Multiobjective Optimization Framework for Cooperative Adaptive Cruise Control Vehicles in the Automated Vehicle Platooning Environment

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Automated longitudinal control technology has been tested through cooperative adaptive cruise control (CACC), which is envisioned to improve highway mobility drastically by forming a vehicle platoon with short headway while maintaining stable traffic flow under disturbances. Compared with previous research efforts with the pseudomultiobjective optimization process, this paper proposes an automated longitudinal control framework based on multiobjective optimization (MOOP) for CACC by taking into consideration four optimization objectives: mobility, safety, driver comfort, and fuel consumption. Of the target time headways that have been tested, the proposed CACC platoon control method achieved the best performance with 0.9- and 0.6-s target time headways. Compared with a non-optimization-based CACC, the MOOP CACC achieved 98%, 93%, 42%, and 33% objective value reductions of time headway deviation, unsafe condition, jitter, and instantaneous fuel consumption, respectively. In comparison with a single-objective-optimization-based approach, which optimized only one of the four proposed objectives, it was shown that the MOOP-based CACC maintained a good balance between all of the objective functions and achieved Pareto optimality for the entire platoon.

According to the *2012 Urban Mobility Report*, roadway congestion in the United States has caused significant negative effects (approximately 5.5 billion extra hours, 2.9 billion gal of wasted fuel, and 56 billion lb of additional carbon dioxide) (*1*). All of these negative effects resulted in a US$121 billion bill in 2011. Necessary steps making the surface transportation smarter, safer, and greener need to be taken. It is believed that a more efficient surface transportation system could be achieved via connected vehicle (CV) technologies, owing to the rapid advancement of information and communication technologies. CV technologies have gained increasing traction for their promising capability to drastically enhance the performance of the transportation system. The Intelligent Transportation Systems Joint Program Office in the U.S. Department of Transportation initiated the 6-year CV Pilot Deployment Program in 2013 (*2*). And recently, the department has established two primary strategic priorities: realizing CV implementation and advancing automation (*3*).

Of the applications of the advanced driver assistance system, the adaptive cruise control (ACC) system has been extensively studied. Typically, ACC uses a proportional derivative algorithm, which controls the acceleration of a following vehicle on the basis of the bumper-to-bumper gap and relative speed with respect to the preceding vehicle (*4*). Lidar or other sensing technologies are adopted to obtain the necessary data. Powered by dedicated short-range radio, two-way vehicle-to-infrastructure or vehicle-to-vehicle (V2V) wireless communication is available for transmitting instantaneous vehicular information (e.g., speed, distance headway, and acceleration) under the CV environment. Hence, cooperative adaptive cruise control (CACC) can be considered as an evolution of commercially available ACC with an additional layer of connectivity. By forming a cooperative vehicular platoon with a short intraplatoon time headway (e.g., 0.9 s), CACC promises to drastically improve highway mobility.

As CACC technology has become more and more mature, a systemwide optimal controlling scheme for CACC platooning has become crucial in ensuring the full use of the technology. That is, a realistic and practical method should consider the major aspects (e.g., mobility performance, safety performance, and environmental impact) of vehicular longitudinal control in a dynamic traffic context. Furthermore, it also should be generic such that a great variety of objectives could be seamlessly incorporated. Non-optimization (*5*) or pseudomultiobjective optimization (*6, 7*) is somehow inadequate in providing such generality, as well as flexibility. To tackle that issue, this paper proposes a multiobjective optimization-based framework to determine optimal driving maneuvers for CACC [also known as multiobjective optimization (MOOP) CACC] in the automated platooning condition. The proposed MOOP CACC method is able to adopt a wide range of objectives and find multiple trade-off optimal solutions with vehicular information disseminated under the connected–automated vehicle environment.

The rest of this paper is organized as follows. The current state of CACC research, as well as the optimization-based algorithm, is summarized next. The research gap for approaching CACC in the traffic engineering perspective is identified subsequently. The proposed vehicle control algorithm is then discussed, followed by the simulation study. Concluding remarks and future research are presented in the final section.

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LITERATURE REVIEW

Vehicle Longitudinal Control

Van Arem et al. proposed a metamodel (i.e., sustainable mobility methods for the intelligent transport systems integrated full-range speed assistant), which supported the development of the advanced driver assistance system in the assessment of technical functionality (*8*). Three advanced driver assistance system models were derived from the metamodel: (*a*) an ACC algorithm, (*b*) a time headway CACC algorithm, and (*c*) an average-speed CACC algorithm. Safety, string stability, and a comfort measure were used to evaluate the performance of these algorithms. Simulation and real-world experiments have demonstrated the successful implementation according to expectations.

Wang et al. developed a rolling horizon control framework, under which different control objects were optimized (*4*). The framework included an enhanced predictive ACC algorithm, with an explicit safety mechanism and a fuel consumption objective function, and two multianticipative CACC algorithms: one with perfect knowledge of a following car and one without (*3, 4*). The authors reported that the cooperation between equipped vehicles and human drivers could dampen traffic disturbances in acceleration and increase the queue discharging rate.

Incorporating the power output of the preceding vehicle, an extended intelligent driver model was proposed by Li et al. (*9*). Linear stability analysis showed that the consideration of the power output of a preceding vehicle could improve traffic flow stability. Montanaro et al. put forward an extended CACC algorithm, under which the communication was asymmetrical (*10*). The objective of the algorithm was to make the controlled vehicle attain the velocity of the leading vehicle and the predetermined gap. Ge and Orosz performed a vehicle dynamic with delayed acceleration feedback of a CACC platoon system (*11*).

Field tests of the platooning behavior of CACC-enabled vehicles were reported. Safe Road Trains for the Environment (SARTRE) had developed and successfully demonstrated a solution that involved a platoon of vehicles led by a professionally driven truck on a freeway segment in a mixed traffic environment (*12*). The PATH program integrated the V2V communication capability into the ACC system and conducted an experiment of longitudinal motion control of eight vehicles on a closed highway segment (*13*). Relevant field tests of the CACC concept can also be found elsewhere (*14–18*). Because of safety and expenditure concerns (e.g., ITS infrastructure availability, administrative issues, and budgetary constraints), a field experiment of the CACC algorithm has been restricted to an isolated test environment and experienced difficulties in scalability.

