream as a whole using aggregate values of the traffic stream. To

analyze the behavior or reactions of a single vehicle, one must choose microscopic models.

Multiple microscopic models have been developed over the past 60 years to describe different aspects of vehicle behavior. All these models can be divided into four main categories: route choice models, lane change models, gap acceptance models, and car following models. Route choice models have been used to predict a vehicle's route choice. These models can be deterministic, probabilistic, or dynamic, and most models involve some form of logit or probit model. Lane change models became more prevalent in the early 1980s. Lane change models incorporate a gap acceptance model, along with an algorithm to predict when a driver would choose to change lanes, what lane the driver would chose, and when the driver would actually merge. Mandatory lane change models are when the driver must change lanes (for example, a driver merging over to use an onramp or off ramp, or a driver merging over due to a work zone). Gap acceptance models are used to predict the gap accepted by a merging vehicle from one lane of traffic to another. Car following models describe how a vehicle drives on a segment of roadway, both when it's the lead vehicle and when it's following another vehicle.

Lane change models cannot operate without a working gap acceptance model. A lane change model describes everything that goes into a driver's decision to change lanes, whereas the gap acceptance model determines whether or not the driver will accept a gap once the decision to change lanes has been made.

Gap acceptance models have been around since 1961, and are used to determine acceptable gaps chosen by merging vehicles in a stream of traffic. Weiss (1961) [15] created the first gap acceptance model. It assumed an infinitely long line of cars traveling at constant random speeds where passing is always possible, and occurs without any change in speeds. A statistical analysis of his model revealed that the probability of passing or being passed by n cars in time t is described by a Poisson distribution. Although this model emphasized desired speed, it had no acceleration aspects, no reaction to stimuli, and assumed passing was always possible. The model was limited in its use and applications.

Daganzo (1981) [16] created a Multinomial Probit Model used to determine the mean critical gap, the mean critical lag (which is the first gap considered by a driver) and the variances in both. Studies revealed the mean critical gap to be significantly smaller than mean critical lag. The model worked well when data was plentiful. It demonstrated the use of maximum likelihood to determine the parameters of gap acceptance functions that vary from driver to driver, and it accounted for driver variation. However, the model could only estimate mean critical gap, mean critical lag, and the variances of both when one is known, making the model not statistically estimable and impractical for implementation. Also, the model did not work unless within driver variation or across driver variation function is normalized.

Mahmassani, Yosef, Hani and Sheffi, (1981) [17] created a probit model which assumes a normal distribution of gaps across gaps and drivers. The model showed that

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on average, the critical gap of drivers is decreasing as they wait for an acceptable gap, and that the effect of the number of gaps rejected on the critical gap was significant. The model showed that over time, the critical gap became smaller (as time passed, the driver felt increasing pressure to accept gaps, and eventually the driver accepted a gap that he/she previously would have rejected). Unfortunately, this study was performed for signalized intersections and not merging traffic nearing a work zone, therefore the results of this study cannot be directly applied.

Makigami et al. (1988) [18], and Ahammed et al. (2008) [19], determined that at least 85% of merging drivers is a typical target used in practice. Therefore, the 85th percentile of merging drivers should be used in a model, and the 85th percentile of merging distance from a work zone will be crucial.

Weng and Meng (2011) [20] proposed lane-based speed-flow models, incorporating traffic conflicts among the lanes. A desired merging location model is then developed that determines where drivers start to consider merging, and a binary logit model that is applied to estimate the probabilities that drivers will merge into current adjacent gaps. The methodology focuses on speed-flow relationship and driver merging behavior in work zones merging area. According to Weng and Meng,

> *"…findings show that the speed-flow relationship in the through lane is affected by the merge lane traffic under uncongested circumstances."*

The model finds the 85th percentile of merging distance using a merging model. This model, however, is only a gap acceptance model, despite having a direct relationship with car-following. A model that incorporated both car-following and gap acceptance would be a better implementation of this model.

Zhu et al (2011) [21] adopt an existing traffic flow model and modify empirically derived coefficients within the model by altering an optimal velocity model and incorporating safe lane-changing rules for two-lane traffic flow. The model, however, cannot be used for anything other than two-lane traffic flow.

Yang and Koutsopoulos (1996) [22] create a rule-based lane change model acceptable for freeways only. Lane change scenarios were identified, and priorities were explicitly modeled for drivers who faced conflicting goals. There was no formal estimation of parameters, and no validation for the model was performed. This model did attempt, however, to identify when and why a driver would begin to think about changing lanes.

Lane change models are inherently different from gap acceptance models. Most lane change models incorporate some form of gap acceptance model; however, they have a series of steps leading up to the gap acceptance model that determine parameters in the lane change model. Ahmed, Ben-Akiva, Koutsopoulos, and Mishalani (1996) developed a lane change model structured as a decision tree that attempted to integrate gap

acceptance elements with the urgency to perform a lane change maneuver [23]. Below is

a figure depicting the entire lane-change model:
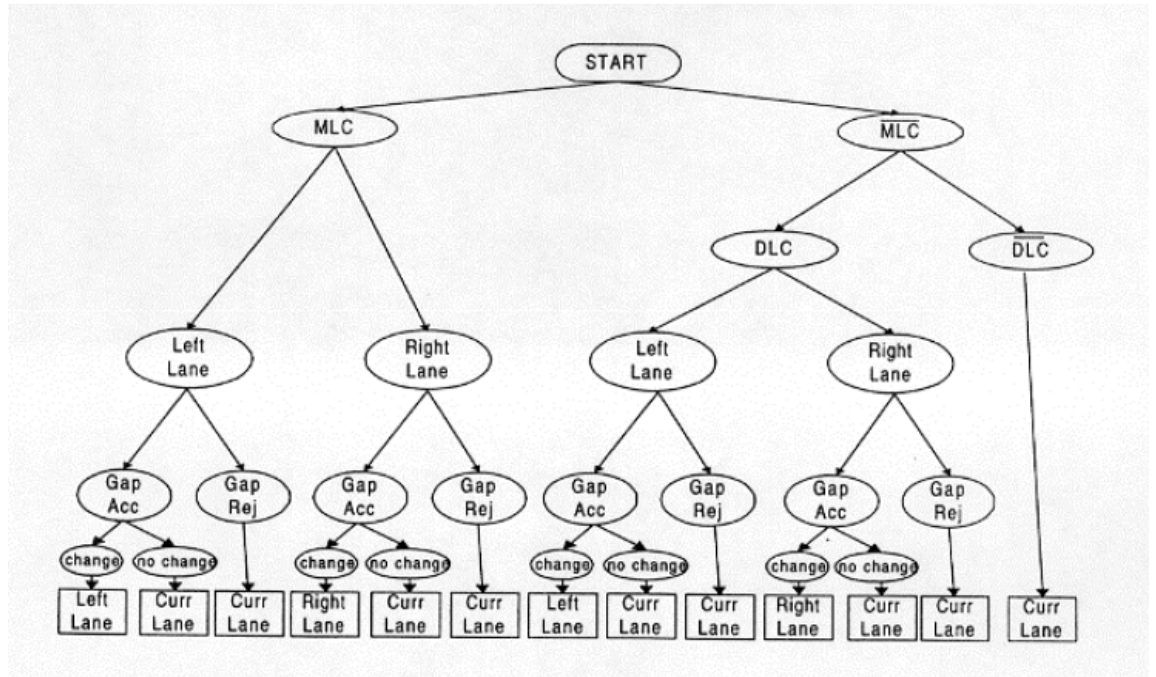


**Figure 1: The Lane Change Model Structure [23]**

The figure shows the difference between Mandatory Lane Change (when a lane

will cease to operate, "MLC" in the above figure) and Decision Lane Change ($\overline{\text{MLC}}$

indicates where lane change is not mandatory, DLC indicates when a driver decides to

change lanes, and $\overline{\text{DLC}}$ indicates when a driver decides not to change lanes). The driver

must then choose between the left lane and the right lane. In a work zone where a lane is

closed, the lane change model would be MLC, and the lane choice would be made for the

driver depending on what lane is closed.

To calibrate the gap acceptance for this model, they propose a field study in a location where the lane change is mandatory (MLC), and where there is only one lane to choose, therefore making the first real choice in the model the gap acceptance model. The following figure depicts what the model would look like when merging from a freeway on-ramp.
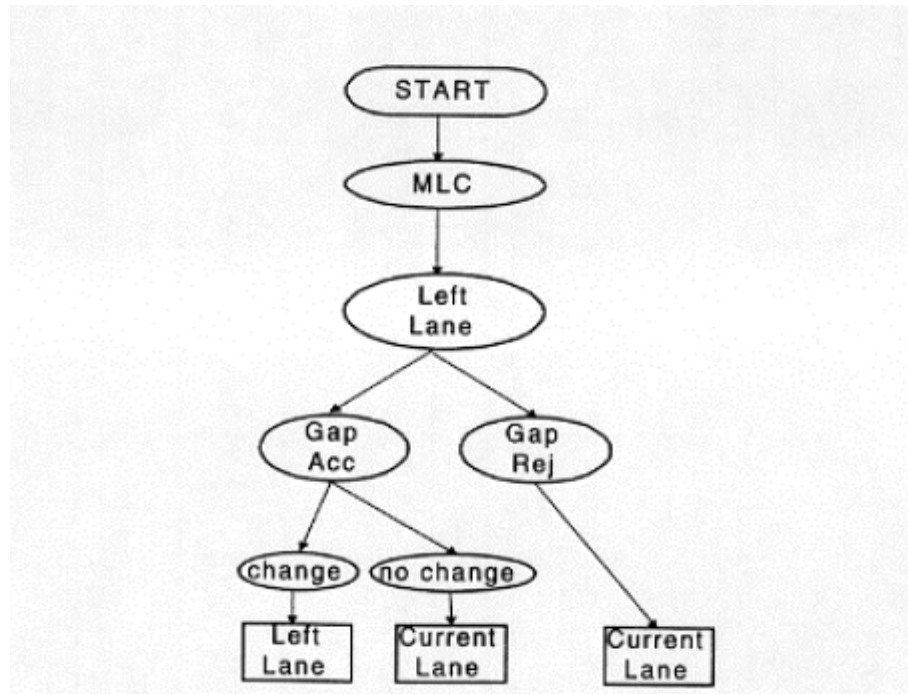


**Figure 2: Lane Change Model Structure for Freeway On-Ramp Merging [23]**

Yang and Koutsopoulos calibrate the gap acceptance model for mandatory lane change with one lane to choose from using this technique. However, they do not formally estimate parameters for the rest of the model, nor do they estimate gap acceptance for other portions of the model (for instance, decision lane change). If a middle lane is closed and the driver has both the right and left lanes available, the model

does not take into account a driver who chooses the right lane because there are no acceptable gaps in the left lane (since gap acceptance is further down the model from lane choice). This model does not take into account the pressures a driver feels as the driver approaches the point of lane closure; it simply estimates the average value for each parameter, independent of a vehicle's proximity to the point of lane closure (other studies indicated that drivers will accept smaller gaps as time progresses).

This model, along with others (Tarko (1998) [24], Hou et al. (2013) [25], Weng and Meng (2011a) [26]), uses a decision tree to determine lane change and gap acceptance. Although these models provide a logical linear model for a driver's thought and decision process, they lack the incorporation of a dynamic "urgency" variable created to capture the growing necessity to merge in a lane closure situation. The "mandatory" lane change model is static, and does not change with a driver's proximity to the point of lane closure. In the field, drivers behave differently the longer they wait for an acceptable gap, sometimes accepting gaps that were previously unacceptable, and sometimes taking a completely different course of action such as a detour or slowing to a complete stop at the point of lane closure. The linear structure of these models also deny them the ability to incorporate the impacts of external roadway stimuli, such as ITS technologies or alternative work zone signage strategies, limiting the degree of usability these models have.

Toledo et al. (2007) [27] discussed these issues when using a MLC/DLC decision tree model, such as the one proposed by Ahmed et al (1996) [23]. Toledo [27] found that

the MLC/DLC model structure was too rigid and did not permit for events such as an overtake during an MLC scenario. This meant that drivers could not change lanes to improve traffic conditions when a mandatory lane change was in effect. When using these models with a microsimulator, the results were unrealistic traffic flows. A new model was proposed that integrated mandatory and discretionary lane change parameters, allowing drivers to jointly consider the two.

All these models estimate gap acceptance and lane change independent of car-following and proximity to a work zone. Because of this, they do not encapsulate all roadway stimuli experienced by the driver, therefore they cannot predict a driver's reaction that has been influenced by these stimuli (for instance, the disconnect between car-following and gap acceptance models creates a situation where drivers who accelerate or decelerate to find an acceptable gap are not taken into account). These models can potentially portray inaccurate vehicle behaviors.

A disconnect is forged between longitudinal and horizontal vehicle behavior when the car-following and lane changing algorithms are assessed independently. This disconnect fails to relate subtle interrelated variables that influence driver behaviors and driver decision-making as a whole, rather than piece-wise. By deterministically assessing these behaviors independently, related longitudinal and horizontal behaviors and driver decisions are disjointed, and the effects of some horizontal variables on longitudinal vehicle behavior are lost (and vise-versa).

Toledo et al. (2007) [28] discusses the advantages to creating a model that integrates acceleration (car-following), lane-changing, and car-following models. According to Toledo, most models assume drivers react to past traffic conditions immediately and make instantaneous decisions, and that different driving decisions (such as acceleration and lane changing) are made independently. Toledo explains that some lane changing decisions are made in reaction to acceleration decisions, and vise-versa. A model framework is developed based on short-term goals and short-term plans in an attempt to capture the inter-dependencies between lane changing and acceleration models. A model that could show the impacts of acceleration and car-following variables on lane-change decisions, or vise-versa, could more accurately model traffic flow under various conditions.

The integrated model structure proposed by Toledo, unfortunately, includes a decision tree that divides this integrated model into different models, disassociating and separating vital components to the model that are inter-related in the field. Although the overall goal for this model was to integrate acceleration and lane-change, the rigid structure of this decision tree independently assess driver decisions and estimates lane-change and car-following decisions using separate equations [28].

These models lack the ability to estimate the impact of some car-following variables, such as slow moving traffic, on lane-change behaviors. In some work zones with heavy congestion, some vehicles wait until the last minute to merge because the closing lane is flowing much faster than other traffic. By modeling lane-change decisions

independently of car-following, the mandatory lane change decision cannot be delayed until the point of lane closure to satisfy the driver's desired speed (desired speed is a car-following variable). There is no way to quantify the preconceived plan that these drivers have of merging at the point of lane closure using modern microscopic models.

In addition, when driver parameters are estimated differently for different sets of equations (i.e. a safe driving parameter in car-following and gap acceptance), situations arise in simulation that are contrary to real-life circumstances. Even in a program as advanced as VISSIM, car-following and lane change parameters are estimated and statistically generated independently for each vehicle, sometimes creating vehicles that behave cautiously in car-following yet overly aggressive in gap acceptance.

Current microscopic models employ separate equations to describe different movements a vehicle will make. The lateral and horizontal behaviors are described using car-following and lane-changing equations. No current microscopic model exists that can simultaneously quantify the lateral and horizontal movements of a vehicle. Some lane-changing behaviors are influenced by other variables than those found in lane-changing models (such as those found in car-following equations). In the field, a lane change can sometimes be observed as a reaction to multiple variables acting upon the driver, resulting in a cumulative driver response. No current microscopic model possesses the ability to simultaneously quantify and predict the aggregate effects of all roadway variables on a driver, resulting in a driver's response; they can only predict a driver's lane changing response or a driver's car following response.

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In addition, current microscopic models are based off observations made on how a vehicle behaves. Controlling each vehicle is a driver; therefore, a model based off real-world observations would model a driver, how/when a driver observes various stimuli on and off the roadway, and how the driver responds to these stimuli. Other microscopic models may include a driver's reactions to some stimuli, but no model is based on the driver and how the driver perceives stimuli. A more true-to-life microscopic model would be a "driver-centric" model, based on the driver rather than on observations made about the vehicle.

A model must be created that can simultaneously quantify the impact of these parameters. Different aspects of a vehicle's movement are not completely independent of each other; therefore they should not be represented with different models. To accurately model vehicle behavior, there should be a model that predicts horizontal and longitudinal vehicle movements together, a model that simultaneously quantifies the impacts of roadway variables on car-following and lane-changing behaviors, and a model that directly assesses how car-following variables can influence lane-changing behavior, or vice-versa. In the field, a driver may make a decision based on both horizontal and longitudinal variables; therefore, a true microscopic model would be able to simultaneously quantify multiple roadway stimuli and predict the driver's cumulative reaction to everything, rather than as independent horizontal and longitudinal responses.

There is no microscopic model currently in use that describes a vehicle's horizontal and longitudinal movements simultaneously. To truly model what makes a driver change lanes and when the driver chooses to change lanes, all variables influencing this decision should be taken into account in one model. The model should be driver-centric, and should quantify and "weigh in" on all pressures the driver feels on and off the roadway.

To accurately depict vehicle movement through a work zone, it is crucial that lane-change behavior (and, ipso-facto, gap acceptance behavior) be accurately modeled. To accurately model a driver's response to change lanes, all roadway stimuli influencing this decision must be taken into account. An accurate work zone model should be able to quantify various roadway stimuli, demonstrate the impact of these stimuli on each other, and accurately predict the response of a driver to these stimuli as a whole.

## 2.2    Different Drivers Drive Differently

It's not outrageous to think that different driver populations might have different driver behaviors. So why then, in microscopic modeling, is the entire driving population described using one distribution, one set of equations, and one set of variables? It seems intuitive that different drivers might govern the way they drive based on different models; for instance, a new driver might adhere strictly to the rules outlined by the DMV in the new driver handbook, yet may lack the practical experience to know when (and how) to avoid conflicts, when to begin braking for a pedestrian in a crosswalk, or even how to

interact with other vehicles.  Older drivers may be more cautious and might brake earlier, however due to diminished visual and cognitive abilities they may not be able to react appropriately to a situation or react in the same time frame as a younger driver.  These differences exist not only between older vs. younger drivers, but drivers who are distracted vs. vigilant in the driving task, drivers who are impaired with alcohol or other drugs, even drivers who are unfamiliar with the roadway (and rely solely on signage and roadway markings to accomplish the driving task, rather than someone who is familiar with the roadway).

At what point does creating an accurate model become infeasible?  How many different models should be/need to be created?  A model should be accurate, but it must be useful and usable (an aspect of the model that will diminish if individual models are generated and calibrated for every driver on a roadway; the more sub-models that need calibration, the harder it is to use the model as a whole).

Studies revealed that certain activities performed while driving, a driver's age, any inebriation, or even driver familiarity can greatly affect and alter driver behavior. Some of these studies unearthed results showing vast differences between driver behaviors, and they begin to provoke the thought that it might be worth our while to describe these drivers and their effects in our microscopic model using separate algorithms, and it might be more accurate to model populations separately rather than trying to describe all drivers using one set of algorithm.

### 2.2.1 Performing tasks while driving

Performing tasks such as talking, reading, texting, etc. while driving distracts a driver from their primary task, therefore altering driver behavior. Published research demonstrate differences in driver behavior and driver performance when a driver is distracted and/or has additional visual and cognitive loading. When a driver is otherwise occupied and/or is performing a secondary or multiple tasks, it is generally believed that a driver's abilities to safely and accurately complete the driving task begin to diminish. This compromises a driver's performance, and causes visible alterations to driver behavior and how a vehicle: interacts with other vehicles, interacts with elements in the environment, obeys rules of the road/posted speed limits, etc.

Engstrom et al (2005) [29], investigates In Vehicle Information Systems (IVIS), such as GPS and cell phones, due to the increasing number of in-vehicle systems that drivers interact with while performing the driving task. These systems introduce secondary tasks that the driver must perform concurrently with driving (the driver's primary task). When the driver is forced to look in places other than the roadway (to perform these secondary tasks), the driver's visual load is being challenged; when using hands-free devices such as voice-based solutions for cell phones, studies have reported an increase in the driver's cognitive load and a degrading effects in event detection performance. The research in Engstrom et al (2005) was designed to investigate the visual and cognitive demand on driving performance and driver state using surrogate (artificial) In-vehicle Information Systems (S-IVIS). Tests were conducted in static simulators, moving base simulators, and in the field.

The study by Engstrom shows that cognitive and visual load affect driving performance in different ways. Overall, increased visual demands lead to reduction in speed and an increase in lane-keeping variation. The increased visual demands also caused drivers to have large steering corrections. Cognitive load, however, had no effect on speed, and reduced lane-keeping variation, as well as an increase in gaze concentration towards the road center. Both tasks induced increased steering activity (during the visual task, this was to correct for heading error that built up during glances away from the roadway, whereas the increased steering activity during the auditory task appeared to be a side-effect of the increased gaze concentration towards the center of the roadway). [29]

Divers reported a feeling of decreased driving performance when performing secondary tasks introduced by an IVIS, including auditory tasks that did not require the driver to alter their field of vision.

In terms of testing drivers using driving simulators vs. field studies in the road, field results were consistent with results obtained in the simulator. Physiological workload seemed to be slightly higher in the field, but this was explained by the increase in actual risk that one experiences in the field vs. a simulator.

Engstrom et al (2005) [29] discovered that the driving task takes both visual and mental focus, and that any task (visual or cognitive) which derails focus from the driving

task will result in a decrease in driver performance. Therefore, tasks that introduce a mental load will affect a driver's performance, and subsequently alter driver behavior.

In addition, it was found that simulators could be used effectively to collect driver data regarding distracted driving, driver behaviors, driver loading, etc. This study (Engstrom et al (2005)) utilized features of a driving simulator that are unavailable when performing data collection in the field (such as eye-tracking gear and software, full control over environment and environmental elements, ensured consistency in the test among test subjects, etc.). [29]

It is important to capture drivers who use IVIS while driving when considering microscopic modeling. This population of drivers have altered driver behavior (therefore making traditional algorithms incorrect), but these drivers could potentially cause incidents on a roadway because of their distractions. Even with laws being passed regarding texting and driving, there will still be a subset of drivers who continue to text and drive, and their effects on the roadway and on traffic flow should be considered in an accurate microscopic model.

Schlehofer et al (2010) [30] investigates the impacts of cell phones on drivers and driving behavior. Approximately 86% of college drivers occasionally talk on a phone while driving. Cell phone use is involved in at least 21% of all accidents. Cell phone usage while driving contributes an estimated 2600 deaths, 330,000 moderate to critical injuries, and 1.5 million instances of property damage annually in the U.S. How do cell

phones and how does cell phone usage impact college-aged drivers? How do college-aged drivers perceive their driving abilities with and without cell phones, and how does this play a role in cell phone usage while driving? Why is it that drivers use cell phones, despite the horrific statistics associated with driving while talking on a cell phone?

In Schlehofer et al (2010), [30] 69 college students were involved in a study predicting the impacts of cell phone usage on driving abilities. Initially, each driver was given a survey and asked to predict their driving performance when using a cell phone (i.e. conversation) and when not using a cell phone. These same drivers were then placed in a driving simulator, and their driving performance (with and without cell phone usage) was assessed.

The study found that drivers overestimated their own personal driving ability while underestimating the impacts of driving while using a cell phone. In addition, a strong correlation was observed between drivers who perceived themselves to be good at compensating for driving distractions, drivers who overestimated their performance on the driving simulator, and those who had high illusory control and drivers who use a cell phone while driving in everyday life. In addition, it was discovered that drivers who talked more frequently on a cell phone while driving had worse real-world driving records.

It was concluded that a driver's illusion of control and perceptions of being a "good driver" (especially while driving distracted) can partially explain a driver's

decision to use a cell phone while driving, despite the negative statistics associated with cell phone usage while driving.

This study was not alone in its findings regarding a driver's illusions of driving skill. Other projects, including Svenson (1981) [31] have investigated how drivers rank themselves among other drivers, and concluded that most drivers studied thought themselves to be much better than average. As a matter of fact, Svenson found that 87.5% of the American students surveyed thought they were in the top $30^{th}$ percentile in terms of driving skill (this is, of course, a mathematical impossibility).

Schlehofer et al (2010) [30] grants credence to the belief that for different driver populations, a driver's "self-perception" (such as being a better-than-average driver even when distracted) can influence driving habits. Drivers of a certain predisposition concerning their abilities as a driver are more apt to partake in specific distracting activity.

A microscopic driving model based on different driver populations could capture and model this phenomenon. Theoretically, a model constructed of multiple models for sub-populations of drivers could easily incorporate varying possibilities of cell phone usage based on driving style for varying driving populations. In addition, drivers who are more apt to use a cell phone while driving can be identified, and accurate "operating while using a cell phone" models can be applied to the correct drivers (or drivers who are more suspect to use a cell phone while driving). Driving while using a cell phone can

therefore be modeled for drivers who are more likely to drive distracted. The drivers who are more likely to drive while using a cell phone can be identified and a "driving while using a cell phone" model can be applied to those drivers, and the "driving while using a cell phone" model can be accurately calibrated to show how each sub-population of driver operates while using a cell phone.

However, current microscopic models do not divide the driving population into sub-populations with varying driving models. Therefore, if cell phone usage and the effects of cell phone usage were incorporated into a modern-day microscopic model, it: 1.) could not identify the drivers most likely to use a cell phone and would apply its "driving while using a cell phone" model at random to the driving population, and 2.) could not model how driving while a cell phone effects different populations differently (since it would only have one generic "driving while talking on a cell phone" model rather than a "Male, Age 16-25, Familiar with a roadway," a "Male, Age 25-55, Familiar with a roadway"… etc. model, the status-quo for microscopic modeling will not capture the subtle variances in driving behavior exhibited between driver populations).

Distracted driving also impacts roadway and traffic conditions negatively (since negative impacts on traffic flow are one of the problems that microscopic modeling is supposed to help predict and identify, the absence of distracted drivers and their impact in current microscopic models is unsettling). Traffic laws such as the no texting law have been put into place to try and mediate these problems, but despite efforts to remove these distracted drivers from the road, they still exist. It is known that distracted drivers have a

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negative impact on safety, and recent studies have shown they also negatively impact traffic flow, creating delays and adding to congestion. Vladisavljevic et al (2009) [32] found significant addition to delays when examining distracted drivers. Cooper et al (2009) [33] discovered that driver distraction and traffic congestion played a significant role in mean speed, lane change frequency, and the likelihood of remaining behind a slower-moving lead vehicle. These are major alterations to driver behavior, all of which can easily be captured in a microscopic model. Cooper (2009) also suggests "cell phone drivers" may have profound and unexpected consequences for traffic efficiency, proving that distracted driving can affect traffic flow conditions.

From these studies, it becomes evident that microscopic models would be more accurate if distracted drivers operated using a separate algorithm. In addition, distracted drivers play an un-ignorable role in congestion, and predicting the adverse impacts of distracted drivers on a roadway is an ability that current microscopic models do not possess (because they have no separate "distracted driver" model; everything is included in the same set of equations, same algorithm, same distribution).

### 2.2.2   *Driver age and driver behavior*

Numerous studies have indicated that older drivers behave much differently than other drivers. From the way they scan the roadway (patterns, frequency, when they look and what they look for), to their diminished cognitive, visual, and physical abilities, older drivers operate differently than other vehicles on the roadway. Currently, microscopic models do not include an older driver model, and do not distinguish between older

drivers and other drivers in a driving population. One of the arguments in this literature review is that a more accurate microscopic model would be a series of sub-models (rather than the status quo of fitting all drivers to one model). The following research papers investigate and explain the numerous ways in which older driver behavior differs from other drivers, and help establish the main arguments posed in this literature review.

Roadway scanning patterns and roadway scanning frequencies were found to be inadequate in the older driver population. Pollatsek et al (2012) [34] searched for possible reasons as to why older drivers age 65+ have upwards of three times as many crashes at intersections as drivers ages 35-64. Pollatsek used both on road field studies and driving simulators to investigate how older drivers scan the roadway at intersections. Studies confirmed that older drivers tended to fixate on regions in intersections significantly less frequently than younger, experienced drivers. These regions, defined as *potential threat regions*, were locations that need to be monitored just before and immediately after a driver enters the intersection. Monitoring these locations ensures that additional cross-traffic has not materialized (taking a primary secondary and sometimes tertiary scan of these locations before, during, and after approaching and departing an intersection). The study concluded with a training program that helped retrain older drivers to glance at intersections not only when they are approaching them, but making a secondary glance at the intersection while deciding whether or not it's safe to go, and making a tertiary glance while the driver is performing the maneuver at the intersection to ensure that no additional traffic has/is approaching.

Other papers have found similar results. Romoser et al (2009) [35] investigated older driver behavior at T- and four-way intersections due to an overrepresentation of older drivers at intersection angle crashes. The study found that older drivers tended to make fewer side-to-side scans at intersections than middle age drivers (scanning before, during, and after executing a maneuver at an intersection). Romoser investigated both physical and cognitive decline in older drivers to determine if the fewer glances were correlated with the level of either physical or cognitive decline in older drivers. After testing 54 older drivers between the ages of 70 and 89, a correlation was found to exist between cognitive (but not physical) decline and the decrease in side-to-side scanning while turning.

As a follow-up study to Romoser et al (2009), Romoser et al (2013) [36] attempts to analyze the difference in scanning behavior at intersections between experienced younger drivers and older drivers. By monitoring driver's point-of-gaze as they traversed simulated intersections in a driving simulator (with hidden hazards), researchers evaluated four hypothesis in an attempt to explain why older drivers typically fail to properly scan intersections: 1.) difficulties executing head movements, 2.) decreases in working memory capacity, 3.) increased distractibility, and 4.) failure to recall specific scanning patterns. Results from this study confirmed none of the hypotheses posed, however, they supported the idea that drivers have limited attention, and when they become fixated on the task at hand (such as maintaining the vehicles heading in the intended pathway of the vehicle) their abilities to monitor hazardous areas outside the intended path of travel diminishes. Despite having a lower scanning frequency, it was

found that older drivers approached some situations that were potentially hazardous by slowing down.  It was postulated that "made up" for the lack of roadway scanning.


Emerson et al (2012) [37] wrote a paper aimed at developing a predictive model for real-life driving outcomes in older drivers.  100 older drivers (ages 65-89) were tested in visual, motor, and neuropsychological performance to establish a baseline.  Demographics, driving history, and history of on-road errors were also included.  Findings for this research concluded:


> *"Multivariate models using "off-road" predictors revealed (a) age and Contrast Sensitivity as best predictors for driving cessation; (b) education, weekly mileage, and Auditory Verbal Learning Task-Recall for moving violations; and (c) education, number of crashes over the past year, Auditory Verbal Learning Task-Recall, and Trail Making Test (B-A) for crashes.*


> *…Diminished visual, motor, and cognitive abilities in older drivers can be easily and noninvasively monitored with standardized off-road tests, and performances on these measures predict involvement in motor vehicle crashes and driving cessation, even in the absence of a neurological disorder."*

Older drivers have different abilities than other drivers on the roadway. Visual, motor, and neuropsychological skills in older drivers are usually less than that of other drivers. Older drivers have less ability to sense/observe problems on the roadway, have difficulties processing these problems (not only processing these problems in a quick and decisive manner, but also coming up with a "correct", effective solution), and then a diminished ability to quickly and accurately execute a solution. In some cases, older drivers should consider alternative forms of transportation other than driving.

Studies have also been done regarding older drivers and work zones. According to Heaslip, Collura, and Knodler (2011) [38], older drivers have a particularly difficult time navigating a work zone. The problem is significant enough where the Federal Highway Administration (FHWA) published a book, *Highway Design Handbook for Older Drivers and Pedestrians*, [39] in an attempt to mitigate the increased risk older drivers have when traversing a work zone. The results of Heaslip, Collura, and Knodler showed significant differences between the traveling speed of older driver and other drivers while navigating a work zone. Additionally, traveling speeds varied depending on the type of design features incorporated into work zone design (for example, VMS boards affected older drivers differently than other vehicles. In addition, VMS boards affected older drivers differently than static signage or arrow boards and transition tapers). This confirms: 1.) that older drivers behave differently than other drivers, especially when traversing a work zone, and 2.) different design elements can affect different populations differently, and different design elements have different effects.

Older drivers are not the only drivers who have an increased crash and death rate; according to a study in 1972, U.S. teens are said to experience five times as many crash deaths as drivers between the ages of 35 and 64.  Mourant and Rockwell (1972) [40] devised an experiment to examine younger driver behavior and compare scanning patters to drivers with more experience.  Three levels of novice drivers were established and tested against a control group of experienced drivers: Level 1 was drivers with zero driving experience, Level 2 was drivers who were halfway compete with drivers' education, and Level 3 contained drivers who recently acquired their license.   All drivers were placed in vehicles and scanning patterns at stop signs and intersections was analyzed, along with scanning patterns on the highway while performing lane changes. Results indicated that the novice groups focused mainly on lane markings near their vehicles, had a narrow horizontal scanning range, sampled their mirrors much less (approximately half) than experienced drivers, and sampled their speedometer much more frequently (approximately twice) than experienced drivers.  Experienced drivers were said to scan further down the road and had a much wider horizontal scanning range. Results for the scanning patterns of novice drivers were similar to those of drivers under the influence of alcohol.

It is evident from these studies that drivers of different ages clearly have different driver behaviors.  To most accurately describe each population, it is conceivable that three separate driving models should be constructed: one for younger drivers (Ages 18-25), one for middle aged drivers (Ages 25-55) and one for older drivers (Ages 55+).  All three populations have different scanning patterns, approach intersections differently,

have different abilities (cognitive and physical), and behave significantly different from each other when driving.

When considering microscopic modeling, older drivers and younger drivers should not be modeled using the same algorithms as the rest of the driving population. For older drivers, this is not only because of diminished abilities to perceive their driving environment, but their abilities to process what they see and then accurately execute a proper reaction. For younger drivers, this is due to their narrow scanning habits, constant monitoring of variables such as speed, and lack of scanning mirrors to detect obstacles and vehicles surrounding them. Because of their different driving abilities and styles, an alternative model should be constructed to better describe older drivers and younger drivers.

This conclusion can be extrapolated and applied onto other areas, such as unfamiliar drivers (who may not know about blind spots/areas of major concern on a road way and will not focus their attention in the same place as drivers who are familiar with the roadway and the problems/tendencies associated with the roadway), and even drivers who are in free-flow conditions vs. congested conditions.

### 2.2.3 *Drugs, alcohol, and driver behavior*

It probably comes as little surprise that drugs and alcohol, both of which inhibit and alter our thought processes, can alter our driver behaviors. Laws (such as DUI and OUI laws) have been passed due to negative associations between driver behavior and

drivers who are currently under the influence of drugs or alcohol. The following research paper was specifically about the effects that drugs and alcohol have on driver behavior and how the driving behavior of a driver currently under the influence differs greatly from other drivers.

Kelly et al (2004) [41] conducted a massive literature review about drugged driving to assess drugged driving, the impacts of drugged driving, and determine whether or not it should be a major concern and/or plays a significant and dangerous role on our roadways.

Drugged driving has approximately a 4% prevalence in a 12-month span. Studies, however, have reported that 25% of accidents involved drivers who tested positive for drugs. Males make up the majority of drugged driving cases. The most common drugs involved in drugged driving are (in descending order): cannabis, benzodiazepines (such as Valium), cocaine, amphetamines and opioids. In conclusion, drugged driving should be a major concern because of the dangerous role it plays.

Different drugs effected drivers differently and effect different driver populations differently; therefore, not all drugged drivers using different drugs (or combination of drugs) exhibit similar driver behavior. For instance, opioids (such as methadone) have been found to effect reaction time, information processing, and visual acuity in drivers who are non-opioid users, however, there was little to no evidence of performance decrements in methadone maintenance (MM) patients. Ecstasy (MDMA), a stimulant,

has exhibited impairment in attention, perception, and memory, whereas studies involving driving under the influence of cocaine (another stimulant) have found evidence of both decreased and increased performance, as well as no effect. There is no "one size fits all" model to describe how all drugged drivers behave; therefore assessments must be made on an individual level.

The overall effect of drugged driving, however, is negative.

Drugged driving contributes to 25% of all accidents despite only 4% of all drivers partaking in drugged driving over the course of a year, meaning it impacts our roadways greatly. Attention to this problem must be made. However, there are no design elements that can be incorporated into roadway design to help curb some of these accidents associated with drugged driving; because of the varying effects of different drugs on different populations (in addition to the low number of drivers who are driving drugged), there are no "cure-all" design elements that can be constructed. In addition, any model that tries to capture the effects of drugs on drivers (and in return, examine that driver's impact on a roadway in terms of safety and functionality), would have to vary from driver to driver.

Current models try to fit driving populations to one model, governed by one all-inclusive statistical distribution. In order to capture the effects of drugs on a driver, models must be created and calibrated on an individual basis, capturing the effects of each drug on each sub-population of driver. If there were a microscopic driving model

whose infrastructure included separate models for separate driving populations and that could assess the effects of adding each driver-altering substance individually (rather than lumping them together), then this model could capably model the effects of drugged driving.

Although portions of this research are years away from impacting policy-makers, it finds use in our purpose here. Drivers under the influence of drugs and/or alcohol have distinctly different driving patterns from other drivers. It wouldn't be accurate to try and describe the driving behavior of a drugged or drunk driver using algorithms devised to describe the rest of the ambient traffic; additionally, it would be incorrect to include these drugged and drunk drivers in any algorithm devised to describe how regular traffic flows. Therefore, a separate model and set of algorithms should be developed for drivers who are under the influence of drugs or alcohol.

### 2.2.4    *Different drivers react differently to signage*

The status quo for microscopic models does have some provisions made for how signage affects drivers. However, these are usually individual studies that demonstrate how the introduction of one roadway element effects the population as a whole, and a microscopic model is created that describes only traffic flow through the corridor studied and with only the specific signage studied. If an engineer or a planner wanted to see how multiple signage elements affected a driving population, or see how a sign such as "Left Lane Closed Ahead" affected younger commuters differently than older drivers who are new to the roadway (younger familiar drivers may not feel "pressured" by the signage

and might continue at their usual speed and merge later, or may be aware of the closing lane before the signage and might merge out of the closing lane far in advance of the signage, while older drivers who are unfamiliar with the roadway might slow down and merge out of the closing lane at the earliest possible moment), they cannot answer their questions using a microscopic model because no microscopic models exist that can perform this analysis.  No available model can aggregate signage effects and predict vehicle movements, and no available model demonstrates the discrete differences in driver patterns and driver behaviors among different populations of drivers in reaction to roadway signage or elements.

Multiple research projects have been performed investigating how roadway layouts affect drivers and driving populations.  These projects provide proof that roadway elements effect driver behavior in specific manner, and grant credence to the notion that a more advanced microscopic model could capture these discrete specific changes in driver behavior caused by various roadway layouts and signage elements.

Research was conducted in 2005 by Bisantz et al [42] to answer the question: how should decision-making information be conveyed (such as "Left Lane Closed ahead") to a motorist such that the motorist can make an informed decision prior to the location at which the decision must be made?

Research goals for Bisantz et al (2005)  include: 1.) extension of a 2002 study by comparing graded icon sets with other graphical representations (colored icons),

linguistics, and numerical representation; 2.) investigate how useful each representation is when the response is no longer yes/no but is now graduated; 3.) to see if vague linguistic representations carry the same and/or similar effects to vague graphical representations.

First experiment showed that decisions were made in a quicker time interval when the information conveyed was less specific and contained less detail.  Sometimes, quick symbols provided a faster recognition time and response time, although no statistically significant difference existed in terms of performance between recognition using symbols, graphs, or text.

There are negative impacts when using displays that contain close spatial proximity between relevant and irrelevant items.  The user has a difficult time filtering out the irrelevant information and jumbles the two together.  If there is important information that a user must gain from a display, it is best if only the important information is included on the display and/or that irrelevant information is minimized.

If two different messages are displayed in close proximity, the result can be an overlay in messages.  The user may combine the message's meanings and get both messages entirely wrong.  The number of tasks given to each user should be limited, and different tasks should be presented with sufficient time and space between messages, otherwise task/instruction sets may be overlaid and blended together.

These lessons can be applied to roadways and roadway signage placement within the US.

### 2.2.4.1  Too much information

On our roadways, there is a concept called *oversignage.*  Areas of incredibly high sign placement frequencies and/or traffic control design element densities usually over stimulate the driver, and the driver fails to complete some and/or all tasks conveyed using the signage.  If there are too many roadway elements placed in one area, it can overwhelm the driver.

### 2.2.4.2  Pictorial representations are sometimes better

Some roadway studies found that drivers react quicker to pictorial representations than dictated instructions on roadway signage.  For instance, when conveying the message "Left Lane Closed, Merge Right" it might be quicker for the driver to react to a W4-2 sign:



Depending on the complexity of the message, some information can be lost and/or can be difficult to convey using pictures, and text must be used instead.

### 2.2.4.3  One message per sign

Each sign conveys only one thought so that messages are not blended together.  For instance, you'd never see a roadway sign that said "Left Lane Closed Ahead.  Also,

No Parking Here to Corner." To avoid confusion, these messages are always conveyed using two separate signs.

*2.2.4.4 Signs are designed to convey a clear, complete, and simple message*

Included in the five tasks that a traffic control element must perform to be effective is "convey a clear and simple message," meaning that excess words/irrelevant information must be eliminated.

Most relevant to the purposes outlined in this literature review, Bisantz et al [42] describes how different display elements convey different messages differently. This is not a concept that is captured in modern microscopic models.

Another paper by Theeuwes and Godthep (1995) [43] demonstrates the power roadway elements can have in making motorist operation through a corridor a "self-explaining" experience. The paper attempts to answer the questions: How potential errors occurring in traffic can be reduced by revisiting the layout of the road environment? How design principles can reduce the probability of an error when executing the traffic task? For the purpose of this literature review, Theeuwes and Godthep (1995) [43] answered the question: what are the effects of allocating signage to expected or unexpected locations on the roadway, and would it aid in making the expected driving behaviors of roadways more "self-explanatory" to the driver.

