Supplemental Data Set: **Fine-Tuning ADAS Algorithm Parameters for Optimizing Traffic Safety and Mobility in Connected Vehicle Environment**

# Methodology

A major assumption in this study is that a driver makes behavior changes only when the ADAS is interacting with the driver. If the ADAS does not provide warning or advisory information, the driver is assumed to behave similarly to the non-ADAS equipped drivers. The methodology framework for identifying the optimal ADAS algorithm parameter set is illustrated by **Fig. 1**. The framework elaborates major components involved in this research, and governing equations adopted by individual components. Numbers in the shaded circles represent subsections that discuss the corresponding components.



**Fig. 1.** Methodology framework for identifying optimal ADAS configuration.

## *3.1 Identification of target ADAS algorithm parameters*

As one of the most important functions in ADAS, the FCW is considered in the presented study. The FCW function determines the driving behavior criteria based on the kinematic and perceptual approach (Bella and Russo, 2011). With the perceptual approach, an alarm is triggered once the subject driver’s headway or time-to-collision (TTC) to the leading vehicle is lower than the pre-specified critical headway or TTC threshold (Shinar & Schechtman, 2002; Mulder et al., 2004; Mohebbi et al., 2009). On the other hand, the kinematic approach continuously compares the subject driver’s following distance (or spacing) with the warning distance, which is a function of the host vehicle’s speed, the relative speed and spacing between the host vehicle and the leading vehicle. If the spacing is shorter than the warning distance, the ADAS will issue a warning message to the subject driver (Brunson et al., 2002).

In some studies, the perceptual approaches that adopt the TTC based thresholds are reported (Mulder et al., 2004; Mohebbi et al., 2009; Nodine et al., 2011), and in other studies the headway based thresholds are applied (Shinar & Schechtman, 2002; Birrell et al., 2014). The TTC or headway threshold of an ADAS is usually directly set to a fixed value. The reported TTC thresholds range from 2.0 seconds to 5.0 seconds, whereas the headway thresholds are between 0.8 second to 2.0 seconds. Both TTC thresholds and headway thresholds can be adopted to affect the subject driver’s desired car-following distance. In this study, the headway threshold is selected as an ADAS algorithm parameter to be optimized later, because it can be directly associated with the subject driver’s car-following behavior. The boundary of the headway threshold is given as:

 (1)

Above boundary specifies the field within which the search for the optimal headway threshold should be performed.

The kinematic approach adopts algorithms such as the Mazda algorithm (Ararat et al., 2006), the stopping distance algorithm (ISO 15623, 2002), the CAMP algorithm (Kiefer et al., 2003), and the National Highway Traffic Safety Administration (NHTSA) algorithm (Brunson et al., 2002). In this study, the NHTSA algorithm is adopted because it considers different cases as the host vehicle approaches the leading vehicle in a potential collision course. Specific model formulations are applied for computing the warning distance in individual cases. Particularly, when an initially moving leading vehicle stops prior to the host vehicle or the leading vehicle is initially stopped, the following condition should be met:

 (2)

The warning distance is:

 (3)

where is the assumed maximum deceleration of the host vehicle; is the current acceleration of the host vehicle; is the acceleration of the leading vehicle; is the time for the leading vehicle to stop: ; is the time for the host vehicle to stop: if , or ; is the speed of the leading vehicle; is the speed of the host vehicle; is the range rate, which equals to ; and is minimum distance between the leading vehicle and the host vehicle.

When the host vehicle stops while the leading vehicle is still in motion or , the warning distance is:

 (4)

where is the time when is 0: if , otherwise .

The NHTSA algorithm contains three free parameters: the minimum distance between the leading vehicle and the host vehicle (), the perception-reaction time of the subject driver (), and the maximum deceleration of the host vehicle (). These parameters are candidate ADAS algorithm parameters to be optimized, because changing their levels can alter the timing when the ADAS starts to interact with the subject driver. In practice, is usually set to the average vehicle spacing in jam traffic (e.g., 2 meters). The of the subject driver can be obtained from some on-board sensing mechanism that captures the time gap between the onset of the ADAS warning and the onset of the subject driver’s reaction. As the free parameters and can be confidently determined, they are excluded from the optimization study. The remaining parameter is taken as the second ADAS algorithm parameter to be configured. The influence of on the warning distance is visualized by **Fig. 2**.