Compared with a field experiment, simulation is an effective way to scale up the CACC platooning behavior, as well as test the near-future deployment strategies. Few studies approaching CACC from the simulation perspective have been reported. Lee et al. assessed the potential benefits for mobility and safety under a wide range of traffic scenarios with three types of platoon-joining methods (i.e., rear, front, and cut-in join) (*5*). It was concluded that at a market penetration of 30%, the promising mobility benefits of CACC started to show and that a 0.9-s time headway was better than a 0.6-s time headway, according to the surrogate safety assessment model. Arnaout and Bowling constructed a simulation test bed to evaluate three different CACC deployment strategies: (*a*) no CACC vehicle, (*b*) CACC vehicles scattered on all lanes, and (*c*) CACC vehicles with priority access to a high-occupancy-vehicle (HOV) lane in mixed traffic (*19*). The authors concluded that the great potential benefits of CACC could be realized by placing a CACC vehicle on an HOV lane when the market penetration was below 40%; the benefits of CACC in mobility improvement could be realized even in the absence of CACC–HOV dedicated lanes when the market penetration was above 40%.

Multiobjective Optimization

MOOP is the selection of the best solutions concerning multiple conflicting objectives from a set of equally good solutions that constitute a Pareto frontier. The MOOP method has been proposed to deal with complex optimization problems in transportation engineering [e.g., optimal highway asset management (*20*), prioritization transit stop Americans with Disability Act–compliant improvement (*21*), ramp metering (*22*), and evacuation routing (*23*)]. However, most of the reported MOOP methods linearly transformed the multiobjective optimization problem into single-objective optimization (SOOP) through some user-defined parameters (e.g., weight factors) for simplification, resulting in multiobjective linear programming (practically a SOOP). As Deb pointed out, a preference-based (e.g., with assigned weighted factors) MOOP could potentially overlook other optimal solutions, despite a change of preference vector (*24*). In MOOP, it is crucial to find a set of solutions spreading as far as possible in the Pareto frontier before selecting one based on the high-level information. Evolution algorithms (EAs) are efficient for solving MOOP because a population of solutions—instead of one—is evaluated in each iteration. The genetic algorithm (GA), being one of the widely used EAs, mimics the nature of the evolution principle, resulting in a stochastic search for the fittest (optimal) solutions.

In summary, most of the CACC studies have been approached from the electrical or mechanical engineering aspect, dealing with the low-level vehicle controller (e.g., throttle input, break input, and torque output). Only limited CACC field tests in mixed traffic conditions have been conducted because of the various stated concerns. Traffic simulation is a cost-effective way to study the CACC algorithm in large scale from a traffic engineering standpoint. Therefore, instead of assessing the proposed algorithm through string stability analysis, this paper investigates how consistently the MOOP algorithm provides Pareto-optimal solutions; this strategy strikes a balance between all objectives while keeping the preferred objective (e.g., time headway deviation) minimal, yielding a stable optimal platoon. The formulation of a MOOP-based CACC (MOOP CACC) algorithm and the proof-of-concept test on an integrated simulation test bed are presented as well.

METHODOLOGY

Platoon-Based Optimization Algorithm

During each update interval t, the MOOP algorithm optimizes the decision variable (i.e., the acceleration $\ddot{x}$) for each individual vehicle for the next time interval $t + 1$. Each of the four components of the overall objective function is discussed in this section. Since the CACC is approached from a traffic engineering perspective, the low-level control and relevant electrical and mechanical aspects will not be covered. For clarity, the definition of headway in this study is the "time headway between the rear bumper of a leading vehicle and the front bumper of a following vehicle."

Target Time Headway Deviation Objective Function

One appealing benefit of CACC is its cooperative nature. How quickly CACC vehicles form a platoon and how much deviation each vehicle has from the target time headway are crucial. In addition, how swiftly a platoon adjusts and stabilizes under traffic disturbance is important. Therefore, a target time headway deviation objective function is proposed that represents the difference between current time headway and the target time headway. This objective function considers only the absolute deviation of the targeting time headway; that factor means that either the positive or the negative value of deviation is the same in the view of the objective function. The safety issue concerning the positive deviation will be addressed in the subsequent unsafe objective function. The objective function of the targeted time headway deviation to be minimized can be expressed as Equation 1:

$$\sum_{i=1}^{n} \left| H - h_i(t+1) \right| \tag{1}$$

where

H = target time headway for each vehicle of platoon,
$h_i(t+1)$ = time headway of vehicle i at time interval $t+1$, and
n = total number of vehicles in platoon.

According to the equation of motion, the time headway of vehicle i at time interval $(t+1)$ can be expressed as Equation 2:

$$h_i(t+1) = \frac{x_i(t) + [\dot{x}_{i-1}(t) - \dot{x}_i(t)]t + \frac{1}{2}[\ddot{x}_{i-1}(t+1) - \ddot{x}_i(t+1)]t^2}{\dot{x}_i(t) + \ddot{x}_i(t+1)t} \tag{2}$$

where

t = optimization interval for algorithm,
$x_i(t)$ = bumper-to-bumper (rear-to-front) distance of vehicle i to its preceding vehicle at time interval t,
$\dot{x}_i(t)$ = speed for vehicle i at time interval t,
$\dot{x}_{i-1}(t)$ = speed for vehicle $i-1$ at time interval t,
$\ddot{x}_i(t+1)$ = acceleration for vehicle i at time interval $t+1$, and
$\ddot{x}_{i-1}(t+1)$ = acceleration for vehicle $i-1$ at time interval $t+1$.

Unsafe Condition Objective Function

Safety is vitally important in designing a vehicular longitudinal control algorithm. Maximization of safety also means the minimization of a critical or unsafe condition. Wang et al. proposed a safety objective function in which the penalty was assessed exponentially when the vehicle instantaneous gap was smaller than the predefined critical distance (*6*). For the consistency of the discussion, the objective function of an unsafe condition is adopted and is to be minimized. Because a sufficiently safe distance also depends on the current speed of a pair of vehicles, the use of time headway is proposed; speed is already factored in, in the algorithm. With such a conversion, the objective function of an unsafe condition can be expressed as in Equation 3:

$$\sum_{i=1}^{n} \exp\left(\frac{h_{i,0}}{h_i(t+1)}\right) \tag{3}$$

where $h_{i,0}$ is the minimum time headway defined by the driver of vehicle i and $h_i(t+1)$ is the predicted time headway for vehicle i at time interval $t+1$.