Roadway users build up an abstract representation in their head of what certain roadways look like and specific characteristics on those roadways. These roadway prototypes are built only in the heads of drivers, and they reflect how the driver behaves on certain roadways. Mazet and Dubois (1988) stated that different categories of roadway that require the same type of behavior will subjectively be represented by the same prototype by the driver. Riesmersma (1988) discovered in a study that in built-up areas, roadway users have a loose subjective categorization for roadway criteria, and define the safe speed based on the effort it would take to keep the vehicle on the road (instead of the probability of encountering another roadway user). Riesmersma (1988) also found that outside the built-up areas, some roadway elements (such as a hard shoulder) were absent from subjective categorization, and that high speed roads were more often than not automatically categorized as a motorway (or freeway) despite missing vital elements that a motorway (or freeway) might have.

In addition, objects (given a specific roadway context) that are likely to be found in a specific scene often occupy specific positions in that scene. More importantly, contextual information plays a major role in how a driver scans everyday traffic scenes (for example, a "No Right on Red" sign at a signalized intersection can usually be found across the street. A driver approaching a red signal might scan this location for this sign. In a location with heavy pedestrian traffic, they might also scan the crosswalks). An object placed in an unusual location would violate the driver's expectancy and the driver would run the risk of not seeing the sign due to its placement/location.

Riesmersma (1988) conducted an experiment to prove that the location of sign placement along a roadside plays a significant role in the percentage of drivers who will see the sign and react to it. Drivers were asked to travel through one of two nearly identical intersections in an urban environment: one intersection had a traffic sign positioned in an expected location, the other had a traffic sign positioned in an unexpected location. At the intersection with a traffic sign placed in an expected location, drivers spent 1112ms scanning the scene and only 6% of drivers failed to obey the traffic sign. At the intersection with a traffic sign placed in an unexpected location, drivers spent 1745ms scanning the scene, and 33% of drivers failed to adhere to the traffic sign.

To be more thorough, additional tests should have been run. A degree of "unexpected location" should be established (for example , if a sign is usually mounted across a signalized intersection on a pole, what are the effects of mounting it next to the signal on the wire? Also, at a signalized intersection, if a high priority sign, such as the signal itself, were placed in a very unexpected or unusual location, would it have the same failure rate as a "No Right Turn on Red" sign?).

Riesmersma (1988) concluded that drivers build categorizations of roadways and classify roadway categorizations based on the way they drive on them. These classifications determine not only driving behavior, but they also determine the roadway elements that driver's expect to find on these roadways (and where these elements are expected to be located). In certain settings, drivers will expect to see roadway elements

in specific places, and drivers will scan those locations when searching for/trying to discriminate the presence of these roadway elements.

In a roadway where expected driver behavior is self-explanatory to the driver, roadway elements (such as signage) must be mounted consistently in the same locations. In addition, by altering the surroundings, driver behaviors can be altered and drivers will "automatically" classify the roadway differently and drive appropriately.

For example, in order to ensure all drivers will see and adhere to speed limit signs, they must be mounted in the same location (on the side of the road) and in the same manner. If not, drivers run the risk of missing that vital piece of information because they might be scanning in another location.

In another example, driver behavior can be changed by altering the environment/changing the surroundings. By narrowing the roadway and placing urban features (such as sidewalks, trees, crosswalks, etc.) drivers might reclassify a roadway from being a motorway/freeway-like roadway to an urban roadway and will reduce their speed automatically.

For the purposes of this literature review, Theeuwes and Godthep (1995) [43] sheds light on the concept that, not only signage choice, but signage placement plays a crucial role in driver behavior. In current microsimulation softwares (such as VISSIM and CORSIM), those that have the ability to input signage and/or traffic signals do not

account for how drivers react differently to signage that is placed in different or

"unexpected" locations, nor do they have the ability to simulate how variations in signage

placement might affect different sub-populations (for example, a "No Right On Red" sign

should be placed across an intersection so that the driver can observe the sign while

stopped at a stop bar. A more experienced driver might naturally look in this location to

see if it's permissible to take a right on red, and might miss the signage if it's placed prior

to the intersection. However, novice drivers who have not developed this sort of driver

expectancy might be searching for the signage as they travel towards the intersection. In

addition, drivers familiar with the roadway might not need the signage because they

might have preexisting knowledge of a prohibited right turn movement during a red ball

indication). It is not outrageous to think that different populations might react differently

to signage placement.

These studies demonstrate how different signage and signage placement affect

driver behaviors. The results of other studies can be extrapolated to hypothesize that

signage might affect different driver populations differently as well, and one signage

element might have a varied influence between driver sub-populations (for example,

unfamiliar drivers who rely on the signage for navigation vs. very familiar drivers who

know the roadway well, older drivers who might drive a bit more cautiously and might

expect to see signage in certain locations vs. younger drivers who might adhere more

loosely to signage and might look in unusual location to find signage elements). Whether

or not these hypotheses are true, it is evident that neither is accounted for in current microscopic models.

## 2.2.4.5   *Work zone specific signage*

Many studies have been conducted to assess driver behavior varies for different driving populations when presented with different work zone set-up strategies and elements.

A 2001 study performed by the Oregon Department of Transportation assessed the impact of different arrow panel displays in temporary work zones. Specifically, the study evaluated the effectiveness of a "sequentially flashing diamond" arrow panel display as advance caution warning in temporary work zones by collecting speed data and comparing $85^{th}$ percentile speeds from the "sequentially flashing diamond" to baseline conditions (no display), a "flashing line" display, and a "flashing four corner" display. For all display modes, the $85^{th}$ percentile speeds were found to be lower than their corresponding hourly baseline speeds, with the "sequentially flashing diamond" display showing the greatest speed reductions from baseline. This study demonstrated that even when work zone set-ups are identical, a different display message on an arrow board can influence different driver behavior. [44]

Other studies have shown that, in addition to advanced warning signage, delineation can influence driver behaviors such as traveling speeds. In a driving simulator-based study, investigators at the University of Iowa found that average speed,

standard deviation of speed, and horizontal position within the driving lane varied for different the work zone delineation strategies (42" channelizers vs. barrels vs. jersey barriers). Additionally, this study found variations in average speed when the data was examined according to driver gender (male vs. female) and driver age (middle-aged vs. senior). The study found senior drivers to have a slower average speed than middle aged drivers regardless of work zone delineation. Horizontal distance from the work zone showed strong divides across driving populations, with middle aged females maintaining a lane position further from the work zone than male drivers (middle aged males, and senior males) and senior females driving the closest to the work zone. Within each subpopulation of driver (senior male, middle-aged male, senior female, and middle-aged female), delineation also influenced horizontal lane position; work zone set-ups that used barrels for delineation showed drivers to maintain the furthest horizontal distance from the work zone, while jersey barriers showed drivers to maintain the closest horizontal distance to the work zone, and channelizers to be between barrels and jersey barriers for every population of driver. This study not only demonstrated that different work zone delineation devices influence distinctly different driver behaviors, but also that driver behaviors differs across driver age and gender. [45]

Some studies have shown that different driver merge behaviors can impact work zone capacity. Queue jumping, lane-straddling (to prevent others from passing), tailgating, forced late mergers, and other aggressive behaviors, have a significant impact on maximum flow rates [46]. Even practices considered "safe", such as excessive headways or slower traveling speeds, can cause reduced flow in a taper zone [46]. These

and other driver behaviors can be influenced by work zone set-up elements and strategies. The influence of different work zone set-ups on driver behavior, and therefore on work zone operations, is a well-known phenomenon. In fact, the FHWA Office of Operations has an entire webpage that highlights studies performed that investigated impacts of variable work zones set-up strategies on driver behaviors and work zone operations [47].

### 2.2.5 *Variations in driver error*

Driver Error plays an undeniably large role in the number of accidents on US roadways. Various studies have been performed on the subject, and it's been estimated that driver errors contribute to anywhere between 75-90% of all crashes on U.S. roadways.

Salmon et. al. (2011) [48] was a project focused on studying driver error, real-time, in the field. Instrumented vehicles have recently allowed for in-depth data collection in the field (rather than use a driving simulator). The research objective of Salmon et. al. (2011) was to demonstrate a framework for a method of investigating driver errors in the field using an instrumented vehicle. 25 subjects drove along a predetermined route in an instrumented vehicle, and in-vehicle observers (aided with on-board devices) recorded instances of driver error and data associated with the error.

298 driver errors were made over the course of this study. The most common driver errors recorded were: speeding (95), failure to indicate (74), indicator activated too early (15), traveling too fast for a turn (14), braking late and hard (13), accelerating too

fast (12), and lane excursion (leaving the lane without the purpose of performing a maneuver, 12). These errors were then broken down by category. The largest categories were: violations (143), misjudgments (44), failure to act (28), action mistimed (23), and too much action (20).

Salmon et. al. (2011) broke the driver errors down by technical classification, however, (considering the motivation for Salmon et. al. (2011) was that driver errors contribute to 75-90% of all crashes) it was surprising that the researchers did not subsequently classify these errors in terms of severity and/or by propensity of each error to create a crash and/or by what percentages of total crashes each error classification contributes to the total crashes in the U.S. Salmon et. al. (2011) would have been much more useful if the author compared the total number of driver errors made to the role each one of these driver errors plays in our roadways. For instance, the three leading contributing factors to fatal car crashes are speeding, alcohol, and lack of seatbelt use. If the author addressed the fact that almost 1/3 of the total observed driver errors were also a leading cause of death on U.S. roadways (speeding), then the data could have been put to practical use. The entire data set (not just speeding) could have been processed by contribution to crashes, and the study would have had a greater impact.

Some argue that simulator data, although very close, is not the same as field data because simulators lack the "real danger" that field data has. The argument (whether it's right or wrong) is that drivers will never experience fear in a simulator to the same degree

that they do in the field, therefore field data will always be slightly different.  Whenever there is a choice, some believe that field data is the optimal choice.

Salmon et. al. (2011) presents a new approach to collecting driver-related data in the field.  By using an instrumented vehicle and an observer, field data can be collected specific to each driver.  The range of data that can be collected using an observer and an instrumented vehicle is similar to that obtained in a driving simulator, and in both scenarios driver-specific data (such as eye and head movements) can be collected (which is not the case when using other data collection methods, such as roadside cameras, ATR and ACR tubes, which can only collect data pertaining to each vehicle).

Unfortunately, studies have shown that driver behavior is almost always different when a driver has no passenger.  Seatbelt studies, speed studies, even driver distraction studies have yielded positive results confirming major alterations in driver behavior when a passenger is present.  Even if interactions were minimized between the observer and the driver (which in this study, they were not) and even if the passenger was not visible to the driver, the driver's mere knowledge of the presence of a passenger will alter the driver's driving behavior/style/choices/etc.  Most trips in the U.S. are made by commuters who travel with no passenger; therefore, it is important that passenger-less driver behavior is investigated for any study concerning overall driver behavior.

Despite laying the framework for a driver data collection system that operates in the field, previous studies can be referenced to conclude that this system will not always

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yield correct results. Despite the bias that some researchers have about simulators, there are no studies that definitively prove that driver-specific simulator data is flawed in any way.

From previous studies (conducted by Romoser) in this literature review, it has been established that older drivers are more prone to make certain driver errors at intersections than others, but is this pattern applicable to other driving populations? Do certain driver populations make specific driver errors more frequently than others? It can be concluded from Salmon et al (2011) that driver errors play a significant role and must be accounted for when describing traffic (such as in a microscopic model), and from the results of Salmon et al (2011) in conjunction with previous results from Romoser, it is safe to conclude that driving simulators provide an adequate platform for examining driver errors in specific driver populations.

For a microscopic model to truly be accurate, it should account for the typical driver errors made by different driving populations, and should reflect these driving errors for each sub-population of driver in its driving model.

### 2.2.6   *Driver familiarity and driver behavior*

As previously mentioned in this literature review, driver familiarity can alter driver behaviors. There are measurable differences in driver behaviors (such as speed) between drivers who are familiar with a roadway vs. those who are unfamiliar with a

roadway. An accurate microscopic model should be capable of capturing and modeling these differences.

Heaslip, Louisell, and Collura (2008) [49] investigated the effects of different driver populations on work zone capacity, specifically on driver familiarity, driver adaptability, driver aggressiveness, and driver accommodation. The paper suggests that driver familiarity has significant effects driver behavior through a work zone, and subsequently affects traffic flow conditions and the capacity of a work zone. In addition, the paper also concluded that driver behaviors, such as driver accommodations of others or driver aggressiveness in maneuvers, varies depending on the driver population. All these factors have a profound impact on the capacity of a work zone. From Heaslip, Louisell, and Collura (2008), it can be concluded that driver familiarity profoundly impacts driver behaviors through a work zone (to the extent that it could have advanced effects on the capacity of a work zone) Additionally, driver behavioral attributes such as aggressiveness and accommodation vary from driver population to driver population, and they also have a profound impact on a work zone's capacity. An accurate microscopic work zone model should capture these differences in driver behavior between populations and accurately assign these attributes to the right sub-population of driver. Additionally, it should model familiar and unfamiliar drivers separately due to the major differences in driver behavior associated with each population.

## 2.3    Car Following Behaviors and the "Spiral" Trend

Car-Following (CF) behavior has been studied for over 50 years [50]. Empirical studies of car following behavior have shown that as a subject vehicle (vehicle $i$) approaches a lead vehicle (vehicle $pc$) and enters car following behavior, a "spiral" trend can be observed when plotting Car-Following Distance (distance between the subject vehicle and the lead vehicle) vs. Relative Speed (velocity of the subject vehicle (vehicle $i$) minus velocity of the lead vehicle) for time T = t. Figure 3 illustrates the "spiral" trends observed in empirical studies of car following behaviors when plotting Car Following Distance ($\Delta$x) vs. Relative Speed ($\Delta$v, or $V_i$-$V_{pc}$).
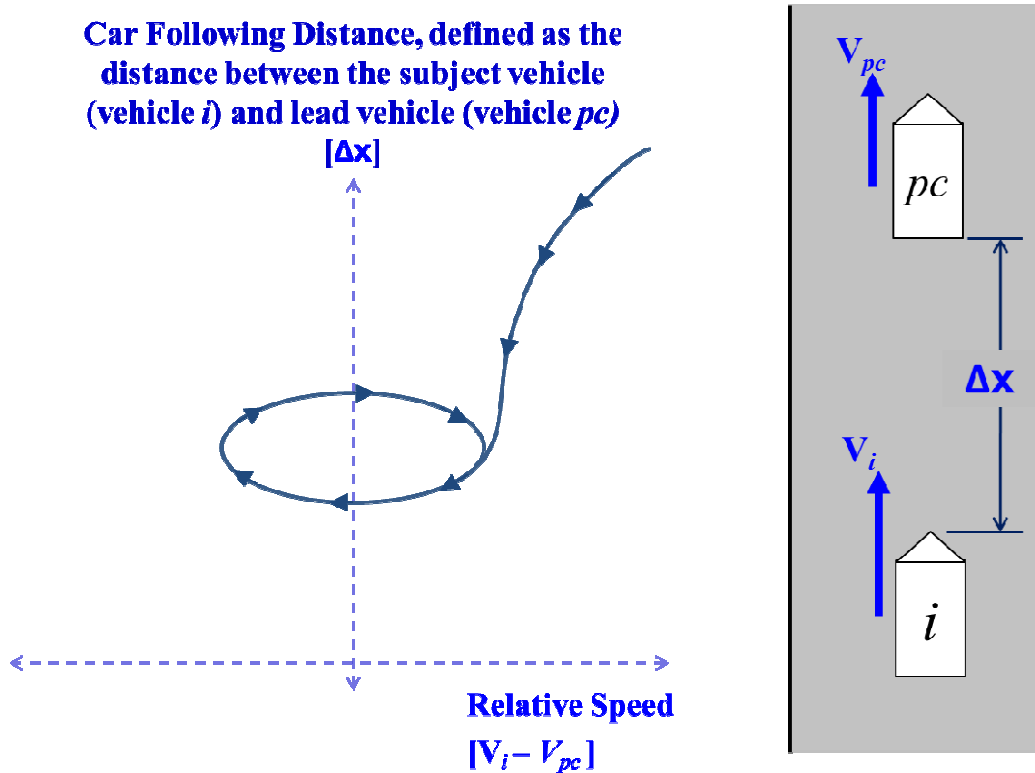


**Figure 3: "Spiral" trends observed in car following behaviors**

### 2.3.1 Newell, 1961

In 1961, Newell proposed a non-linear car following model. This model

calculated a vehicles speed at a given time, t, based on a driver's perception-reaction

time, desired speed, and parameters that adjust the variable spacing between the subject

vehicle, vehicle *i*, and the lead vehicle, vehicle *j*. The spacing between vehicle *i* and the

lead vehicle was empirically derived. Although Newell's model describes the fact that

variable spacing does occur, it does not offer an explanation for why the driver chooses

the variable spacing at variable times, claiming that an additional variable that:

> *"No motivation for this choice is proposed other than the*
>
> *claim that it has approximately the correct shape and is*
>
> *reasonably simple."*

Newell's model, however, is the first to acknowledge that when in car following, the

spacing between the lead vehicle and the subject vehicle is not consistent, and is in fact

variable. By incorporating variable spacing into his algorithms for velocity, Newell

acknowledged that the velocity of the following vehicle was also variable. [51]

### 2.3.2 General Motors (GM) Models, 1950's through 1960's

Some models related spacing to attractive and repellent forces, similar to those in

Coulomb's law for Electro statistics. Four (4) General Motors car-following models

were developed in the late 1950's/early 1960's, that calculated vehicle spacing as a

function of repellent forces that exist between vehicles, similar to electrons being repelled

by a negative charge. The variable spacing in these models results from the vehicle's

speed; as vehicles travel faster, the spacing becomes greater. Unfortunately, by tying

vehicle spacing directly to vehicle velocity, some of the GM models did not work at slow speeds or when traffic stops; they were constructed such that if the lead vehicle stopped, the following vehicle stopped *inside* the lead vehicle.  Additionally, the GM models ignore any unsatisfied desire for mobility.  Despite these flaws, the GM models did attempt to explain variable spacing between the lead vehicle and the following vehicle using repellent "forces". [52] [53]

### 2.3.3  Gipps, 1981

The Gipps car-following model employs a safety rule to determine vehicle spacing.  According to the safety rule, driver *i* (of the following vehicle) leaves enough space between themselves and the lead vehicle such that the driver has enough room to respond and decelerate at a given rate in order to safely stop behind the lead vehicle, should the lead vehicle apply an emergency brake.  Gipps model provides an optimistic view of the driving population; if everyone left enough room to safely stop, there would be no rear-end crashes.  Gipps model is not an accurate depiction of the driving population, as many drivers follow much closer than what could be considered safe car following distances.  Gipps model does, however, acknowledge variable spacing, although it does not accurately depict the driving population.  [54]

Although they acknowledge that vehicle spacing can change, all of the models reviewed thus far do *not* produce the "spiral" trend found in empirically collected car-following data.  Most of these models tie spacing to speed, so the minor fluctuations in traveling speed would not make major differences in the spacing of these models.

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Although some may reproduce small "spirals", they will not reproduce the spirals observed in empirically collected data. They do not accurately reflect the driving population's behavior, and in practice have proven inaccurate. For all of these models, variable spacing was the focus of their models, not the reproduction of this "spiral" trend.

### 2.3.4 Wiedemann, 1974

While studying car-following behavior of drivers, a "spiral" trend was observed by German psychologist Rainer Wiedemann when plotting relative distance vs. relative speed of the subject vehicle and leading vehicle; this "spiral" was the focal point of the 1974 car following model he developed for his dissertation [55]. This model, Wiedemann '74, is shown in Figure 4.
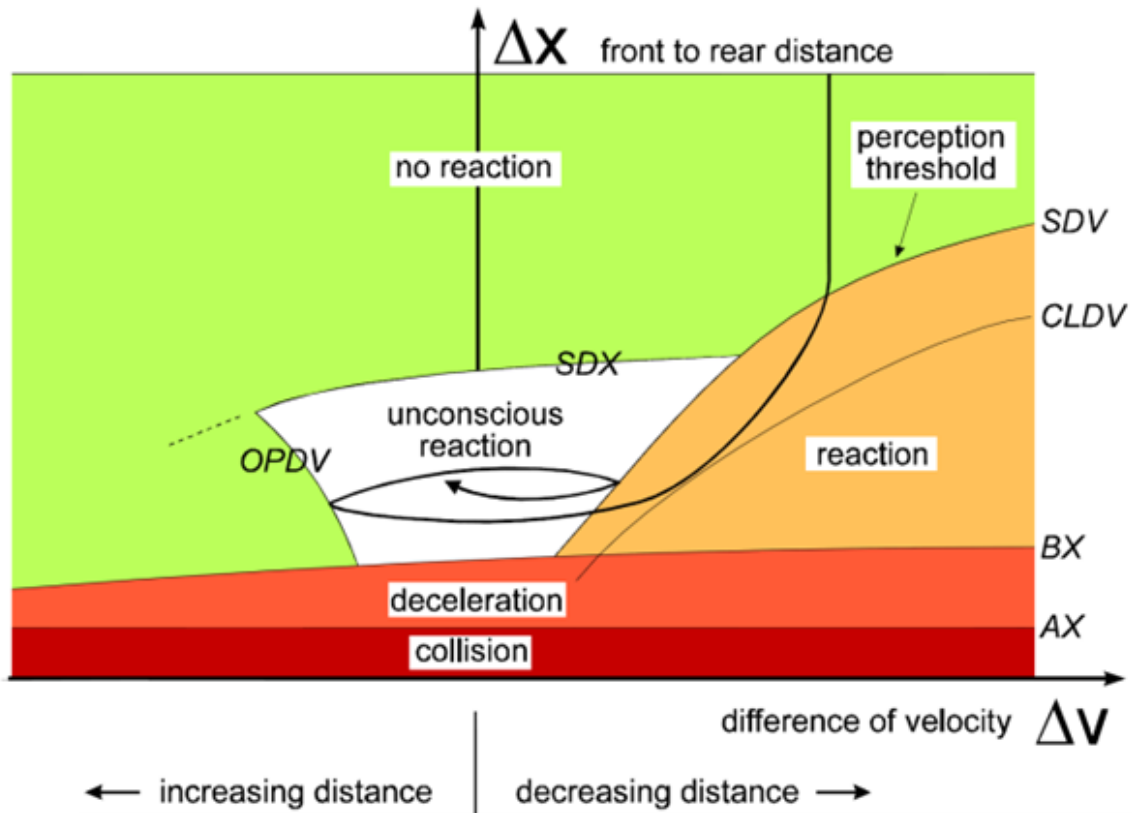
**Figure 4: Wiedemann's Car-Following Model, 1974 [55]**

Figure 4 shows Wiedemann's 1974 car following model on a plot of relative distance vs. relative speed. Wiedemann's model replicates the "spiral" trend observed in car following empirical studies through the use of multiple coefficients, including: BX, AX, CLDV, SDV, SDX, and OPDV. [55]

According to Wiedemann's 1974 model, if driver i is closer than threshold "BX", no matter the relative speed, driver $i$ is assumed to decelerate. SDV and CLDV define the $\Delta x / \Delta v$ threshold where driver $i$ decelerates, in scenarios where the driver $i$ is approaching the lead vehicle and slowly reduces speed to match that of the lead vehicle. The "perception threshold", SDV, shows the threshold for which vehicles begin to react

to the lead vehicle (calling this the "perception threshold" inaccurately represents the activity here; this threshold depicts reaction).  [55]

The trademark feature of Wiedemann's car-following model is what his model calls the 'unconscious reaction', which occurs in the white area delineated by thresholds SDX, OPDV, SDV, and BX.  Wiedemann observed that headway and relative speed fluctuates between two vehicles, and is never completely consistent.  This fluctuation is not purposeful; rather, it is the result of a driver subconsciously adjusting his/her car following behavior to match the speed of the lead vehicle while maintaining a safe headway.  This unconscious reaction shows the location where a driver's headway and relative speed are adjusted slightly and unconsciously. [55]

There are a few terms used improperly in Wiedemann's description of his model. First, "unconscious" should be "subconscious", since unconscious individuals cannot drive, and since what Wiedemann is describing is a subconscious reaction relating to relative speed and relative distance on the part of the driver.  Additionally, the "perception threshold" should read "reaction threshold", as perception and reaction are two distinctively different activities and this threshold depicts the relative speed and headway where a reaction is observed.

Wiedemann's model has proven to be an improvement in the status-quo for microscopic car-following models.  By capturing a dynamic headway, facilitated through the "spiral" trend witnessed in car following, this model recreates a behavior that others

do not.  Professor Wiedemann's model is described as a scientific behavioral model

Wiedemann's model is used in traffic simulation software packages such as VISSIM

[56].


Because of the many coefficients in Wiedemann's model that require calibration,

using this model in simulation can prove difficult.  In a VISSIM simulation, Wiedemann

74 requires calibration of 10 variables [CCO (Standstill distance), CC1 (Headway Time),

CC2 (Following Variation), CC3 (Threshold for entering following), CC4 (Negative

following threshold), CC5 (Positive following threshold), CC6 (Speed dependency of

Oscillation), CC7 (Oscillation acceleration), CC8 (Standstill acceleration), and CC9

(Acceleration at 80 km/h)] for every simulation [57].  This is because driving populations

vary from location to location, as do driving behaviors.  VISSIM is designed for use by

planners and engineers to compare various design alternatives; however, the data

collection required for calibrating these coefficients is inconsistent with the data that a

planner or engineer collects when redesigning a roadway.  A typical engineering firm

does not have instruments to collect calibration data for, say, "Negative following

thresholds"; instead, firms are limited to collecting vehicle volumes, roadway geometry,

traveling speeds, the percentage of drivers who are commuters (by using video cameras

and plate recognition software), and in some cases (such as when collecting belt usage

rates for NHTSA studies) engineers can collect data such as driver age, gender, and

ethnicity, vehicle classification, the presence of a front seat passenger, and that

passenger's age, gender, and ethnicity [58] [59].  A more robust dataset than that

available is required to calibrate Wiedemann's model [60].  Calibrating VISSIM,

especially for mixed traffic, is a notoriously difficult task that often requires unique and innovative data collection strategies [57] [61] [62].  Methodologies for calibrating the 10 (or even a subset of the 10) parameters of Wiedemann '74 for use in a VISSIM simulation are non-traditional and often not practical for a typical engineering firm; creating a methodology, no matter how unpractical it is, often merits publication and/or presentation at some of the more prestigious venues in transportation research [57] [61] [62].  Calibrating Wiedemann's model is not a streamlined, simple, or easy task for users.

Studies have revealed another flaw in the Wiedemann car following model caused by the model's inability to vary subconscious reaction thresholds according to traveling speed.  The Wiedemann car-following defines different regimes using thresholds; these thresholds determine the $\Delta X$ vs $\Delta V$ relationship that the subject vehicle reacts to the lead vehicle. Some thresholds are defined using a speed parameter, allowing the unconscious reaction thresholds to vary according to the traveling speed of the subject vehicle. However, not all of the thresholds in Wiedemann's model vary with the traveling speed of the subject vehicle; some are calculated solely using the difference in speed between the subject vehicle and the lead vehicle. Higgs et al (2011) analyzed the Wiedemann car following model using car following periods that occur at different speeds, and compared the model to naturalistic data.  Results from this study showed that the thresholds are not constant, but vary over different speeds. [63]

Additionally, Wiedemann's model does not incorporate decision-making algorithms, and forces the spiral trend through the use of coefficients (rather than walking

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each driver through the established steps of roadway observation→ driver decision-making process → driver reaction).  The "spiral" trend is forced using coefficients.  By forcing this "spiral" trend to occur (rather than creating a decision-making process where this trend naturally occurs), Wiedemann's model does not represent real-world driving behavior when modeling the following scenarios: approaching, closely approaching, acceleration following, and deceleration following [60].   Furthermore, Wiedemann's model is incapable of capturing a passing and hook-following (a scenario that occurs after a faster lead vehicle merges in front of the subject vehicle. The subject vehicle driver then decides to "hook" on to the lead vehicle, accelerating to match the lead vehicle's speed), which is essential in special scenarios where merging is expected, such as emergencies and work zones. [60]

In an effort to make models that more accurately reflect driver behavior, Federal Highway Administration's (FHWA) Exploratory Advanced Research Program (EAR) worked with FHWA Turner Fairbank Highway Research Center (TFHRC), Virginia Tech, University of Arizona, and others in an agent-based modeling initiative.  As part of this initiative, the acceleration equations in Wiedemann's model were replaced with the Gazis-Herman-Rothery model (GHR).  The coefficients of the new Wiedemann w/ GHR model were given a different set of calibration parameters to reflect the following scenarios: approaching, closely approaching, acceleration following, and deceleration following.  Calibrated to 4 different drivers and validated against empirically collected naturalistic data, this new model resulted in a 5 to 43 percent error reduction when compared to the unaltered Wiedemann model.  A comparison of naturalistic driver data

and predictions from Wiedemann's car-following model and Wiedemann with w/ GHR model (developed by Virginia Tech during the FHWA EAR agent-based modeling initiative) can be seen in Figure 5. From this figure, it can be seen that Wiedemann's model does not accurately reflect trends observed in the naturalistic driver data. Unfortunately, this figure also shows that, despite a 5 to 43 percent reduction in error, the enhanced Wiedemann w/ GHR model also does not match the naturalistic driver data. [60]
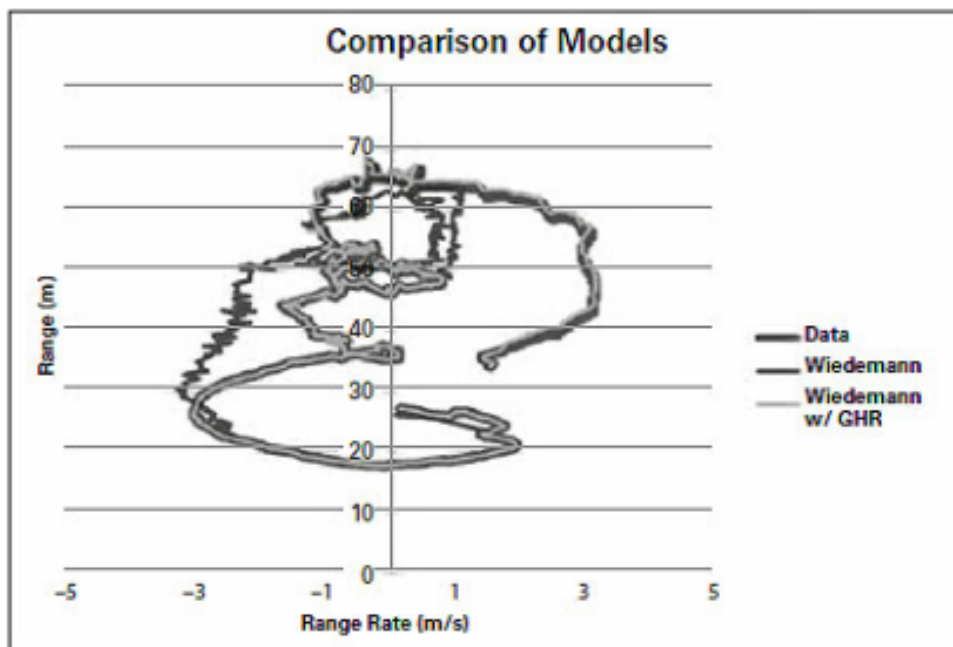


**Figure 5: Naturalistic driver data -vs.- Wiedemann -vs.- Wiedemann w/ GHR model**

Note that in Figure 5, the Wiedemann w/ GHR model seems to match the naturalistic driving data exactly when relative speed is positive. This is because the same dataset was used to calibrate *and* validate the Wiedemann w/ GHR (validation of the model being this plot in Figure 5). It is incorrect to use the same dataset for model

calibration and validation.  If one chooses to use the same dataset, they could observe

identical trends, as seen here.  [60]

To summarize, Wiedemann's car following model is capable of replicating the

"spiral" trend that is empirically observed in car following, but because of its model

architecture and multiple variables and coefficients, the model can be unwieldy and

inaccurate, and therefore is not always suitable for use by transportation practitioners

such as planners and engineers. By forcing the "spiral" trend in car following behavior

using rigid algorithms with multiple coefficients and variables, Wiedemann's model does

not accurately reflect how roadway stimuli impact the driver.  Wiedemann's model is

designed to force a the "spiral" trend, rather than witnessing this "spiral" trend naturally

by accurately modeling a driver decision-making process. Wiedemann's model is rigidly

fixed, and is only designed to reflect car following in one scenario.  Even when it is

enhanced by additional models and calibrated and validated using the same dataset,

Wiedemann's is incapable of accurately modeling the car following behaviors of basic

scenarios, such as acceleration and deceleration.

### 2.3.5   *Vector-based model for car-following: Wang and Wu (2003)*

Although many car following models have been created, only one attempt at

creating a vector-based car following model could be found.  Wang and Wu (2003)

created a vector-based car following model to show the different acceleration speeds and

following distances seen in mixed-mode traffic.  They weighed vectors to demonstrate

the impacts of a rickshaw vs. bicycle vs. pedestrian vs. passenger car (at the time of this

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research, certain portions of China were experiencing multiple vehicle types using the same roadway at once).  The model was not validated formally, but a logical 'step through' of the model was performed to show that the model would work in a scenario where two modes were traveling in the same direction.  However, what this 2003 publication did not reveal was when velocity vectors were not parallel, this model predicted the two modes would steer into each other and accelerate.  This occurred when two vehicles were traveling head-on or with vectors slightly skewed (such as when there is a bend in the road). [64]

### 2.3.6    Turner Fairbank Highway Research Center (TFHRC) Living Laboratory

It is established that driver behavior changes when a driver enters a work zone. When considering work zone design alternatives, engineers and planners are encouraged to predict the impacts of individual elements for each alternative using calibrated microscopic simulation software packages [8].  However, "work zone" is not a direct input for most microscopic simulation packages; to simulate the impacts of a work zone, engineers need to manually adjust calibration factors so that they reflect the driving behavior of the existing population through a work zone.

Despite trends reported from numerous investigations on how work zone driver behavior varies across different driver populations and according to set-up strategies and roadway elements (ex. older driver vs. younger driver reaction to work zone delineation alternatives x, y, and z), there is a general lack of knowledge regarding how an individual driver's behavior changes when entering/traversing a work zone.  This lack of knowledge

forces engineers and planners to "guess" when adjusting driver behavior calibration factors to simulate a work zone in microscopic models. [65]

With the goal of collecting data to describe changes in driver behavior that occur in work zones, a team of researchers at FHWA Turner Fairbank Highway Research Center (TFHRC) instrumented a vehicle and freeway work zone to collect driver behavior data needed for calibrating psycho-physical car following models. A sport utility vehicle was equipped with GPS, radar, sensors, and software to capture information on the gaps between vehicles and the speed oscillations of drivers. The location, speed, and acceleration of roadway objects (including other vehicles) were captured and reported. Video cameras were mounted to the front and rear of each vehicle to supplement the dataset. Software designed for Automated Cruise Control (ACC) was used to marry the video and GPS/radar/sensor data, assigning unique identifying numbers to each object encountered on the roadway. [65]

64 volunteers drove the instrumented vehicle along I-95 between Springfield and Lorton, VA, through stretches of freeway both with and without work zones. Drivers had no knowledge of the purpose of the study. Each driver spent an average of 2-3 hours each driving on the freeway. [65]

From this study, car following scenarios were successfully identified, and naturalistic car following data describing relative distance and relative velocity were successfully obtained. Figure 6 below plots the car following data (Relative Speed

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[m/s] vs. Distance to Vehicle Ahead [m]) for Driver 29, collected using the TFHRC

Living Laboratory. This data is unfiltered and includes all car following data (data for all

lead vehicles and all scenarios encountered by Driver 29).
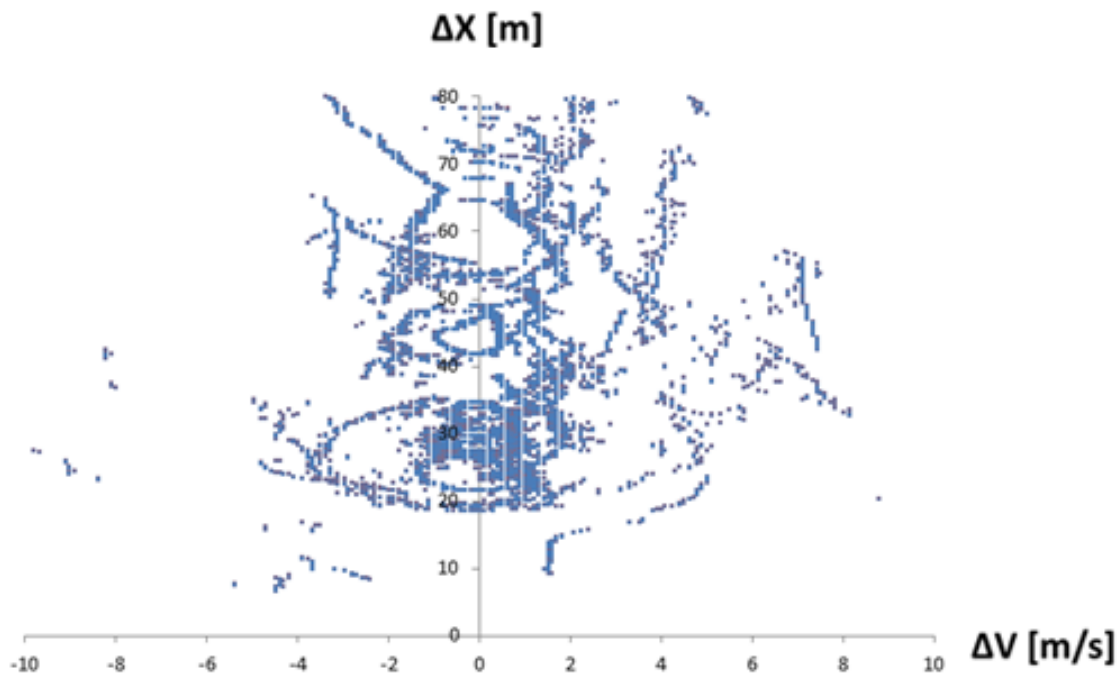


**Figure 6: Unfiltered car following data, Driver 29**

While most trends in Figure 6 (like the "spiral") are consistent with what is

expected in car-following, some of the observable trends conflict with what is expected;

this is because Figure 6 includes data for all vehicles that were lead vehicle in front of

Driver 29 during the experiment. For example, it appears some trends exist where a

driver is accelerating toward the lead vehicle despite already traveling faster than the lead

vehicle and in close proximity; this is a scenario where the lead vehicle was merging off

the freeway and departing the lane, so Driver 29 accelerated as the lead vehicle slowly

merged over. Even if by only 1 foot, the lead vehicle is still, technically, in front of

driver 29, so the data is reported as "car following" even though Driver 29 expects the lead vehicle to depart the lane space.  Another example, it appears that multiple relative distance/relative velocity relationships exist for one vehicle at the same time; that is because this dataset includes all lead vehicles, and two trajectories overlapped and then diverged.  Additionally, Figure 6 was constructed using car following data collected within and outside of the work zone.  Even though Figure 6 shows expected trends in car following, it does not provide a clear view of normal car following behavior in a work zone because the data has not been filtered to remove unusual events (such as the lead vehicle merging off the freeway), and includes data collected for all lead vehicles, work zone and non-work zone, from the 2-3 hour data collection period.

To obtain a clear view of car following behavior through a work zone, it is necessary to remove the "noise" of events besides car following and to limit the dataset to show car following between the test driver and only one lead vehicle.  Data from Driver 15 was filtered to report the normal work zone car following relationship between Driver 15 and one lead vehicle.  This data was plotted in Figure 7.
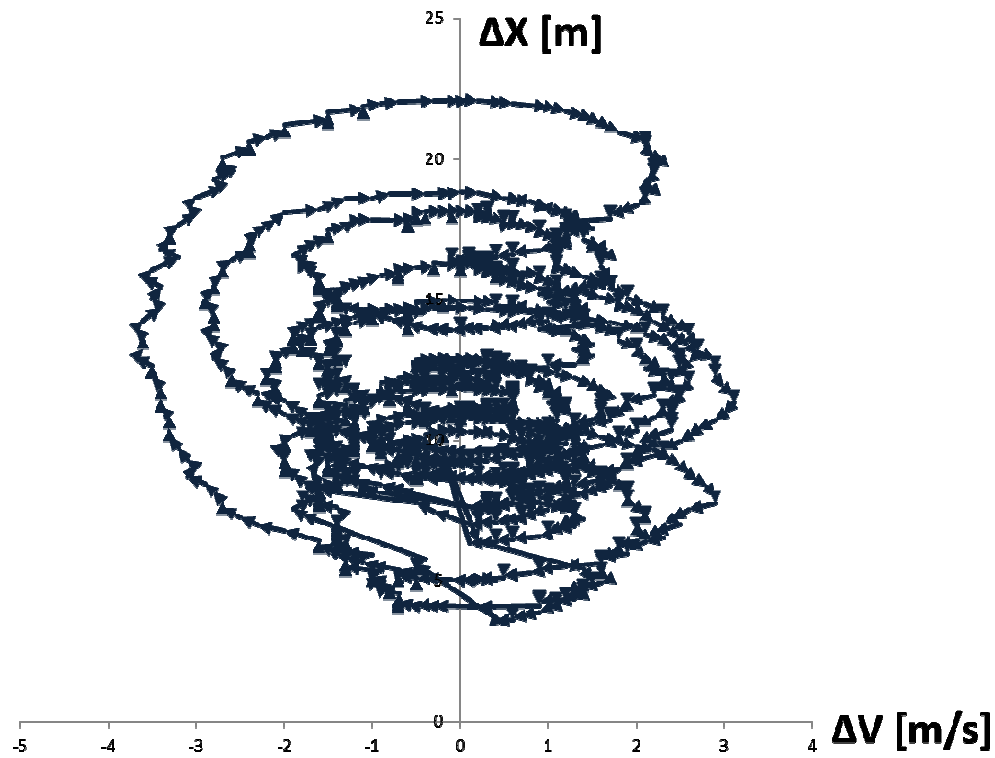
**Figure 7: Filtered car following data, Driver 15 (simple car following)**

Figure 7 plots the car following data (Relative Speed [m/s] vs. Distance to

Vehicle Ahead [m]) for Driver 15, collected using the TFHRC Living Laboratory, filtered

to show simple car following between Driver 15 and a single lead vehicle; this data

shows the normal car following relationship between one lead vehicle and Driver 15.