Parameters used in this plot: initial speed of the leading vehicle = 30 m/s; deceleration of the leading vehicle = -0.55g; PRT = 1.4 s; and D0 = 2 m.

**Fig. 2.** Warning distance under various levels.

The existing studies adopt in a range between 0.27g and 0.75g (, gravity acceleration) (Brunson et al., 2002; Lee et al., 2002). A smaller would result in a longer warning distance and earlier collision warning, and a larger shorter warning distance and later collision warning. In this case, the boundary of the warning distance threshold is given as:

 (5)

## *3.2 Modeling driver behavior adaptation with car-following model*

According to the existing studies as listed in **Table 1**, the FCW function of the ADAS primarily impact subject drivers’ behavior regarding the PRT and time headway. The headway adaptation arises because the ADAS continuously reminds the subject driver of her real-time headway via a color-based human machine interface (e.g., red icon means a lower than threshold headway and green icon means larger). In this case, the subject driver can easily maintain her headway in a safe and consistent level and the headway records are closely distributed around the headway threshold set by the ADAS.

When modeling drivers’ headway adaptation, the uncertainty of a driver’s compliance level to the ADAS information needs to be considered. To this end, a compliance index is assigned to each of the modeled drivers. The index is a random integer that ranges between 0 and 100. A driver with a compliance index of 0 completely ignores the information sent by the ADAS, whereas a driver with a compliance index of 100 completely follows the instructions given by the ADAS. In this case, the ADAS-affected headway is mathematically given as:

 (6)

where all parameters have been defined previously.

The PRT is defined as the time gap between the onset of a traffic event (such as the braking light of the leading vehicle is on) and the onset of the subject driver’s response to the event. As stated by Treiber and Kesting (2013), the PRT contains the mental processing time, the movement or action time, and the technical response time of the vehicle. The mental processing time is the duration in which the driver assesses the traffic condition and decides proper actions to take. It is further divided into the sensation time, the perception time, the situation awareness time, and the decision time (see **Fig. 3**).



**Fig. 3.** Components of PRT.

The PRT reduction is observed as the ADAS sends collision warnings. Before the warning is issued, the ADAS has completed the sensation, perception and situation recognition in the background for the subject driver. Then the driver only needs to confirm the information and take proper reaction. Since the ADAS can perform the sensation, perception and situation recognition tasks much faster than the human driver, it helps reduce the total time required by the driver in response to an event. In addition, upon receiving the message, the subject driver becomes aware of the imminence of a potential collision and understands where the risk comes from (i.e., from the leading vehicle). The Highway Safety Manual (AASHTO, 2010) reported that a human driver generally responds much faster to expected events than to unexpected events. Above discussion explains why the PRT of an ADAS-equipped driver can be reduced. When the ADAS is involved in the driver’s decision-making process, the driver’s PRT is defined as the summation of the information processing time, the decision time, the movement time, and the technical response time, as shown by **Fig. 3**. The information processing time is the time period required by the driver to process the ADAS information.

**Table 1** reveals that the PRT reduction of an ADAS-equipped driver could be in a range of 10% to 50%. Such an uncertainty can also be modeled by incorporating the driver compliance index:

 (7)

These ADAS-affected driving behaviors are incorporated into the Intelligent Driver Model (IDM, see Treiber et al., 2006) as desired headway parameters and perception-reaction time parameters, respectively. The modified IDM is mathematically represented by the following equations:

 (8)

 (9)

where is time interval; is desired speed; is the maximum acceleration; is the comfortable deceleration; is the minimum spacing; and and are model parameters. When implementing Equation (8) and (9) in a numeric simulation environment, the transition between two distinct car-following states is considered. The two states are defined by Equation (7): the normal state where the PRT of an ADAS-equipped driver is equal to , and the motivated state where the PRT is reduced due to the influence of the ADAS. The transition between the two states is modeled according to two rules:

* Rule 1: If an equipped driver was in the normal state in previous time step and the ADAS begins to provide collision warning at the current time step, the driver immediately starts updating her acceleration with the reduced PRT at the current time step, until the ADAS warning is off. This rule implies that the transition from the normal state to the motivated state takes place instantly.
* Rule 2: If an equipped driver was in the motivated state in previous time step and the ADAS stops interacting with the driver at the current time step, the driver will maintain the acceleration of the previous time step for a period of seconds. If it changes back to the motivated state during the period , Rule 2 is terminated and Rule 1 is applied. Otherwise, the driver will complete the period and then start updating the acceleration with . This rule implies that the motivated state transits to the normal state with a period of delay. The delay is assumed to be equal to .

After incorporating the PRT term into the IDM, the model will produce vehicle collisions. Nonetheless, realistic modeling of traffic accidents is beyond the capability of the modified IDM. Thus, these artificial collisions are removed from the numeric simulation algorithm. To this end, a vehicle trajectory check module is developed to screen the trajectory of individual modeled vehicle in each simulation time step. If a vehicle is found to collide with another vehicle in the next time step, the PRT term is temporarily relaxed from Equation (8) and the acceleration of the vehicle is updated without delay term. As a result, the undesirable collisions are avoided.

## *3.3 Identification of optimal ADAS algorithm parameter set*

To search for the optimal ADAS algorithm parameter levels, the functional relationships between the parameters and the measures of effectiveness (MOE) regarding the safety and mobility performance should be firstly determined. In this study, the functional relationships are identified by using the factorial design (FD) method, which is commonly adopted to study the effect of individual factors and their interaction effects on a concerned response variable through randomized experiments (Montgomery, 2008). As mentioned in **Section 3.1**, the headway threshold and the assumed maximum deceleration of the host vehicle are the concerned parameters in this study. A 3-level by 2-factor design is employed to guide the experiments (see filled dots in **Fig. 4**). Particularly, multiple simulation experiments are conducted at each point and the experiment results are applied for determining the main effects and interaction effects of and on the MOEs. The functional relationship can be represented by the following equation:

 (10)

where is the value of a MOE; represents type of the MOE; is the model coefficient; and is the vector of the concerned factors.



**Fig. 4.** Diagram of factorial design.

In this study, the MOE for the safety performance is the average number of conflicts per hour. The occurrence of a conflict is identified by using the TTC measure. The TTC is defined as the time remaining until a collision will occur between two vehicles if their collision course and speed difference are maintained (Hayward, 1972). If at some time the TTC of a subject driver drops below a threshold TTC, it indicates the start of a conflict; and later as the TTC rises above the threshold again, the conflict is ended. The TTC is mathematically given

 (11)

where is the spacing between the leading vehicle and the subject vehicle; is the speed of the leading vehicle; and is the speed of the subject vehicle. In this research, the threshold TTC is 1.5 seconds, as recommended by Gettman et al., (2008).

The MOEs for the mobility performance are the highway throughput in number of vehicles per hour per lane (veh/hr/ln) and the average travel delay per vehicle (s/veh). The delay is the computed as the difference between a driver’s actual travel time through a road segment and the travel time the driver would have if she travels at the free flow speed of the road segment. It is computed by the following equation:

 (12)

where is the actual travel time of driver ; is the length of the study site; and is the free flow speed.

The optimal and that enable the maximum throughput and minimum delay and number of conflicts are obtained through a multi-objective optimization programing.

 (13)

where ; ; ; the constraint represents exogenous parameters (in comparison to endogenous parameters such as the driving behaviors) that affect dynamics of a traffic flow stream at a study highway facility. In this study, includes the highway facility type (e.g., basic freeway segment, freeway weaving/merging/diverging segment, arterial or intersection), traffic demand, fleet composition, and free flow speed. The optimal set of the ADAS parameters are found if for some neighborhood of there does not exist a such that and

 (14)

where usually contains multiple points. While moving from one point to another, there is always a certain amount of sacrifice in one MOE to achieve a certain amount of gain in the other(s). The optimization programing is implemented in Matlab by using its optimization tool box.