Vehicular Jitter Objective Function

Vehicular jitter is defined as the switch between acceleration and deceleration. The magnitude of the acceleration change should not be overlooked. For instance, even if a vehicle does not switch between acceleration and deceleration, a drastic change in acceleration or vice versa can result in riding discomfort. The discomfort threshold is also a dependent of speed because a 2 m/s^2 deceleration yields a significant difference in riding comfort at high speed (e.g., 110 km/h) compared with at much lower speed (e.g., 40 km/h). Therefore, a coefficient beta that adjusts the acceleration effect in different vehicle speeds was adopted. The vehicular jitter to be minimized can be formulated as Equation 4:

$$\sum_{i=1}^{n} \exp\left(\beta \frac{\left|\ddot{x}_i(t+1) - \ddot{x}_i(t)\right|}{\ddot{x}_{\text{comfort}}}\right) \tag{4}$$

where β is the adjustment coefficient for speed and $\ddot{x}_{\text{comfort}}$ is the comfortable acceleration threshold.

Fuel Consumption Objective Function

The fourth objective function to be minimized is fuel consumption. Because of the microscopic nature of the CACC algorithm, an operation-level emission model is desired. Rakha et al. proposed a microscopic emission model that is capable of estimating accumulated environmental effects (i.e., fuel consumption and carbon dioxide) for an individual vehicle (*25*). The instantaneous vehicle speed and acceleration rate are used for the models, yielding a second-by-second resolution estimation of the fuel consumption, as shown in Equation 5:

$$\begin{cases} \exp\left(\sum_{i=0}^{3}\sum_{j=0}^{3}\left(L_{i,j}^{e} \times \dot{x}_i \times \ddot{x}_j\right)\right) & \text{for } \ddot{x} \geq 0 \\ \exp\left(\sum_{i=0}^{3}\sum_{j=0}^{3}\left(M_{i,j}^{e} \times \dot{x}_i \times \ddot{x}_j\right)\right) & \text{for } \ddot{x} < 0 \end{cases} \tag{5}$$

Here, $L_{i,j}^{e}$ and $\mathrm{M}_{i,j}^{e}$ are regression coefficients for the measure of effectiveness (e.g., fuel consumption). Note that the acceleration does not factor in slope effects (*5*).

Constraints

Besides the safety penalty in the objective function, additional constraints are required to ensure the safety performance of the algorithm. A minimal time headway constraint for each following vehicle is proposed. A safety factor is also incorporated for the circumstance in which communication is temporarily disrupted; this circumstance, however, will not be covered in this study. The collision avoidance constraint for each vehicle is expressed as Equation 6. For the leader of the platoon, a simple time headway control algorithm whose main objective is to keep a safety time headway with the preceding vehicle as shown in Equation 7 is adopted under the assumption that the vehicle gap is detected by an onboard sensor and that the preceding vehicle is not a CACC vehicle.

$$\frac{x_i(t+1)}{\dot{x}_i(t+1)} \geq \gamma h_{i,\min} \tag{6}$$

where

γ = additional safety factor for time headway,
$h_{i,\min}$ = user-defined minimal time headway for vehicle i,
$x_i(t+1)$ = bumper-to-bumper distance for vehicle i to preceding vehicle at time interval $t+1$, and
$\dot{x}_i(t+1)$ = speed for vehicle i at time interval $t+1$.

$$\frac{x_1(t+1)}{\dot{x}_1(t+1)} \geq \gamma h_{\mathrm{LV},\min} \tag{7}$$

where $h_{\mathrm{LV},\min}$ is the minimum time headway for a platoon leader.

CACC vehicles should be closely platooned together to fully utilize the short time headway enabled by V2V communication. If the intraplatoon time headway exceeds a certain threshold, it may be more beneficial to split the original platoon into two and have each platoon conduct its own optimization. To fully explore the potential of CACC, a maximum time headway constraint is expected to make the platoon more effective and robust; that outcome can be expressed as Equation 8. For the leader of a platoon, however, the maximum time headway does not apply at this stage to provide more flexibility for the overall platoon during optimization and traffic disturbance.

$$\frac{x_i(t+1)}{\dot{x}_i(t+1)} \leq h_{\max} \tag{8}$$

where $h_{\max}$ is the maximum time headway for the following vehicle.

The power train capability (e.g., acceleration and braking power) of a vehicle should also be considered to prevent the algorithm from yielding unrealistic accelerations. It is assumed that such power train information for each vehicle would be disseminated within the platoon under the CV environment. In actual deployment on the roadway, it is very likely that a heterogeneous vehicle platoon is controlled, and the individual vehicle power train constraint can be expressed as Equation 9. Typically, a 3 m/s^2 rate is applied as the maximum deceleration rate for field deployment and a 2 m/s^2 of acceleration could be considered as the comfortable value (*26*).

$$\ddot{x}_{i,\min} \leq \ddot{x}_i \leq \ddot{x}_{i,\max} \tag{9}$$

where $\ddot{x}_{i,\min}$ is the minimum acceleration of vehicle i and $\ddot{x}_{i,\max}$ is the maximum acceleration of vehicle *i*.

The last constraint is the roadway geometry constraint, including minimum and maximum allowable speeds. Only speed limits are considered in this study, as displayed in Equation 10. This information is assumed to be disseminated via vehicle-to-infrastructure under the CV environment.

$$\dot{x}_{\min} \leq \dot{x}_i \leq \dot{x}_{\max} \tag{10}$$

where $\dot{x}_{\min}$ is the minimum allowable speed on a particular roadway and $\dot{x}_{\max}$ is the maximum allowable speed on a particular roadway.

Because of the importance of safety, both time headway constraints have to be satisfied. The physical limitation of the power train should be a hard constraint as well. One may argue that the speed limit should be a soft constraint, but at this stage, it was programmed as a hard constraint to ensure that the initial point of the GA search was within the feasible region. In retrospect, the overall system to be optimized is shown below, with the decision variable $\ddot{x}_i(t+1)$.