From Figure 7, a clear clockwise "spiral" pattern is observable, with no unusual trends.

Most of these spirals exist between 8 and 15 meters behind the lead vehicle, and within

+/- 2m/s relative speed of the lead vehicle.  Some spirals deviate from this norm, ranging

from 5 to 23 meters behind the lead vehicle between -4 and 3 m/s relative speed of the

lead vehicle. This plot (Figure 7) shows normal car following for driver 15 behind one lead vehicle while traversing a work zone. This dataset would be ideal for validating normal car following behaviors predicted in a new work zone microscopic model.

Driver 15 is a middle-aged female, 27-years old. Driver 15 was tested on a Tuesday afternoon August 20th 2013 on freeways near Turner Fairbank Highway Research Center in McLain, VA. Driver 15 traversed freeway segments both with and without a work zone.

## 2.4    Field Theory in Psychology

In psychology, there exists a social behavioral theory called Field Theory. The theory was developed by Kurt Lewin, a Gestalt psychologist, in the 1940's [66]. The theory was developed originally for use in social situations, but has made a significant contribution to the fields of social science, psychology, social psychology, organizational development, process management, and change management.[67] Field theory is characterized as a method of analyzing causal relations and of building scientific constructs [67].

Field theory is a psychological construct used to examine patterns of interaction between the individual and the total field, or environment [66]. It provides a framework for looking at the factors (forces) that influence an agent in a situation, originally social situations [68]. Field theory takes into account two types of forces: those that are driving movement toward a goal (helping forces), or those that blocking movement toward a goal

(hindering forces) [68]. These forces are brought about by external stimuli, experienced by the agent.

Field theory shows the changes in an individual's *life space* depending on how an individual internalizes external stimuli [69]. The theory states that behavior must be derived from a totality of coexisting facts, and that these coexisting facts make up a *dynamic field* [66]. Therefore, the state of any part of the field depends on every other part of it [66].

From field theory, a basic framework for social interaction can be constructed. Each individual, or agent, has a life space (or field) that exists around them. External stimuli exist in this life space. Each stimulus has a different set of forces associated with it, depending on how the agent internalizes the existence/presence of the stimuli. The resulting forces govern the agent and dictate a response (or a lack of a response). Forces can have an attracting or repelling quality, and there can be/are multiple forces in each life space. The cumulative effect of these forces dictates how the agent will behave, act, interact, and the choices the agent will make.

Field theory and force field analysis have applications in numerous areas. In business management, force field analysis is used to help make decisions by analyzing the forces for and against a change, and helps management communicate the reasoning behind its decision [70], [71]. By mapping out and quantifying the driving and restraining forces of a desired or present state, management can come to a meaningful

conclusion and construct a powerful argument for or against their decision [71]. By mapping out and quantifying each force associated with a decision (to remain at a present state or to change to a desired state), field theory can be used to predict decisions made by any agent.

Field theory and force field analysis are agent-based constructs upon which an analysis for how an individual behaves can be established, based on the forces experienced by the agent, brought about by external stimuli, and internalized by the agent based on variables specific to that agent. As microscopic modeling is used to describe and predict the actions and reactions of individual vehicles, so does force field analysis describe and predict the actions and reactions of an agent in a social environment. However, in modern microscopic models, a vehicle's actions and reactions are based on observations made about a vehicle. Furthermore, microscopic models are divided, and usually consist of separate lane-changing and car-following models, designed to describe how a vehicle moves among lanes and down a roadway, respectively. Force field analysis takes into account all forces experienced by an agent and predicts reactions to the cumulative forces [72]. Field theory states that in order to perform an analysis, the state of any part of the field depends on every other part of it [66].

Lewin also characterized organizational management styles and cultures in terms of leadership climates [73]. Essentially, with authoritarian environments a leader determines policy with techniques and steps for work tasks for workers, and offers praise and criticism for work done (both praise and criticism being motivational tools), whereas

in a democratic climate work division and choices are made collectively by the workers, and praise and criticism are objective [73]. In practice, the organization found in authoritarian environments reflects the organizational abilities of the leader, whereas in democratic environments organization can be more chaotic. In transportation, work zones can be perceived in some instances as a little bit of both. Lane closure is authoritarian because it is forced upon a driver, dictated to the driver via signage, and the criticism would be the legal repercussions if the driver does not merge. However, the task of merging is democratic because the actual merge maneuvers are left entirely to the drivers. In this additional way, work zones and the merging task can fit more of Lewin's models.

Some psychologists tried to apply Lewin's research to a driving model. Gibson and Crooks (1938) [74] pointed out that not much has been done in terms of describing driving behavior using a psychology model. According to the paper, a psychology-based driving model would need: 1.) a systematic set of concepts which can describe what happens when a person drives an automobile, and 2.) practical and psychological validation. Initially, Gibson attempts to construct a psychological driving model based on habits, attitudes, and response sequences; however, this approach was met with little to no success.

Gibson concluded that the driving model was predominantly a perceptual task, so he constructed a second model that would analyze driver behavior on a perceptual level. Rather than employing habitual or behavior models, this model was based on spatial

models that utilized the "field" of the driver, based loosely on concepts outlined in Lewin

(1936) [75].  This model found some success.  Gibson assumed similarities between

driving and walking in that both tasks required locomotion through a field of space, and

that the sole difference between driving and walking was the use of a tool (in this case, a

vehicle).  This tool grants the driver a certain set of abilities and capabilities to navigate

the path, based on input of the environment to the driver using the driver's visual field.


In his work, Gibson defines a *field of safe travel*.  The field of safe travel is

comprised of elements crucial to travel in an automobile and bound by the roadway and

roadway stimuli.  Elements in the roadway alter and shape the field of safe travel.

Ultimately, it is best to think of Gibson's field of safe travel as a field defining the

possible paths which a vehicle may traverse unimpeded.  Figure 3 below shows the field

of safe travel as defined by Gibson.
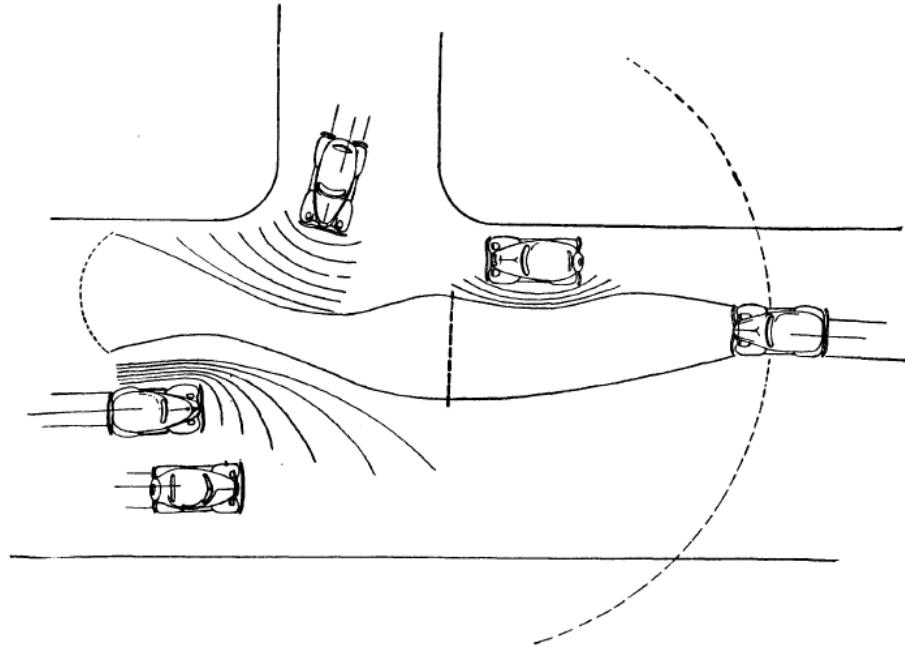
**Figure 8: Field of Safe Travel and Minimum Stopping Zone of a driver in traffic [74]**

The field of safe travel has been used indirectly in numerous studies. Primarily, it has been used in pedestrian crossing studies to define the threshold that pedestrians must cross into to impede vehicular travel [76], but it also finds application in visual and cognitive loading studies [77], [78], and is used to define the threshold in front of a vehicle that a stimuli must cross into in order to effect driver behavior [79], [80], [81], [82]. This threshold, for the most part, has been reduced to the cross-sectional area directly in front of the vehicle.

Although Gibson's model found success, there are gaps in his research from a microscopic modeling standpoint. 1.) Gibson's model was not applied or used to develop any sort of microscopic model, nor was Gibson's model ever calibrated. Gibson only proposes a theoretical model as an alternative to viewing a driver's experience. 2.)

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Gibson's model is only concerned with the area that the vehicle can travel forward into, and not adjacent areas and/or any stimuli behind or next to the vehicle. For this reason, even if Gibson's model were calibrated and adopted to construct a microscopic model, it could not model lane-change behavior, nor would it show the influence of stimuli on the driver, visible to the driver but located outside the field of safe travel. For this reason, Gibson's theoretical model can only find use when determining how a vehicle might react to stimuli that appears directly in the trajectory of the vehicle. Gibson attempts to describe variables such as 'desired speed' using 'driver hurry,' however his definitions are loose and cannot be directly applied.

As a psychologist, Gibson tried to model other behaviors using a perceptual field, however, found criticism from his peers. The main piece of criticism Gibson's models received was that his perceptual models failed to address an organism or person who sensed their environment using other senses, such as touch or sound [83]. In addition, there was some failure in Gibson's work to describe how different organisms experience their environments differently, and how a stimuli observed by one organism might be interpreted differently and/or might cause different reactions in another organism [83]. In psychology, the lack of a sensory surface and/or auditory sense could disprove his perception-only based model

However, this does not have to be the case in driving models. The touch senses a driver experiences on a roadway include "g-forces" while turning, accelerating, and braking, and feedback from a steering wheel and brake pedal. These are all examples of

things felt AFTER a driver has begun a maneuver, and these touch senses are used by the driver primarily to make adjustments to a maneuver.  Whatever stimuli caused the maneuver, be it a vehicle/pedestrian/cyclist/other stimuli, was already sensed, and the reaction to that stimuli was already being carried out.  Visual perception is used to sense the presence of these stimuli, causing a reaction.  When describing how a driver might react to roadway elements (and when trying to build a model describing driver behavior as a function of the elements surrounding the driver), the visual field should be used.  The sense of touch plays little to none in terms of constructing a microscopic model that describes driver reactions to roadway stimuli; the sense of touch is not a factor when calibrating a model that predicts driver reactions and driver behavior based on observations made about roadway stimuli (because the task of observing roadway stimuli is purely visual).

## 2.5     Summary of Literature Review

Based on the literature reviewed above, the following conclusions support the research proposed in this prospectus:

- **Current microscopic models do not simultaneously predict lateral and horizontal movements.** Elements that effect lateral driver behavior are not reflected in horizontal driver behavior, and vise-versa.  This creates potentially inaccurate situations.  In addition, in microscopic simulation packages, factors of safety are sometimes generated independently for the algorithms describing

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lateral and horizontal vehicle movements, creating vehicles that could provide ample safe headway when following another vehicle but will cut-off a vehicle in the neighboring lane, accepting a minimal gap.

- **Algorithms governing vehicle movements in current microscopic models are stochastic and deterministic, and not explanatory. Current models do not utilize a decision-making algorithm to predict driver behaviors and driver decision-making.** The algorithms for microscopic models are statistical distributions of observed vehicle movements, and are not based on how each driver scans the roadway and surrounding environment, internalizes the presence of various roadway stimuli, and reacts based on how the driver perceives these stimuli. For instance, previous studies examined in this literature review reveal gap acceptance models generated by observing vehicles merging onto a freeway via access ramp. Results indicated that a certain percentage of them merged "x" distance away from the end of the acceleration lane. These models made no attempt to describe how elements such as the driver's speed, the speed of surrounding vehicles, the location and placement of other vehicles in relation to the driver (perhaps the driver didn't accept the immediate gap because they saw another at the tail of a queue of vehicles) effect the decisions a driver makes. Current models are based off statistical representations of field observations, and do not attempt to describe how each roadway stimuli observed by the driver affects the driver and contributes to the driver's overall decisions.

- **Current microscopic models describe the entire driving population with one set of algorithms, rather than modeling distinctly different driving**

**populations (that exhibit vastly different driving behaviors) with different sets of algorithms.** From this literature it is inherent that different populations of drivers exist, categorized by factors such as a driver's age, and a driver's familiarity with the roadway. These driver populations operate differently on roadways, have various tendencies/driver errors associated with them, and have very different driver behaviors. To more accurately describe traffic in microscopic modeling, it would be more effective to create a model based off multiple models, with separate algorithms describing the driver behaviors of separate driver populations.

- **Different driver populations scan roadways differently, and element that is not captured in current microscopic models.** In order to react to a stimulus on a roadway, a driver must first observe each stimulus. If different driving populations scan the roadway differently, then driving populations will not react in the same manner to the presence of roadway stimuli (because these stimuli went unobserved). Current microscopic models (and microscopic simulation softwares) assume that all roadway stimuli are observed by the driver. All models determine a driver's behavior based on statistical distributions created using collected data for vehicles observed in the field (i.e. 50% of all vehicles will yield by "x" feet on oncoming traffic). This of course is not a reflection of what occurs in real life on roadways, and therefore is an inaccurate representation of how vehicles on a roadway behave. It would be more accurate to describe vehicle interactions (with roadway stimuli and with other vehicles) by identifying when a

driver would likely observe the stimuli, then reacting as that driver would to each observed stimuli.

- **Stimuli and roadway elements affect driver behaviors, and to some extent alter driver behaviors differently for separate driver populations; this is not captured or reflected in current microscopic models.** Signage placement affects familiar drivers differently than unfamiliar drivers, as well as effects older drivers differently from younger drivers. Older drivers have different tendencies when they approach a possible hazardous situation (i.e. slow down but do not significantly increase roadway scanning frequency) than younger drivers (i.e. no significant decrease in speeds but a significant increase in roadway scanning patterns and frequencies). Distractions such as GPS, cell phones, and tasks that place a high visual or cognitive demand on drivers effect drivers tremendously, but have varying effects from driver sub-population to driver sub-population. Current microscopic models lack the ability to: 1.) capture the effects of stimuli (such as cell phones) and roadway elements (such as signage and signage placement) on drivers in a roadway, 2.) describe how these stimuli effect different population of driver differently, and 3.) do not attempt to incorporate these drivers into the model nor show their effects on traffic flow and/or other vehicles, despite the increasing importance placed on distracted and drugged driving or research conducted demonstrating the adverse effects of distracted driving on traffic flow conditions for an entire roadway.

- **When plotting relative distance to the lead vehicle vs. relative speed between the subject driver and the lead vehicle, naturalistic driver data collected for**

**normal car following behavior shows a "spiral" trend.** A valid car following

models should be capable of replicating this spiral trend. Some models have

acknowledged variable headway but failed to capture the "spiral", \ fail to

accurately describe the driving population, and/or lack an explanation for why

headway varies. Other models have replicated this spiral using a "forced"

approach, rather than witnessing this spiral as the result of algorithms that

replicate a driver's perception → recognition → decision making → reaction

process. Models that "force" this spiral to occur risk being inaccurate when

modeling basic scenarios that require some level of change and decision-making

on the part of the driver.

- **Although Gibson's visual field models for psychology were criticized, they**

  **find potential use in developing a microscopic model.** Fundamentals from

  Gibson's theoretical driving model, such as the "field of safe travel," have already

  found applications in driving studies. Gibson's model in its current state cannot

  accurately describe driver behavior, nor could it be used directly to develop a

  microscopic driving model. However, Gibson's theories do demonstrate how a

  visual field of perception can be used in a model to describe driver behaviors, and

  how this visual field can introduce psychological elements that are lost in other

  microscopic models.

Employing some sort of visual field to scan for driving stimuli, it could be

possible to develop a microscopic model that would capture how a diver perceives

roadway stimuli. From there, these stimuli can be internalized by the driver, and

in turn, the driver can formulate reactions, and the effects of each roadway stimuli on the driver could be modeled.

- **There is a possibility that Kurt Lewin's field theory can be used as a basic framework for a new microscopic model.** Field theory has the capability of predicting the actions of an agent when multiple stimuli are present. Field theory can also capture and model the subtle differences in the impact that a single stimuli has between one person and another.

# CHAPTER 3

# RESEARCH OBJECTIVE

The objective of this research is to develop the framework and general model architecture for a new microscopic model, Modified Field Theory, based on Lewin's Field Theory. This model will incorporate social-psychological theory directly into model algorithms, modeling each driver's decision-making process and demonstrating how each roadway stimulus impacts each population of driver.

The new model, Modified Field Theory, will utilize Lewin's force field analysis and will be tailored to model traffic flow through a four-lane freeway with a right lane closure work zone set-up. This new model will attempt to incorporate observed major stimuli collectively, much like a driver assesses observed stimuli simultaneously while driving through a work zone. The model will assess the pressures (also referred to as forces or valences), resolving these pressures and predicting an overall driver response using Lewin's Force Field Analysis. In addition, the model will be designed to incorporate the effects of other stimuli, such as work zone signage. By developing a model based on each driver's perception/reaction to major roadway stimuli, more realistic explanation and prediction of a driver's behavior and its impacts can be achieved.

Modified Field Theory is an attempt to quantify and model all pressures and forces on a roadway that could influence a driver to make a decision, whether it's roadway signage, other vehicles on the road, lane closure, etc. Modified Field Theory

converts all roadway stimuli into forces, putting the driver and the driver's decision at the center of the model. In the field, the driver controls the vehicle; so will it be in Modified Field Theory.

This model will constructed such that it addresses the gaps in existing models as identified in literature. Specifically, this new model must:

- **Be flexible enough to add new stimuli without re-writing model algorithms.**

- **Simultaneously quantify of car following (CF) and lane changing (LC) variables, calculating the total impact of stimuli on driver behavior in two dimensions. Predict the driver behavior in 2 dimensions.**

- **Model the driver decision-making process, showing the influence each roadway element has on the driver's decisions.**

- **Model and reflect the variable driver behaviors, described in the literature review, that exist between/among different driving populations.**

The potential use of Modified Field Theory for modeling work zone freeway with lane closure scenarios must be demonstrated. Although multiple stimuli (and their associated impact/effects on each sub-population of driver) need to be calibrated and validated before this model is implementable, this research will focus on calibrating this model for a simple car-following scenario through a freeway work zone experiencing lane closure. The model will be validated using the Federal Highway Administration (FHWA) Turner Fairbank Highway Research Center (TFHRC) Living Laboratory freeway work zone car following data collected. In particular, the simple car following

dataset described in the literature review (refined to remove all stimuli except for the lead vehicle and the desired speed of vehicle $i$) will be used. Modified Field Theory is not purposely designed to replicate the "spiral" trends witnessed in car-following, so if the calibrated simple car-following Modified Field Theory model replicates the "spiral" trends then the model will be considered valid.

# CHAPTER 4

# MODIFIED FIELD THEORY

## 4.1    Overview

Modified Field Theory is a new microscopic traffic flow theory from which a new microscopic traffic flow model can be built.  Modified Field Theory is based off the concept that each driver reacts to stimulants they perceive on and off the roadway. Stimulants include but are not limited to, other vehicles, lane markings, signage, pressure to adhere to a schedule or set arrival time, and desired speed.  Each stimulant has a perceived force associated with it, which may vary from driver to driver.  Each driver reacts to the forces they perceive, influencing travel speed, lane choice/lane change, and driver behavior.  By attempting to replicate the driver's decision-making process, Modified Field Theory is an explanatory model that transcends the limitations of existing descriptive models, which simply seek to duplicate the end-result of the decision-making process (aka, the decision itself).  By using vectors and vector fields to model the impact each stimulant has on the subject driver, the divided architecture of existing models is avoided.  Finally, by dividing and separately modeling the physical world and cognitive map, disassociations between "what's really there" and what each driver "thinks is there" can be modeled, giving Modified Field Theory the ability to model the impacts of perception-limiting situations and phenomena, such as distracted driving or blind spots.

Since the concept of responding to stimuli (perception-reaction) is a well-established concept when describing driver behavior, it is arguable that Modified Field Theory is more "real to life" than other microscopic models, and has algorithms developed based on "what's really going on". By including all stimuli affecting the driver, Modified Field Theory can show a driver's cumulative response to roadway stimuli, whereas other models describe individual aspects of how a driver behaves. Complex situations with multiple roadway stimuli can be modeled and analyzed, and all stimuli will be taken into account, each stimulus carrying the appropriate weighted influence on the driver.

## 4.2    Different Drivers will be Modeled Differently

Literature explains that some driving populations exhibit measurably different driving behaviors. Existing microscopic models allow for the user to adjust for these differences by quantifying unmeasurable values across the entire driving population. This results in many models being constructed without proper calibration.

This model needs to be usable by practitioners. This means that model needs to be constructed such that calibration for use by engineers and planners is accomplishable using the traffic data collection methods currently employed by practitioners. Studies have shown that variables, such as a driver's age, can be estimated, and whether or not a driver is a commuter can be inferred depending on whether or not the same vehicle with

the same license plate can be observed in the same place around the same time on two different days.

Different drivers drive differently. They exhibit measurable differences in driving behavior. Literature reports different driving behaviors across the population using measurable standards. Parameters for calibrating the driving population in Modified Field Theory will be based off these different driving populations, as described in the literature.

The following parameters are used to divide the driving population into different sub-populations. These 'divides' were selected because literature suggested that drivers of these various populations exhibit different driving behaviors, and because these divides are all measurable by today's practitioners.

The divides are:

- Free Flow vs. Congested Conditions

- Familiar (commuter) vs. unfamiliar (non-commuter)

- Male vs. Female

- Younger (under 25 years old) vs. Middle-aged (25 to 55 years old) vs. Older (55+ years old)

Each of these parameters is measurable by today's standards for practitioners. Additionally, literature reports distinctly different driving behaviors across these parameters.

Using these divides, the algorithms that define the scan patters and valences in the cognitive map for an Older Male Driver Familiar with an area in Free Flow will be different than those for the same driver in Congested Conditions, or if the driver is Unfamiliar with the area.  The same driver would be different as a Female, or as a Middle-Aged or Younger driver.  Sub-populations of driver are defined across all 4 parameters.

## 4.3     Model Architecture

In this new model architecture, the physical world is modeled separately from each driver's cognitive map.  As a driver scans the roadway environment in the physical world, stimuli are perceived.  The presence, location, and status of each stimulant is transferred to the driver's cognitive map, along with certain information about vehicle $i$. In the cognitive map, the driver updates the status of each roadway stimulant.  The driver then associates positive (attractive) or negative (repellant) valences (also known as forces) with each stimulant.  Using Force Field Analysis, the driver's decision-making process is modeled and the overall impact of these valences is resolved, yielding the drivers desired response.  The driver's desired response is then fed back into the physical world, manifesting as a change in acceleration, travel direction, or roadway scanning pattern(s) of the subject driver.

### 4.3.1 *The Physical World*

The "physical world" is an accurate reflection of the driving environment. In the physical world, the laws of physics apply (this includes, coefficients of friction, braking distances, max acceleration/deceleration, sight distances, and other laws. The dynamic nature of these laws, such as changes in max acceleration/deceleration when a vehicle is traveling uphill/downhill, is also captured). Lewin is a Gestalt psychologist, and Field Theory is a Gestalt theory, therefore all elements events and rules within the physical environment need to be included.

### 4.3.1.1 *Glance Patterns*

Just as an agent scans their environment in Lewin's Field Theory, so does a driver scan the driving environment. Each driver glances from their vehicle, scanning the various zones that surround them. Figure 9 illustrates what these glance zones could look like. From literature it is known that the order and frequency that drivers scan these zones, as well as the shape and size of visible space that defines each zone, can vary depending on the vehicle (for example, some vehicles have blind spots), driver (for example, older drivers exhibit different roadway scanning patterns than younger drivers, usually performing a primary but not a secondary or tertiary glance to the conflicting movement [34], [35], [36]) , and status of the driver (for example, the roadway scanning patterns of a driver who is texting and driving will be different than that of other drivers). Therefore, in MFT, these zones, their locations/dimensions, glance patterns, glance rates, and perception times per zone, will depend on both the driver and the vehicle type.

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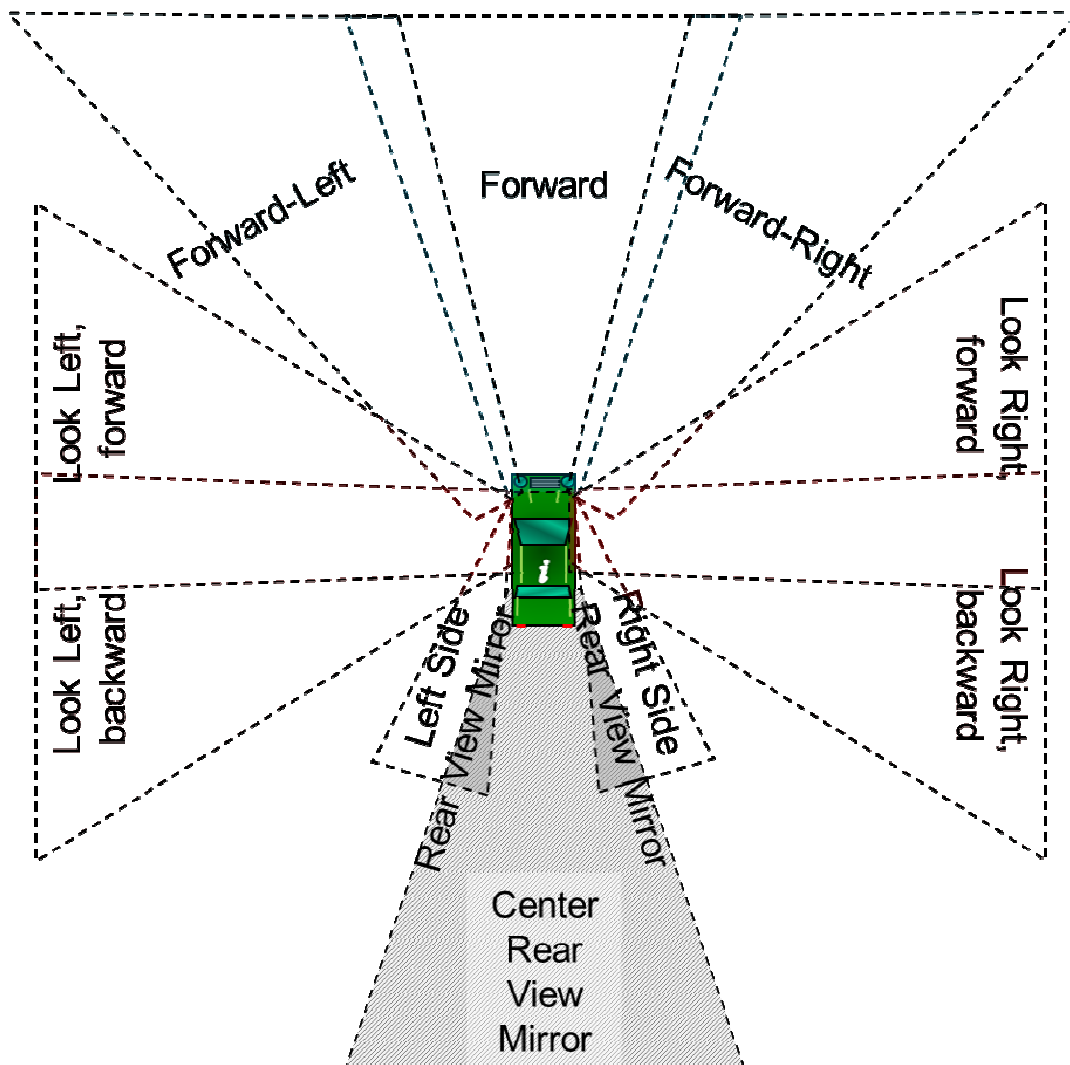
**Figure 9: Modified Field Theory—Physical World. Glance patterns and zones**

Glance patterns can be changed, adjusted, or influenced based on a stimulant perceived in the cognitive map or on a driver's desired reaction. Stimuli and/or desired behaviors that alter a driver's glance patterns and/or frequencies are built into the roadway scanning algorithms for the select zones. For example, a freeway driver that

desires to merge right may glance at the right-forward, right-backward, and right side rear view before executing a merge maneuver.

Glance rates and perception times can be calibrated using naturalistic driving data with eye tracking or simulator data with eye tracking. Perception-realization time is the time between glancing at a zone and 'uploading' stimuli within that zone to the cognitive map.

Zone shape and size, glance patterns, glance rates, and perception times will vary depending on the vehicle, driver, and any driver activities. Figure 10 illustrates how activities (such as texting and driving) or vehicle classification (such as a heavy vehicle) could alter the shape/size of these zones, glance patterns, glance rates, and perception times. For a heavy vehicle (Figure 10, right), there are known blind spots; unless the driver's roadway scanning abilities are enhanced (such as through V2V technology), the driver cannot perceive stimuli that exist in these blind spots. A driver who is texting and driving (Figure 10, left) is probably looking down at their phone and forward in the direction of travel; therefore, the glance is limited to glancing in the direction of travel (forward) and glancing at a phone (not viewing the roadway environment). Additionally, delayed perception times might be observed due to the added cognitive load.
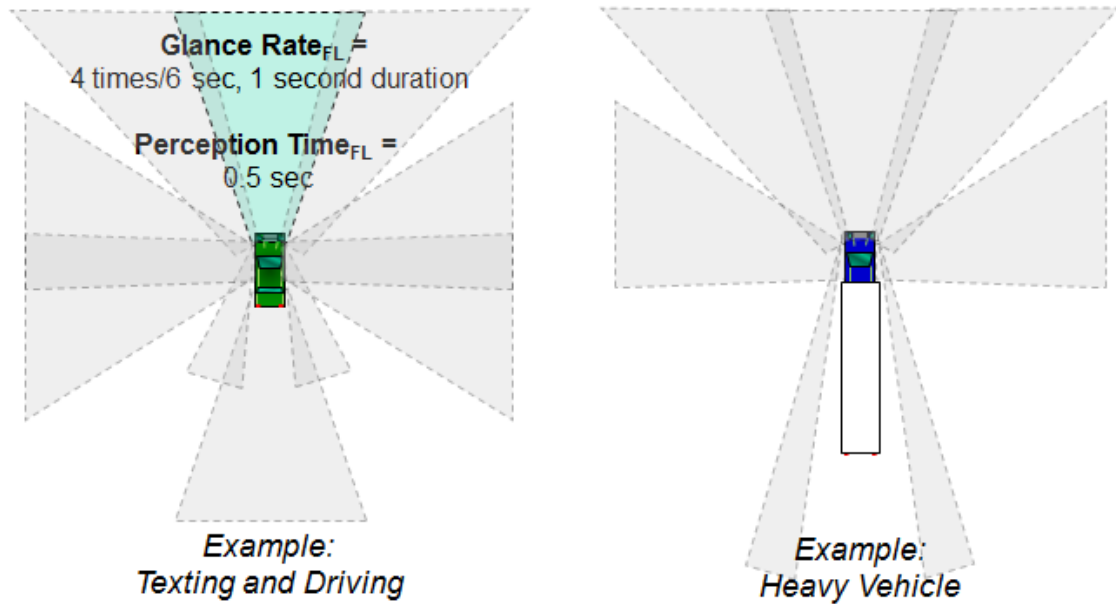
**Figure 10: Scanning patterns: texting and driving (left) and heavy vehicles (right)**

Figure 10 demonstrates how variable scan patterns (scan zones and scan frequencies) in MFT can be used to model the impacts of driver activities (such as texting and driving, left) and vehicle classification (such as heavy vehicle, right) on roadway scanning--zones, glance patterns, glance rates, and perception times.

*4.3.1.2   Observed stimuli and their status.*

As a zone is being 'scanned', stimuli that are present in that zone (and their status) will be perceived after the set perception time for that zone.  The status of observed stimuli includes characteristics of each stimulus, such as: location, status of elements (such as "on" or "off" for a center high mount brake light), velocity (for moving objects. This requires two scans or one prolonged scan, since the instantaneous velocity of an object is not something that can be seen.  Velocity is perceived when location changes over time), and message (for signage).

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Figure 11 shows driver *i* (in the green passenger car) scanning the roadway environment directly ahead at time T = t.  At time step T = t + perception time, driver *i* perceives the black car (leading car), its location, and the W4-2 work zone signage.  The message conveyed in the W4-2 signage may require additional time for comprehension, therefore, the message won't be perceived in the cognitive map until T = t + perception time for W4-2.  The velocity of the black car (lead vehicle) cannot be "seen" at time T = t + perception time.  Velocity of other vehicles requires two scans or a long continuous scan, as instantaneous velocity cannot be 'seen'.  If driver *i* is performing a prolonged continuous forward scan, it is possible for the velocity of this lead vehicle to be perceived over the duration of this one scan.  In this scenario, perception time for the velocity of the lead vehicle will be T = t + perception time for velocity.
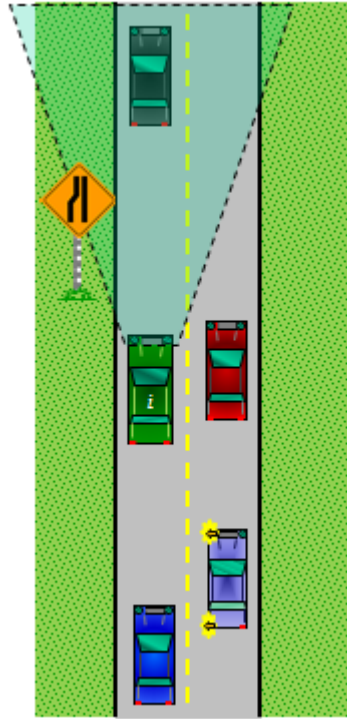


**Figure 11: Driver *i* scans the roadway environment**

Perceived stimuli and their status are then 'uploaded' to the driver's cognitive map. Figure 12 shows the cognitive map for the driver in Figure 11. In this example, driver *i* is performing a long, continuous forward scan, and has not scanned to the right or toward the back right in quite some time; this creates inconsistencies between the physical world and the cognitive map. The location of red car and purple car, as well as the blinker status of the purple car, have changed since driver *i* last perceived them; these changes went unperceived, and therefore do not exist in the cognitive map.
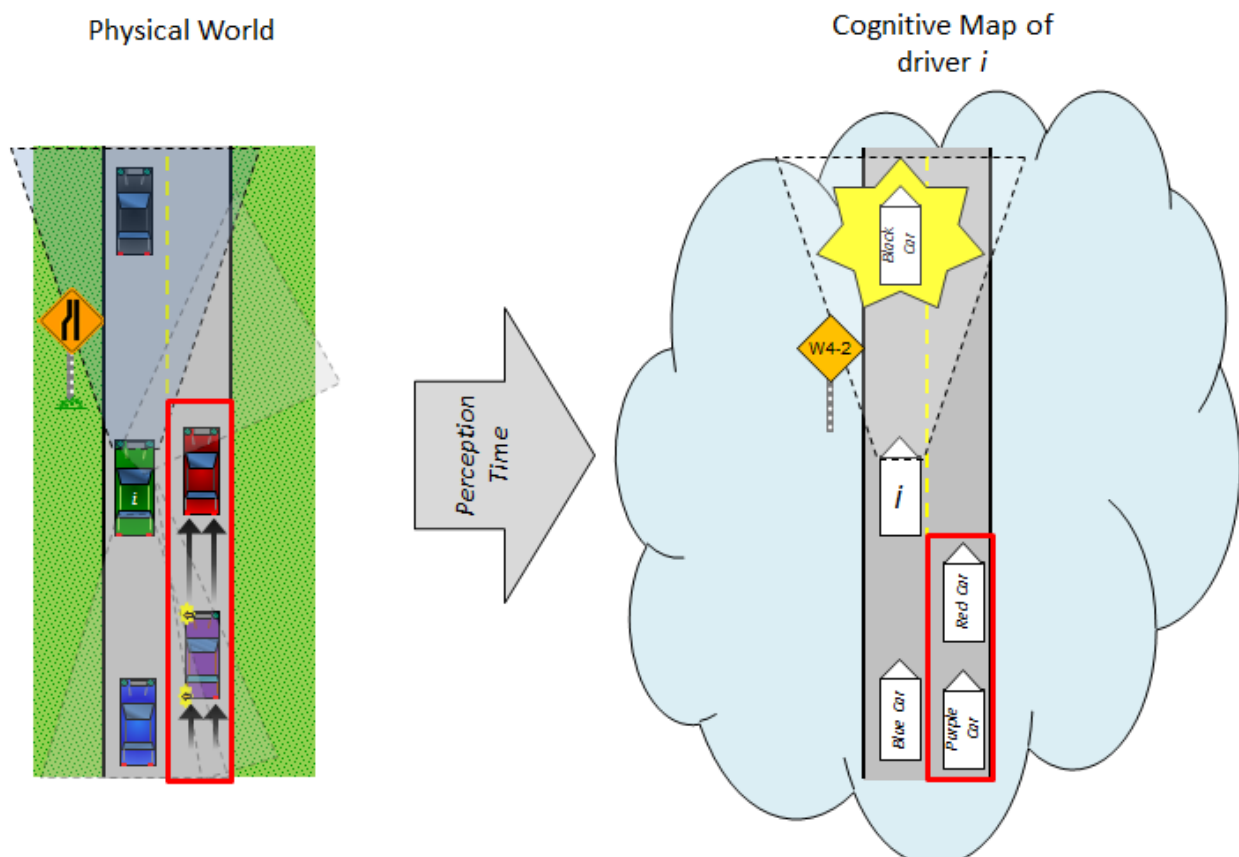


**Figure 12: Perceived stimuli are uploaded into a driver's cognitive map.**

### 4.3.2 The Cognitive Map

The Cognitive Map is a term in psychology, relating to the world as one perceives it. In Modified Field Theory, the Cognitive Map is not a model of the 'real world', but a model of the world as perceived by the driver. It is the location where driver decisions are made. Objects are placed within the Cognitive Map based on how they were observed/perceived. The driver 'feels' certain ways about certain objects, and perceives attractive or repulsive valences with each object. The total effect of all these valences influences the driver's behavior, ultimately governing the desired reaction of the driver. This desired reaction feeds back into the Real World, influencing the driver's next set of actions (response). In Modified Field Theory, the Cognitive Map models the world according to each driver, and is the single location where decisions are made.

The Cognitive Map enables Modified Field Theory to model the effects of the human factor on driver behavior. Disconnects between the Real World and the Cognitive Map, caused by misplaced stimuli stemming from inadequate roadway scanning, misconceptions of the laws of physics or what 'safe' following distance is, can be modeled. A driver's personal choice or predisposition (for example, a driver who would rather pass close to a passenger car than a semi) can be included. By disassociating the world where the driver makes their decision (the Cognitive Map) and the environment as it actually exists (the Real World), Modified Field Theory is

*4.3.2.1   How does the Cognitive Map work?*

The Cognitive Map is constructed based on how the driver perceives their

environment and roadway layout is.  This includes the existence of, status of, and

location of stimuli as they were perceived.  The same stimulus perceived in the same

relative location could elicit different reactions, pending the status of that stimulus.  For

example, consider the center high mount stop light (CHMSL) of a leading vehicle and its

two statuses: on (lit) and off (dim).  Literature suggests a driver will react differently to a

lit CHMSL than a dim one (which in some cases was correlated to a reduction in rear-end

collisions [84]).  If a driver does not observe something in the physical world, it will not

be perceived and therefore will not carry over to the cognitive map.


The driver associates certain valences, or forces, with each stimulus based on how

they are perceived and based on how the driver 'feels' about the presence and status of

each stimulus.  These valences represent the impact each stimulus has on the driver.  The

driver's decision-making process is modeled by resolving the vectors generated by these

valences using Force Field Analysis.  The resulting vector is the desired reaction of driver

*i,* both in direction and magnitude.  If the desired reaction is greater than the driver's

stress tolerance (or threshold), it is transferred from the cognitive map back into the

physical world, influencing driver behaviors.


*4.3.2.2   "Ghost Stimuli"*

Some drivers react to a stimulus without first observing it; they project the

presence of this stimulus (or something representing this stimulus) in their Cognitive Map

behind a blind spot or in an un-observable location, based on driving experience or driver expectancy.  For example, consider the scenario of a stopped bus with a crosswalk in front of the bus.   Some drivers might slow down when passing the bus, expecting a transit rider to cross the street, emerging from the blind spot created by the presence of a bus.  Other drivers will continue to drive through the intersection, and having not seen the stimulus, will not react to the stimulus.

Modified Field Theory will model this phenomenon through "Ghost Stimuli".  Some drivers, through driving experience, expect certain stimuli to be present despite not having seen them.  Commuters and older drivers (drivers who have experience in the specific scenario) will project "Ghost Stimuli" where appropriate.

### 4.3.2.3   Perceived characteristics

For each observed stimulus, a set of characteristics can be observed and perceived.  This includes presence (the fact that the stimulus exists), status (examples include a lit versus dim CMBHL, the light configuration used on an arrow board, the message in a variable message sign, the assumed age of a driver in another vehicle, whether or not the neighboring vehicle has been weaving, etc.), location of driver $i$ relative to the stimulus, and velocity of the stimulus.  When a stimulus is observed, these characteristics are perceived and built into the driver's cognitive map.  Figure 13 illustrates these characteristics.
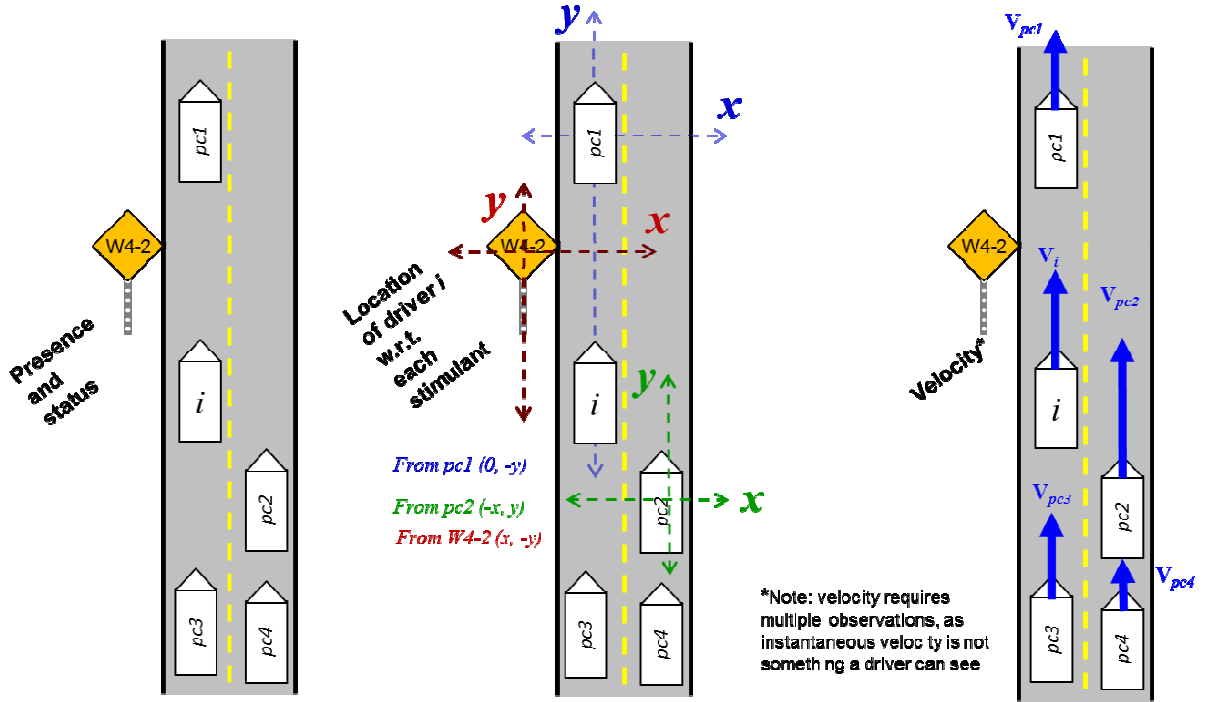
**Figure 13: Characteristics of observed stimulus perceived in the Cognitive Map.**

It is important to note that a driver cannot "see" instantaneous velocity. Our perceptions of velocity are estimated when an object is observed at two different relative locations at two different times. The fact that a driver cannot "see" instantaneous velocity is reflected in the model algorithms. This will differ for enhanced vehicles or drivers (such as automated vehicles) equipped with either radar or communications technologies that allow the driver to know the instantaneous velocity of other vehicles. (In the case of automated vehicles, the vehicle itself perceives the roadway in a certain manner, making its own set of decisions, and on occasion "overrides" the driver to avoid potentially hazardous or wasteful situations. Of course, the 'decision-making' algorithms for automated vehicles are predefined according to Standards and the manufacturer).

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*4.3.2.4    Valences*

Based on how the driver perceives each stimulus, the driver will associate attractive (positive) or repulsive (negative) valences with each stimulus. Figure14 below shows sample valences, or *force fields* associated with sample stimuli. Force fields vary in intensity, from stimulant to stimulant, according to how each stimulus was perceived in the Physical World. This notion of valences is adopted directly from Lewin's Field Theory.
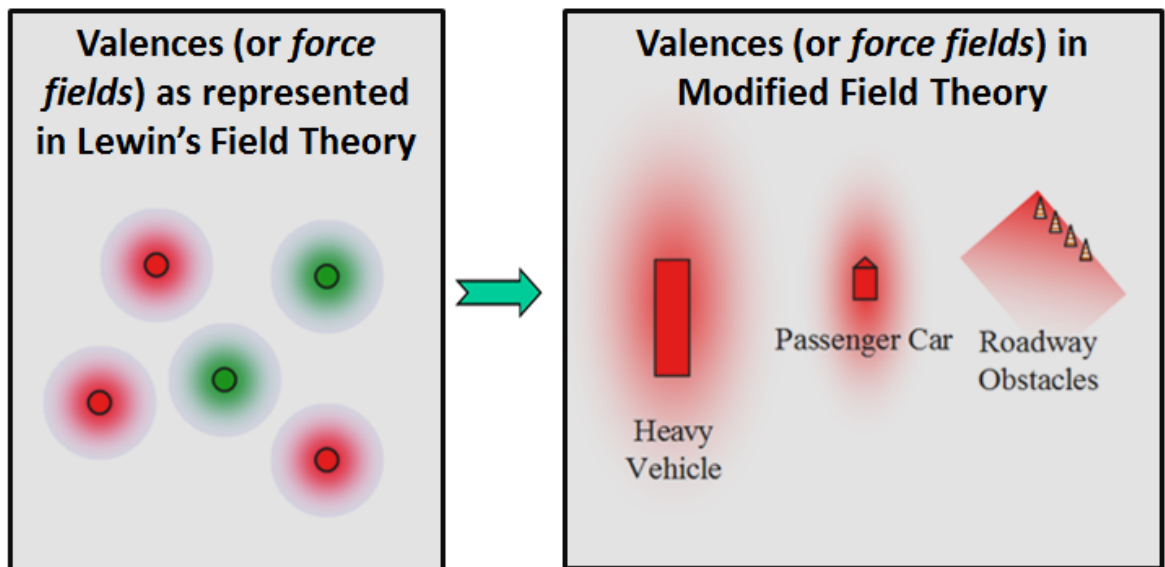


**Figure 14: Valences (or force fields), adopted from Lewin's Field Theory.**

In Figure 14, the intensity of the red color indicates the intensity of the force associated with each stimulant, at a set distance from that stimulant. In these examples, the force becomes more intense with proximity to the stimulant. Stimulants have varying forces, and force fields vary in intensity, size, and shape. For example, the force field associated with a heavy vehicle is larger than that associated with a passenger car. For

safety reasons (including blind spots in a heavy vehicle), fewer vehicles can be observed tailgating a tractor trailer than passenger cars; the force fields reflect that difference.

The intensity of these forces is determined using the algorithms defined using the algorithms in Chapter 4.4 of this dissertation. All algorithms will be vectors or vector fields. Algorithms for the valences in the cognitive map include: minimum force required to elicit a response in driver $i$ (Threshold), Desired Speed (driver that perceive themselves to be traveling "too fast" or "too slow" with both elicit forces), forces from other vehicles (proximity algorithm and relative velocity algorithm), and any other stimuli, (signage, delineation, pavement marking, edge of roadway, pedestrians, environmental factors such as weather and lighting, etc.). Lewin was a Gestalt psychologist. "Gestalt" means 'total' or 'complete' in German. Field Theory views the entire observable field, everything the field contains and everything about the contents of the field, and predicts the desired response of each agent based on the total cumulative influence of all perceived variables. Modified Field Theory is a modified version of Lewin's Field Theory, applying some of the fundamental rules in the creation of a microscopic traffic flow theory that models the driver's decision-making. In order for Modified Field Theory to function properly, the impact of *all* perceived stimuli must be modeled. Therefore, any possible perception about any observable stimulant that could influence the driver in any form will require algorithms in the cognitive map. One cannot accurately apply Modified Field Theory partially.

*4.3.2.5   Valences are resolved using Force Field Analysis*

The total influence of these valences on driver *i* at time T = t is resolved through Force Field Analysis.  Force Field Analysis is simply adding all the force vectors created by the valences.  The resulting vector is the desired reaction of driver *i*.  If the magnitude of this resulting vector is enough to overcome the driver's Threshold, then this vector goes back into the physical world as the driver's desired reaction.  Figure 15 below demonstrates an example of force field analysis.  In this scenario, observed stimuli for driver *i* are the lead vehicle, (pc1) the vehicle in the neighboring lane (pc2), Roadway delineation (the dotted yellow lines), desired speed of driver *i,* and the "No Passing on the Right" rule.  These stimuli each have their own influential force on the behaviors of driver *i,* shown as vectors (note, the force from some of these stimuli might be greater or less for other drivers.  For example, the "No Passing on the Right" rule might be strictly adhered to by some drivers, and completely disregarded by others.  These differences will manifest as variations in the direction and/or magnitude of the force vector from this stimulus on driver *i*).  The sum of the vectors yields the total influence of all observed stimuli at time T = t on the driver, and if the magnitude of this resulting vector is greater than the driver's threshold, this vector also shows the desired driver reaction.  In Figure 15, the sum of the forces is enough to overwhelm both this driver's threshold and regard for the "No Passing on the Right" rule, so the desired driver reaction is accelerate and merge right.  Note, if pc1 was a police car, a significant increase in magnitude for vectors associated with 'the rules of the road' might be observable.
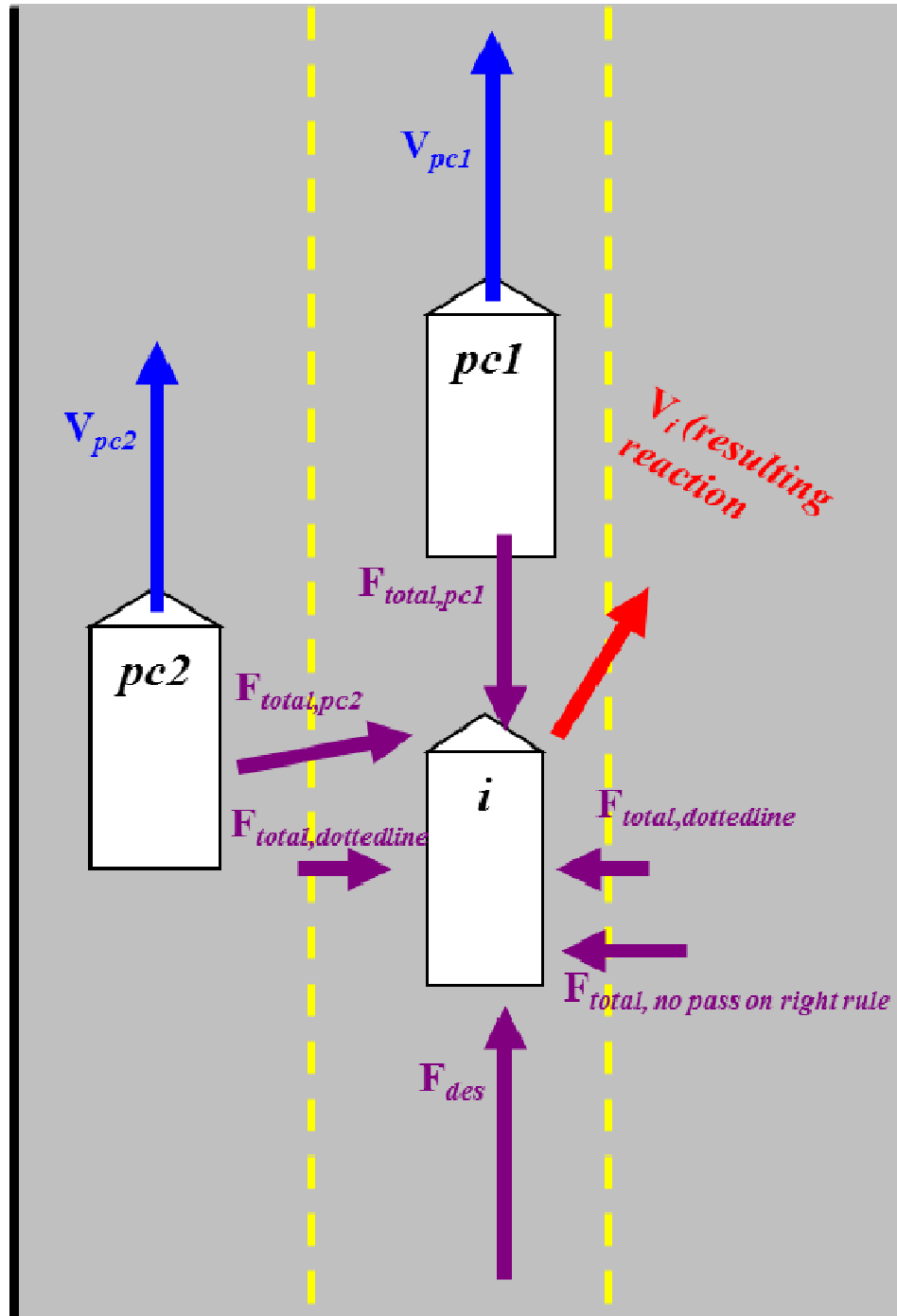
**Figure 15: Example, force vectors and resulting desired driver reaction**

Refer back to the scenario depicted in Figure 12.  In the Cognitive Map of driver *i*

(which differed from the Real World due to the sudden acceleration of the red and purple

cars), valences are assigned for each stimulus according to how they were last observed.

These valences simplified to a single force vectors for each stimulus. Adding the vectors in Force Field Analysis (Figure 16 below), the desired reaction of driver *i* is found.
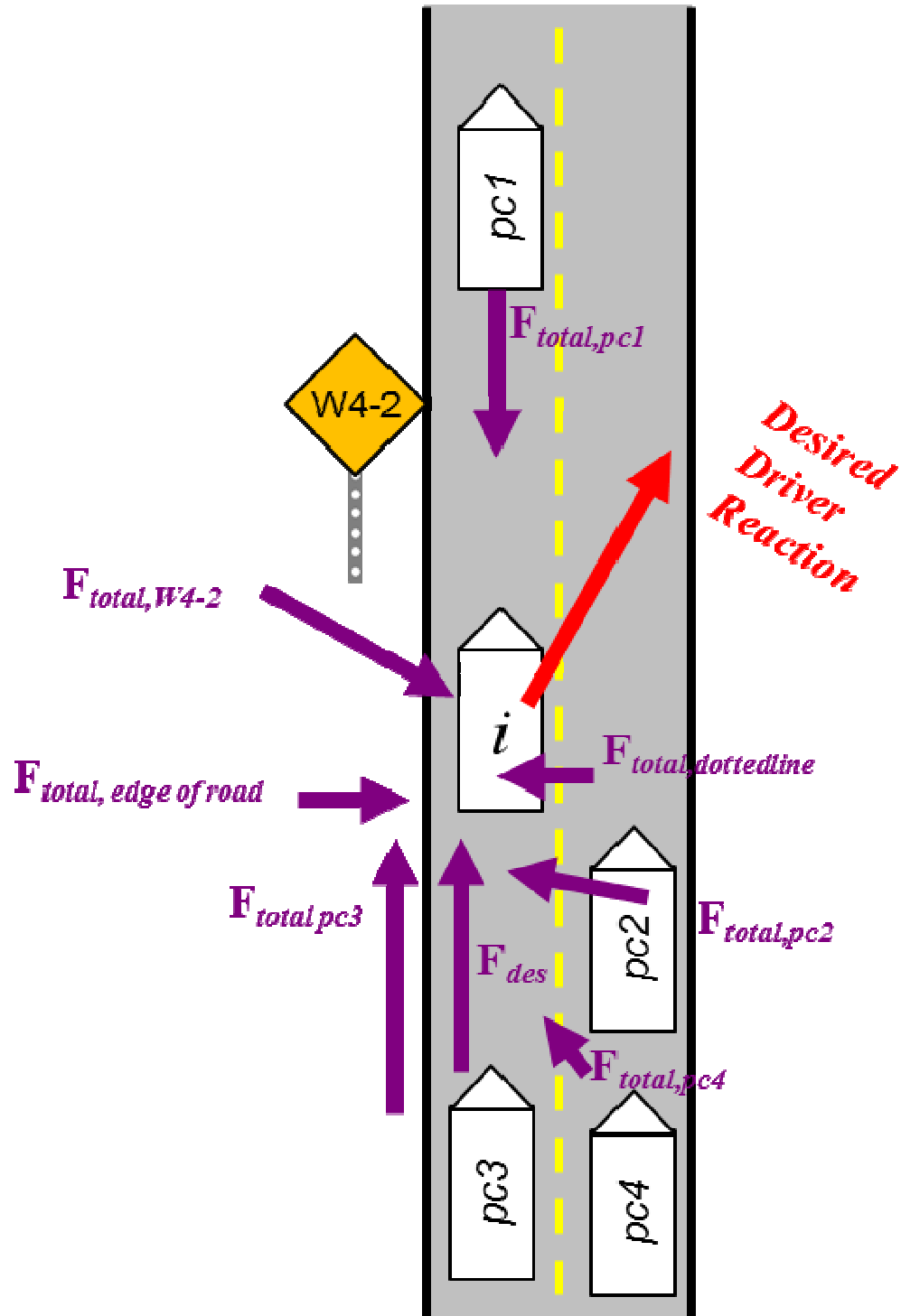


**Figure 16: Desired driver reaction of scenario depicted in Figure 12**

The magnitude of this desired reaction is greater than the driver's Threshold, so the driver's desired reaction is then sent back to the Physical World where it influences the driver's behavior (Figure 17, below), manifesting as a change in acceleration for vehicle $i$ or change in roadway scanning patterns for driver $i$. Fortunately, in the scenario depicted, the roadway scanning algorithms for this driver indicate that this driver performs a secondary glance before executing a lane change a maneuver. Driver $i$ turns on the right signal indicator and glances right to see the red car in a new location. The newly perceived location and speed for the red car are sent to driver $i$'s Cognitive Map, the driver decides not to merge at that particular time, and the cycle continues. (Note: had this been a driver who does not perform a secondary glance before executing a maneuver, such as the older drivers described by Romoser et. al. [34], [35], [36], this scenario would have resulted in a crash).
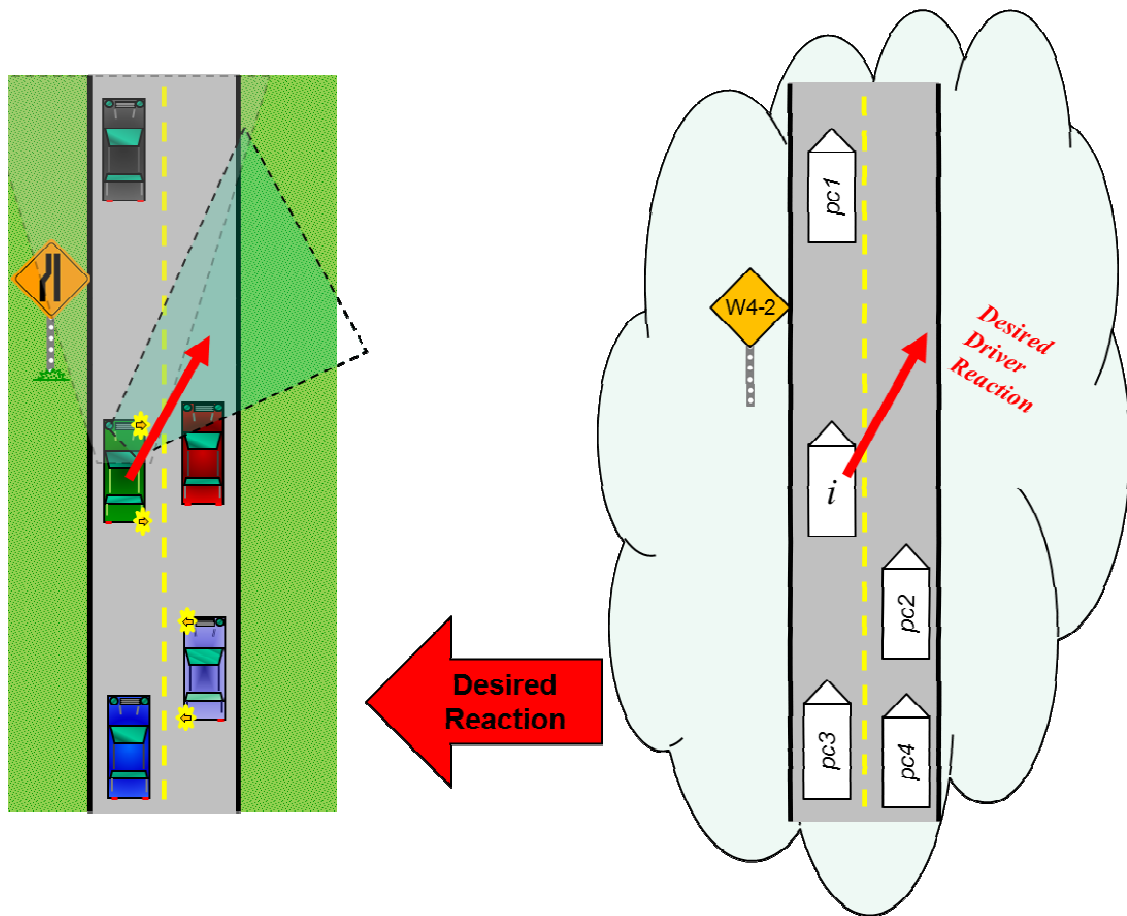
**Figure 17: The desired reaction is sent to the Physical World**

### 4.3.3 Does this Model Architecture address the objectives?

To address the objectives for this model architecture, Modified Field Theory needs to:

- **…be flexible enough to add new stimuli without re-writing model algorithms.**
  As new roadway elements are developed, existing models lack flexibility in their architecture incorporate new elements.

- **…model the driver decision-making process, showing the influence each roadway element has on the driver's decisions.** Existing models are deterministic

rather than explanatory. This means that they predict driver behaviors using a statistical distribution of observed driver reactions, rather than attempting to replicate the decision-making process. This model needs to replicate the decision-making process at some level.

- **…model and reflect the variable driver behaviors, described in the literature review, that exist between/among different driving populations**. Existing models use the same algorithms for all drivers, and use the same statistical distribution for coefficients across the entire driving population. In theory, existing models could generate a driver that exhibits the car-following behavior of an older woman but the gap acceptance of a teen male. Literature explains that these drivers exhibit unique driving behavior, from roadway scanning to how the drivers react to different elements. This model architecture should have separate models to reflect the distinctly different driving behaviors of different driving populations. Additionally, data collection required for calibrating a regional model needs to be within the capabilities of current engineering firms.

- **…simultaneously quantify of car following (CF) and lane changing (LC) variables, calculating the total impact of stimuli on driver behavior in two dimensions. Predict the driver behavior in 2 dimensions.** Model architecture for existing models feature a rigid divide between the lateral and horizontal algorithms for predicting driver behaviors. Because of this, a vehicle in front of driver $i$ and in the neighboring right lane, trying to merge in front of driver $i$, will (according to existing models) have no impact on the car-following behaviors of driver $i$. Driver behaviors must be predicted in two dimensions.

*Below is an explanation for how the model architecture for Modified Field Theory meets these objectives:*

**…be flexible enough to add new stimuli without re-writing model algorithms.** Each stimulant is individually calibrated. Model algorithms originate (0, 0) from stimulant (rather than the driver, like other models). To add new stimulants, calibrate each stimulant and add to the existing model. Algorithms in the cognitive map will not require re-writing. For stimuli that may alter roadway scanning behavior, an exception rule needs to be written and added to the existing zonal scanning algorithms.

**…model the driver decision-making process, showing the influence each roadway element has on the driver's decisions**. Using a modification of Lewin's field theory, MFT quantifies the total impact of observed stimuli on each driver and uses that to predict driver behavior. This is not a statistical distribution of observed driver behaviors; rather, it is a set of algorithms that describe the decision-making process, and the influence each observed stimulant has on each driver.

Also, by converting the influence of all roadway stimuli into forces, an "apples to apples" comparison can be made, making Modified Field Theory a platform upon which any stimuli (and any combination of stimuli) can be modeled. Additional stimuli can be added to the model by simply calibrating the forces associated with them, making Modified Field Theory expandable and "updateable." Through this, Modified Field

Theory could potentially be a long-lived model, updatable to include new results from agent-based vehicle movement research.

**…model and reflect the variable driver behaviors, described in the literature review, that exist between/among different driving populations**. Modified Field Theory features algorithms calibrated for specific driving sub-populations. These sub-populations are defined in the literature review as exhibiting different driving behaviors. Sub-population parameters include:

- Older/middle aged/younger drivers

- Familiar/unfamiliar

- Male/female

- Congested conditions/free-flow conditions

By calibrating valence algorithms specific to each driving sub-population, (such as older male driver familiar with the roadway) variable driver reactions to one stimulant are captured. In addition, Perception-Reaction time is variable.

For other populations, such as distracted drivers, algorithms defining scan patterns and frequencies can be modified.

**…simultaneously quantify of car following (CF) and lane changing (LC) variables, calculating the total impact of stimuli on driver behavior in two dimensions. Predict the driver behavior in 2 dimensions.** Using vectors in the

Cognitive Map, the influence each stimulus has on the driver has magnitude and 2-dimensional direction.

## 4.4    Potential Applications

The underlying structure of Modified Field Theory was built to allow flexibility for the addition of new stimuli.  While the algorithms in some microscopic models need to be rewritten to accommodate new roadway elements, MFT adds additional roadway stimuli by defining and calibrating the forces associated with the new stimulus and adding the stimulus to the existing model.  This grants Modified Field Theory a degree of versatility, allowing it to adapt to any situation and integrate the effects of additional external stimuli.  Modified Field Theory can model the effects of new and developing ITS solutions, as well as some other current "hot topics" in transportation engineering such as distracted or compromised driving, road rage, and even alterations in route choice due to congestion or due to a driver's desire to "keep moving" rather than sit in traffic.

### 4.4.1   ITS solutions

According to AASHTO's Four-Point Plan for Urban Mobility, applying Intelligent Transportation Systems (ITS) is part of the solution to our capacity needs [1]. Chu [85] explains that Intelligent Transportation Systems (ITS) has been used in some cases as an attempt to alleviate some of the congestion caused by work zones.  ITS technologies have proven to be successful in alleviating work zone congestion in the past; RITA documented an ITS implementation in California in October 2004, where Automated Workzone Information Systems (AWIS) was used to yielded a 50% reduction

in maximum average peak delay [11].  However, planners and engineers currently do not possess the ability to predict the impacts of ITS applications, such as AWIS, in the field on any given work zone, nor do they have the ability to predict subsequent reductions in delay [85].

Chen [86] explains that traffic simulation, specifically microsimulation, can be used to aid the accurate and optimal implementation of ITS solutions to work zones by predicting the impacts of various ITS solutions on a work zone.  Vehicles respond to ITS solutions on a "per vehicle" basis, therefore microsimulation could provide the optimal platform to identify the aggregate effects of an ITS work zone solution on a work zone.

In the Traffic Analysis Toolbox Volume IX [8], Wunderlich et al explains that microscopic modeling can also be used to manage traffic, address constructability, and staging.  Corridor and network management strategies can be effective in improving traffic flow through and around a work zone.  Microscopic models have the ability to model corridor and network management strategies and analyze their impacts, whereas other models lack this ability.  These strategies could be very effective in improving traffic flow through and around a work zone.  Using microscopic simulation, the optimal solution or set of solutions for each work zone can be identified and employed.

In addition, Wunderlich et al [8] explained that microscopic models are created using a higher level of detail than other traffic flow models, and therefore have the ability to provide a more detailed analysis than other traffic flow models.  Microscopic models,

however, require more input data and are more complex than other modeling methods. To accurately incorporate the effects of new ITS and traffic management strategies, the equation governing some microscopic models must be altered, and in some cases, the structure of these equations is changed.

An optimal work zone model should be a microscopic model that is able to model all ITS technologies and corridor and network management strategies. The effects of new ITS solutions and traffic management strategies should be easily calibrated and added to this model. The model structure should be such that new traffic management strategies can be incorporated and modeled easily and accurately with little to no changes in the actual model structure. The model should respond accurately to new traffic management solutions without challenging or compromising the integrity of the model structure.

Current microscopic models lack the ability to model all ITS technologies and corridor and network management strategies, and calibrating these models to include new ITS technologies can be a long an involved process that sometimes challenges the model's structure. In some instances, researchers have had to develop entirely new equations to model the impacts of one ITS solution. A new adaptable model should be created in a way such that new and developing ITS technologies and other traffic alleviation strategies can easily be incorporated.

Calibrating, assessing, and adding the impacts of new technologies (ITS), design elements (such as adjusting taper length, altering closure strategy, or modifying signage), and other traffic management strategies can be achieved in Modified Field Theory by adding, calibrating, or changing a perceived force, all without changing the model structure. The model structure of field theory has a driver perceiving a stimulant and then reacting to the perceived force, which makes adding new stimulants (such as a different pavement marking, or new ITS technology) to the model simple.

Moreover, Modified Field Theory could directly model the impacts of existing roadway elements and roadway phenomena. Modified Field Theory could directly model how roadway signage affects the driver (some signage makes drivers more "alert, i.e. "School Zone" signs may provoke a driver to slow down and cautiously scan the road for pedestrians. This can be modeled in Modified Field Theory by simply expanding the driver's perception bubble once the proper signage has entered the bubble. Some signage, such as VMS boards on freeways that indicate which lanes are flowing poorly, or signage indicating a merge or lane closure, may provoke a driver to look for a lane-change opportunity. This can be achieved by adding a repelling force in the closing lane once this signage has entered the driver's perception bubble. Also, this signage could change a driver's perception bubble, causing the driver to scan more frequently for a gap or further down a lane). By directly integrating elements such as the impacts of signage on a driver, the model becomes more "true to life."

In terms of developing an accurate work zone microscopic model, future work zones will possibly contain other external stimuli, such as ITS or signage, which need to be accounted for. Modified Field Theory could accurately predict the impact of an ITS technology, such as AWIS, in a work zone.

### 4.4.2 Automated vehicles and mixed-mode traffic

Algorithms will be established that govern automated vehicles, from how they sense other objects on the roadway (roadway scanning), communications and processing time required (perception-reaction time), and algorithms that define how the automated vehicle will react in certain scenarios (desired response). Modified Field Theory's framework and model architecture can be used directly to model automated vehicles. The task of customizing equations for automated vehicles would be simpler than adding a driving population, since standards for roadway scanning and predicted reaction will already be defined.

### 4.4.3 Compromised driving

Driving under the influence of alcohol or other drugs, distracted driving, and "road rage" impact roadway and traffic conditions negatively. Traffic laws such as the no texting laws or DUI laws have been put into place to try and mediate these problems, and officers are allowed to write citations for drivers who drive too aggressively. Despite efforts to remove these compromised drivers from the road, they still exist. It is known that distracted and compromised drivers have negative impacts on safety, but recent

studies have shown that they also have a negative impact on traffic flow, creating delays and adding to congestion [87].

The impacts of a driver whose abilities have been compromised due to frustration, alcohol, or distractions have gone relatively unaddressed in microscopic modeling, especially in assessing their impacts on traffic flow conditions and operations. Some studies have attempted to asses these impacts, but have conflicting results. Some studies that attempted to model aggressive drivers yielded a high flow rate for aggressive drivers, but with a low stability in overall traffic flow [88], whereas other studies indicate that specific aggressive driver behavior is associated with actual and perceived delays in travel and congestion for all roadway users [89]. Most main stream traffic simulation programs, such as CORSIM and VISSIM, lack the ability to directly input a compromised driver into a model. However, with Modified Field Theory, it would be possible to model these drivers and predict their potential impacts on traffic conditions.

Distracted and intoxicated drivers could be modeled by decreasing the 'refresh rate' of the perception bubble. Distracted drivers don't observe roadway hazards as often as they should because of their distraction, causing a delay in reaction time. By slowing down how often the perception bubble updates, a situation could be created where the distracted driver is aware of a stimulus at the 'last minute,' (when the stimulus is within close proximity of the subject vehicle), causing the subject driver to perform an evasive maneuver (such as slamming on their brakes or veering into another lane), similar to what

can be seen in the field. Distractions can be calibrated and modeled, and the impacts of distracted drivers on traffic flow could be predicted.

A driver's frustration, or "road rage," can not only be modeled in Modified Field Theory, but it can be predicted. When a driver experiences one or two stimuli at a time, he can analyze the situation and react appropriately to those stimuli. When surrounded by multiple stimuli, a driver may begin to feel overwhelmed, and may have a harder time coming up with an appropriate reaction for these stimuli. If the forces associated with those multiple stimuli are intense, the driver will almost certainly feel pressured to make an immediate, and sometimes impulsive, decision. If a driver finds themselves in a situation where they are surrounded by pressures and are unable to balance them, or if the driver is stuck in stop-and-go traffic and cannot equalize the force from their desired speed, or a driver is in a lane that closes yet feels pressure from surrounding vehicles that inhibits him from merging, the driver may feel 'under pressure' and become aggravated. This pressure, over time, may lead to a driver behaving impulsively, erratically, or exhibiting other characteristics associated with "road rage."

In Modified Field Theory, forces associated with stimuli are modeled. If a driver is surrounded by stimuli and forces, and cannot remove himself from the situation, the driver will experience the "pressure" from these forces over a prolonged period of time. If properly calibrated, this pressure felt over time could help predict locations or areas where drivers feel uncomfortable or may succumb to "road rage." In this way, Modified Field Theory can predict instances where "road rage" can be provoked, and if certain

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work zone set-ups will create areas, either in the merge or the queue, where "road rage" could occur.  This, theoretically, could allow engineers to avoid creating set-ups that create excessive instances of "road rage."   Figure 18 below depicts an instance where "road rage" might be provoked.
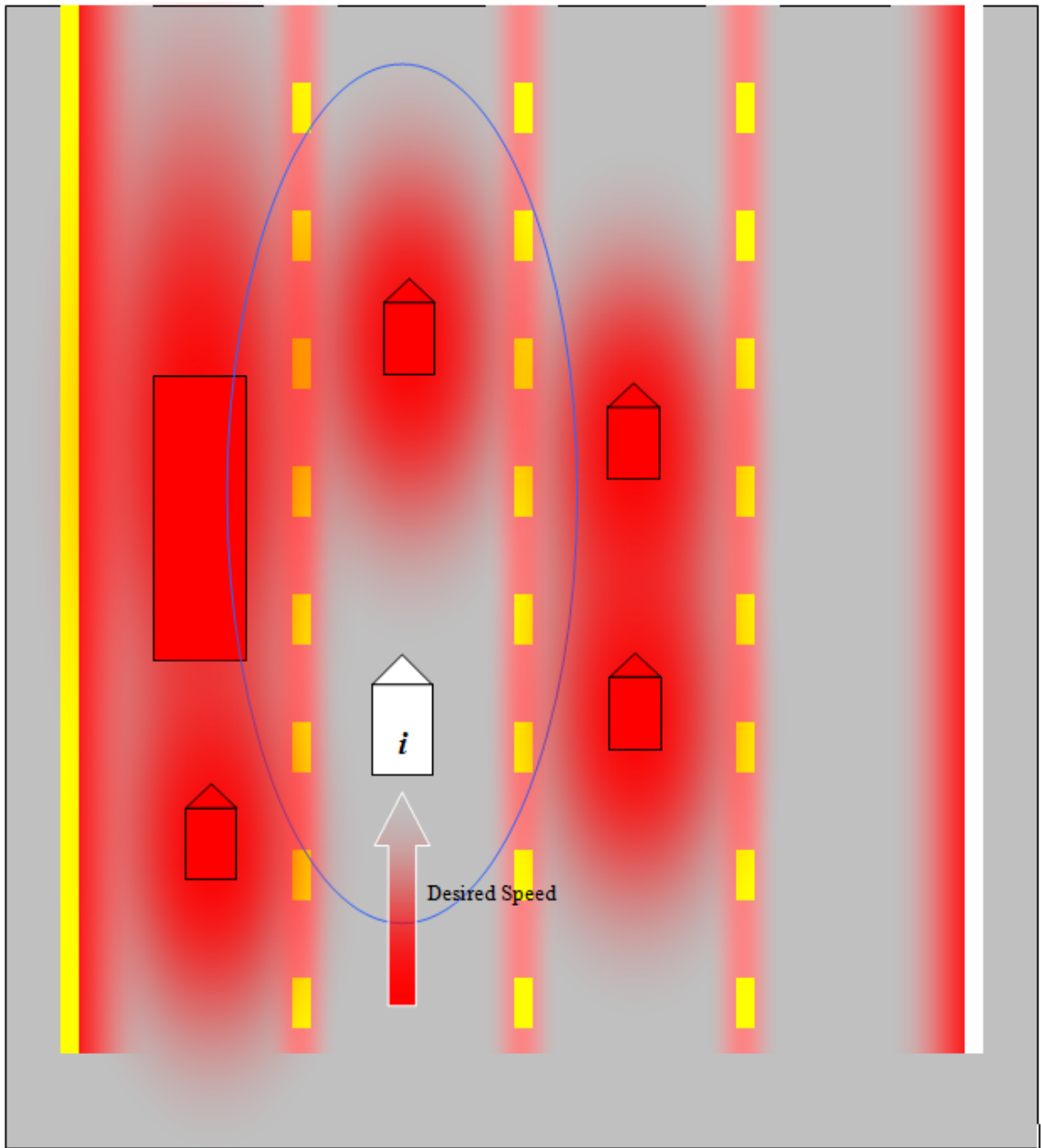
**Figure 18: Sample scenario where "road rage" may be provoked**

### 4.4.4   Route choice

Theoretically it is possible to model route choice into Modified Field Theory.  An algorithm, based on varying schedules and value of time functions, can be made to determine and calibrate a "quickest route" or "cheapest route" force to be integrated into Modified Field Theory.  If correctly calibrated and applied, this would grant planners the ability to predict changes in route choice due to congestion or a driver's desire to keep moving.  This algorithm could be based on current equations that attempt to monetize travel time, since these equations already begin to establish the "apples to apples" comparison that Modified Field Theory (using money rather than force).

Alternatively, some driver's would rather spend a few more minutes traveling to avoid traffic jams.  Although the route might be quicker and shorter with the added delays of congestion, some drivers choose to take an alternate route to avoid sitting in traffic.  Using the Desired Speed force in Modified Field Theory, this phenomenon can be calibrated and added to the model, granting planners the ability to predict the number of routes that will change due to a driver's desire to keep moving.

### 4.4.5   Freeway work zones with lane closure

Some freeway work zones close one lane at a time.  The lane closure forces vehicles traveling in the closed lane to merge onto an available lane prior to the start of the taper zone.  Some vehicles merge immediately, whereas others wait until they cannot travel any further without merging.  To model the lane closure, a work zone

force will be added in the lane that is closing, forcing vehicles traveling in the closing lane to merge to another lane.

Each work zone on a freeway contains a traffic control zone. The traffic control zone consists of an Advanced Warning Area which tells traffic what to expect ahead (this is where signage for the work zone begins, informing the driver about the presence of the work zone), the Taper Area which moves traffic from its normal path (this is the area where cones are laid out, moving traffic over), a Buffer Area which provides workers and traffic additional space for protection within the work zone, a Shadow Vehicle Area which provides a temporary barrier for worker safety, the actual Work Area which is set aside for workers, equipment, and material storage, and then another Taper Area to allow traffic to resume it's normal flow [90]. The portions of the traffic control zone that affect a merging vehicle are the Advanced Warning Area and the Taper Area, therefore, they will be included in this model.

Figure 19 below illustrates how this work zone force will be added to Modified Field Theory. Signage begins in the Advanced Warning Area, alerting the driver that the Taper Area will begin in "XX" miles. A force begins to develop in the closing lane, growing with intensity as the driver approaches the Taper Area. Other forces, such as the desire to stay in one's lane or the presence of other vehicles, might overpower the work zone force initially; however the growing intensity of the work zone force will eventually cause the vehicle to merge.