$$\min\left\{\sum_{i=1}^{n}\left|H-h_i(t+1)\right|;\sum_{i=1}^{n}\exp\left(\frac{h_{i,0}}{h_i(t+1)}\right);\right.$$
$$\sum_{i=1}^{n}\exp\left(\beta\frac{\left|\ddot{x}_i(t+1)-\ddot{x}_i(t)\right|}{\ddot{x}_{\text{comfort}}}\right)$$

$$\left.\begin{cases}\exp\left(\sum_{i=0}^{3}\sum_{j=0}^{3}\left(L_{i,j}^{e}\times\dot{x}_i\times\ddot{x}_j\right)\right) & \text{for } \ddot{x}\geq 0\\ \exp\left(\sum_{i=0}^{3}\sum_{j=0}^{3}\left(M_{i,j}^{e}\times\dot{x}_i\times\ddot{x}_j\right)\right) & \text{for } \ddot{x}<0\end{cases}\right\}$$

subject to

$$\begin{cases}\dfrac{x_1(t+1)}{\dot{x}_1(t+1)}\geq\gamma h_{\mathrm{LV},\min} & i=1\\ \dfrac{x_1(t+1)}{\dot{x}_i(t+1)}\geq\gamma h_{i,\min} & i=2,3,\ldots n\end{cases}$$

$$\ddot{x}_{i,\min}\leq\ddot{x}_i\leq\ddot{x}_{i,\max} \qquad i=1,2,\ldots n$$

$$\dot{x}_{\min}\leq\dot{x}_i\leq\dot{x}_{\max} \qquad i=1,2,\ldots n$$

Genetic Algorithm

Inspired by the principle of natural genetics and selection, GAs use this fundamental concept to perform optimization with minimal problem information (*24*). This study used the MATLAB built-in elitist multiobjective GA, which is a variant of the Nondominated Sorting GA II (NSGA-II) (*27*). The GA selects individuals on the basis of nondominated rank (i.e., fitness value) and the diversity of the individual in the current generation. Despite the efficiency of the GA in solving multiobjective optimization, it does not guarantee a global optimal solution because of the probabilistic search. For that very reason, GA solutions are unlikely to be contained by local optima. While the GA is not able to guarantee an optimal solution, numerous research efforts have proved that the GA produces "desirable" solutions, particularly in the case of handling a complicated search space. By tuning the GA parameters (e.g., population size and mutation probability), one can further decrease the likelihood of a local optimal. In each iteration, 35% of the population from the Pareto frontier is selected for crossover and mutation for the next generation. After each iteration, a set of optimal solutions is obtained from the Pareto frontier, which is made up of nondominated and equally good solutions. From these solutions, one optimal solution based on the predetermined primary objective function (e.g., mobility, safety, and fuel consumption objective function) has to be chosen from the Pareto frontier. In this study, the 15th percentile of the time headway deviation objective in the entire set of Pareto-optimal solutions was selected as the optimal solution for each vehicle.

EVALUATION

Simulation Test Bed

To demonstrate the effectiveness of the proposed MOOP CACC control, proof-of-concept tests were conducted in a microscopic simulation framework, which was made up of a Vissim and Vissim component object model interface and a vehicle control algorithm built with the MATLAB multiobjective GA solver (*28*). The high-level framework architecture is shown in Figure 1. Vissim, a microscopic traffic simulation model, was used to mimic human drivers' normal driving behavior. It is based on the Wiedemann 99 car-following model (*29*), which uses a set of parameters to mimic the most likely generic human drivers after proper calibration with field data (*30*). The parameter set used in this study has been calibrated in another calibration study with multiple data sources to ensure the degree of realism. During each updating interval, instantaneous speed, acceleration, and gaps, along with other predefined parameters, were input into the MOOP CACC algorithm. The output of the algorithm was the optimal acceleration for the next time interval for each vehicle in a platoon. A hypothetical 14.5-km freeway segment with one lane was used to conduct the simulation with the following assumptions:

- V2V communication is perfect, with no packet drops and radio interference.
- CACC platoon to be optimized is composed of CACC vehicles only.
- Homogeneous vehicles are assumed (e.g., same acceleration threshold and same vehicle length).
- Vehicle model is excluded; input to the plant (i.e., intended acceleration) equals the output (realized acceleration).
- Leader of the platoon operates under relaxed maximum time headway constraints, allowing more flexible reactions to the preceding non-CACC vehicle.
- Driving behavior parameters from a calibrated Vissim network located on Interstate Highway 66 in Fairfax County, Virginia, are assumed as a subset to represent a human driver.

Experiment Design

A human-driven vehicle was placed on the network, followed by a platoon made up of five CACC-equipped vehicles. With the feasible range of predetermined time headway, five CACC vehicles were set with randomized desired speeds around the speed limit. After traveling a predetermined distance (i.e., 1.2 km), all CACC vehicles received a command to form a platoon. The simulation resolution was set to 10 steps per second, which means Vissim computes the vehicular behavior every 0.1 s. The MOOP algorithm computed the optimal acceleration for each individual vehicle in the platoon and updated the acceleration rates every 0.5 s. The parameters used are summarized in Table 1. Two types of experiments were conducted: (*a*) validation of the MOOP CACC compared with other vehicle algorithms and (*b*) analysis of the output from the MOOP CACC and SOOP CACC algorithms with the same set of objective functions.

The CACC vehicle platoon was set to follow the non-CACC vehicle, whose speed profile was predetermined, as shown in Figure 2. The predetermined speed profile of the non-CACC leading vehicle is used only to provide a controlled scenario in which the performance of different controllers could be compared. A CACC vehicle knows only the instantaneous speed of the non-CACC leading vehicle rather than the complete speed profile. The reactions for the following CACC vehicles were observed and analyzed.

Five vehicle algorithms were tested: (*a*) human driver [calibrated Wiedemann 99 model (*29*)], (*b*) CACC algorithm proposed by Lee et al. with discrete acceleration rates [fixed value (FV) CACC] (*5*), (*c*) proposed MOOP CACC with a 1.4-s target time headway, (*d*) proposed MOOP CACC with a 0.9-s target time headway, and (*e*) proposed MOOP CACC with a 0.6-s target time headway.

TABLE 1 Simulation Parameters

Parameter	Value	Parameter	Value
H	0.6, 0.9, or 1.4 s	$h_{\mathrm{LV,min}}$	1.7 s
$h_{i,\max}$	2.1 s	$h_{i,\min}$	0.4, 0.6, or 1.0 s
$h_{i,0}$	1.0 s	$\ddot{x}_{\mathrm{comfort}}$	1.0 m/s^2
$\ddot{x}_{i,\min}$	−3 m/s^2	$\ddot{x}_{i,\max}$	2 m/s^2
$\dot{x}_{\max}$	35 m/s	$\dot{x}_{\min}$	21 m/s
β	1	γ	1.1

Results

The platoon behavior is shown in Figure 3. Compared with that of human drivers, the speed change of the MOOP CACC was more

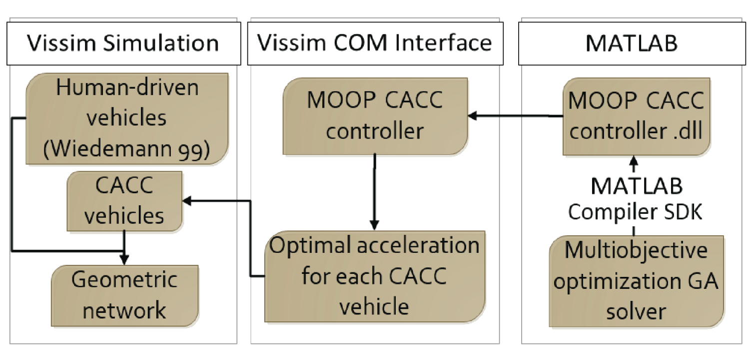


FIGURE 1 Simulation framework.