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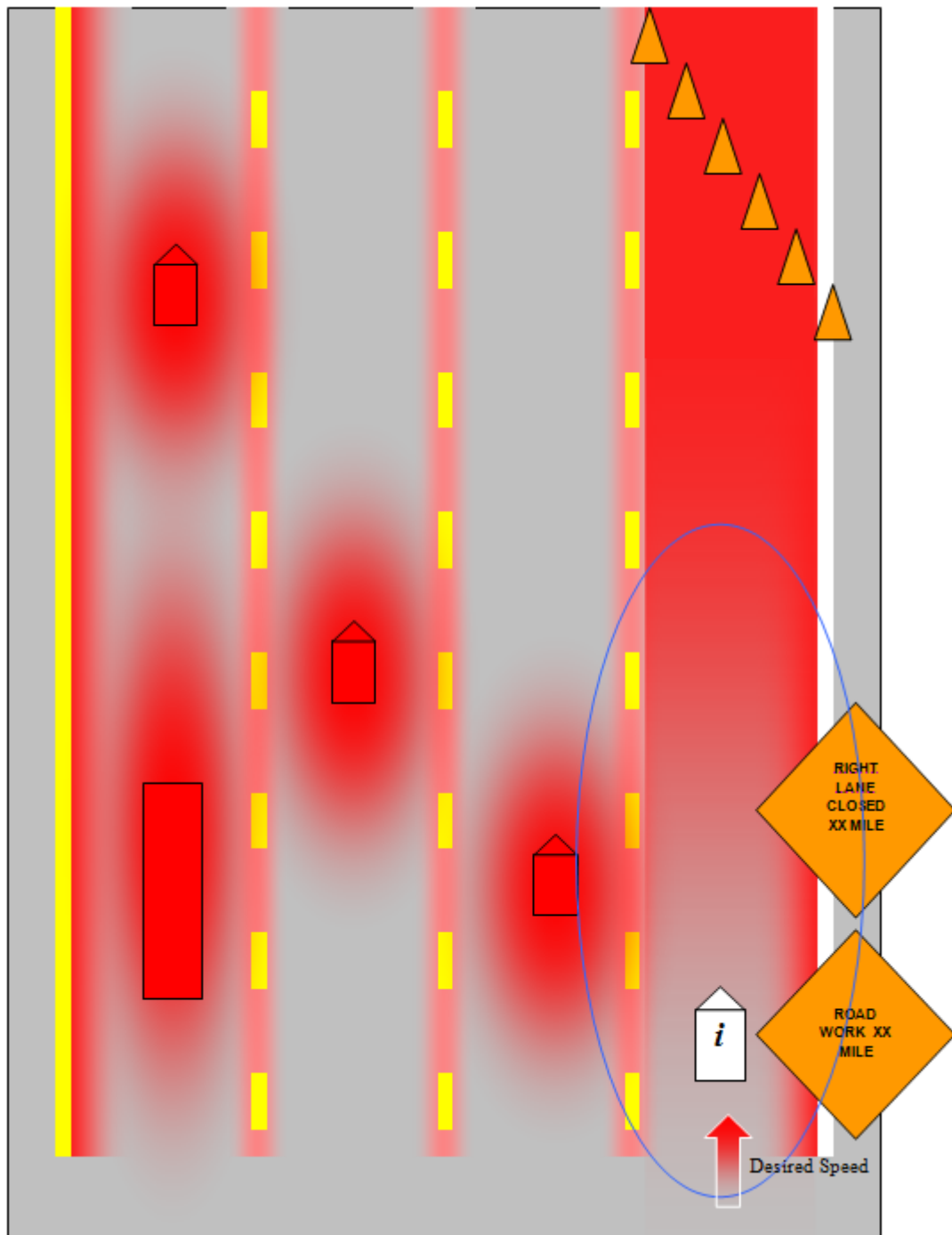
**Figure 19: Modified Field Theory with added work zone force**

Previous studies have shown that a vehicle over time will accept a gap that it has previously rejected [17]. Figure 20 shows this phenomena using Modified Field Theory. Vehicle "*i*" is traveling in an Advanced Warning Area towards a work zone alongside two vehicles in the neighboring lane. An ambient force, caused by the presence of the two other vehicles, can be observed in the gap between them. In the diagram to the left, vehicle "*i*" has just entered the Advanced Warning Area, and the work zone force is far less intense than the force created by the presence of both vehicles to the left and the force keeping vehicle "*i*" from crossing the dotted line. However, in the diagram to the right, vehicle "*i*" is much closer to the work zone, and the work zone force is greater than all other forces combined. In the diagram to the right, the work zone force is much greater than the ambient force in the gap, and vehicle "*i*" will merge between the two vehicles despite having rejected that gap previously.

Additionally, in Figure 20, the influence of work zone force on a vehicle's speed can be seen. In the diagram to the left, the Desired Speed force of vehicle "*i*" is far greater than the work zone force, so the Desired Speed will prevail and will push vehicle "*i*" forward. However, in the diagram to the right, the work zone force is greater than the force of Desired Speed, so if vehicle "*i*" were to remain in its current lane it would slow down. With multiple forces experienced by a vehicle, if the gap and work zone forces are intense and the work zone force does not overpower the force in the gap, it might overpower Desired Speed and cause the vehicle to slow down.

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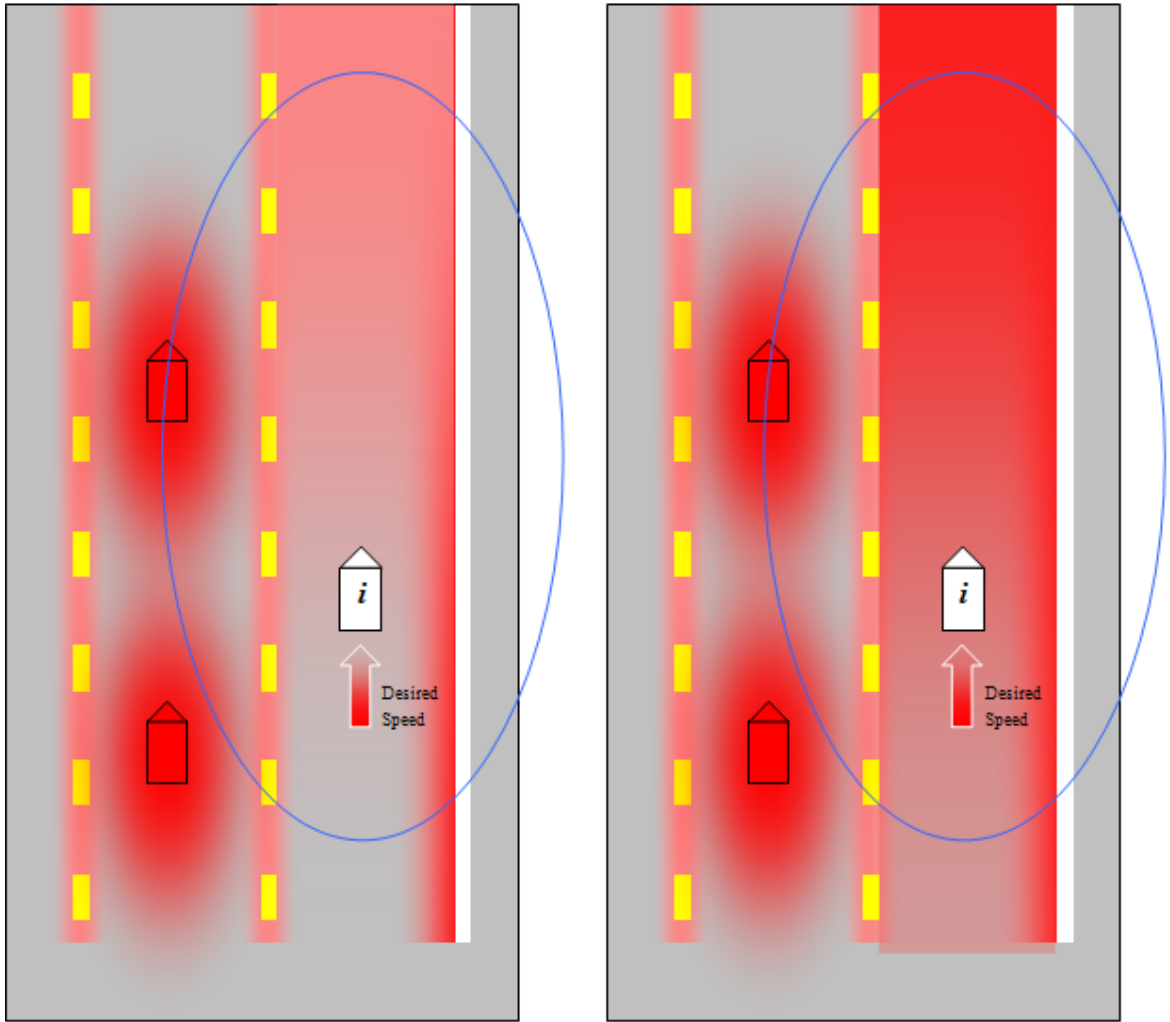
**Figure 20: Vehicle *i* traveling in the advanced warning area far from the taper zone (Left) and closer to the taper area (Right)**

## 4.5 Model Algorithms (Cognitive Map)

This section defines the algorithms used to model the force each roadway stimulus has on the driver. These forces exist only in the driver's cognitive map. Forces are modeled using vectors and vector fields. The total force from all perceived stimuli at time $T = t$ is the total impact on driver $i$ at time $T = t$. Resolving these vectors through Force Field Analysis yields the desired driver reaction. If the desired driver reaction is greater than the driver's threshold, the driver reacts.

Forces emanate from the center of each stimulus (making the observed center of the stimulus $(0, 0)$ for each set of equations). In many cases, the force field surrounding each stimulus is represented using a vector field that emanates from the center of the stimulus.

Every equation has a calibration factor, c. This calibration factor is used to calibrate the magnitude of one force vector relative to the magnitude of other force vectors for other stimuli. For example, consider a driver who is twice as stressed by their proximity to other vehicles than by not traveling their desired speed; their "c" calibration factor for desired speed would be half that of proximity. Without the "c" calibration factors, there is no way to adjust the magnitude of these vectors in relation to each other. During model calibration, these "c" calibration factors are the main variables being adjusted.

### 4.5.1 *Threshold*

Drivers do not react to every force experienced; this is because every driver has a minimum required force to elicit a reaction.  This minimum force required, positive or negative, to elicit a response from a driver is defined as the driver's Threshold.  Threshold will vary from driver to driver.

The Threshold ensures that the model does not predict driver reactions for the small desired reactions, making the model more 'true to life'.  The Threshold also grants the model the ability to distinguish between drivers who are unwilling to yield to certain stimuli (and may be considered 'reckless') and those who simply did not observe a stimulus (i.e. a distracted driver who scans portions of the roadway infrequently, therefore not perceiving crucial stimuli that would otherwise alter driver behavior).  For instance, some drivers traveling in a left hand lane on a freeway will move over when another vehicle tailgates them, whereas other drivers do not; some drivers do not move over because they haven't checked their rear-view mirror and are unaware that a vehicle behind them, some do not move because they don't have an opportunity to safely move to the right lane (other forces are inhibiting them from moving), and some do not move because they do not feel that they need to (their minimum threshold to elicit a reaction has not been breached).

Without the Threshold, all drivers in this model will seldom deviate from optimal, adjusting speed and course for all events and all stimuli observed.

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### 4.5.2 Desired speed

The Desired speed force for driver *i* is created by the discrepancy between the driver's perceived speed and desired speed at a given point in time. The desired speed force vector, $\vec{F}_{des}$, will be calculated as the difference between the desired speed vector, $\vec{V}_{des}$, and the driver's speed vector, $\vec{V}_i$:

$$\vec{F}_{des} = c_{des}(\vec{V}_{des} - \vec{V}_i)$$

### 4.5.3 Other vehicles on the roadway

Consider another vehicle on the roadway, vehicle *pc*. The total force vector, $\vec{F}_{total,pc}$, created by other vehicles, experienced by driver *i* at any given time, is the sum of forces created by proximity to vehicle pc, $\overline{F}_{proximity,pc}$, (the physical location of the observed vehicle in relation to the subject vehicle, vehicle *i*) and those created by differences in the velocities of vehicle *i* and vehicle *pc* vectors, $\vec{F}_{v,pc}$:

$$\overline{F}_{total,pc} = \overline{F}_{V,pc} + \overline{F}_{proximity,pc}$$

### 4.5.3.1 Proximity

For algorithms within the Cognitive Map in Modified Field Theory, the X and Y axis are always centered (0, 0) at the center of the stimulus. In part, this is what gives

MFT's architecture the flexibility to add new stimuli without altering the fundamental algorithms. If the X and Y axis were centered on vehicle *i* then many of these equations would not work. Figure 21 below shows the X and Y axis, centered on stimulus vehicle *pc*. In this figure, vehicle *i* is located at point (x, -y).
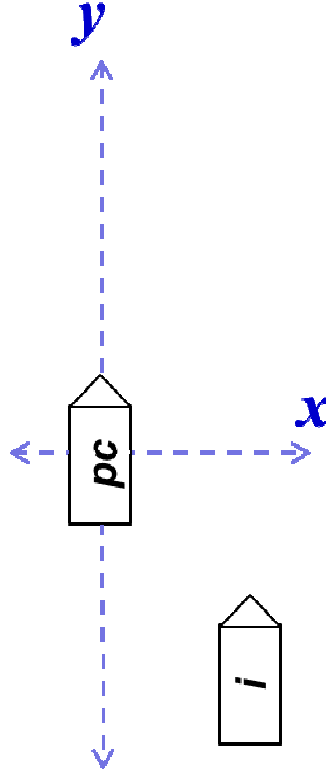


**Figure 21: X- and Y- axis centered on the stimulus vehicle *pc*.**

The force created by proximity to vehicle pc, $\bar{F}_{proximity,pc}$, is found using the vector field equation:

$$\bar{F}_{proximity,pc} = c_{x,pc} \cdot \frac{m_{pc} \cdot x}{(x^2 + y^2)} \hat{i} + c_{y,pc} \cdot \frac{n_{pc} \cdot y}{(x^2 + y^2)} \hat{j}$$

where:

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$\vec{F}_{proximity, pc}$ = The force experienced by driver $i$, due to the presence of the stimulus

$pc$ (passenger car) when driver $i$ is located at coordinates $(x, y)$ on a

plane where the origin $(0, 0)$ is located at the center of the stimulus,

$pc$. **[m/seconds$^2$]**

- This force is experienced after driver $i$ has observed the

  stimulus

- When no other stimulus is observed by driver $i$, and when the

  force caused by differences in the velocity vector does not

  influence driver $i$ (when driver $i$ and observed stimulus $pc$ are

  traveling at the same speed and in the same direction), this

  force is equal to the acceleration vector of driver $i$ in response

  to the presence and proximity of stimulus $pc$

$x$ = x-dimensional location of driver $i$ in relation to stimulus $pc$ on a coordinate

plane where the origin $(0, 0)$ is located at the center of stimulus $pc$ **[m]**

$y$ = y-dimensional location of driver $i$ in relation to stimulus $pc$ on a coordinate

plane where the origin $(0, 0)$ is located at the center of stimulus $pc$ **[m]**

$m_{pc}$ = calibration factor used to modify the shape of the vector field in the x-

direction **[m$^2$/seconds$^2$]**

$n_{pc}$ = calibration factor used to modify the shape of the vector field in the y-

direction **[m$^2$/seconds$^2$]**

$c_{x,pc}$ = calibration factor used to adjust the magnitude of the x-directional force,

exerted by stimulus *pc*, relative to the x-directional force exerted by other

stimuli (for example, $c_{x,\text{roadway obstruction}} > c_{x,\text{dotted lane markation}}$)

$c_{y,pc}$ = calibration factor used to adjust the magnitude of the y-directional force,

exerted by stimulus *pc*, relative to the y-directional force exerted by other

stimuli (for example, $c_{y,\text{roadway obstruction}} > c_{y,\text{dotted lane markation}}$)

As previously stated, $c_{x,pc}$ and $c_{y,pc}$ are necessary in modeling a network

containing multiple stimuli.

The vector field generated by this equation radiates from the center. The shape of

the vector field is determined by calibration factors $m_{pc}$ and $n_{pc}$. It is assumed that,

because a passenger car is longer than it is wide, that $n_{pc}$ is larger than $m_{pc}$. Figure 22

below shows the vector field when that $n_{pc} = m_{pc}$, and Figure 23 shows the vector field

where that $n_{pc}$ is larger than $m_{pc}$. It's important to note how the vectors that comprise this

vector field change in both magnitude and direction when $n_{pc}$ and $m_{pc}$ are adjusted.
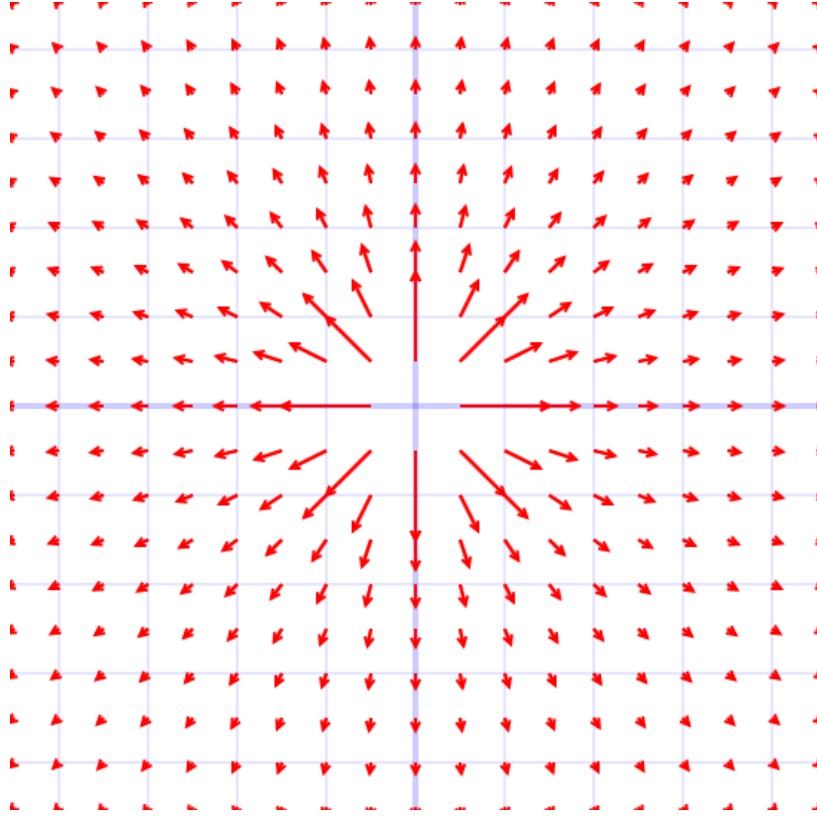
**Figure 22: Proximity force vector field for stimulus** *pc* **when** $n_{pc} = m_{pc}$
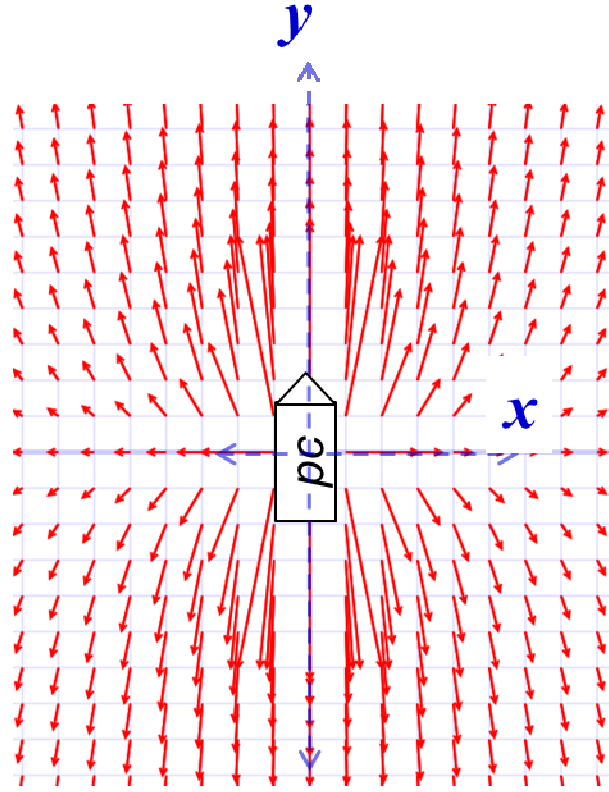
**Figure 23: Proximity force vector field for stimulus *pc* when $n_{pc}$ = 5($m_{pc}$).**

### 4.5.3.2  Difference in velocity vectors

$\overline{F}_{V,pc}$ , the force vector that results from the differences in velocities between the stimulus vehicle (vehicle *pc*) and the subject vehicle (vehicle *i*), is dependent on the distance between the two vehicles, *d*, the velocity vector of the stimulus (vehicle *pc*), $\vec{V}_{pc}$, and the velocity of the subject vehicle (vehicle *i*), $\vec{V}_i$ . This force vector can be found using the equation:

$$\overline{F}_V = c_{v,pc} \frac{\overline{V}_{pc} - \overline{V}_i}{d^2}$$

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where:

$\overline{F}_{V,pc}$   =   The force vector that results from the differences in velocities

between the stimulus vehicle (vehicle $pc$) and the subject vehicle

(vehicle $i$).   **[m/seconds$^2$]**

$\vec{V}_{pc}$   =   The velocity vector of the stimulus (vehicle $pc$).   **[m/seconds]**

$\vec{V}_i$   =   The velocity vector of the subject vehicle (vehicle $i$). **[m/seconds]**

$d$   =   The distance between the two vehicles.   **[m]**

$c_{v,pc}$ =   The calibration factor used to adjust the magnitude of the velocity

force relative to the force exerted by other stimuli.

Including a distance term in the velocity equation does two things. 1—it makes this force greater when two objects are closer, and 2—it avoids problems experienced by other models, such as the earlier GM models, where velocity terms were not bound by relative distance and vehicles were stopping inside each other rather than one behind the other.

Modified Field Theory algorithms were constructed such that they would avoid the problems encountered in other vector-based models. Unlike Wang and Wu (2003) [64], MFT will not predict that vehicles accelerate towards each other when velocity vectors are skewed. Quite the opposite, when velocity vectors indicate a potential crash could occur, MFT shows a strong desire to alter course from both drivers. In the

presence of other perceived stimuli (such as other vehicles), this course change would

navigate around other vehicles or simply slow down. [64]


To avoid this problem, MFT subtracts the velocity vector of vehicle *i* from the

velocity vector of vehicle *pc.* Figure 24 below depicts the scenario of a head-on collision

and shows how the resulting force vector on vehicle *i* created by the force associated with

differences in velocity will be an extreme force that would stop the collision. Figure 25

shows that, by subtracting the vectors, even when velocity vectors are skewed (and are

not head-on), if the vectors indicate a potential or eventual collision and the driver

perceives it, driver *i* will react appropriately to avoid the collision (and not steer and

speed into the collision). In Figure 25, the velocity vectors will eventually intersect,

causing a collision, if the driver of vehicle *i* does not react. Figure 26 illustrates how a

driver would react in this scenario according to MFT. [Note: in vector addition, it is

easier to depict adding a negative vector than subtracting a positive vector]
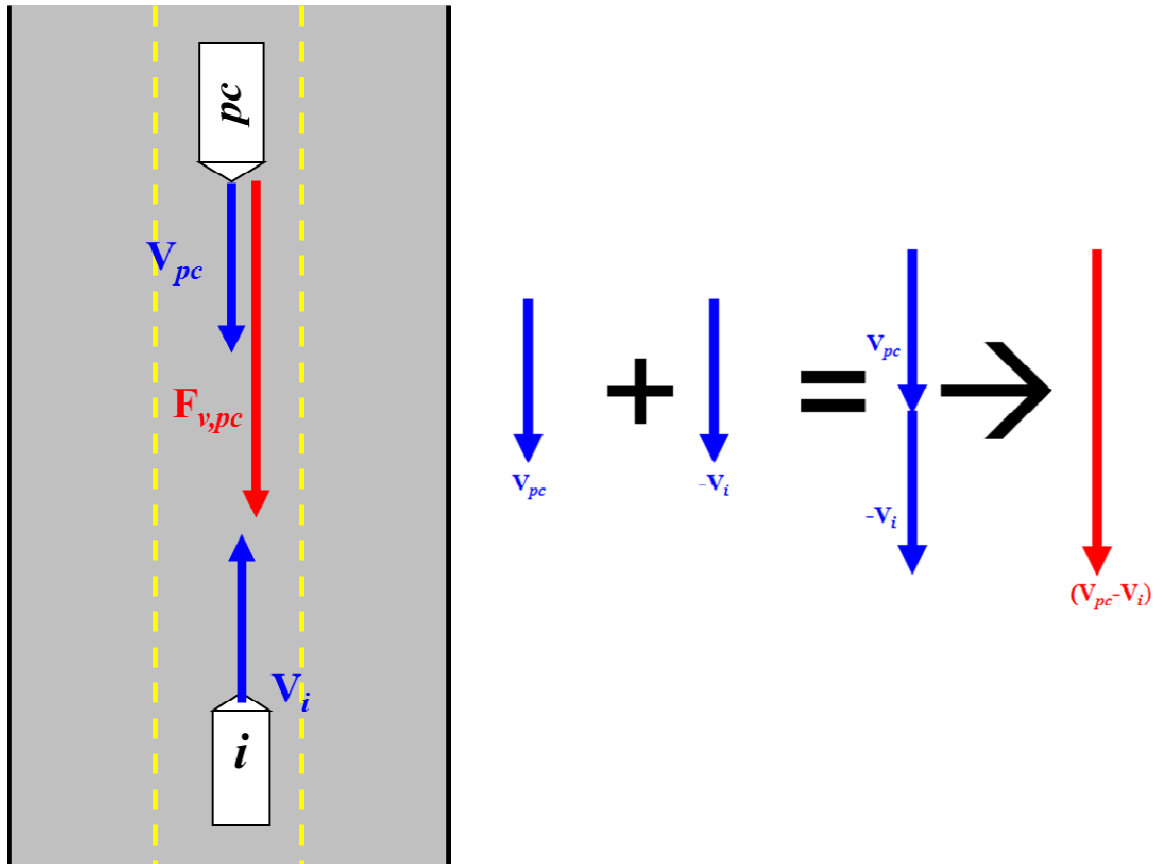
**Figure 24: Velocity force vector in a head-on scenario.**
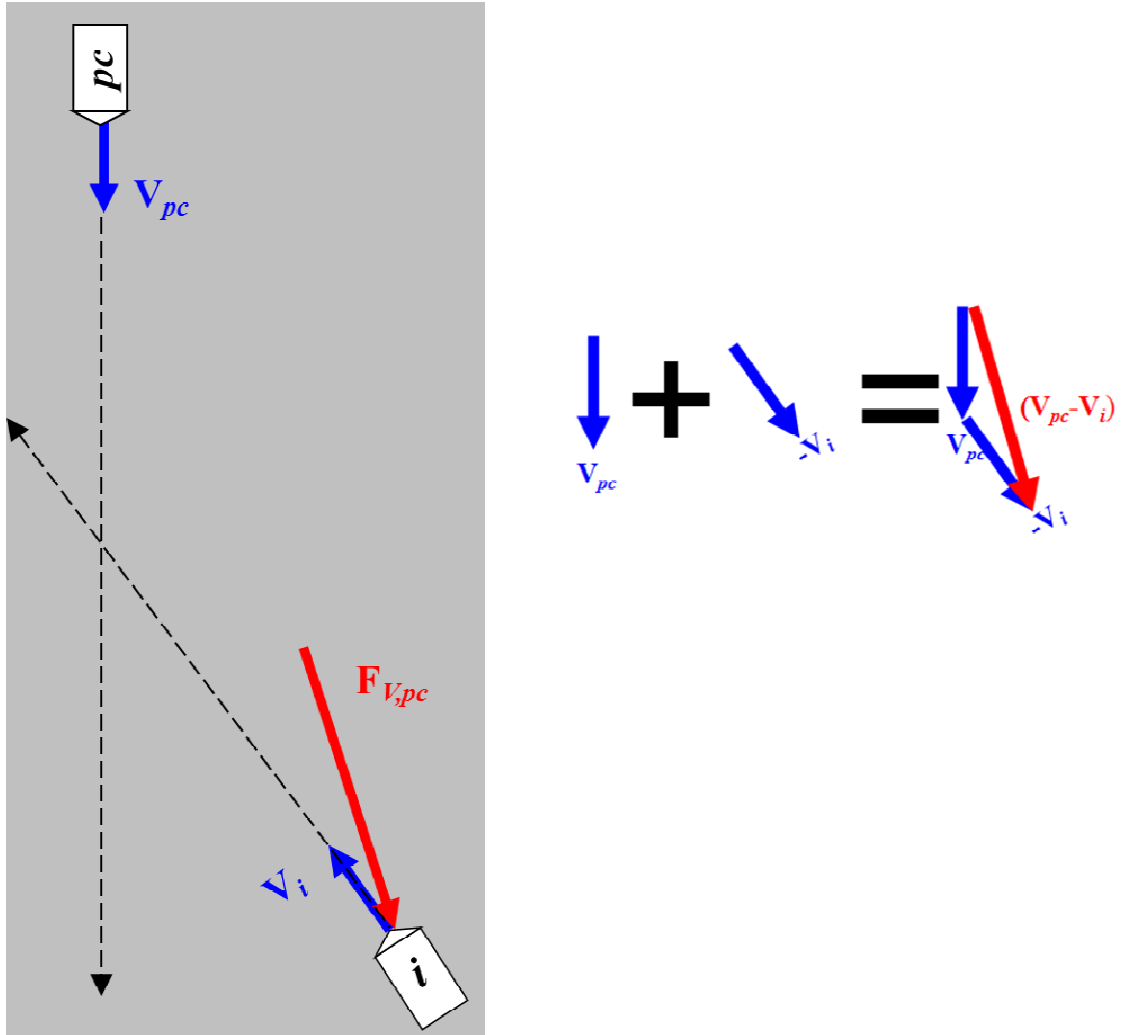
**Figure 25: Velocity force vector in non-head-on scenario with impending collision**

### 4.5.4   Fixed objects on the roadway

A fixed object (such as a pothole or a road cone) has no velocity; however, proximity is still of concern.  The proximity force vector field for fixed objects within the roadway will be the same equation as for proximity to other vehicles, given in Chapter 4.4.3.  The identifier "pc" will be changed to reflect the ID of the fixed object.

### 4.5.5  Delineation

Delineation, such as pavement markings (dotted and dashed yellow lines, solid white lines, and other paint-based delineators) and work zone delineation (road cones, barrels, jersey barriers, and other 3-dimensional delineators) serves to push vehicles away from the line.  Some delineation (such as jersey barriers) can cause deceleration. Delineators are fixed objects, and forces experienced by delineators are caused by proximity to the delineator.

The equation for the force field created by roadway delineation is:

$$\bar{F}_{proximity,dl} = c_{x,dl} \cdot \frac{m_{dl}}{(x)}\hat{i} + c_{y,dl} \cdot n_{dl}\hat{j}$$

where:

$\bar{F}_{proximity,dl}$ =  The force experienced by driver $i$, due to the presence of the stimulus

$dl$ (roadway delineation) when driver $i$ is located at coordinates ($x$, $y$) on a plane where the origin (0, 0) is located at the center of the stimulus, $dl$. **[m/seconds$^2$]**

$x$ =   x-dimensional location of driver $i$ in relation to stimulus $dl$ on a coordinate plane where the origin (0, 0) is located at the center of stimulus $dl$ **[m]**

$m_{dl}$ =   calibration factor used to modify the shape of the vector field in the x-direction **[m$^2$/seconds$^2$]**

$n_{dl}=$ calibration factor used to modify the shape of the vector field in the

y-direction **[m²/seconds²]**

$c_{x,dl}=$ calibration factor used to adjust the magnitude of the x-directional

force, exerted by stimulus *dl*, relative to the x-directional force

exerted by other stimuli (for example, $c_{x,\text{roadway obstruction}} > c_{x,\text{dotted lane}}$

$_\text{markation})$

$c_{y,dl}=$ calibration factor used to adjust the magnitude of the y-directional

force, exerted by stimulus *dl*, relative to the y-directional force

exerted by other stimuli (for example, $c_{y,\text{roadway obstruction}} > c_{y,\text{dotted lane}}$

$_\text{markation})$

If the roadway delineation causes deceleration (as it sometimes does in the case of jersey barriers and barrels), the coefficient $n_{dl}$ can be adjusted such that the force pushes "backward". Figure 26 shows the force fields where $n_{dl} = 0$ and $n_{dl} > 0$.
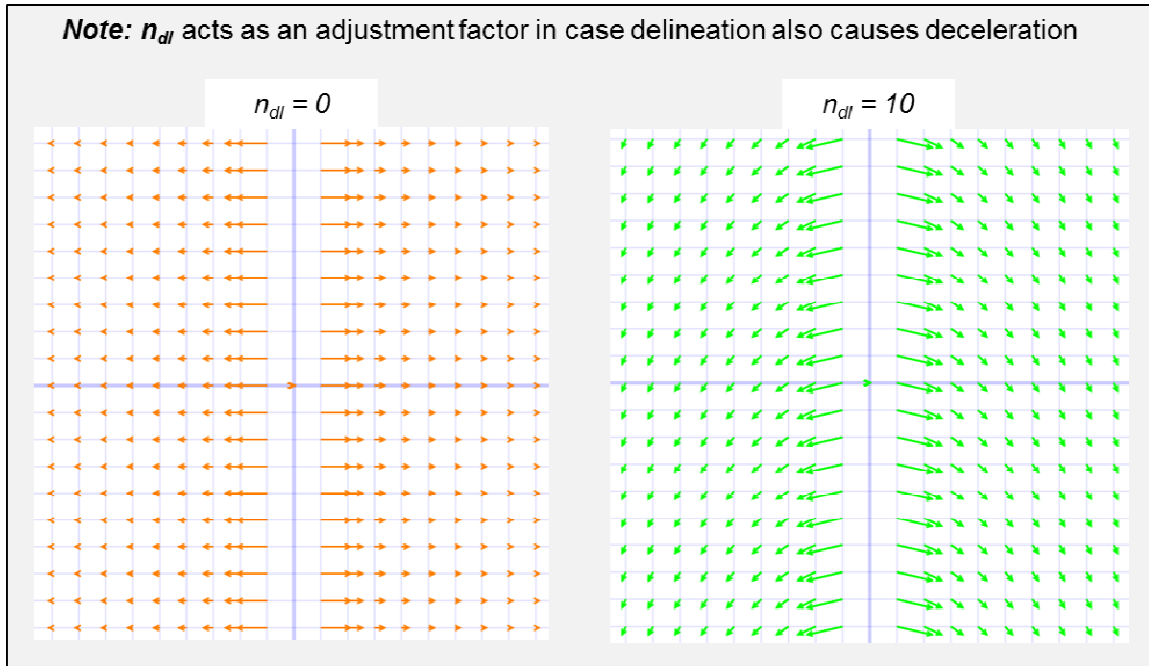
**Figure 26: Force Fields for roadway delineation (including pavement markings). If the delineation causes deceleration, $n_{dl} > 0$**

### 4.5.6 *Work zone signage (W4-2)*

The W4-2 signage is often used in work zones experiencing lane closure. This signage is typically placed between ¼ and ½ mile from the start of the taper zone, to warn drivers of the upcoming lane closure. After drivers pass this signage, they feel a growing need to merge from the closing lane. They may not be able to see a work zone, but in their cognitive maps, they know one is approaching. Figure 27 shows W4-2 signage.
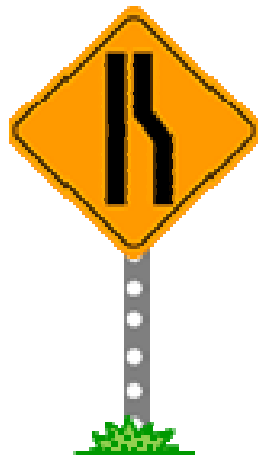


**Figure 27: W4-2 work zone signage, often used to indicate lane closure**

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The force generated by the W4-2 sign is only perceived by driver traversing the closing lane. This force is not perceived by drivers who have already merged from the closing lane into the neighboring lane, or by drivers who were already traveling in the non-closing lane. Additionally, once the driver has passed the start of the taper zone, no force will be felt by this signage. To rephrase succinctly, the force field created by this signage is bound to the length of roadway before the start of the taper, only in the closing lane.

The force field generated by this signage can be calculated using the equation:

$$\vec{F}_{w4-2} = c_{x,w4-2} \cdot \frac{m_{w4-2}}{(x)} \hat{i} + c_{y,w4-2} \cdot \frac{n_{w4-2}}{(y-d_{taper})} \hat{j}$$

where:

$\vec{F}_{W4-2} =$      The force experienced by driver $i$, due to the presence of the stimulus *W4-2* when driver $i$ is located at coordinates $(x, y)$ on a plane where the origin $(0, 0)$ is located at the center of the stimulus, *W4-2*. **[m/seconds²]**

$x =$      x-dimensional location of driver $i$ in relation to stimulus *W4-2* on a coordinate plane where the origin $(0, 0)$ is located at the center of stimulus *W4-2* **[m]**

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$y =$      y-dimensional location of driver $i$ in relation to stimulus *W4-2* on a coordinate plane where the origin (0, 0) is located at the center of stimulus *W4-2* **[m]**

$d_{taper} =$      y-dimensional distance between the stimulus *W4-2* and the start of the taper zone **[m]**

*(Note: if this distance is posted on the W4-2, ex. "merge in ¼ mile," then use the distance reported, as this is the distance to the taper as perceived by the driver)*

$m_{W4-2} =$      calibration factor used to modify the shape of the vector field in the x-direction **[m²/seconds²]**

$n_{W4-2} =$      calibration factor used to modify the shape of the vector field in the y-direction **[m²/seconds²]**

$c_{x,W4-2} =$      calibration factor used to adjust the magnitude of the x-directional force, exerted by stimulus *W4-2*, relative to the x-directional force exerted by other stimuli (for example, $c_{x,roadway\ obstruction} > c_{x,dotted\ lane\ markation}$)

$c_{y,W4-2} =$      calibration factor used to adjust the magnitude of the y-directional force, exerted by stimulus *W4-2*, relative to the y-directional force exerted by other stimuli (for example, $c_{y,roadway\ obstruction} > c_{y,dotted\ lane\ markation}$)

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The vector field generated using this equation is shown in Figure 28. The W4-2 signage is shown at the origin (0, 0).
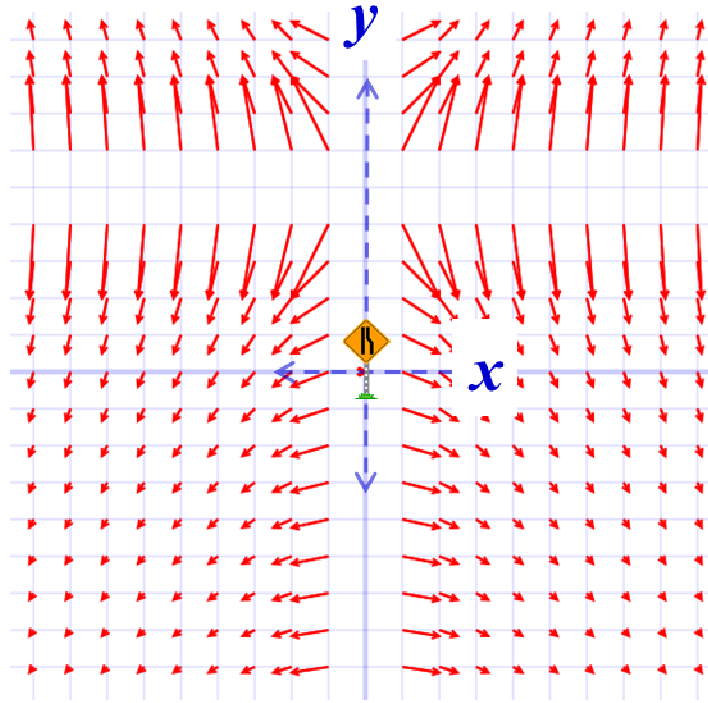


**Figure 28: Force field generated by W4-2 signage.**

From a first glance, this equation might not seem like a good fit for the W4-2 sign. The objective is to create a force field that pushes driver *i* over to the adjacent lane and slows them if they remain in the lane, and that gradually grows as the driver approaches the start of the taper zone. That is precisely what this vector field is doing. Figure 29 overlays the force field generated by the W4-2 onto a segment of roadway. From this overlay, it can be seen that the force gradually grows until the start of the work zone. Remember that this force field is bound only to the closing lane, only for roadway before the start of the taper zone.
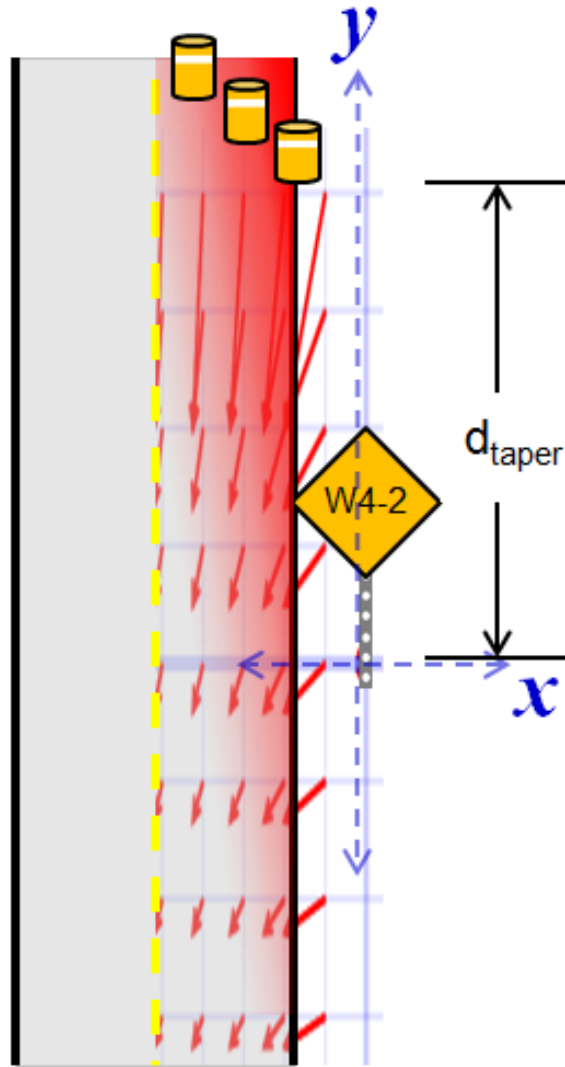
**Figure 29: W4-2 force field on a segment of freeway containing a work zone.**

### 4.5.7 *Desired Lane*

The desired lane force is the only strictly attractive (rather than repulsive) force field in this dissertation. The desired lane pulls the driver towards the center of the lane that they want to be in.

The equation for the desired lane force field is:

$$\vec{F}_{desiredlane} = c_{x,desiredlane} \cdot m_{desiredlane}(-x)\hat{i} + c_{y,desiredlane} \cdot n_{desiredlane}\hat{j}$$

where:

$\vec{F}_{desiredlane} =$    The force experienced by driver $i$ attracting the driver toward the center of their desired lane. Driver $i$ is located at coordinates $(x, y)$ on a plane where the origin $(0, 0)$ is located at the center of the desired lane. **[m/seconds²]**

$x =$    x-dimensional location of driver $i$ on a coordinate plane where the origin $(0, 0)$ is located at the center of the desired lane **[m]**

$y =$    y- dimensional location of driver $i$ on a coordinate plane where the origin $(0, 0)$ is located at the center of the desired lane **[m]**

$m_{desiredlane} =$    calibration factor used to modify the shape of the vector field in the x-direction

$n_{desiredlane} =$    calibration factor used to modify the shape of the vector field in the y-direction

$c_{x,desiredlane} =$    calibration factor used to adjust the magnitude of the x-directional force, exerted by the desired lane, relative to the x-directional force exerted by other stimuli (for example, $c_{x,roadway\ obstruction} > c_{x,dotted\ lane\ markation}$)

$c_{y,desiredlane} =$    calibration factor used to adjust the magnitude of the y-directional force, exerted by the desired lane, relative to the y-directional force

exerted by other stimuli (for example, $c_{y,\text{roadway obstruction}} > c_{y,\text{dotted lane markation}}$)

The vector field created by the desired lane is depicted in Figure 30 (left). Figure 30 also shows this force field overlaid on top of a segment of roadway, with the desired lane being the leftmost lane (right). The further away from the desired lane that driver $i$ is, the stronger the attractive force is.
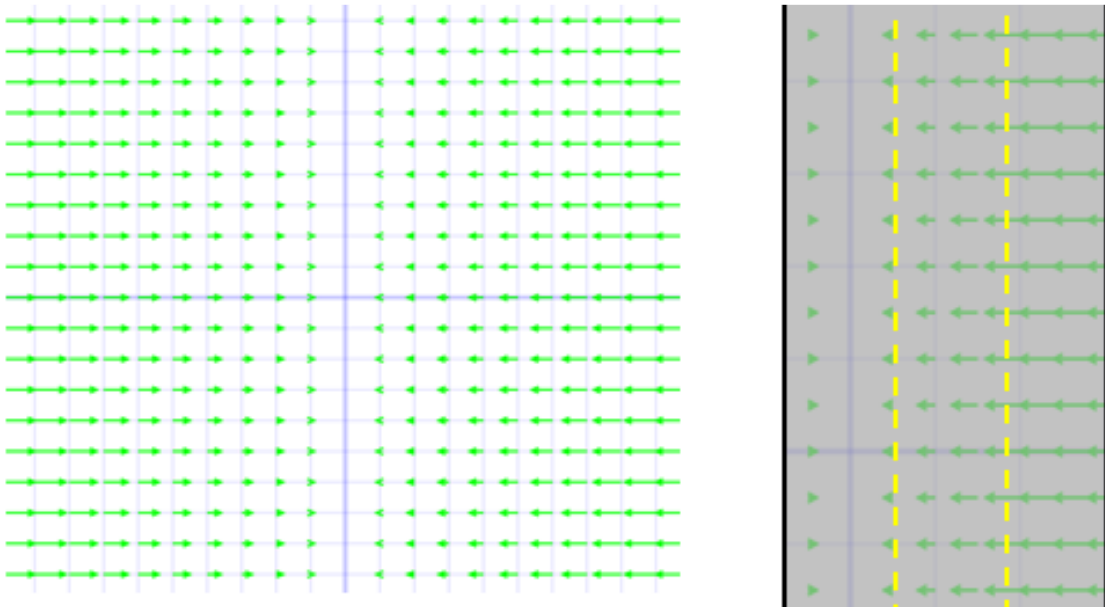


**Figure 30: Attractive force field that emanates from the center of the desired lane.**
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# CHAPTER 5

# MODELING SIMPLE CAR-FOLLOWING THROUGH A FREEWAY WORK ZONE

In this chapter, Modified Field Theory is used to model an agent in a simple car following scenario through a freeway work zone with lane closure. Car following behavior for the agent is plotted on a graph that compares the distance to the lead vehicle (commonly referred to as ΔX) and the relative speed of the subject vehicle to the lead vehicle (commonly referred to ΔV) at various time steps.

This plot (ΔX vs. ΔV) is used to describe car-following behaviors. Researchers (such as Wiedemann and Turner Fairbank Highway Research Center) have employed this methodology to examine the relationship between the relative speed and relative distance of the lead vehicle and the subject vehicle, and how this relationship changes over time. The "movement" of these points along the graph (which yields a circular/spiral trend when plotting empirically collected data) describes the car following behavior of the subject vehicle.

As described in the literature review, a "spiral" trend can be observed in car following behavior. Federal Highway Administration's (FHWA) Turner Fairbank Highway Research Center (TFHRC) has developed a methodology for collecting naturalistic freeway work zone normal car following data using an instrumented vehicle.

The relative speed vs. relative distance plot of an agent generated using Modified

Field Theory is compared to the relative speed vs. relative distance plot of Driver 15 from

the freeway work zone normal car following data collected using the TFHRC Living

Laboratory.  By comparing trends predicted in MFT to those seen in the empirically

collected data, MFT is validated for simple car following through a freeway work zone

with lane closure.


## 5.1     Definition: Simple Car Following Through a Freeway Work Zone

A simple freeway car following scenario is assumed.    Figure 3 (Chapter 2.3)

shows a simple car following scenario. In this scenario, vehicle $i$ is following the lead

vehicle, vehicle $pc$.  The only forces experienced by driver $i$ are from desired speed,

proximity to the lead vehicle, and relative velocity to the lead vehicle.  No other stimuli

are perceived, and no other forces are experienced.   There is only one lane (no

opportunity to pass).  There are no curves, there are no roadside stimuli.


Figure 31 depicts this simple car following scenario in Modified Field Theory.

Variables are observed in the physical world, and after the appropriate perception time,

are updated in the Cognitive Map (it is important to note that not all variables are

perceived at the same time.  Speed of the lead vehicle, for example, requires multiple

roadway scans, therefore has a longer perception time than relative location).  These

variables are plugged into the appropriate MFT equations to generate the vectors

representing the "force" or influence each stimulus plays on driver $i$ at a given analysis

time.  The driver response is predicted, and goes back into the Physical World, manifesting as a change in acceleration.  The process continues.
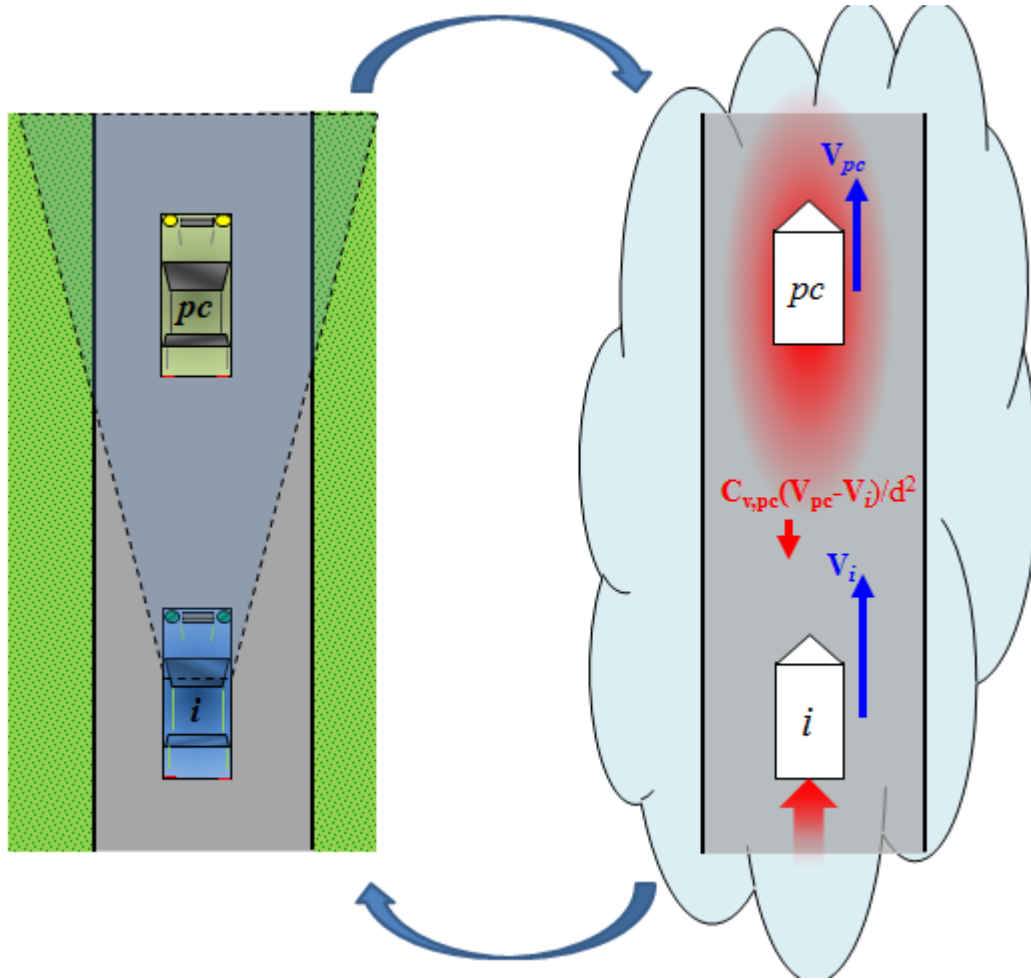


**Figure 31:  Definition of test scenario in Modified Field Theory**

### *5.1.1   Physical World, simple car following through a freeway work zone*

Figure 32 shows the variables scanned in the physical world at time $T = t$ for the simple car following scenario being investigated.  In the physical world, the only stimuli perceived are the lead vehicle and the desired speed.  For these stimuli, distance to the

lead vehicle (d), length of the lead vehicle (L), and speed of the lead vehicle ($V_{pc}$).

Driver *i* continually scans the roadway ahead.
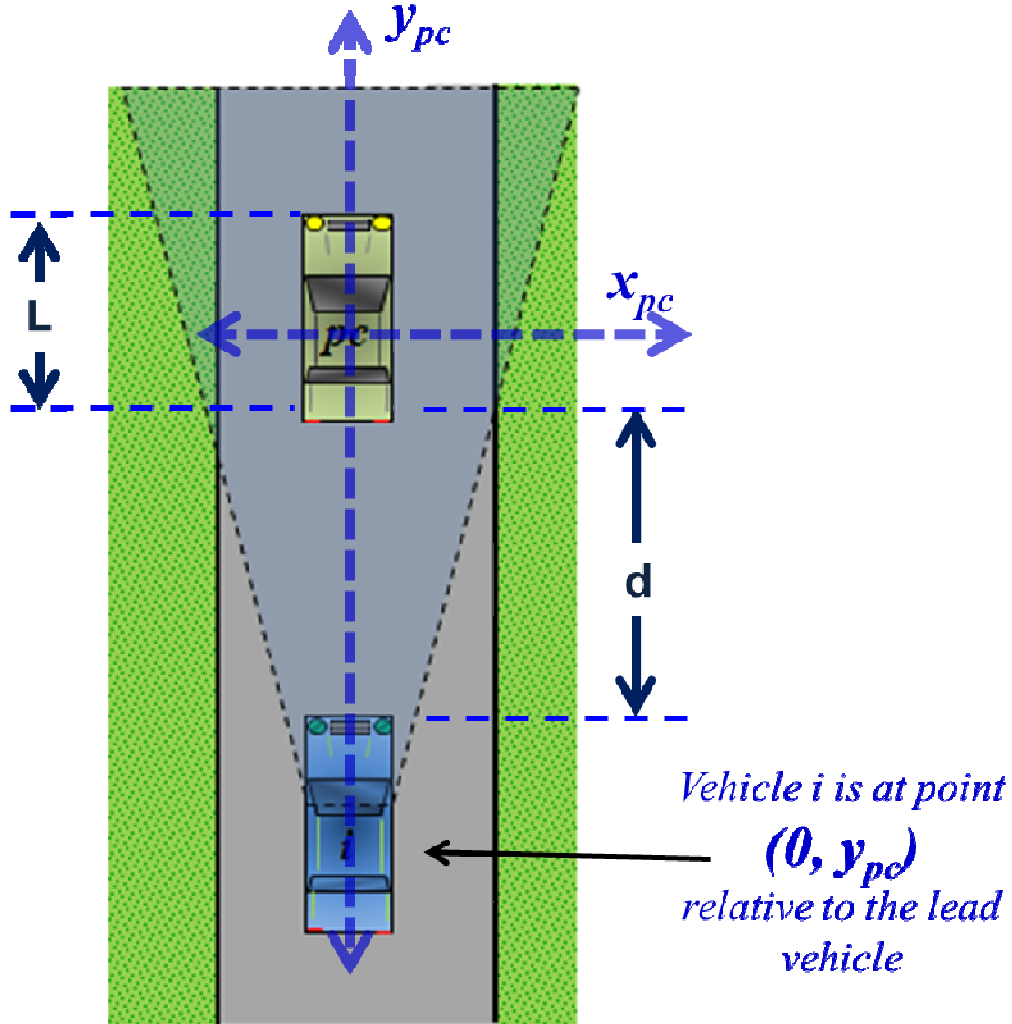


**Figure 32: Simplified freeway work zone car following in MFT at time T = t**

Because this is simplified car following, it is assumed that vehicle *i* is directly

behind the lead vehicle, vehicle *pc*. Because of this, $y_{pc}$ will always be a negative value.

Additionally, because vehicle *i* is assumed to be directly behind the lead vehicle, $x_{pc} = 0$.

"d," the distance between vehicle *i* and vehicle *pc,* is a variable in the relative velocity

force equation used in the Cognitive Map. Because of this simplified scenario, "d" can be expressed in terms of $y_{pc}$ and $L$ (the length of the lead vehicle); "d" is equal to:

$$d = (-y_{pc})-(L \, / \, 2)$$

Where $y_{pc}$ is a negative value, showing the relative position of vehicle $i$ to the lead vehicle, vehicle $pc$, and L is the length of the lead vehicle.

$L$ is assumed to be 20 feet. Since this analysis is done in meters, $L = 20$ feet = 6.096 meters, and $L \, / \, 2 = 3.048$ meters.

$y_{pc}$ is also expressible using the distance between the two vehicles, d:

$$y_{pc} = -d-(L \, / \, 2)$$

It is important to express $y_{pc}$ as a function of $d$, since TFHRC Living Laboratory data for Driver 15 reports distance to the lead vehicle, velocity of the lead vehicle, and velocity of the subject vehicle, at time $T = t$.

It is unknown whether or not the addition of work zone delineation will impact car following in this scenario. However, if such a force exists, the Modified Field Theory algorithms allow for work zone delineation to add a "backward" force that slows driver $i$ the same way a lower desired speed would. As the MFT algorithms simplify, it becomes

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increasingly difficult to distinguish between this force and actual desired speed without

additional car following datasets for the same driver $i$, traveling on the same freeway in

the same scenario, without a work zone present.  These additional datasets were not

available.  For this reasons, during model calibration, the work zone delineation

"backward" force is assumed to be negligible for the sake of model simplicity.  Any

impact work zone delineation has on the speed of driver $i$ is accounted for in the desired

speed of driver $i$.  Therefore, these sets of algorithms show the desired work zone speed,

and not normal desired speed.


### *5.1.2   Cognitive Map, simple car following through a freeway work zone*

What variables are used in Force Field Analysis at time $T = t$?

Figure 33 depicts the stimuli and their characteristics (variables) internalized in

the Cognitive Map at time $T = t$.  Because of perception times, the velocity of the lead

vehicle in the Cognitive Map at time $T = t$ is $V_{pc \text{ @ time } T = t - (perception\ time\ for\ velocity)}$, the

velocity of the subject vehicle in the Cognitive Map at time $T = t$ is $V_{i \text{ @ time } T = t - (perception}$

$_{time\ for\ velocity\ of\ vehicle\ i)}$, the distance between the subject vehicle in the Cognitive Map at time

$T = t$ is $d_{\text{ @ time } T = t - (perception\ time\ for\ velocity\ of\ vehicle\ i)}$, and the relative position of the subject

vehicle to the lead vehicle (in a coordinate system where (0, 0) is centered on the lead

vehicle) is $y_{pc \text{ @ time } T = t - (perception\ time\ for\ proximity)}$, which is expressible as $y_{pc \text{ @ time } T = t - }$

$_{(perception\ time\ for\ proximity)} = - d_{\text{@ time } T = t - (perception\ time\ for\ proximity)} - (L/2)$, where L is the length of

the lead vehicle.
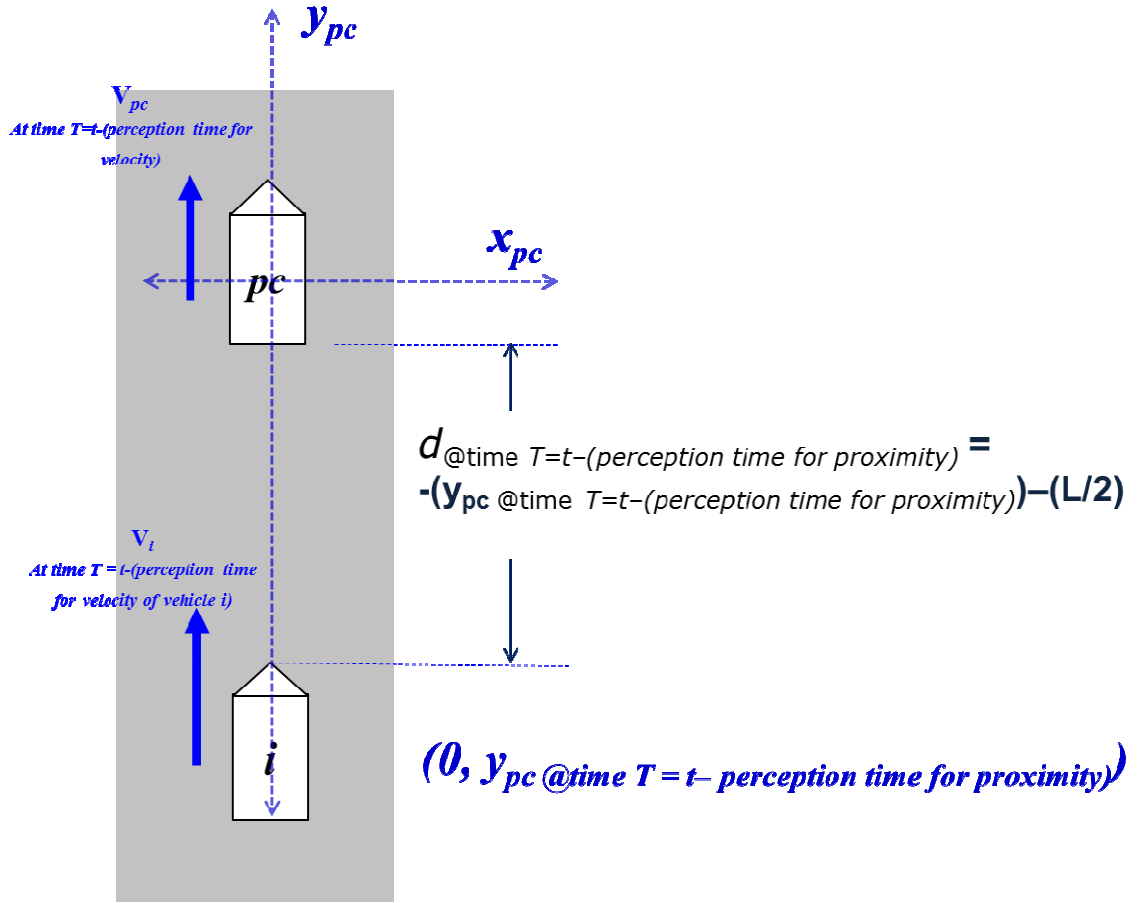
**Figure 33: Characteristics of observed stimuli in the Cognitive Map at time T = t.**

Identified later in this chapter are the calibration variables for each algorithm that are used to describe various driving populations. Calibrating these variables will adjust the influence that each valence has on different drivers, and will ultimately show how different drivers react in this car-following scenario. These calibration variables are identified in the equations. They are:

- Desired Speed, $V_{des}$

- Influence of Desired Speed, $c_{des}$

- Force Field shaping variable for Proximity to $pc$, $n_{pc}$ (in this scenario, it is assumed that $n_{pc} = 5$)

- Influence of Proximity to $pc$, $c_{pc}$

- Influence of Relative speed to $pc$, $c_{v,pc}$

- Driver Threshold

- perception time for proximity [s]

- perception time for velocity [s]

- perception time for velocity of vehicle $i$ [s]

### 5.1.2.1  Variable Perception times for velocity and relative position

In the physical world, it is assumed that the driver is continuously scanning the roadway environment directly ahead.  The agent's eyes are fixed forward; therefore perception reaction time is fixed.  However, the agent is expected to perceive the speed and relative location of the lead vehicles at different times.

Whereas an agent can 'see' relative location (i.e. "the lead vehicle is 5 meters in front of me"), an agent cannot 'see' instantaneous speed.  Our concept of speed comes from perceiving the lead vehicle at one location at time T = t, and a second location at time T = t +1.  The speed of the lead vehicle is estimated by the agent when the agent compares two perceived relative distances at two different times.  Both relative distances need to be perceived before relative velocity can be estimated; this means that the minimum time for perceiving velocity of the lead vehicle is (the perception-reaction time

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for proximity) + (minimum required time between two observed relative distances to estimate relative velocity) = (perception-reaction time for velocity).

Therefore, in Modified Field Theory, when driver $i$ makes a decision at time T = t, the location of the lead will be the location of the vehicle in the physical world at time step:

$$T = t - (perception\ time\ for\ proximity)$$

…where "$t$" is the current time step for the model, and "(*perception time for proximity*)" is the perception time for proximity.

Similarly, when driver $i$ makes a decision at time step T = t, the speed of the lead vehicle in their cognitive map will be the speed of the vehicle in the physical world at time step:

$$T = t - (perception\ time\ for\ velocity)$$

…where *(perception time for velocity)* refers to the time it takes for the driver to compare two different relative locations at two different times and infer the lead vehicle velocity.  As stated before, perception time for velocity will always be greater than perception time for proximity.

The subject vehicle is equipped with a speedometer.  Therefore, the instantaneous speed of the subject vehicle *is* observable by the driver, and the subject driver does not need to interpolate speed using two relative positions.  The perception time for the velocity of the subject vehicle, vehicle *i*, is the same time as *(perception time for proximity)*.


### 5.1.2.2  Forces on driver i at time T = t

The only forces experienced by driver *i* are from desired speed, proximity to the lead vehicle, and relative velocity to the lead vehicle.


(As previously stated) Variable perception times for different characteristics or variables means that the values for $V_i$, $y_{pc}$, $d$, and $V_{pc}$ assessed in the cognitive map at time T = t are from different times in the Physical World.  Also, $x = 0$, and $y_{pc}$ is always negative (since the subject vehicle is always behind the lead vehicle), making $d = (-y_{pc})$-$(L / 2)$.  Keeping this in mind, each algorithm identified in this scenario will be adjusted for this simple car following scenario.


The only forces experienced by driver *i* are from desired speed, proximity to the lead vehicle, and relative velocity to the lead vehicle.  The total force on driver *i* at time T = t is equal to:

$$\overline{F}_{total} = \overline{F}_{total,pc} + \overline{F}_{des}$$

…where

$\overline{F}_{total}$ = The total forces experienced by driver $i$ at time T = t (in this

simplified car following scenario).

$\overline{F}_{total,pc}$ = The total force from the lead vehicle experienced by driver $i$ at

time T = t (in this simplified car following scenario).

$\overline{F}_{des}$ = The force from the desired speed at time T = t (in this simplified car

following scenario).

The force from desired speed, $F_{des}$, at time T = t, for this simplified car-following

scenario, is:

$$\overline{F}_{des} = c_{des}(V_{des} - V_i) =$$

$$\overline{F}_{des} = c_{des}(V_{des} - V_{i\ @\ timeT=t-(\text{perception velocity vehicle}\,i)})$$

To illustrate each force's influence on the car following behavior of the subject

vehicle, the desired reaction caused only by the desired speed force, experienced by an

agent with desired speed of 30 m/s following a lead vehicle at 27 m/s is calculated and

shown graphically for various Δv vs Δx relationships in Figure 34.  In this figure, green

represents acceleration, and red represents deceleration.  Since in this example, the lead

vehicle is traveling at 27 m/s and the subject vehicle has a desired speed of 30 m/s, the

subject vehicle experiencing a force of acceleration from this valence when Δv is less

than a relative speed of (30 m/s – 27 m/s =) 3 m/s.  A $c_{des}$ was required to generate this

figure; in this figure, $c_{des} = 0.5$.

$$\overline{F}_{total} = \overline{F}_{totalpc} + \boxed{\overline{F}_{des}}$$

## Desired Speed
### (in simplified Car Following scenario)
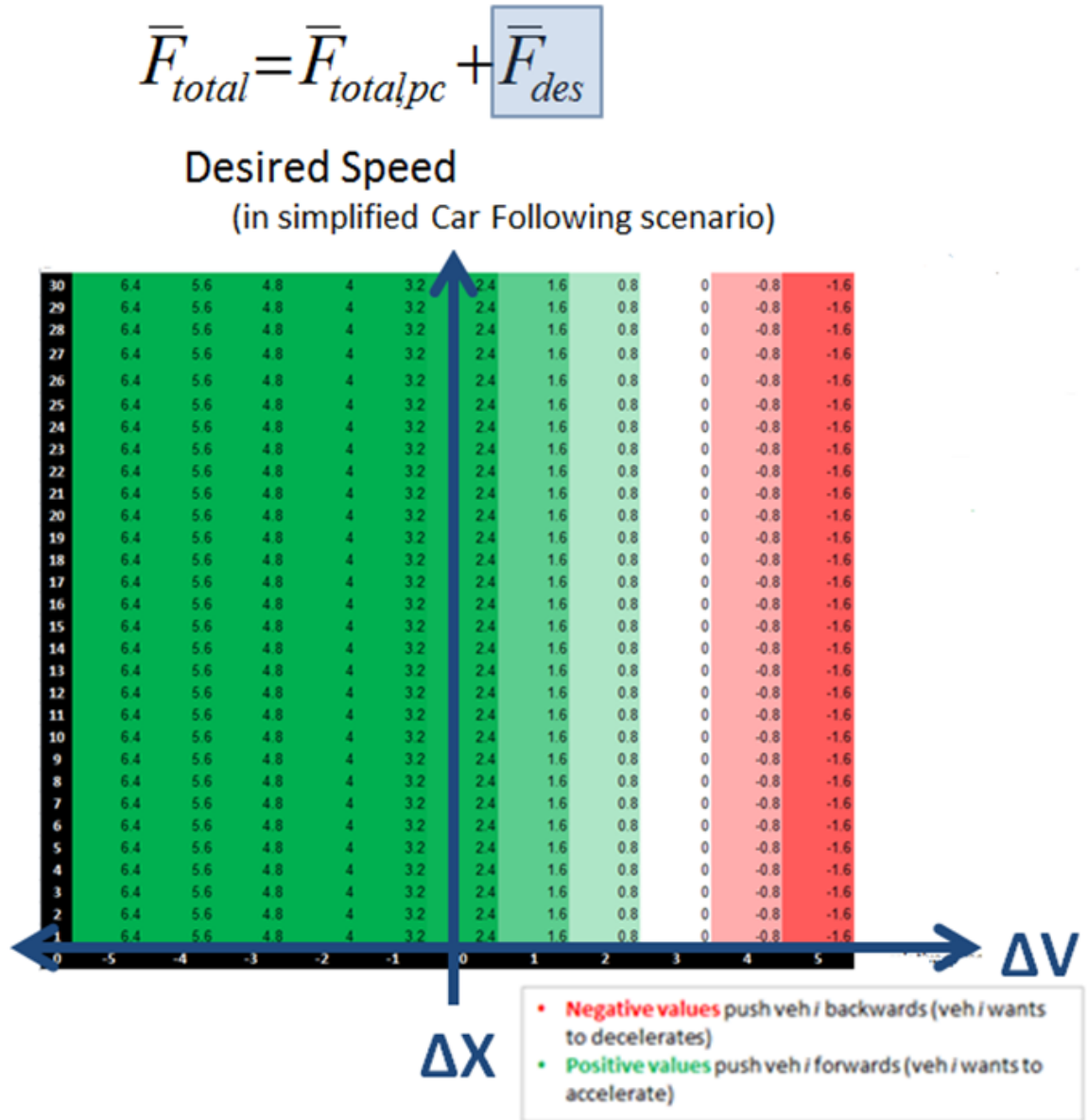


**Figure 34: Desired driver reaction as a result of the Desired Speed force**

*[Note: similar figures will be used to demonstrate the influence of proximity to the lead vehicle (Figure 35), relative velocity to the lead vehicle (Figure 36), the total influence of the lead vehicle (Figure 37), and the total desired reaction of the agent due to the cumulative forces at time T = t (Figure 38)].*

The total force from the lead vehicle, $F_{total,pc}$, at time $T = t$, is the sum of the force from proximity ($F_{proximity,pc}$) and the force from relative velocity ($F_{V,pc}$) :

$$\bar{F}_{total,pc} = \bar{F}_{V,pc} + \bar{F}_{proximity,pc}$$

The force from proximity ($F_{proximity,pc}$) in this car following scenario is equal to:

$$\bar{F}_{proximity,pc} = c_{x,pc} \cdot \frac{m_{pc} \cdot (0)}{((0)^2 + (-d - L/2)^2)} \hat{i} + c_{y,pc} \cdot \frac{n_{pc} \cdot (-d + L/2)}{((0)^2 + (-d - L/2)^2)} \hat{j} =$$

$$\bar{F}_{proximity,pc} = -\frac{c_{y,pc} \cdot n_{pc}}{(d_{(@ \text{ time } T = t - (\text{perception reaction for proximity}))} + L/2} \hat{j}$$

Figure 35 illustrates the influence of the force from proximity to the lead vehicle ($F_{proximity,pc}$) on the behavior of the subject vehicle (or agent), in this simplified car following scenario, for various $\Delta v$ vs $\Delta x$ relationships. In this figure, green represents acceleration, and red represents deceleration. Values for $n_{pc}$ and $c_{y,pc}$ were required to create this figure; in this figure, $n_{pc} = 5$ and $c_{y,pc} = 2$. From Figure 35, it can be seen that the closer the subject vehicle is to the lead vehicle, the greater the influence of the proximity force.

$$\bar{F}_{total} = \bar{\bar{F}}_{total,pc} + \bar{F}_{des}$$

$$\bar{F}_{total,pc} = \bar{F}_{V,pc} + \bar{F}_{proximity,pc}$$

Force created by proximity to lead vehicle, *pc*

$$\bar{F}_{proximity,pc} = -\frac{c_{y,pc} \cdot n_{pc}}{\left(d_{(@\,time\,T\,=\,t\,-\,(perception\,reaction\,for\,proximity\,))} + L/2\right)}\hat{j}$$
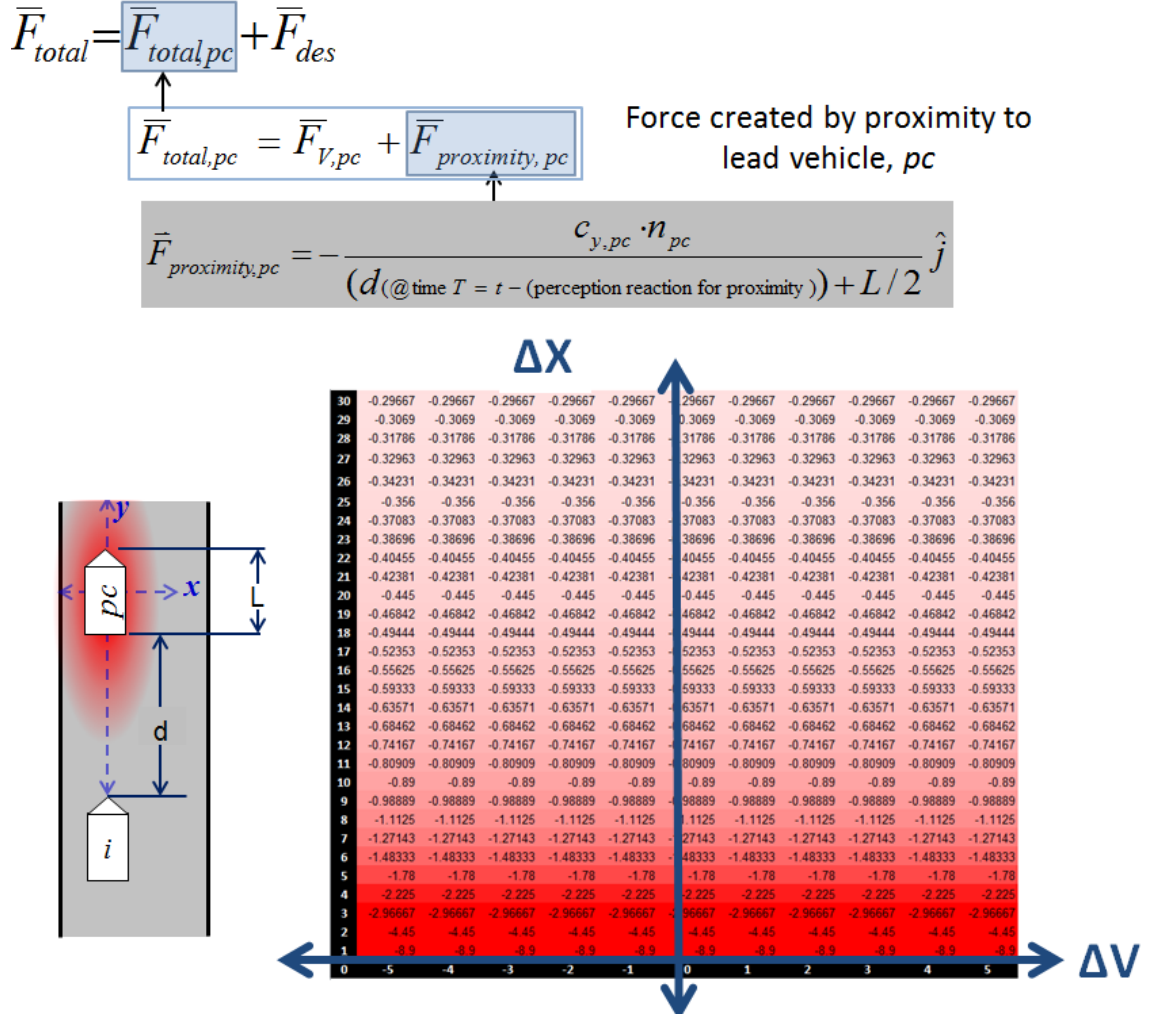


**Figure 35: Desired driver reaction as a result of the Proximity to lead vehicle force**

The force from relative velocity ($F_{V,pc}$) in this car following scenario is equal to:

$$\bar{F}_V = c_{v,pc}\frac{\bar{V}_{pc\,(@\,time\,T=t-1-(perception\,reaction\,for\,velocity\,))} - \bar{V}_{i\,(@\,time\,T=t-(perception\,reaction\,for\,velocity\,of\,vehicle\,i\,))}}{\left(d_{(@\,time\,T\,=\,t\,-\,(perception\,reaction\,for\,proximity\,))}\right)^2}$$

Figure 36 illustrates the influence of the force from relative velocity to the lead vehicle ($F_{V,pc}$) on the behavior of the subject vehicle (or agent), in this simplified car

following scenario, for various Δv vs Δx relationships.  In this figure, green represents

acceleration, and red represents deceleration.   Values for $c_{v,pc}$ were required to create this

figure; in this figure, and $c_{v,pc} = 2$.  From Figure 36, it is observed that a negative relative

velocity will influence an acceleration reaction in the subject vehicle, and a positive

relative velocity will influence a deceleration reaction in the subject vehicle. The closer

the subject vehicle is to the lead vehicle, the greater the influence of this force.

$$\overline{F}_{total} = \boxed{\overline{F}_{total\,pc}} + \overline{F}_{des}$$

$$\boxed{\overline{F}_{total,pc}} = \boxed{\overline{F}_{V,pc}} + \overline{F}_{proximity,\,pc}$$

Force created by difference in velocity vectors between vehicle $i$ and $pc$

$$\overline{F}_V = c_{v,pc} \frac{\overline{V}_{pc(@\ time\ T=t-1-(perception\ reaction\ for\ velocity))} - \overline{V}_{i(@\ time\ T=t-(perception\ reaction\ for\ velocity\ of\ vehicle\ i))}}{(d_{(@\ time\ T\ =\ t\ -\ (perception\ reaction\ for\ proximity))})^2}$$

[m]
d=

| d | ΔX col1 | col2 | col3 | col4 | col5 | | col1 | col2 | col3 | col4 | col5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 30 | 0.111111 | 0.088889 | 0.066667 | 0.04 | | 0 | -0.02222 | -0.04444 | -0.06667 | -0.08889 | -0.11111 |
| 29 | 0.118906 | 0.095125 | 0.071344 | 0.04 | | 0 | -0.02378 | -0.04756 | -0.07134 | -0.09512 | -0.11891 |
| 28 | 0.127551 | 0.102041 | 0.076531 | 0.05102 | 0.02551 | 0 | -0.02551 | -0.05102 | -0.07653 | -0.10204 | -0.12755 |
| 27 | 0.137174 | 0.109739 | 0.082305 | 0.05487 | 0.027435 | 0 | -0.02743 | -0.05487 | -0.0823 | -0.10974 | -0.13717 |
| 26 | 0.147929 | 0.118343 | 0.088757 | 0.059172 | 0.029586 | 0 | -0.02959 | -0.05917 | -0.08876 | -0.11834 | -0.14793 |
| 25 | 0.16 | 0.128 | 0.096 | 0.064 | 0.032 | 0 | -0.032 | -0.064 | -0.096 | -0.128 | -0.16 |
| 24 | 0.173611 | 0.138889 | 0.104167 | 0.069444 | 0.034722 | 0 | -0.03472 | -0.06944 | -0.10417 | -0.13889 | -0.17361 |
| 23 | 0.189036 | 0.151229 | 0.113422 | 0.075614 | 0.037807 | 0 | -0.03781 | -0.07561 | -0.11342 | -0.15123 | -0.18904 |
| 22 | 0.206612 | 0.165289 | 0.123967 | 0.082645 | 0.041322 | 0 | -0.04132 | -0.08264 | -0.12397 | -0.16529 | -0.20661 |
| 21 | 0.226757 | 0.181406 | 0.136054 | 0.090703 | 0.045351 | 0 | -0.04535 | -0.0907 | -0.13605 | -0.18141 | -0.22676 |
| 20 | 0.25 | 0.2 | 0.15 | 0.1 | 0.05 | 0 | -0.05 | -0.1 | -0.15 | -0.2 | -0.25 |
| 19 | 0.277008 | 0.221607 | 0.166205 | 0.110803 | 0.055402 | 0 | -0.0554 | -0.1108 | -0.1662 | -0.22161 | -0.27701 |
| 18 | 0.308642 | 0.246914 | 0.185185 | 0.123457 | 0.061728 | 0 | -0.06173 | -0.12346 | -0.18519 | -0.24691 | -0.30864 |
| 17 | 0.346021 | 0.276817 | 0.207612 | 0.138408 | 0.069204 | 0 | -0.0692 | -0.13841 | -0.20761 | -0.27682 | -0.34602 |
| 16 | 0.390625 | 0.3125 | 0.234375 | 0.15625 | 0.078125 | 0 | -0.07813 | -0.15625 | -0.23438 | -0.3125 | -0.39063 |
| 15 | 0.444444 | 0.355556 | 0.266667 | 0.177778 | 0.088889 | 0 | -0.08889 | -0.17778 | -0.26667 | -0.35556 | -0.44444 |
| 14 | 0.510204 | 0.408163 | 0.306122 | 0.204082 | 0.102041 | 0 | -0.10204 | -0.20408 | -0.30612 | -0.40816 | -0.5102 |
| 13 | 0.591716 | 0.473373 | 0.35503 | 0.236686 | 0.118343 | 0 | -0.11834 | -0.23669 | -0.35503 | -0.47337 | -0.59172 |
| 12 | 0.694444 | 0.555556 | 0.416667 | 0.277778 | 0.138889 | 0 | -0.13889 | -0.27778 | -0.41667 | -0.55556 | -0.69444 |
| 11 | 0.826446 | 0.661157 | 0.495868 | 0.330579 | 0.165289 | 0 | -0.16529 | -0.33058 | -0.49587 | -0.66116 | -0.82645 |
| 10 | 1 | 0.8 | 0.6 | 0.4 | 0.2 | 0 | -0.2 | -0.4 | -0.6 | -0.8 | -1 |
| 9 | 1.234568 | 0.987654 | 0.740741 | 0.493827 | 0.246914 | 0 | -0.24691 | -0.49383 | -0.74074 | -0.98765 | -1.23457 |
| 8 | 1.5625 | 1.25 | 0.9375 | 0.625 | 0.3125 | 0 | -0.3125 | -0.625 | -0.9375 | -1.25 | -1.5625 |
| 7 | 2.040816 | 1.632653 | 1.22449 | 0.816327 | 0.408163 | 0 | -0.40816 | -0.81633 | -1.22449 | -1.63265 | -2.04082 |
| 6 | 2.777778 | 2.222222 | 1.666667 | 1.111111 | 0.555556 | 0 | -0.55556 | -1.11111 | -1.66667 | -2.22222 | -2.77778 |
| 5 | 4 | 3.2 | 2.4 | 1.6 | 0.8 | 0 | -0.8 | -1.6 | -2.4 | -3.2 | -4 |
| 4 | 6.25 | 5 | 3.75 | 2.5 | 1.25 | 0 | -1.25 | -2.5 | -3.75 | -5 | -6.25 |
| 3 | 11.11111 | 8.888889 | 6.666667 | 4.444444 | 2.222222 | 0 | -2.22222 | -4.44444 | -6.66667 | -8.88889 | -11.1111 |
| 2 | 25 | 20 | 15 | 10 | 5 | 0 | -5 | -10 | -15 | -20 | -25 |
| 1 | 100 | 80 | 60 | 40 | 20 | 0 | -20 | -40 | -60 | -80 | -100 |
| 0 | -5 | -4 | -3 | -2 | -1 | | 1 | 2 | 3 | 4 | 5 | ΔV |