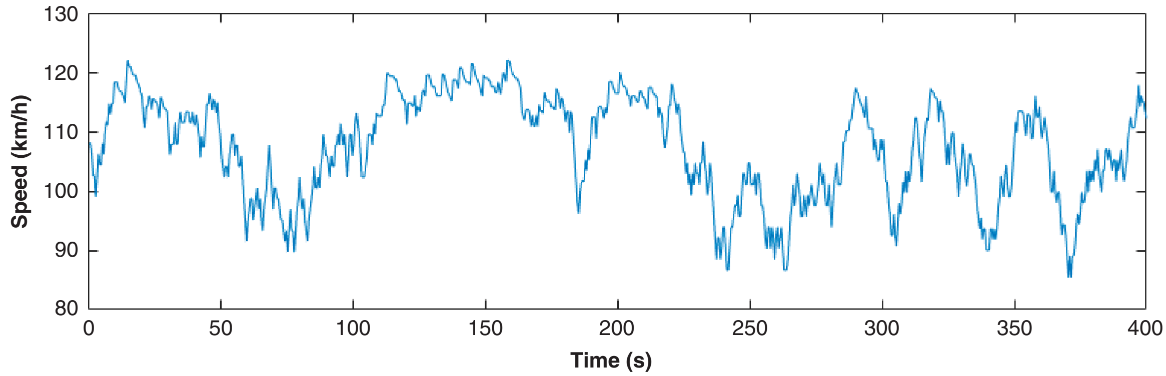


FIGURE 2 Speed profile of non-CACC vehicle.

responsive to the leading vehicle with minimal delay, indicating that the CACC vehicles were able to maintain a coherent speed profile. It was also seen that the first vehicle in the CACC platoon exhibited relatively greater reaction to its preceding vehicle, but it helped to dampen the shock wave propagation to the rest of the platoon.

Figure 4*a* shows that all three MOOP CACC algorithms converged to the target time headway and maintained minimal deviations despite traffic disturbance. The mean time headway deviation of the FV CACC algorithm was 0.89 s, and human drivers exhibited a time headway deviation as high as 3.86 s. Figure 4*b* shows that the human driver platoon had the highest unsafe objective function value, 6.87; whereas the MOOP CACC yielded, at worst, an objective function value of 0.182. For the jitter objective function, the human driver was the lowest of all algorithms, as shown in Figure 4*c*. It is understandable that the simulated human driving behaviors achieved greatest riding comfort. However, the mean of the MOOP CACC algorithm with a 1.4-s time headway was only 2% higher than human drivers in regard to the jitter objective function value. For the fuel consumption in Figure 4*d*, the analysis of variance test showed that the means of the MOOP CACC with a 0.6-s and 0.9-s time headway were statistically identical, and both were different from the other three algorithms (i.e., human, FV CACC, and MOOP CACC with 1.4-s time headways). The MOOP CACC with a 1.4-s target time headway has the lowest mean of fuel consumption.

To further investigate the performance of MOOP, four scenarios with different objective functions were designed to compare the performance of SOOP and MOOP (with a 0.9-s intraplatoon time