(Labels in figure: $V_{pc}$, $pc$, $F_{v,pc}$, $V_i$, $d$, $i$)

**Figure 36: Desired driver reaction as a result of the Relative Velocity to lead vehicle force**

The total force from the lead vehicle, $F_{total,pc}$, at time T = t, was previously stated to be the sum of the force from proximity ($F_{proximity,pc}$) and the force from relative velocity ($F_{V,pc}$):

$$\overline{F}_{total,pc} = \overline{F}_{V,pc} + \overline{F}_{proximity,pc}$$

By adding values from Figure 35 and Figure 36, Figure 37 illustrates the total influence from the lead vehicle ($F_{total,pc}$) on the behavior of the subject vehicle (or agent), in this simplified car following scenario, for various Δv vs Δx relationships.  In this figure, green represents acceleration, and red represents deceleration.   From Figure 37, trends can be observed that cause the subject vehicle to decelerate hard in a scenario that could cause a collision (i.e., subject vehicle is traveling faster than the lead vehicle but is in close proximity), but in a scenario where the subject vehicle is in close proximity to the lead vehicle and the lead vehicle is traveling substantially faster than the subject vehicle, the subject vehicle accelerates.  Note that in this scenario, this acceleration cannot cause a collision; when relative velocity nears zero, a deceleration can be observed again.

$$\bar{F}_{total} = \boxed{\bar{F}_{totalpc}} + \bar{F}_{des}$$

$$\boxed{\bar{F}_{total,pc} = \bar{F}_{V,pc} + \bar{F}_{proximity,\,pc}}$$

Total forces from stimulant, *pc* (passenger car, lead vehicle)
proximity + difference in velocity

**ΔX**

| ΔX | ΔV=-5 | -4 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 30 | -0.30556 | -0.31111 | -0.31667 | -0.32222 | -0.32778 | -0.33333 | -0.33889 | -0.34444 | -0.35 | -0.35556 | -0.36111 |
| 29 | -0.3151 | -0.32105 | -0.32699 | -0.33294 | -0.33888 | -0.34483 | -0.35077 | -0.35672 | -0.36266 | -0.36861 | -0.37455 |
| 28 | -0.32526 | -0.33163 | -0.33801 | -0.34439 | -0.35077 | -0.35714 | -0.36352 | -0.3699 | -0.37628 | -0.38265 | -0.38903 |
| 27 | -0.33608 | -0.34294 | -0.34979 | -0.35665 | -0.36351 | -0.37037 | -0.37723 | -0.38409 | -0.39095 | -0.39781 | -0.40466 |
| 26 | -0.34763 | -0.35503 | -0.36243 | -0.36982 | -0.37722 | -0.38462 | -0.39201 | -0.39941 | -0.4068 | -0.4142 | -0.4216 |
| 25 | -0.36 | -0.368 | -0.376 | -0.384 | -0.392 | -0.4 | -0.408 | -0.416 | -0.424 | -0.432 | -0.44 |
| 24 | -0.37326 | -0.38194 | -0.39063 | -0.39931 | -0.40799 | -0.41667 | -0.42535 | -0.43403 | -0.44271 | -0.45139 | -0.46007 |
| 23 | -0.38752 | -0.39698 | -0.40643 | -0.41588 | -0.42533 | -0.43478 | -0.44423 | -0.45369 | -0.46314 | -0.47259 | -0.48204 |
| 22 | -0.40289 | -0.41322 | -0.42355 | -0.43388 | -0.44421 | -0.45455 | -0.46488 | -0.47521 | -0.48554 | -0.49587 | -0.5062 |
| 21 | -0.4195 | -0.43084 | -0.44218 | -0.45351 | -0.46485 | -0.47619 | -0.48753 | -0.49887 | -0.5102 | -0.52154 | -0.53288 |
| 20 | -0.4375 | -0.45 | -0.4625 | -0.475 | -0.4875 | -0.5 | -0.5125 | -0.525 | -0.5375 | -0.55 | -0.5625 |
| 19 | -0.45706 | -0.47091 | -0.48476 | -0.49861 | -0.51247 | -0.52632 | -0.54017 | -0.55402 | -0.56787 | -0.58172 | -0.59557 |
| 18 | -0.4784 | -0.49383 | -0.50926 | -0.52469 | -0.54012 | -0.55556 | -0.57099 | -0.58642 | -0.60185 | -0.61728 | -0.63272 |
| 17 | -0.50173 | -0.51903 | -0.53633 | -0.55363 | -0.57093 | -0.58824 | -0.60554 | -0.62284 | -0.64014 | -0.65744 | -0.67474 |
| 16 | -0.52734 | -0.54688 | -0.56641 | -0.58594 | -0.60547 | -0.625 | -0.64453 | -0.66406 | -0.68359 | -0.70313 | -0.72266 |
| 15 | -0.55556 | -0.57778 | -0.6 | -0.62222 | -0.64444 | -0.66667 | -0.68889 | -0.71111 | -0.73333 | -0.75556 | -0.77778 |
| 14 | -0.58673 | -0.61224 | -0.63776 | -0.66327 | -0.68878 | -0.71429 | -0.7398 | -0.76531 | -0.79082 | -0.81633 | -0.84184 |
| 13 | -0.6213 | -0.65089 | -0.68047 | -0.71006 | -0.73964 | -0.76923 | -0.79882 | -0.8284 | -0.85799 | -0.88757 | -0.91716 |
| 12 | -0.65972 | -0.69444 | -0.72917 | -0.76389 | -0.79861 | -0.83333 | -0.86806 | -0.90278 | -0.9375 | -0.97222 | -1.00694 |
| 11 | -0.70248 | -0.7438 | -0.78512 | -0.82645 | -0.86777 | -0.90909 | -0.95041 | -0.99174 | -1.03306 | -1.07438 | -1.1157 |
| 10 | -0.75 | -0.8 | -0.85 | -0.9 | -0.95 | -1 | -1.05 | -1.1 | -1.15 | -1.2 | -1.25 |
| 9 | -0.80247 | -0.8642 | -0.92593 | -0.98765 | -1.04938 | -1.11111 | -1.17284 | -1.23457 | -1.2963 | -1.35802 | -1.41975 |
| 8 | -0.85938 | -0.9375 | -1.01563 | -1.09375 | -1.17188 | -1.25 | -1.32813 | -1.40625 | -1.48438 | -1.5625 | -1.64063 |
| 7 | -0.91837 | -1.02041 | -1.12245 | -1.22449 | -1.32653 | -1.42857 | -1.53061 | -1.63265 | -1.73469 | -1.83673 | -1.93878 |
| 6 | -0.97222 | -1.11111 | -1.25 | -1.38889 | -1.52778 | -1.66667 | -1.80556 | -1.94444 | -2.08333 | -2.22222 | -2.36111 |
| 5 | -1 | -1.2 | -1.4 | -1.6 | -1.8 | -2 | -2.2 | -2.4 | -2.6 | -2.8 | -3 |
| 4 | -0.9375 | -1.25 | -1.5625 | -1.875 | -2.1875 | -2.5 | -2.8125 | -3.125 | -3.4375 | -3.75 | -4.0625 |
| 3 | -0.55556 | -1.11111 | -1.66667 | -2.22222 | -2.77778 | -3.33333 | -3.88889 | -4.44444 | -5 | -5.55556 | -6.11111 |
| 2 | 1.25 | 0 | -1.25 | -2.5 | -3.75 | -5 | -6.25 | -7.5 | -8.75 | -10 | -11.25 |
| 1 | 15 | 10 | 5 | 0 | -5 | -10 | -15 | -20 | -25 | -30 | -35 |
| 0 | -5 | -4 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 4 | 5 |

**ΔV**

**Figure 37: Desired driver reaction as a result of the total lead vehicle force**

When considering only at the forces created by the lead vehicle (and not those of desired speed), the subject vehicle will decelerate and travel away from the lead vehicle; the subject vehicle will not maintain car following. This is expected; without desired

speed, in a scenario where the only perceived stimulus is the presence of another vehicle, the subject driver's only concern is to avoid a crash and travel with traffic.

The total force on driver $i$ at time $T = t$ in this simplified car following scenario is equal to $\overline{F}_{total} = \overline{F}_{total,pc} + \overline{F}_{des}$. By adding the total forces from the lead vehicle (Figure 37) and the total forces from desired speed (Figure 34), the total influence on the subject vehicle (or agent) at time $T = t$ is shown for various $\Delta v$ vs $\Delta x$ relationships with the lead vehicle (vehicle $pc$). Figure 38 shows the total force.

$$\overline{F}_{total} = \overline{F}_{totalpc} + \overline{F}_{des}$$

Total Forces acting on driver $i$ in the car-following scenario, at time $T = t$

**ΔX** (axis, vertical)

| ΔX | -5 | -4 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 30 | 3.67778 | 3.17556 | 2.67333 | 2.17111 | 1.66889 | 1.16667 | 0.66444 | 0.16222 | -0.34 | -0.84222 | -1.34444 |
| 29 | 3.66706 | 3.16468 | 2.66231 | 2.15993 | 1.65755 | 1.15517 | 0.65279 | 0.15042 | -0.35196 | -0.85434 | -1.35672 |
| 28 | 3.65561 | 3.15306 | 2.65051 | 2.14796 | 1.64541 | 1.14286 | 0.64031 | 0.13776 | -0.3648 | -0.86735 | -1.3699 |
| 27 | 3.64335 | 3.1406 | 2.63786 | 2.13512 | 1.63237 | 1.12963 | 0.62689 | 0.12414 | -0.3786 | -0.88134 | -1.38409 |
| 26 | 3.63018 | 3.12722 | 2.62426 | 2.1213 | 1.61834 | 1.11538 | 0.61243 | 0.10947 | -0.39349 | -0.89645 | -1.39941 |
| 25 | 3.616 | 3.1128 | 2.6096 | 2.1064 | 1.6032 | 1.1 | 0.5968 | 0.0936 | -0.4096 | -0.9128 | -1.416 |
| 24 | 3.60069 | 3.09722 | 2.59375 | 2.09028 | 1.58681 | 1.08333 | 0.57986 | 0.07639 | -0.42708 | -0.93056 | -1.43403 |
| 23 | 3.58412 | 3.08034 | 2.57656 | 2.07278 | 1.569 | 1.06522 | 0.56144 | 0.05766 | -0.44612 | -0.94991 | -1.45369 |
| 22 | 3.56612 | 3.06198 | 2.55785 | 2.05372 | 1.54959 | 1.04545 | 0.54132 | 0.03719 | -0.46694 | -0.97107 | -1.47521 |
| 21 | 3.54649 | 3.04195 | 2.53741 | 2.03288 | 1.52834 | 1.02381 | 0.51927 | 0.01474 | -0.4898 | -0.99433 | -1.49887 |
| 20 | 3.525 | 3.02 | 2.515 | 2.01 | 1.505 | 1 | 0.495 | -0.01 | -0.515 | -1.02 | -1.525 |
| 19 | 3.50139 | 2.99584 | 2.4903 | 1.98476 | 1.47922 | 0.97368 | 0.46814 | -0.0374 | -0.54294 | -1.04848 | -1.55402 |
| 18 | 3.47531 | 2.96914 | 2.46296 | 1.95679 | 1.45062 | 0.94444 | 0.43827 | -0.0679 | -0.57407 | -1.08025 | -1.58642 |
| 17 | 3.44637 | 2.93945 | 2.43253 | 1.92561 | 1.41869 | 0.91176 | 0.40484 | -0.10208 | -0.609 | -1.11592 | -1.62284 |
| 16 | 3.41406 | 2.90625 | 2.39844 | 1.89063 | 1.38281 | 0.875 | 0.36719 | -0.14063 | -0.64844 | -1.15625 | -1.66406 |
| 15 | 3.37778 | 2.86889 | 2.36 | 1.85111 | 1.34222 | 0.83333 | 0.32444 | -0.18444 | -0.69333 | -1.20222 | -1.71111 |
| 14 | 3.33673 | 2.82653 | 2.31633 | 1.80612 | 1.29592 | 0.78571 | 0.27551 | -0.23469 | -0.7449 | -1.2551 | -1.76531 |
| 13 | 3.28994 | 2.77811 | 2.26627 | 1.75444 | 1.2426 | 0.73077 | 0.21893 | -0.2929 | -0.80473 | -1.31657 | -1.8284 |
| 12 | 3.23611 | 2.72222 | 2.20833 | 1.69444 | 1.18056 | 0.66667 | 0.15278 | -0.36111 | -0.875 | -1.38889 | -1.90278 |
| 11 | 3.17355 | 2.65702 | 2.1405 | 1.62397 | 1.10744 | 0.59091 | 0.07438 | -0.44215 | -0.95868 | -1.47521 | -1.99174 |
| 10 | 3.1 | 2.58 | 2.06 | 1.54 | 1.02 | 0.5 | -0.02 | -0.54 | -1.06 | -1.58 | -2.1 |
| 9 | 3.01235 | 2.48765 | 1.96296 | 1.43827 | 0.91358 | 0.38889 | -0.1358 | -0.66049 | -1.18519 | -1.70988 | -2.23457 |
| 8 | 2.90625 | 2.375 | 1.84375 | 1.3125 | 0.78125 | 0.25 | -0.28125 | -0.8125 | -1.34375 | -1.875 | -2.40625 |
| 7 | 2.77551 | 2.23469 | 1.69388 | 1.15306 | 0.61224 | 0.07143 | -0.46939 | -1.0102 | -1.55102 | -2.09184 | -2.63265 |
| 6 | 2.61111 | 2.05556 | 1.5 | 0.94444 | 0.38889 | -0.16667 | -0.72222 | -1.27778 | -1.83333 | -2.38889 | -2.94444 |
| 5 | 2.4 | 1.82 | 1.24 | 0.66 | 0.08 | -0.5 | -1.08 | -1.66 | -2.24 | -2.82 | -3.4 |
| 4 | 2.125 | 1.5 | 0.875 | 0.25 | -0.375 | -1 | -1.625 | -2.25 | -2.875 | -3.5 | -4.125 |
| 3 | 1.77778 | 1.05556 | 0.33333 | -0.38889 | -1.11111 | -1.83333 | -2.55556 | -3.27778 | -4 | -4.72222 | -5.44444 |
| 2 | 1.5 | 0.5 | -0.5 | -1.5 | -2.5 | -3.5 | -4.5 | -5.5 | -6.5 | -7.5 | -8.5 |
| 1 | 4 | 1.5 | -1 | -3.5 | -6 | -8.5 | -11 | -13.5 | -16 | -18.5 | -21 |
| 0 | -5 | -4 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 4 | 5 |

**ΔV** (axis, horizontal)

Drivers who are less stressed (all coefficients are lower) have a greater 'unchanged' zone

**In this graphic...**

- Lead vehicle maintains consistent speed of 27 m/s

- Desired Speed
  $V_{des,rel} = 30$ m/s
  $C_{des} = 0.5$

- Proximity to $pc$
  $n_{pc} = 5$
  $C_{y,pc} = 2$

- Relative speed to $pc$
  $C_{v,pc} = 2$

**Figure 38: Total desired driver reaction in simplified car-following scenario**

The calibration factors "c" used in the equations for Figure 38 describe the subject driver (or agent). The agent in Figure 38 equally values relative speed and proximity to the lead vehicle (since both $c_{y,pc}$ and $c_{v,pc}$ =2). This agent also values proximity to the lead vehicle and relative velocity to the lead vehicle 4 times greater than achieving their desired speed (since both $c_{y,pc}$ and $c_{v,pc}$ = 2 and $c_{des}$ = 0.5) indicating that crash avoidance is 4 times greater than achieving the desired speed for this particular agent.

Overall, values for the calibration factors of the agent in Figure 38 are relatively low, indicating a driver who isn't as "stressed" about the presence of these stimuli. There is a zone of low "stress" in Figure 38, a zone with a significant amount of white space. Not all drivers associate this level of "stress" and influence with perceived stimuli (some are more influenced by each stimulus and are therefore more "stressed", others have lower influence levels and are therefore less "stressed").

Figure 39 shows a driver who is 5 times as stressed as the agent in Figure 38, with all calibration factors for the agent in Figure 39 being 5 times what they are for the agent in Figure 38 ($c_{y,pc}$ and $c_{v,pc} = 10$ and $c_{des} = 2.5$). This agent experiences significantly higher forces than the agent in Figure 38, and is under a nearly constant stress level.

$$\overline{F}_{total} = \overline{F}_{total,pc} + \overline{F}_{des}$$

**ΔX**

Drivers who are more stressed (all coefficients are higher) are under constant pressure

| ΔX \ ΔV | -5 | -4 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 30 | 22.3889 | 19.3778 | 16.3667 | 13.3556 | 10.3444 | 7.33333 | 4.32222 | 1.31111 | -1.7 | -4.71111 | -7.72222 |
| 29 | 22.3353 | 19.3234 | 16.3115 | 13.2996 | 10.2878 | 7.27586 | 4.26397 | 1.25208 | -1.75981 | -4.7717 | -7.78359 |
| 28 | 22.2781 | 19.2653 | 16.2526 | 13.2398 | 10.227 | 7.21429 | 4.20153 | 1.18878 | -1.82398 | -4.83673 | -7.84949 |
| 27 | 22.2167 | 19.203 | 16.1893 | 13.1756 | 10.1619 | 7.14815 | 4.13443 | 1.12071 | -1.893 | -4.90672 | -7.92044 |
| 26 | 22.1509 | 19.1361 | 16.1213 | 13.1065 | 10.0917 | 7.07692 | 4.06213 | 1.04734 | -1.96746 | -4.98225 | -7.99704 |
| 25 | 22.08 | 19.064 | 16.048 | 13.032 | 10.016 | 7 | 3.984 | 0.968 | -2.048 | -5.064 | -8.08 |
| 24 | 22.0035 | 18.9861 | 15.9688 | 12.9514 | 9.93403 | 6.91667 | 3.89931 | 0.88194 | -2.13542 | -5.15278 | -8.17014 |
| 23 | 21.9206 | 18.9017 | 15.8828 | 12.8639 | 9.84499 | 6.82609 | 3.80718 | 0.78828 | -2.23062 | -5.24953 | -8.26843 |
| 22 | 21.8306 | 18.8099 | 15.7893 | 12.7686 | 9.74793 | 6.72727 | 3.70661 | 0.68595 | -2.33471 | -5.35537 | -8.37603 |
| 21 | 21.7324 | 18.7098 | 15.6871 | 12.6644 | 9.64172 | 6.61905 | 3.59637 | 0.5737 | -2.44898 | -5.47166 | -8.49433 |
| 20 | 21.625 | 18.6 | 15.575 | 12.55 | 9.525 | 6.5 | 3.475 | 0.45 | -2.575 | -5.6 | -8.625 |
| 19 | 21.5069 | 18.4792 | 15.4515 | 12.4238 | 9.39612 | 6.36842 | 3.34072 | 0.31302 | -2.71468 | -5.74238 | -8.77008 |
| 18 | 21.3765 | 18.3457 | 15.3148 | 12.284 | 9.25309 | 6.22222 | 3.19136 | 0.16049 | -2.87037 | -5.90123 | -8.9321 |
| 17 | 21.2318 | 18.1972 | 15.1626 | 12.128 | 9.09343 | 6.05882 | 3.02422 | -0.01038 | -3.04498 | -6.07958 | -9.11419 |
| 16 | 21.0703 | 18.0313 | 14.9922 | 11.9531 | 8.91406 | 5.875 | 2.83594 | -0.20313 | -3.24219 | -6.28125 | -9.32031 |
| 15 | 20.8889 | 17.8444 | 14.8 | 11.7556 | 8.71111 | 5.66667 | 2.62222 | -0.42222 | -3.46667 | -6.51111 | -9.55556 |
| 14 | 20.6837 | 17.6327 | 14.5816 | 11.5306 | 8.47959 | 5.42857 | 2.37755 | -0.67347 | -3.72449 | -6.77551 | -9.82653 |
| 13 | 20.4497 | 17.3905 | 14.3314 | 11.2722 | 8.21302 | 5.16385 | 2.09467 | -0.9645 | -4.02367 | -7.08284 | -10.142 |
| 12 | 20.1806 | 17.1111 | 14.0417 | 10.9722 | 7.90278 | 4.83333 | 1.76389 | -1.30556 | -4.375 | -7.44444 | -10.5139 |
| 11 | 19.8678 | 16.7851 | 13.7025 | 10.6198 | 7.53719 | 4.45455 | 1.3719 | -1.71074 | -4.79339 | -7.87603 | -10.9587 |
| 10 | 19.5 | 16.4 | 13.3 | 10.2 | 7.1 | 4 | 0.9 | -2.2 | -5.3 | -8.4 | -11.5 |
| 9 | 19.0617 | 15.9383 | 12.8148 | 9.69136 | 6.5679 | 3.44444 | 0.32099 | -2.80247 | -5.92593 | -9.04938 | -12.1728 |
| 8 | 18.5313 | 15.375 | 12.2188 | 9.0625 | 5.90625 | 2.75 | -0.40625 | -3.5625 | -6.71875 | -9.875 | -13.0313 |
| 7 | 17.8776 | 14.6735 | 11.4694 | 8.26531 | 5.06122 | 1.85714 | -1.34694 | -4.55102 | -7.7551 | -10.9592 | -14.1633 |
| 6 | 17.0556 | 13.7778 | 10.5 | 7.22222 | 3.94444 | 0.66667 | -2.61111 | -5.88889 | -9.16667 | -12.4444 | -15.7222 |
| 5 | 16 | 12.6 | 9.2 | 5.8 | 2.4 | -1 | -4.4 | -7.8 | -11.2 | -14.6 | -18 |
| 4 | 14.625 | 11 | 7.375 | 3.75 | 0.125 | -3.5 | -7.125 | -10.75 | -14.375 | -18 | -21.625 |
| 3 | 12.8889 | 8.77778 | 4.66667 | 0.55556 | -3.55556 | -7.66667 | -11.7778 | -15.8889 | -20 | -24.1111 | -28.2222 |
| 2 | 11.5 | 6 | 0.5 | -5 | -10.5 | -16 | -21.5 | -27 | -32.5 | -38 | -43.5 |
| 1 | 24 | 11 | -2 | -15 | -28 | -41 | -54 | -67 | -80 | -93 | -106 |
| 0 | -5 | -4 | -3 | -2 | -1 | | 1 | 2 | 3 | 4 | 5 |

**ΔV**

In this graphic...

- Lead vehicle maintains consistent speed of 27 m/s

- Desired Speed
  $V_{des,rel} = 30\,\text{m/s}$
  $c_{des} = 2.5$

- Proximity to *pc*
  $n_{pc} = 5$
  $C_{y,pc} = 10$

- Relative speed to *pc*
  $C_{v,pc} = 10$

*Calibration factors are 5 times greater than the previous agent.*

**Figure 39: Total desired driver reaction in simplified car-following scenario: agent is 5 times more stressed than the agent in Figure 38.**

Consider the agent from Figure 38 in a scenario where he/she is "in a rush." This driver has a desired speed that they'd like to achieve and maintain, and "tailgates" other drivers who are traveling slower than the desired speed. One might assume this agent places a higher value on desired speed ($c_{des} = 1$, rather than 0.5), maintains the same regard for proximity ($c_{y,pc} = 2$), and they want to move as fast as traffic without crashing, so they place a high value on matching the velocity of the lead vehicle ($c_{v,pc} = 20$). Figure 40 shows the car following profile for the agent from Figure 38 "in a rush".

$$\bar{F}_{total}=\bar{F}_{totalpc}+\bar{F}_{des}$$

**ΔX**

| | -5 | -4 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 30 | 6.21444 | 5.39222 | 4.57 | 3.74778 | 2.92556 | 2.10333 | 1.28111 | 0.45889 | -0.36333 | -1.18556 | -2.00778 |
| 29 | 6.21201 | 5.38823 | 4.56445 | 3.74067 | 2.91688 | 2.09931 | 1.26932 | 0.44554 | -0.37824 | -1.20202 | -2.0258 |
| 28 | 6.20969 | 5.38418 | 4.55867 | 3.73316 | 2.90765 | 2.09214 | 1.25663 | 0.43112 | -0.39439 | -1.2199 | -2.04541 |
| 27 | 6.20754 | 5.38011 | 4.55267 | 3.72524 | 2.89781 | 2.09037 | 1.24294 | 0.4155 | -0.41193 | -1.23937 | -2.0668 |
| 26 | 6.20562 | 5.37604 | 4.54645 | 3.71686 | 2.88728 | 2.08769 | 1.22811 | 0.39852 | -0.43107 | -1.26065 | -2.09024 |
| 25 | 6.204 | 5.372 | 4.54 | 3.708 | 2.876 | 2.044 | 1.212 | 0.38 | -0.452 | -1.284 | -2.116 |
| 24 | 6.20278 | 5.36806 | 4.53333 | 3.69861 | 2.86389 | 2.07917 | 1.19444 | 0.35972 | -0.475 | -1.30972 | -2.14444 |
| 23 | 6.20208 | 5.36427 | 4.52647 | 3.68866 | 2.85085 | 2.07304 | 1.17524 | 0.33743 | -0.50038 | -1.33819 | -2.17599 |
| 22 | 6.20207 | 5.36074 | 4.51942 | 3.6781 | 2.83678 | 1.99545 | 1.15413 | 0.31281 | -0.52851 | -1.36983 | -2.21116 |
| 21 | 6.20295 | 5.3576 | 4.51224 | 3.66689 | 2.82154 | 1.99619 | 1.13084 | 0.28549 | -0.55986 | -1.40522 | -2.25057 |
| 20 | 6.205 | 5.355 | 4.505 | 3.655 | 2.805 | 1.955 | 1.105 | 0.255 | -0.595 | -1.445 | -2.295 |
| 19 | 6.20859 | 5.35319 | 4.49778 | 3.64238 | 2.78698 | 1.99158 | 1.07618 | 0.22078 | -0.63463 | -1.49003 | -2.34543 |
| 18 | 6.2142 | 5.35247 | 4.49074 | 3.62901 | 2.76728 | 1.99556 | 1.04383 | 0.1821 | -0.67963 | -1.54136 | -2.40309 |
| 17 | 6.22249 | 5.35329 | 4.48408 | 3.61488 | 2.74567 | 1.89647 | 1.00727 | 0.13806 | -0.73114 | -1.60035 | -2.46955 |
| 16 | 6.23438 | 5.35625 | 4.47813 | 3.6 | 2.72188 | 1.89375 | 0.96563 | 0.0875 | -0.79063 | -1.66875 | -2.54688 |
| 15 | 6.25111 | 5.36222 | 4.47333 | 3.58444 | 2.69556 | 1.86667 | 0.91778 | 0.02889 | -0.86 | -1.74889 | -2.63778 |
| 14 | 6.27449 | 5.37245 | 4.47041 | 3.56837 | 2.66633 | 1.76429 | 0.86224 | -0.0398 | -0.94184 | -1.84388 | -2.74592 |
| 13 | 6.3071 | 5.38876 | 4.47041 | 3.55207 | 2.63373 | 1.71538 | 0.79704 | -0.1213 | -1.03964 | -1.95799 | -2.87633 |
| 12 | 6.35278 | 5.41389 | 4.475 | 3.53611 | 2.59722 | 1.68833 | 0.71944 | -0.21944 | -1.15833 | -2.09722 | -3.03611 |
| 11 | 6.41736 | 5.45207 | 4.48678 | 3.52149 | 2.5562 | 1.59091 | 0.62562 | -0.33967 | -1.30496 | -2.27025 | -3.23554 |
| 10 | 6.51 | 5.51 | 4.51 | 3.51 | 2.51 | 1.51 | 0.51 | -0.49 | -1.49 | -2.49 | -3.49 |
| 9 | 6.64568 | 5.59877 | 4.55185 | 3.50494 | 2.45802 | 1.41111 | 0.3642 | -0.68272 | -1.72963 | -2.77654 | -3.82346 |
| 8 | 6.85 | 5.7375 | 4.625 | 3.5125 | 2.4 | 1.2875 | 0.175 | -0.9375 | -2.05 | -3.1625 | -4.275 |
| 7 | 7.16939 | 5.96122 | 4.75306 | 3.5449 | 2.33673 | 1.12857 | -0.07959 | -1.28776 | -2.49592 | -3.70408 | -4.91224 |
| 6 | 7.69444 | 6.33889 | 4.98333 | 3.62778 | 2.27222 | 0.91667 | -0.43889 | -1.79444 | -3.15 | -4.50556 | -5.86111 |
| 5 | 8.62 | 7.02 | 5.42 | 3.82 | 2.22 | 0.62 | -0.98 | -2.58 | -4.18 | -5.78 | -7.38 |
| 4 | 10.425 | 8.375 | 6.325 | 4.275 | 2.225 | 0.175 | -1.875 | -3.925 | -5.975 | -8.025 | -10.075 |
| 3 | 14.5444 | 11.5222 | 8.5 | 5.47778 | 2.45556 | -0.56667 | -3.58889 | -6.61111 | -9.63333 | -12.6556 | -15.6778 |
| 2 | 26.95 | 21.15 | 15.35 | 9.55 | 3.75 | -2.05 | -7.85 | -13.65 | -19.45 | -25.25 | -31.05 |
| 1 | 97.5 | 76.7 | 55.9 | 35.1 | 14.3 | -6.5 | -27.3 | -48.1 | -68.9 | -89.7 | -110.5 |
| 0 | -5 | -4 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 4 | 5 |

**ΔV**

**In this graphic…**

- Lead vehicle maintains consistent speed of 27 m/s

- Desired Speed
  $V_{des,rel} = 30\,\text{m/s}$
  $c_{des} = 1$

- Proximity to *pc*
  $n_{pc} = 5$
  $c_{pc} = 2$

- Relative speed to *pc*
  $c_{v,pc} = 20$

**Figure 40: Agent from Figure 38 "in a rush"**

The profile in Figure 40 describes a driver who "pushes" the lead vehicle by tailgating. The lead vehicle is traveling slower than the desired speed of the agent; however the agent places a high value on desired speed. The agent travels within close proximity of the lead vehicle, but is especially cautious to match speeds with the lead vehicle (to avoid a crash). When the agent is able to travel their desired speed and is sufficient distance behind the lead vehicle, the agent feels less "stress". As the agent approaches the lead vehicle and is no longer able to maintain the desired speed, the agent begins to tailgate. Note that the agent feels more "stress" when tailgating.

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Consider a scenario where the agent in Figure 38 places a higher value on proximity. The agent from Figure 38 is now driving an expensive new luxury car that belongs to their friend. When the agent parks this car, they choose the spot at the end of the lot with no other cars near it (to avoid "door dings"). The agent wants to stay clear of all other vehicles on the roadway, and values space higher than anything else. One might assume this agent's car following behavior varies drastically from the agent in Figure 40, maintaining their usual value for desired speed ($c_{des} = 0.5$) and relative velocity to the lead vehicle ($c_{v,pc} = 2$), but placing a much higher importance on proximity to the lead vehicle ($c_{y,pc} = 5$). Figure 41 shows the driving profile for this driver.

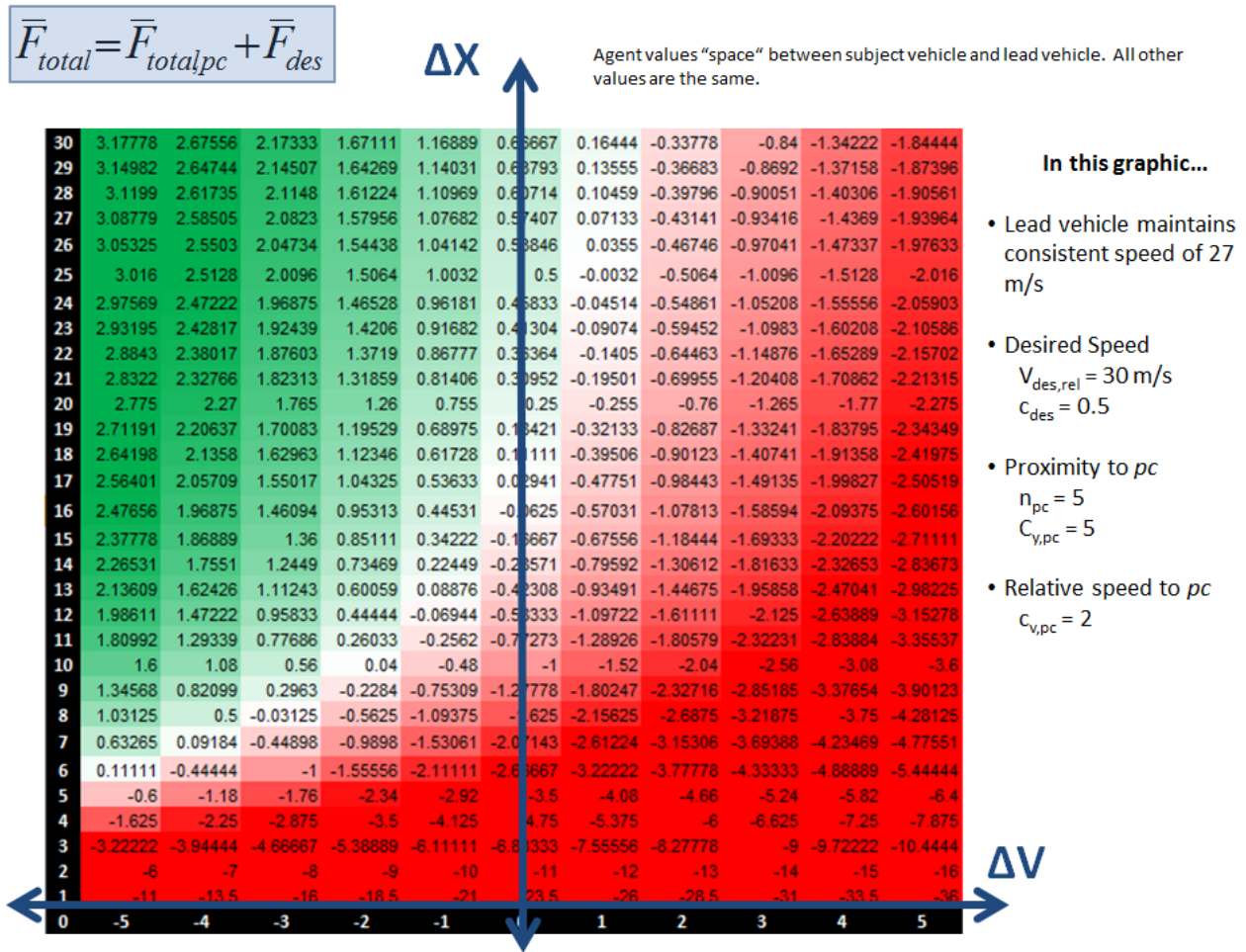$$\overline{F}_{total} = \overline{F}_{totalpc} + \overline{F}_{des}$$

**ΔX**

Agent values "space" between subject vehicle and lead vehicle. All other values are the same.

| | -5 | -4 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 30 | 3.17778 | 2.67556 | 2.17333 | 1.67111 | 1.16889 | 0.66667 | 0.16444 | -0.33778 | -0.84 | -1.34222 | -1.84444 |
| 29 | 3.14982 | 2.64744 | 2.14507 | 1.64269 | 1.14031 | 0.63793 | 0.13555 | -0.36683 | -0.8692 | -1.37158 | -1.87396 |
| 28 | 3.1199 | 2.61735 | 2.1148 | 1.61224 | 1.10969 | 0.60714 | 0.10459 | -0.39796 | -0.90051 | -1.40306 | -1.90561 |
| 27 | 3.08779 | 2.58505 | 2.0823 | 1.57956 | 1.07682 | 0.57407 | 0.07133 | -0.43141 | -0.93416 | -1.4369 | -1.93964 |
| 26 | 3.05325 | 2.5503 | 2.04734 | 1.54438 | 1.04142 | 0.53846 | 0.0355 | -0.46746 | -0.97041 | -1.47337 | -1.97633 |
| 25 | 3.016 | 2.5128 | 2.0096 | 1.5064 | 1.0032 | 0.5 | -0.0032 | -0.5064 | -1.0096 | -1.5128 | -2.016 |
| 24 | 2.97569 | 2.47222 | 1.96875 | 1.46528 | 0.96181 | 0.45833 | -0.04514 | -0.54861 | -1.05208 | -1.55556 | -2.05903 |
| 23 | 2.93195 | 2.42817 | 1.92439 | 1.4206 | 0.91682 | 0.41304 | -0.09074 | -0.59452 | -1.0983 | -1.60208 | -2.10586 |
| 22 | 2.8843 | 2.38017 | 1.87603 | 1.3719 | 0.86777 | 0.36364 | -0.1405 | -0.64463 | -1.14876 | -1.65289 | -2.15702 |
| 21 | 2.8322 | 2.32766 | 1.82313 | 1.31859 | 0.81406 | 0.30952 | -0.19501 | -0.69955 | -1.20408 | -1.70862 | -2.21315 |
| 20 | 2.775 | 2.27 | 1.765 | 1.26 | 0.755 | 0.25 | -0.255 | -0.76 | -1.265 | -1.77 | -2.275 |
| 19 | 2.71191 | 2.20637 | 1.70083 | 1.19529 | 0.68975 | 0.18421 | -0.32133 | -0.82687 | -1.33241 | -1.83795 | -2.34349 |
| 18 | 2.64198 | 2.1358 | 1.62963 | 1.12346 | 0.61728 | 0.11111 | -0.39506 | -0.90123 | -1.40741 | -1.91358 | -2.41975 |
| 17 | 2.56401 | 2.05709 | 1.55017 | 1.04325 | 0.53633 | 0.02941 | -0.47751 | -0.98443 | -1.49135 | -1.99827 | -2.50519 |
| 16 | 2.47656 | 1.96875 | 1.46094 | 0.95313 | 0.44531 | -0.0625 | -0.57031 | -1.07813 | -1.58594 | -2.09375 | -2.60156 |
| 15 | 2.37778 | 1.86889 | 1.36 | 0.85111 | 0.34222 | -0.16667 | -0.67556 | -1.18444 | -1.69333 | -2.20222 | -2.71111 |
| 14 | 2.26531 | 1.7551 | 1.2449 | 0.73469 | 0.22449 | -0.28571 | -0.79592 | -1.30612 | -1.81633 | -2.32653 | -2.83673 |
| 13 | 2.13609 | 1.62426 | 1.11243 | 0.60059 | 0.08876 | -0.42308 | -0.93491 | -1.44675 | -1.95858 | -2.47041 | -2.98225 |
| 12 | 1.98611 | 1.47222 | 0.95833 | 0.44444 | -0.06944 | -0.58333 | -1.09722 | -1.61111 | -2.125 | -2.63889 | -3.15278 |
| 11 | 1.80992 | 1.29339 | 0.77686 | 0.26033 | -0.2562 | -0.77273 | -1.28926 | -1.80579 | -2.32231 | -2.83884 | -3.35537 |
| 10 | 1.6 | 1.08 | 0.56 | 0.04 | -0.48 | -1 | -1.52 | -2.04 | -2.56 | -3.08 | -3.6 |
| 9 | 1.34568 | 0.82099 | 0.2963 | -0.2284 | -0.75309 | -1.27778 | -1.80247 | -2.32716 | -2.85185 | -3.37654 | -3.90123 |
| 8 | 1.03125 | 0.5 | -0.03125 | -0.5625 | -1.09375 | -1.625 | -2.15625 | -2.6875 | -3.21875 | -3.75 | -4.28125 |
| 7 | 0.63265 | 0.09184 | -0.44898 | -0.9898 | -1.53061 | -2.07143 | -2.61224 | -3.15306 | -3.69388 | -4.23469 | -4.77551 |
| 6 | 0.11111 | -0.44444 | -1 | -1.55556 | -2.11111 | -2.66667 | -3.22222 | -3.77778 | -4.33333 | -4.88889 | -5.44444 |
| 5 | -0.6 | -1.18 | -1.76 | -2.34 | -2.92 | -3.5 | -4.08 | -4.66 | -5.24 | -5.82 | -6.4 |
| 4 | -1.625 | -2.25 | -2.875 | -3.5 | -4.125 | -4.75 | -5.375 | -6 | -6.625 | -7.25 | -7.875 |
| 3 | -3.22222 | -3.94444 | -4.66667 | -5.38889 | -6.11111 | -6.83333 | -7.55556 | -8.27778 | -9 | -9.72222 | -10.4444 |
| 2 | -6 | -7 | -8 | -9 | -10 | -11 | -12 | -13 | -14 | -15 | -16 |
| 1 | -11 | -13.5 | -16 | -18.5 | -21 | -23.5 | -26 | -28.5 | -31 | -33.5 | -36 |
| 0 | -5 | -4 | -3 | -2 | -1 | | 1 | 2 | 3 | 4 | 5 |

**ΔV**

In this graphic...

- Lead vehicle maintains consistent speed of 27 m/s

- Desired Speed
  $V_{des,rel} = 30\,\text{m/s}$
  $C_{des} = 0.5$

- Proximity to $pc$
  $n_{pc} = 5$
  $C_{y,pc} = 5$

- Relative speed to $pc$
  $C_{v,pc} = 2$

**Figure 41: Agent from Figure 38, "valuing space" between subject vehicle and lead vehicle.**

Note that in Figure 41, the agent's total stress is much higher when they near the lead vehicle. This driver will maintain a much further following distance than usual.