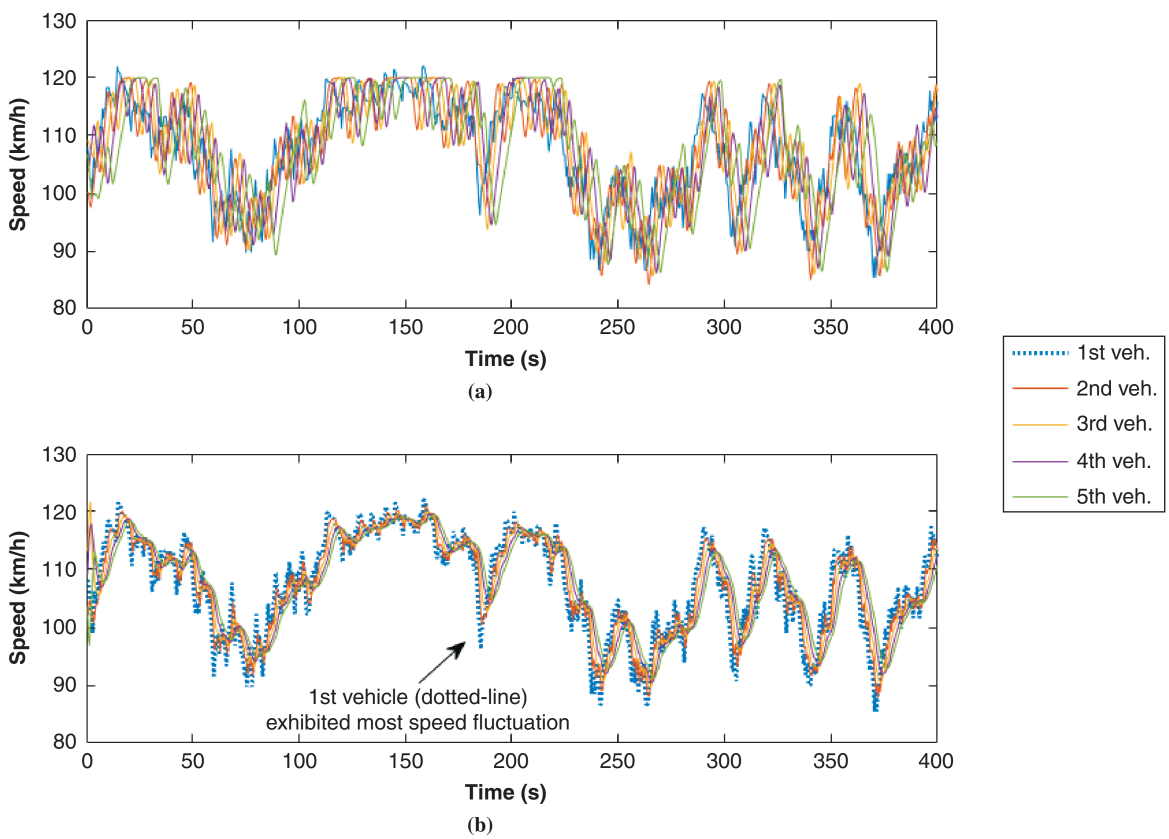
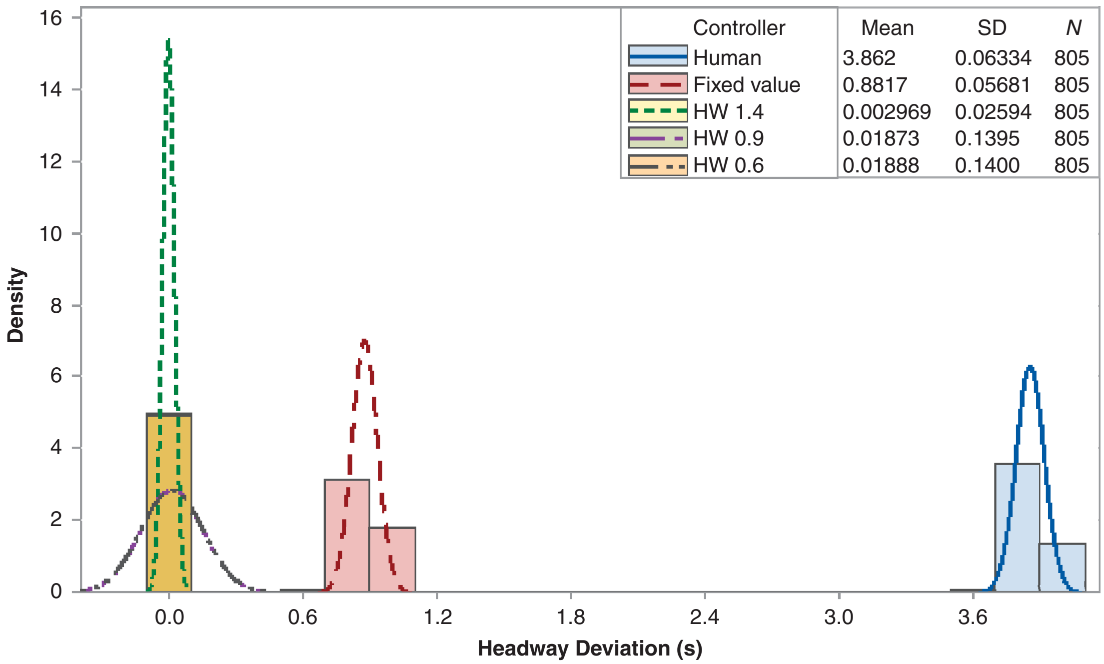
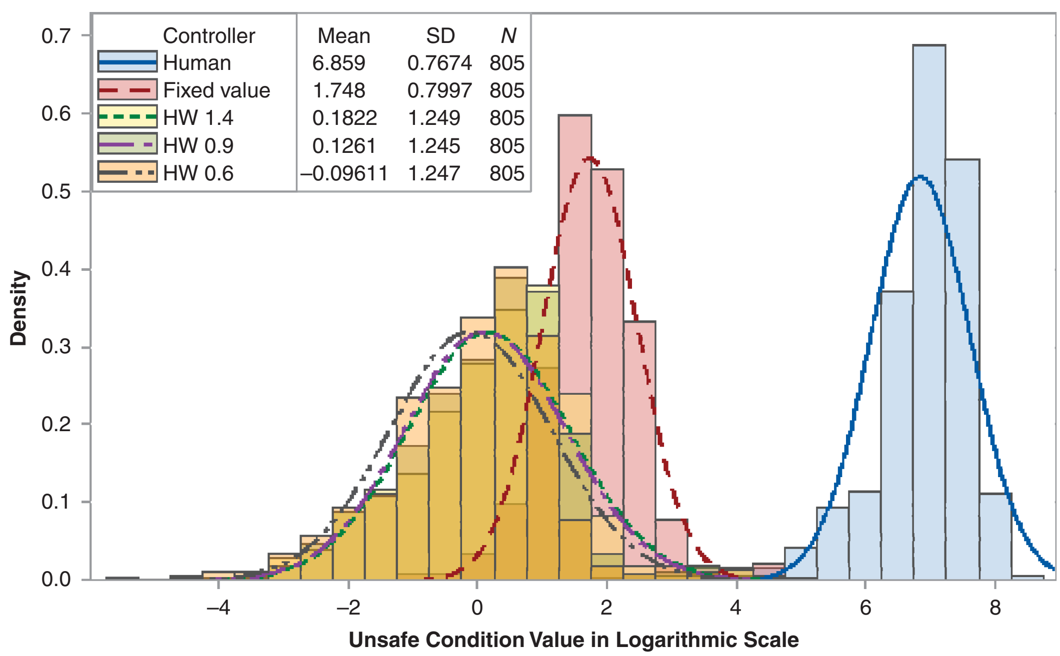


FIGURE 3 Speed profile comparison of human drivers and MOOP CACC vehicles (veh = vehicle).



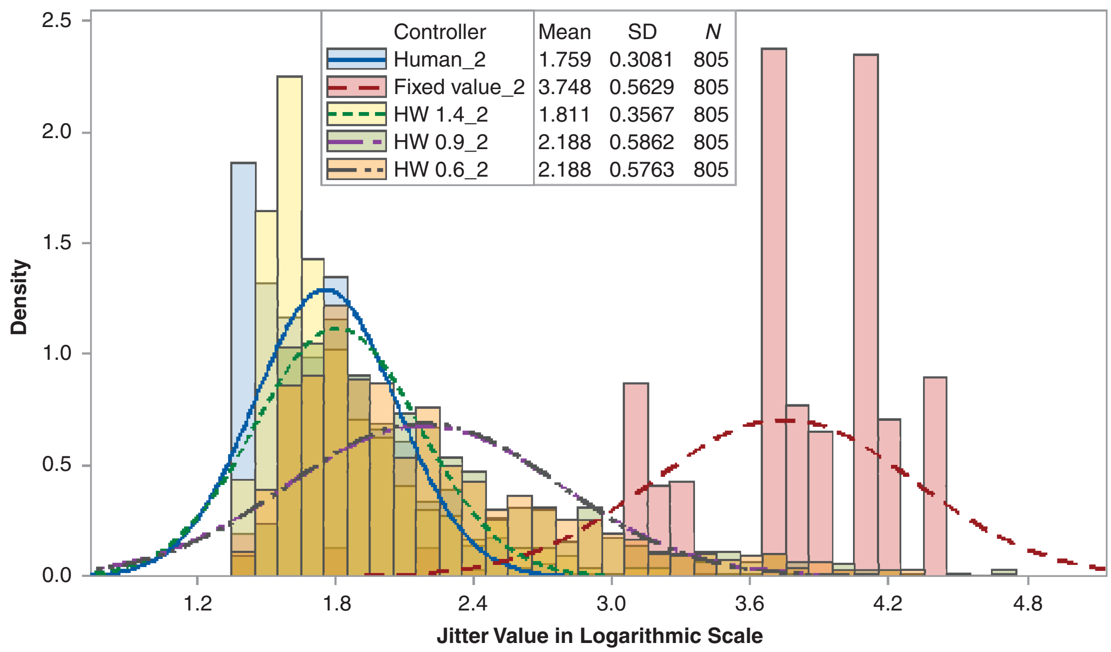
(a)



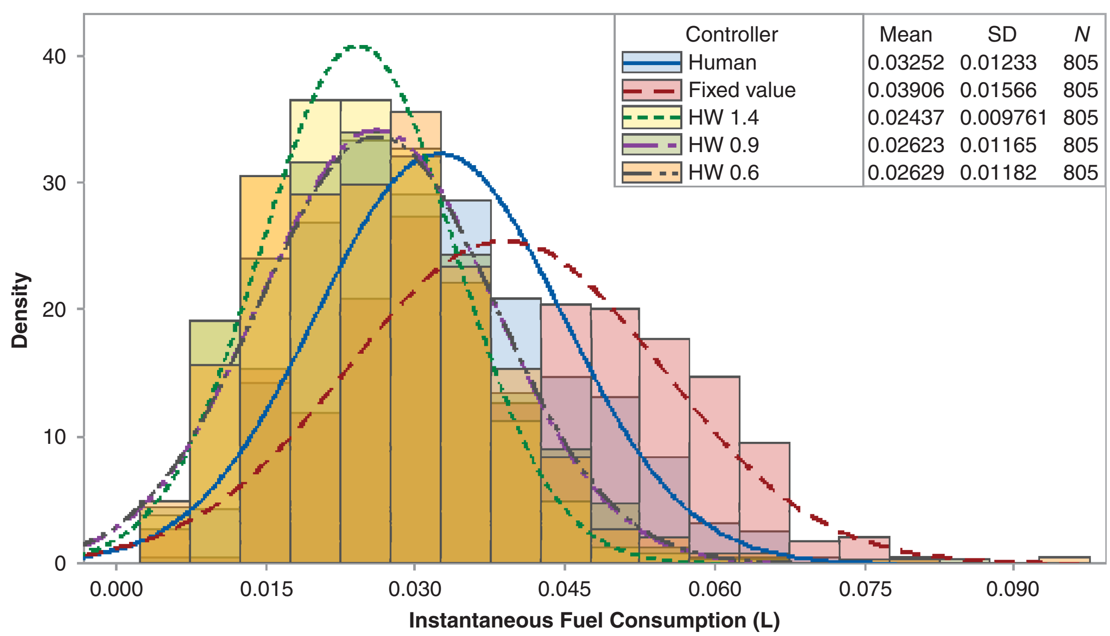
(b)

FIGURE 4 Distributions of objective function values: histogram of (*a*) time headway deviation objective function values and (*b*) unsafe condition objective function values (HW = headway).

(continued)



(c)



(d)

FIGURE 4 *(continued)* Distributions of objective function values: histogram of (*c*) jitter objective function values and (*d*) instantaneous fuel consumption function values (HW = headway).

headway) under the same traffic conditions and constraints. MOOP-1 and MOOP-2 represented that the solution with the 15th and 50th percentile optimal time headway deviation values were selected from the Pareto frontier in each optimization, respectively. The SOOP-1 was the optimization performed on the time headway deviation objective function only. Similarly, the objective function of SOOP-2 dealt with the unsafe condition objective function only.

To evaluate the statistical significance of difference of all objective values of the tested algorithms, the analysis of variance test with the post hoc Tukey's method was conducted (*31*). It is considered to be the most powerful test when all pairwise comparisons are desired (*32*). With a 95% confidence interval for all groups of objective function values, the Tukey's method results are shown in Table 2; mean values that do not share a letter (i.e., group identifier) are considered to be significantly different. For the time headway deviation objective function, the value of SOOP-2 was statistically different from three of its peers. For the unsafe condition objective function, MOOP-2 and SOOP-1 were the same, while the value of MOOP-1 and SOOP-2 belonged to two different groups. With respect to jitter, the objective function values were significantly different. For the fuel consumption objective function values, MOOP-1, MOOP-2, and SOOP-2 belonged to separate groups, while SOOP-1 could be considered to share the same group with either MOOP-1 or MOOP-2.

TABLE 2 Tukey Pairwise Comparison Tests

Algorithm	Time Headway Deviation	Unsafe Condition	Jitter	Fuel Consumption
MOOP-1	A	B	C	B
MOOP-2	A	A	A	A
SOOP-1	A	A	B	A, B
SOOP-2	B	C	D	C

Each of the objective function values was calculated and plotted in box plots in Figure 5. As seen, the objective function values have more outliers in both SOOP scenarios. SOOP-2 outperformed the two MOOPs in minimizing the unsafe condition; that finding is reasonable because the objective function was designed solely to minimize the unsafe condition. However, the standard deviation of SOOP-2 was 0.28 s more than that of MOOP-1 with respect to the target time headway deviation and approximately 97% higher in the unsafe condition than MOOP-1. Similarly, SOOP-1 experienced a higher standard deviation in objective function values by indicating a less stable condition in the platoon. In addition, SOOP-1 seemed to perform worse than SOOP-2 in comparing the mean values.