No matter the speed profile, so long as a realistic agent is represented (i.e. not an agent who would rather rear-end the lead vehicle than slow down), each of these acceleration profiles has a gentle "swish" trend. Enhanced by the disconnect between the physical and cognitive maps and "lag time" created by the variable perception times, this "swish" that exists within each acceleration profile will create a "spiral" trend in car-

following. Figure 42 explains how a "spiral" occurs naturally because of this "swish" and because of the variable perception time lag between the Physical World and the Cognitive Map.
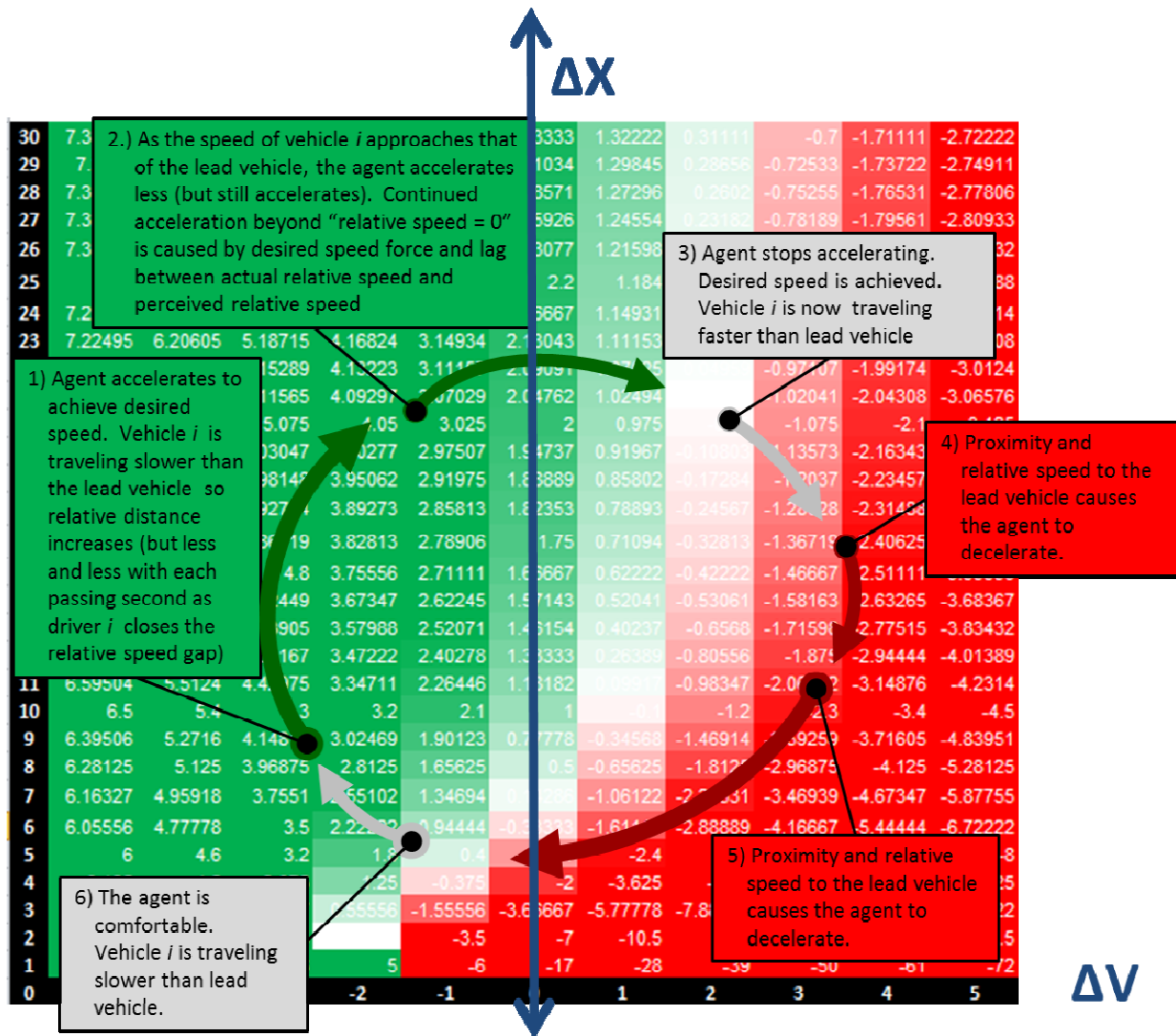


**Figure 42: Car Following "Spiral" trend occurs naturally in the acceleration profile.**

In Modified Field Theory, the "spiral" trend (a trademark of simple car-following behaviors) naturally occurs when an agent is in simple car-following. This trend is not "forced" to occur through algorithms purpose built to replicate this circular pattern (like

in Wiedemann's model).  Neither do the algorithms in MFT report stochastically

collected driver reactions.  Instead, MFT yields the "spiral" car following behavioral

trends as the result of Force Field Analysis resolution of the valences perceived by an

agent at a given time $T = t$ when in a simple car-following scenario.


## 5.2     Calibration

Showing how these speed profiles can replicate a spiral pattern is not enough to

validate Modified Field Theory for a simple car following scenario.  An agent must be

generated using Modified Field Theory, using comparable (but distinctly different) speed

data for the lead vehicle, to the lead vehicle in the validating dataset.  Comparing trends

observed in the empirically collected validation data and the car following data generated

for the agent in Modified Field Theory will validate MFT's simple car-following

abilities.


But first, speed data for the lead vehicle needs to be obtained, and this speed data

must be comparable to the lead vehicle.


### 5.2.1   Agent 1

It would be unrealistic to model car following using a lead vehicle that maintains

one static speed; minor fluctuations in speed are expected.  Additionally, it is not

appropriate to use speed data from the Driver 15 of the FHWA TFHRC Living

Laboratory dataset when constructing the calibrated model; using speed data from two

different sources is required, otherwise common trends may emerge between the calibrated model and the validation data that stem from using the same data. A new dataset for speed data for the lead vehicle must be created, and this dataset must be similar to (but not the same as) the speed data for the lead vehicle for Driver 15. To generate this lead speed data, Agent 1 is created.

Using Modified Field Theory, simplified car-following equations, an agent (Agent 1) was created to serve as a "lead vehicle" for a second agent (Agent 2). Agent 1 is created to synthetically generate a speed profile for a lead vehicle (i.e. the speed of Agent 1 at various times) for Agent 2. This speed profile should be generated such that it is comparable to the speed profile for the lead vehicle in empirically collected data. It would not be realistic to compare empirically collected car following data to Agent 1, since Agent 1 is following a lead vehicle that maintains a constant speed.

Agent 1 followed a lead vehicle that maintained a consistent 7 m/s speed. The calibration factors and variables that describe this agent, *Agent 1,* and the model parameters used, are given in Table 1.

**Table 1: Model parameters and calibration factors for Agent 1**

**Agent 1:**

| Calibrating Desired Speed Force | | Calibrating forces from Proximity to lead vehicle | | Calibrating forces from relative velocity to lead vehicle | | Perception times | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Perception time for proximity | 0.75 | s |
| $V_{des,rel}$ = | 10    m/s | $n_{pc}$ = | 5 | | | | | |
| $c_{des}$ = | 0.82 | $c_{y,pc}$ = | 3 | $c_{v,pc}$ = | 20 | Perception time for velocity | 1.5 | s |

| Threshold (minimum $F_{total}$ to elicit a reaction) | +/- 0.1 | Force units |
|---|---|---|
| Max acceleration, Vehicle $i$ | 5 | m/s/s |
| Max deceleration, Vehicle $i$ | 9.8 | m/s/s |

**Model Parameters:**

| Model time step | 0.75 | seconds |
|---|---|---|
| Starting distance (d) | 25 | meters |
| Length of Lead Vehicle (L) | 6.096 | meters |

Max acceleration and deceleration for the lead vehicle are included in the model, but in this instance did not influence results.  For future uses of this model, max acceleration and deceleration may influence model results. The length of the lead vehicle was assumed to be 20ft, of 6.096 meters.

Using these parameters, simple car following behavior was predicted for Agent 1, following a lead vehicle traveling at a steady 7 m/s.  Figure 43 shows the car following behavior of Agent 1.
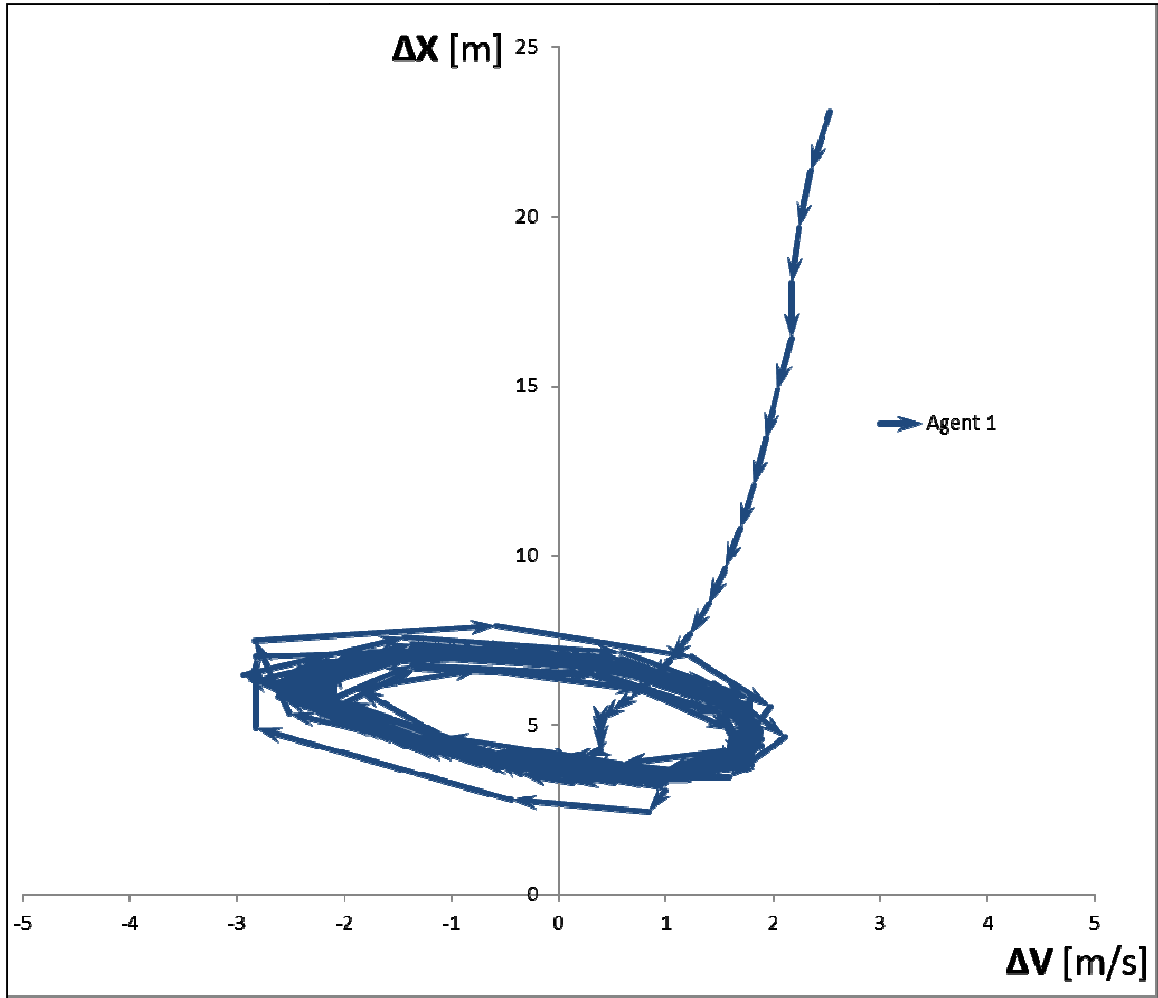
**Figure 43: Car following behavior of Agent 1**

Agent 1 experiences a "spiral" car-following behavior. However, this spiral is "tight" and "neat" when compared to the empirically collected data for Driver 15 from FHWA TFHRC Living Laboratory (Figure 7). This is because Agent 1 is following a lead vehicle that maintains a constant speed. It is important to note that the lead vehicle in the FHWA TFHRC dataset did not maintain a consistent speed. Although Agent 1 shows the same "spiral" patterns as empirically collected data, it lacks the variations seen in empirically collected data, when the lead vehicle speed fluctuates. Without fluctuating

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lead vehicle speed data, Agent 1 is not an entirely realistic representation of car-following data.

Speed data for Agent 1, however, could be used as lead vehicle data for Agent 2. Characteristics of Agent 1's speed data must first be examined and compared against those of Driver 15.

The full speed data for Agent 1 is available in on request.  Statistics describing the speed profile for Agent 1 can be found in the table below (Table 2):

**Table 2: Statistics for speed, acceleration, and deceleration of Agent 1**

| Agent 1 speed data profile | | | Agent 1 acceleration profile | | |
|---|---|---|---|---|---|
| average speed | 7.03 | m/s | average acceleration | 1.16 | m/s/s |
| max speed | 10.00 | m/s | max rate of acceleration | 5.18 | m/s/s |
| min speed | 3.60 | m/s | min rate of acceleration | 0.15 | m/s/s |
| Std dev of speed | 1.53 | | std dev of acceleration | 1.17 | |

| Agent 1 deceleration profile | | |
|---|---|---|
| average deceleration | -1.16 | m/s/s |
| min rate of deceleration | -0.16 | m/s/s |
| max rate of deceleration | -5.34 | m/s/s |
| std dev of deceleration | 1.29 | |

Statistics describing the speed data for the lead vehicle in front of Driver 15 are described in Table 3.  Car following data for FHWA TFHRC Driver 15 shows 142.5 seconds of car following data, with data recorded every 0.1 seconds, making 1425 data points total.

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**Table 3: Statistics for speed, acceleration, and deceleration for the vehicle in front of Driver 15**

| Lead vehicle in front of Driver 15 (FHWA TFHRC Living Laboratory car following data) speed data profile | | |
|---|---|---|
| average speed | 3.95 | m/s |
| max speed | 10.01 | m/s |
| min speed | 0 | m/s |
| Std dev of speed | 1.80 | |

| Lead vehicle in front of Driver 15 (FHWA TFHRC Living Laboratory car following data) acceleration profile | | |
|---|---|---|
| average acceleration | 0.61 | m/s/s |
| max rate of acceleration | 7.64* | m/s/s |
| min rate of acceleration | 0.02 | m/s/s |
| std dev of acceleration | 1.10 | |

| Lead vehicle in front of Driver 15 (FHWA TFHRC Living Laboratory car following data) deceleration profile | | |
|---|---|---|
| average deceleration | -0.64 | m/s/s |
| min rate of deceleration | -0.01 | m/s/s |
| max rate of deceleration | -6.53* | m/s/s |
| std dev of deceleration | 1.05 | |

There were a few outliers within the acceleration and deceleration rates. Outliers could be generated by computer error or false readings (such as acceleration changes reported because the driver hit a pothole). There were six outliers in total, all of which were individually examined.

In the column "max acceleration", there were five total outliers. The first of these outliers occurred at time steps 26.30 seconds (11.85m/s/s), and did not fit the deceleration trend surrounding it; this outlier was discarded. The next outlier, at time step 38.30 seconds, was 10.95 m/s/s, and was bookended by values 1.38 and 1.67 m/s/s. This outlier was discarded. The next outlier, 11.85 m/s/s, occurred at the time step 69.90 seconds,

and was preceded by a deceleration rate of -2.54 m/s/s and followed by an acceleration of 0.10 m/s/s; since this outlier did not fit the existing trend, it was discarded. The final outlier, 24.29 m/s/s, occurred at time step 70.20 seconds, and did not match the acceleration rates that bookended it (0.18 and 1.51m/s/s), so it was discarded.

In the column "max rate of deceleration", there was one outlier total. The outlier occurred at the time step 56.90 seconds, and had a value of -11.33 m/s/s. This outlier was preceded by a deceleration rate of -5.85 and followed by a rate of -3.01m/s/s. Because this rate did not fit the existing trend, and because it was such a strong outlier, it was discarded.

### 5.2.1.1 Comparing the speed profile of Agent 1 to the vehicle leading Driver 15

Statistics describing the speed data for Agent 1 show no unrealistic instances of acceleration or deceleration (max and min acceleration and deceleration are well within the capabilities of an average vehicle). These mild adjustments to acceleration and deceleration yield reasonable speeds that are comparable to data from FHWA TFHRC Living Laboratory Driver 15 lead vehicle data (average of 7.03 m/s, max speed of 10.00 m/s, min speed of 3.60 m/s). Although these speeds seem uncharacteristically slow for freeway flows, they are comparable to the Driver 15 data and will be used.

The data for Driver 15 did include stronger incidents of max acceleration for the lead vehicle. These incidents caused longer "sweeps" within the spiral data. These

"sweeps" will be discussed in the validation section, and by replicating conditions from the field data, will be replicated using MFT.

Because Agent 1's speed, acceleration, and deceleration data are well within the norm, and because they are similar to the lead vehicle speed data collected for Driver 15, they will be used as lead vehicle data for Agent 2, which will be validated against driver 15.

### 5.2.2 Agent 2

Agent 2 follows Agent 1. Table 4 describes Agent 2 and shows the calibration factors used.

**Table 4: Model Parameters and calibration factors for Agent 2**

**Agent 2:**

| Calibrating Desired Speed Force | | Calibrating forces from Proximity to lead vehicle | | Calibrating forces from relative velocity to lead vehicle | | Perception times | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Perception time for proximity | 1 | s |
| $V_{des,rel}$ = | 10 m/s | $n_{pc}$ = | 5 | | | Perception time for velocity | 1.5 | s |
| $c_{des}$ = | 0.82 | $c_{y,pc}$ = | 6.35 | $c_{v,pc}$ = | 5 | | | |

| Threshold (minimum $F_{total}$ to elicit a reaction) | +/- 1 | Force units |
|---|---|---|
| Max acceleration, Vehicle $i$ | 5 | m/s/s |
| Max deceleration, Vehicle $i$ | 9.8 | m/s/s |

**Model Parameters:**

| Model time step | 0.50 | seconds |
|---|---|---|
| Starting distance (d) | 25 | meters |
| Length of Lead Vehicle (L) | 6.096 | meters |

Agent 2 is plot on a graph against Driver 15 data. Figure 44 shows Agent 2's car following trends overlaid on Driver 15.
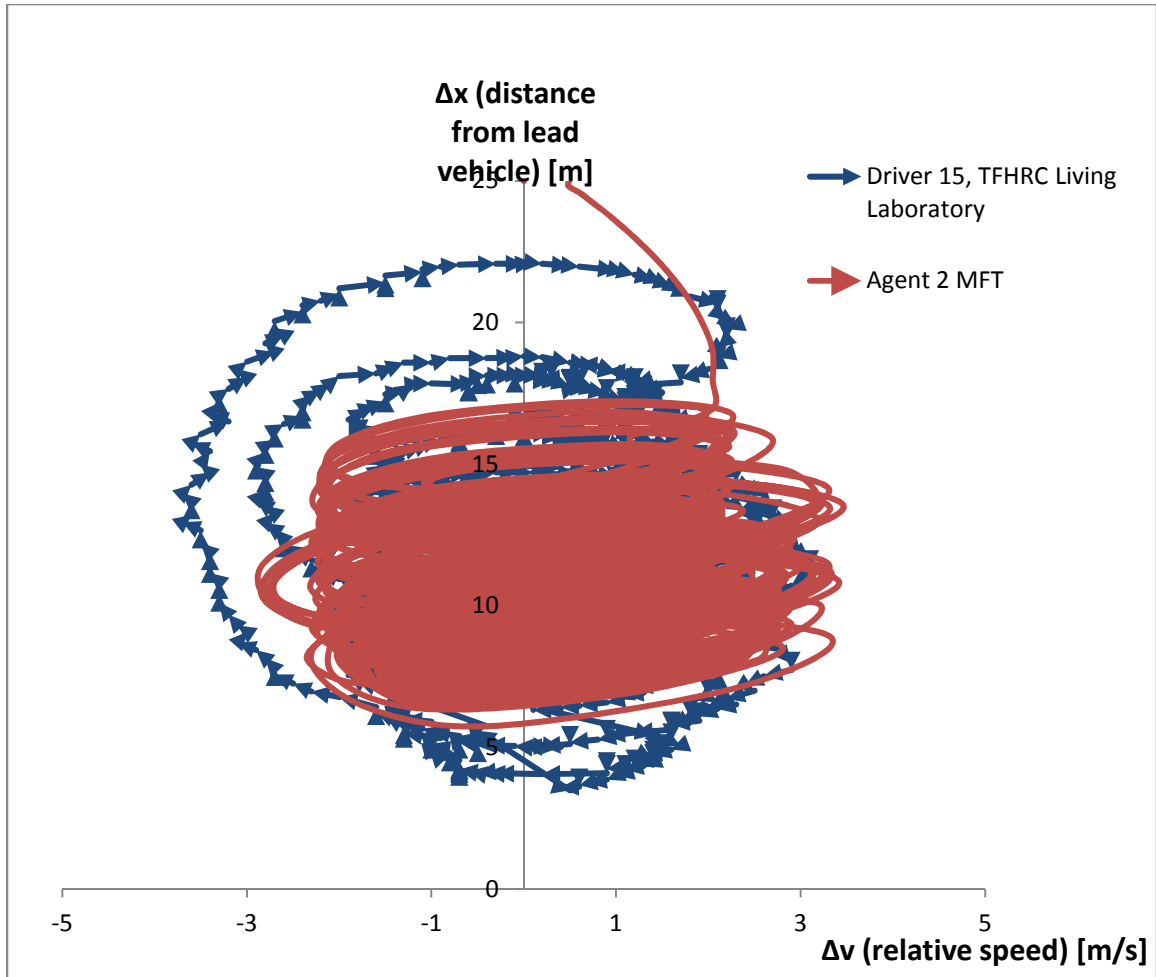


**Figure 44: Car Following behavior of Agent 2 and Driver 15.**

## 5.3    Validation

Modified Field Theory is validated for use modeling simple freeway car-following with lane closure due to a work zone.  Agent 2 from Modified Field Theory follows a similar (yet not the same) lead vehicle as Driver 15.  The car following behavior of the calibrated Agent 2 shows strong resemblance to the car following behavior of the field collected Driver 15.  These spiral car following trends are reflected both in Driver 15 and Agent 2, and these trends occur within the same general area.

This section describes how by comparing the car following behaviors of Agent 2 and Driver 15, Modified Field Theory is validated for use as a car following model in the simple car following scenario described.

### 5.3.1    *Spiral trends in car following*

Figure 44 shows the car following behavior of Agent 2 overlaid on Driver 15.  The "spiral" trends for driver 15 and Agent 2 are similar.  The vast majority of spirals occur in approximately the same area (between relative speeds of -2 and 3, between car following distances of 7.5 and 17 meters).

The spirals themselves are about the same size and shape.  An individual spiral for Driver 15 is typically bound between the relative velocities -2 and 3 m/s, and has a height of approximately 4-7 meters along the relative distance scale.  The spirals generated using Agent 2 are roughly the same dimensions.

## 5.3.2 *"Sweeps"*

There were "long sweeps" observed within the FHWA TFHRC Living Laboratory data for Driver 15 that show driver "spirals" that vary in size and shape from the majority of spirals. Figure 45 highlights an instance where one of these spirals occurs.
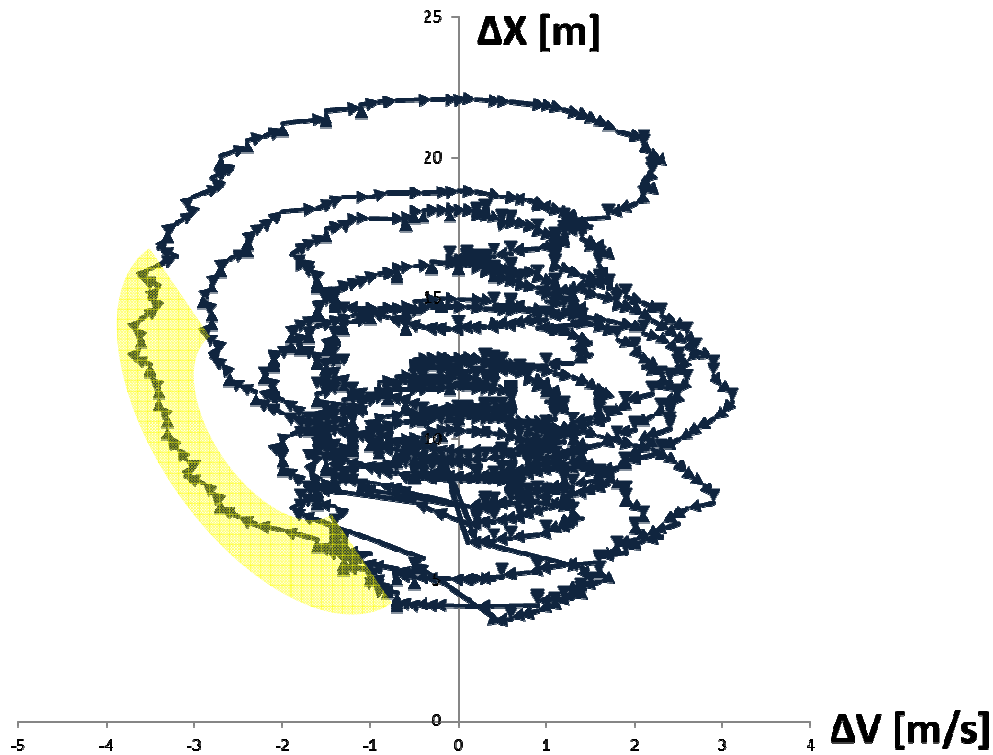


**Figure 45: Long "sweep" in the spiral pattern observed for driver 15**

Examining the lead vehicle during the time period for which this "sweep" spiral occurs, a sudden acceleration of the lead vehicle can be observed. The lead vehicle is traveling 2.26 m/s at the 123.8 second time stamp, and in less than 5 seconds the lead

vehicle increases speed by over 7 m/s, traveling 9.49 m/s at 128.6 second time stamp.

Table 5 shows data for the lead vehicle ahead of Driver 15 during this time period.

**Table 5: Velocity data for Lead Vehicle of Driver 15 during the "sweeping" spiral.**

| Time step (s) | Speed of lead Vehicle (m/s) | Accel. or Decel. of Lead vehicle (m/s/s) |
|---|---|---|
| 123.80 | 2.255504 | 1.77166 |
| 123.90 | 2.452616 | 1.97112 |
| 124.00 | 2.552616 | 1 |
| 124.10 | 2.68637 | 1.33754 |
| 124.20 | 2.670305 | -0.16065 |
| 124.30 | 2.75776 | 0.87455 |
| 124.40 | 2.642327 | -1.15433 |
| 124.50 | 2.706316 | 0.63989 |
| 124.60 | 3.088626 | 3.8231 |
| 124.70 | 3.173193 | 0.84567 |
| 124.80 | 3.373193 | 2 |
| 124.90 | 3.50406 | 1.30867 |
| 125.00 | 3.547471 | 0.43411 |
| 125.10 | 3.693771 | 1.463 |
| 125.20 | 3.74007 | 0.46299 |
| 125.30 | 4.160648 | 4.20578 |
| 125.40 | 4.470937 | 3.10289 |
| 125.50 | 4.670937 | 2 |
| 125.60 | 4.870937 | 2 |
| 125.70 | 4.96868 | 0.97743 |
| 125.80 | 5.176713 | 2.08033 |
| 125.90 | 5.127525 | -0.49188 |
| 126.00 | 5.517868 | 3.90343 |
| 126.10 | 5.736821 | 2.18953 |
| 126.20 | 5.811099 | 0.74278 |
| 126.30 | 6.137452 | 3.26353 |
| 126.40 | 6.237452 | 1 |
| 126.50 | 6.330052 | 0.926 |
| 126.60 | 6.438084 | 1.08032 |
| 126.70 | 6.712994 | 2.7491 |
| 126.80 | 6.975358 | 2.62364 |
| 126.90 | 7.073102 | 0.97744 |
| 127.00 | 7.337723 | 2.64621 |
| 127.10 | 7.512632 | 1.74909 |

| 127.20 | 7.712632 | 2 |
|---|---|---|
| 127.30 | 7.638354 | -0.74278 |
| 127.40 | 7.802975 | 1.64621 |
| 127.50 | 8.108751 | 3.05776 |
| 127.60 | 8.224815 | 1.16064 |
| 127.70 | 8.364346 | 1.39531 |
| 127.80 | 8.603245 | 2.38899 |
| 127.90 | 8.67301 | 0.69765 |
| 128.00 | 8.87301 | 2 |
| 128.10 | 8.824454 | -0.48556 |
| 128.20 | 8.848551 | 0.24097 |
| 128.30 | 9.099995 | 2.51444 |
| 128.40 | 9.128605 | 0.2861 |
| 128.50 | 9.39097 | 2.62365 |
| 128.60 | 9.486457 | 0.95487 |

The sudden and sustained acceleration of the lead vehicle causes a long "sweeping" spiral to occur. The acceleration starts when the lead vehicle is traveling at a speed less than average, and continues for 5 seconds until the lead vehicle reaches a speed near the max velocity (close to 10 m/s). This "sweep" does not match the other spirals for Driver 15.

As part of the validation process for Modified Field Theory, these conditions are replicated for Agent 2 to see if this "sweep" will be predicted by MFT under the same circumstances. First, a time step was located where Agent 1 has neared its minimum velocity (since this long "sweep" began when the lead vehicle ahead of Driver 15 had neared one of its minimum velocities). Time step 59 seconds was selected for Agent 1, since at time step 58.5 Agent 1 was close to one of its slower speeds, 4.59 m/s. The speed profile for Agent 1 was then adjusted such that Agent 1 accelerated 6.5 m/s (to one of its fastest speeds, 10.5 m/s) over the duration of 5.5 seconds (a long, steady

acceleration over the duration of roughly 5 seconds) to mimic the acceleration during the

"sweep" for the lead driver ahead of Driver 15. Table 6 shows how the speed profile for

Agent 1 was altered.

**Table 6: Speed profile adjustments for Agent 1 (before and after) to replicate conditions during the "sweep" observed for Driver 15**

| Time step (s) | Speed (before) | Speed (after) | |
|---|---|---|---|
| 58 | 5.271939804 | 5.271939804 | *(unchanged)* |
| 58.5 | 4.585857345 | 4.585857345 | *(unchanged)* |
| 59 | 6.295552185 | 4 | |
| 59.5 | 8.001600958 | 5.1 | (+1.1) |
| 60 | 8.835909131 | 6.2 | (+1.1) |
| 60.5 | 8.618963471 | 7 | (+0.8) |
| 61 | 7.477987863 | 7.7 | (+0.7) |
| 61.5 | 5.487075968 | 8.2 | (+0.5) |
| 62 | 4.487945888 | 8.6 | (+0.4) |
| 62.5 | 6.062125471 | 8.9 | (+0.3) |
| 63 | 7.844217642 | 9.1 | (+0.2) |
| 63.5 | 8.801981144 | 9.2 | (+0.1) |
| 64 | 8.694266452 | 10 | (+0.8) |
| 64.5 | 7.659958876 | 10.5 | (+0.5) |
| 65 | 5.719580319 | 10 | (-0.5) |
| 65.5 | 4.439526454 | 9 | (-1) |
| 66 | 5.828697315 | 8 | (-1) |
| 66.5 | 7.674479542 | 7.674479542 | *(unchanged)* |
| 67 | 8.749873477 | 8.749873477 | *(unchanged)* |
| 67.5 | 8.749873477 | 8.749873477 | *(unchanged)* |

Figure 46 shows the results of replicating the lead car acceleration behavior that

occured during the "sweep" observed for Driver 15, in Agent 2's car following behavior

using MFT. A "sweep" is observed in Agent 2's car following behavior. This "sweep"

aligns with the "sweep" in Driver 15, creating approximately the same long sweeping

spiral as was witnessed in Driver 15. Note that the lead car speed data used to replicate

this sweep for Agent 2 was not identical to the lead car speed data during the sweep for
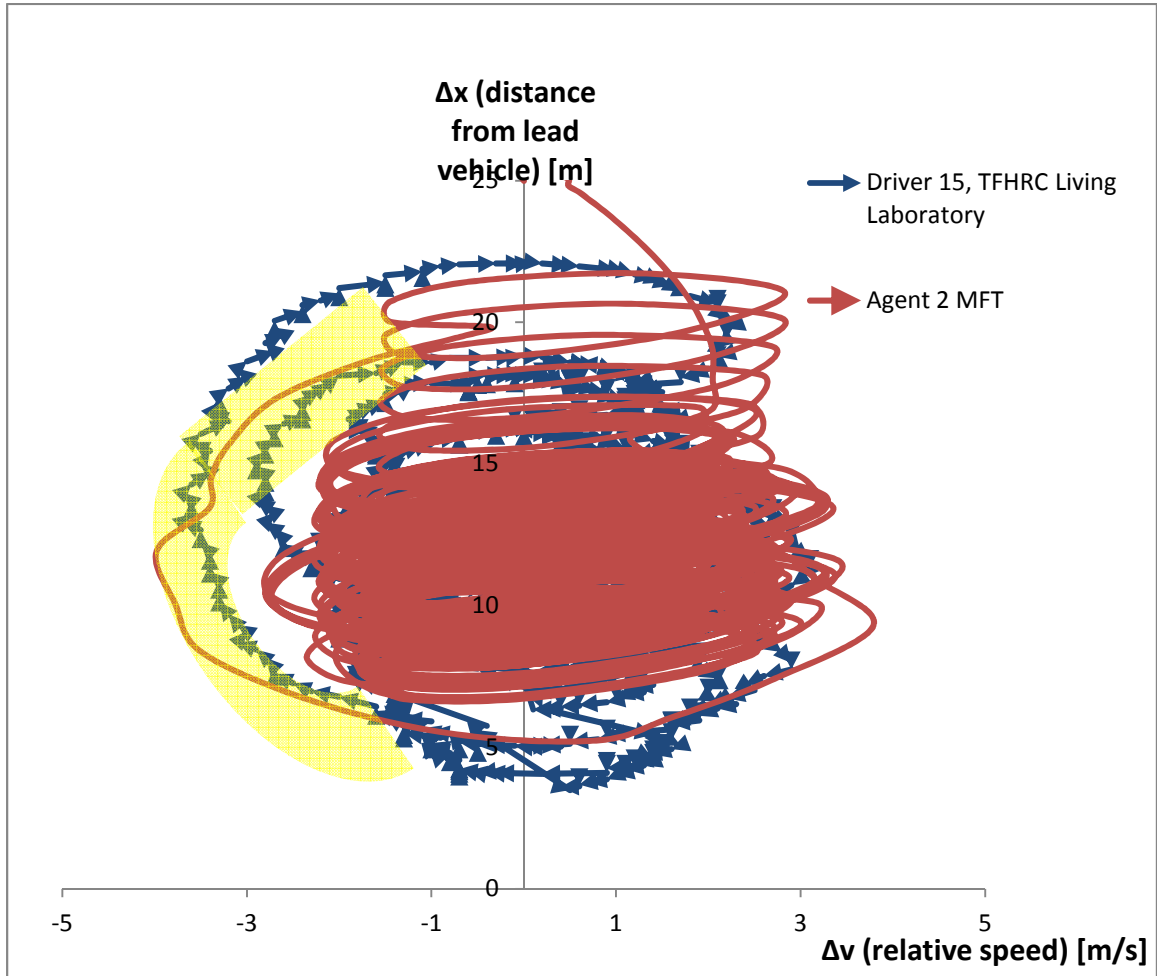
Driver 15, but was comparable.



**Figure 46: MFT with synthetically replicated conditions during the "sweep" observed in Driver 15's car following behavior**

This validation demonstrates that:

1.) Modified Field Theory replicates the spiral pattern found in car following

behavior,

2.) A calibrated agent (Agent 2) can to mimic the spiral patterns (in size, shape, location, and magnitude) of real drivers, driving through freeway work zones experiecing lane closure, and

3.) When unusual events occur within the field collected car following data, by duplicating the circumstances surrounding these events, Modified Field Theory can also repicate these unusual events.

Modified Field Theory has been validated for simple car following through a freeway work zone experiencing lane closure, replicating both the expected and unexpected trends (when conditions surrounding the unusual/unexpected events are synthetically reproduced).

# CHAPTER 6

# CONCLUSION

This research lays the ground work for providing Modified Field Theory the ability to model work zones.  Modified Field Theory has the potential to solve numerous problems with modern-day microscopic models, while maintaining the flexibility and adaptability to model new roadway elements and developing technologies that cannot be modeled using the status quo.  Work zones generate delays world-wide, and to avoid those delays simulation is crucial.  No microscopic model has the ability to readily incorporate the impacts of modern traffic alleviation methods such as ITS technologies; however, Modified Field Theory may have the potential to accommodate all these impacts.  Modified Field Theory has potential for becoming a new microscopic work zone model.

Other variables within Modified Field Theory still need to be calibrated.  However, it is the intent of this research to lay the foundation for a new microscopic model that can easily and more accurately address the numerous concerns associated with microscopic modeling in work zone analysis.

Modified Field Theory will provide a more accurate microscopic model.  Current microscopic models use complex mathematical algorithms to describe how a vehicle can be observed traversing down a roadway.  On the road, however, vehicles are not controlled by complex algorithms; they are controlled by a driver.  When a driver

perceives an obstacle in front of them, they do not begin adding, subtracting, and multiplying; they see the obstacle, realize they do not want to collide with it, then react appropriately either by changing to a lane with no obstacle (if no other vehicles are impeding that decision), or if that is not an option they begin slowing/stopping to avoid a collision. Modified Field Theory is a driver-centric model that puts the driver (and not an equation) at the center of the model, showing how the driver would perceive these external stimuli and how the driver might react.

Because the model is driver-centric, other driving-related variables can easily be added to the model, making the model more "true-to-life" by incorporating stimuli and phenomena that one would expect to see on the roadway. Distracted driving, drunk driving, older drivers and younger drivers, female drivers and male drivers can all be modeled simply by collecting the same data one could collect from a driving simulator. ITS technologies, chevrons (and other pavement markings), new signage, heavy vehicles and EMS vehicles can all be added as well, simply by calibrating their associated forces. The model is more versatile than the status-quo, and can adapt to model any roadway stimuli that exist.

## 6.1    Addresses Gaps Left by Other Models

Because of how the model is constructed and how the model operates, Modified Field Theory addresses some of the gaps left by other microscopic models.

### *6.1.1 Flexible architecture*

The flexible architecture of Modified Field Theory centers algorithms around each additional stimulus, rather than around the subject driver. By doing so, new stimuli can be calibrated and added to the model without re-writing the underlying algorithms.

Additionally, MFT assesses the impacts of stimuli in two dimensions, whereas traditional models feature a hard divide between car following and lane changing behaviors and algorithms. By demonstrating the impacts of a stimulus in two dimensions, MFT is fit to model certain scenarios that existing models cannot (such as hook-following).

### *6.1.2 Different drivers drive differently*

Literature explains that different drivers drive differently. Current models use one set of algorithms and one distribution to stochastically determine driver behavior for the entire driving population. Calibrating these models requires data collection methodologies beyond the capabilities of a typical engineering firm.

Modified Field Theory divides the driving population into sub-populations (older vs. middle-aged vs. younger, male vs. female, unfamiliar vs. commuter, and congested conditions vs. free flow) and models each population using algorithms and distributions specific to each sub-population. Sub-populations are defined such that (1) specific driver populations identified in the literature to have unique driver behaviors are modeled separately, and (2) the percentage of drivers within a network that comprise each sub-

population is quantifiable using data collection methods currently employed by engineering firms, allowing practitioners to calibrate their model for various regions using current practices. MFT retains an element of utility for practitioners while demonstrating the impacts of various driving populations, and allowing the model to be calibrated to fit various regions of the country.

### 6.1.3 *Models the decision-making process*

By (1) dividing the Physical World from the Cognitive Map, and (2) adopting a modified version of Kurt Lewin's Field Theory to model the decision-making process in the Cognitive Map, Modified Field Theory models elements of the decision-making process. MFT is explanatory in nature, demonstrating *why* certain behaviors and phenomena happen. Other models are descriptive and can only tell users *what* typically happens. In addition, modeling the divide between Physical World and Cognitive Maps allows MFT to model how blind spots, additional cognitive loadings, or distracted driving might impact the driving behaviors of a given driving population.

## 6.2    Validated for Simple Car Following Through a Freeway Work Zone

Validated against Driver 15 from the TFHRC Living Laboratory, Agent 2 showed similar trends to the field collected data. The car following behaviors of Agent 2 were able to be manipulated such that unusual trends in the car following behavior of Driver 15 were duplicable.

### 6.2.1  *Spiral trend*

Modified Field Theory was able to replicate the spiral trends found in car-following.  While other models force this spiral to occur through purpose-built algorithms, the spiral in MFT is a bi-product of the multiple forces experienced by a driver at a given point in time and the lag between observation and perception for various roadway stimuli, such as velocity.

### 6.2.2  *"Sweeps"*

Unusual trends in empirically collected data were also replicable in Modified Field Theory when conditions were similar.  Long "sweeping" spirals existed for Driver 15 that were inconsistent with the other spiral trends.  During these "sweeps", it was observed that the lead vehicle (the vehicle in front of Driver 15) had accelerated significantly.  Replicating the acceleration of the lead vehicle in Modified Field Theory, the same long "sweeping" trends could be observed in Agent 2.  This demonstrates that Modified Field Theory can also capture some of the inconsistencies that exist in the real world that aren't reflected in today's microscopic models.

### 6.3  **Next Steps**

Assessing the current status of Modified Field Theory, it lies somewhere on the bottom of the System's Engineering Process (SEP) "V" diagram.  The overall model architecture has been established, and algorithms have been written for some of the basic roadway stimuli.  Many more stimuli need to have their algorithms written.  Other

behaviors, such as lane-changing and hook-following, need to be validated. Once other subcomponents are created and validated, small networks need to be constructed and the model needs to be validated as a network. Finally, the model needs to be validated altogether.

## 6.4 Potential Impact

Modified Field Theory has the potential to resolve some of the more complex issues with microscopic modeling, providing a more usable and accurate microscopic model for freeway work zones. With the number of work zones projected to increase, and with new ITS and operational elements introduced annually, a fully developed and validated Modified Field Theory could provide work zone planners with a more accurate view of how different work zone set-ups and alternatives will impact driver behavior, allowing planners to reduce the negative impacts, such as crashes and delays, associated with work zones.

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