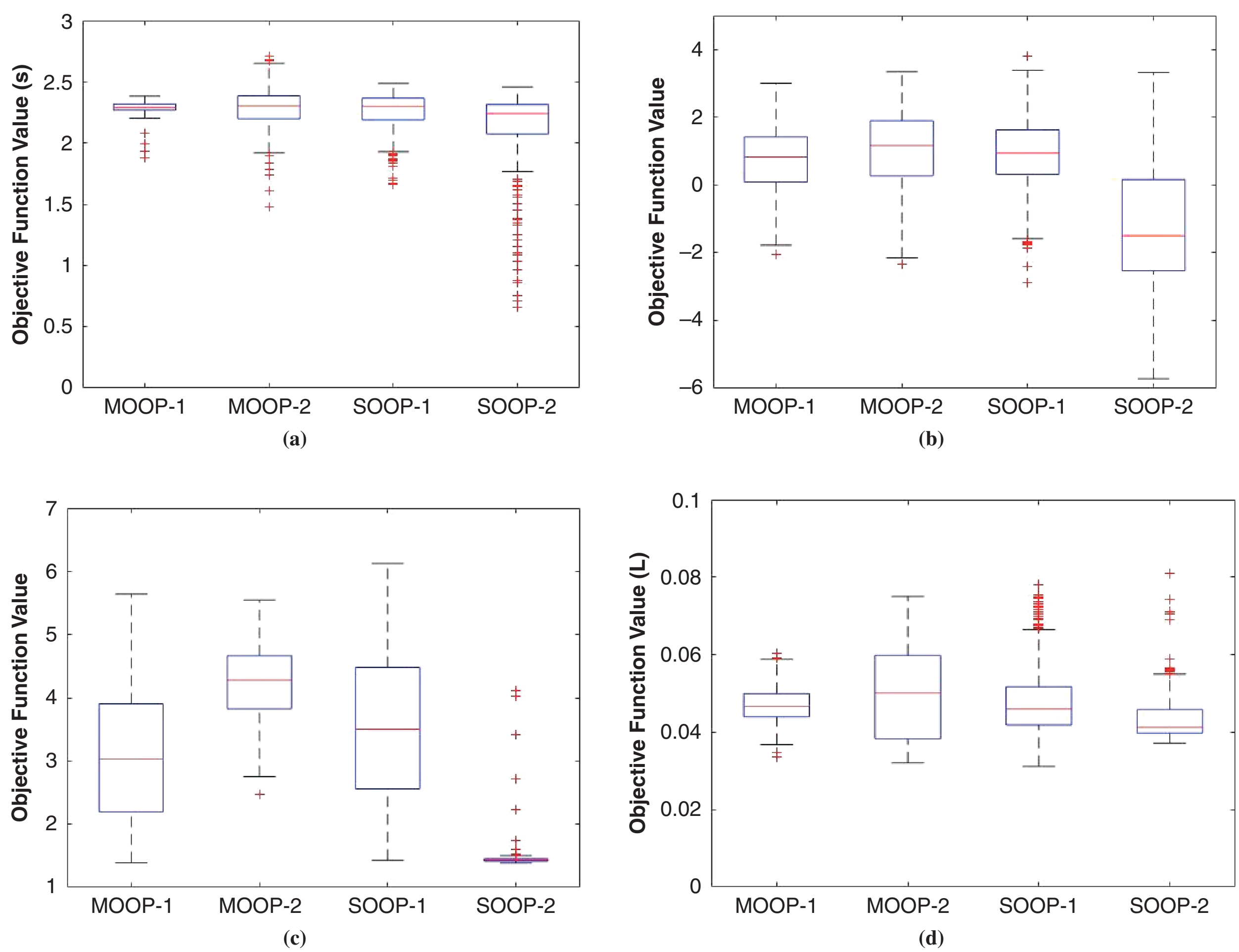


FIGURE 5 Box plot comparison for objective function values: (*a*) platoon time headway deviation objective values, (*b*) platoon unsafe objective function values, (*c*) platoon jitter objective function values, and (*d*) platoon instantaneous fuel consumption objective function values.

However, the standard deviation of SOOP-1 was only half that of SOOP-2; that finding indicates that SOOP-1 performed more consistently and better than SOOP-2. Hence, both MOOP algorithms appeared to have better Pareto optimality. One can also conclude that MOOP-1 performed better than MOOP-2 with most of the aspects considered.

CONCLUSION

An innovative multiobjective-optimization-based cooperative adaptive cruise control (MOOP CACC) algorithm was proposed in this paper. To systematically evaluate the proposed method from a traffic engineering perspective, a simulation framework was developed by integrating Vissim, MATLAB, and the Vissim component object model interface. According to the simulation test results, the target time headway deviations of all MOOP CACC controls were on average 0.96 s less than that of the human driver, which was simulated by the calibrated Wiedemann 99 car-following models in Vissim. The speed disturbance caused by human drivers was also successfully dampened.

In addition, the variants of the MOOP CACC algorithms (e.g., 1.4-, 0.9-, and 0.6-s target time headway) were tested. Simulation results showed that MOOP CACC with a 0.9-s target time headway marginally yielded the better performance in targeted time headway deviation and instantaneous fuel consumption. However, a 0.6-s MOOP CACC is expected to provide a greater increase in the overall carrying capacity than the 0.9-s case. Compared with a previously developed CACC algorithm (i.e., FV CACC), the MOOP CACC exceeded the FV CACC in all four aspects: a 98% reduction in time headway deviation, a 93% reduction in the unsafe condition objective function value, a 42% reduction in the jitter objective function value, and a 33% reduction in instantaneous fuel consumption.

Furthermore, the comparison between the MOOP CACC and the SOOP CACC showed that MOOP kept a good balance among all objectives. On the contrary, both SOOP CACCs generated higher standard deviations: 0.28 s higher in target time headway deviation and approximately 97% higher in unsafe condition, respectively. It was also observed that the SOOP CACC showed difficulties in balancing the overall system objective functions, and it was likely subjected to bias or personal preference, which could limit the search space of the optimization.

Future research will be focused on addressing the assumptions made in the proof-of-concept test. First, the perfect vehicle-to-vehicle communication is unlikely in the real-world scenario. A fail-safe algorithm dealing with an imperfect communication environment should be developed. Second, the algorithm should be evaluated along with a wireless communication simulator with a more realistic updating interval (e.g., higher than 10 Hz). Third, more comparisons with other vehicle longitudinal control algorithms in networkwide performance are desired. Last, the scalability of the MOOP CACC algorithm needs to be further tested in a larger network under mixed traffic conditions. In addition, a decentralized deployment schema will be explored.

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