$CACC_{ga}$: Multi-Objective Optimization of CACC Controller Parameters Using NSGA-III

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***Abstract*—This study investigates the use of Non-dominated Sorting Genetic Algorith III to optimize the hyperparameters of Cooperative Adaptive Cruise Control (CACC) controllers, aiming to enhance performance in dynamic traffic scenarios. The proposed approach, identifies hyperparameter combinations on Pareto fronts based on the reduction of its accumulated error and overshoot, which are related to the system's response time and stability, respectively. The proposed CACC controller, tuned with NSGA-III, achieves an accumulated error of 17.37 and an overshoot of 5.86%, outperforming other controllers in speed and accuracy when responding to variations in the leader vehicle's speed. Moreover, it maintains a constant safe distance between vehicles, which is essential for passenger safety and comfort.**

***Index Terms*—NSGA-III, CACC, Optimization Algorithm.**

I. INTRODUCTION

Adaptive Cruise Control (ACC) is one of Advanced Driver Assistance Systems (ADAS), designed to reduce driver workload while enhancing road safety [3]. Onboard sensors collect real-time data on the ego vehicle's dynamics and its surrounding environment [2]. Distance-measuring sensors—such as radar, lidar, and cameras—estimate the relative position and speed of preceding vehicles, while additional sensors, including vehicle speed and throttle position sensors, provide crucial inputs for longitudinal control [2].

In contrast to traditional ACC systems, which rely exclusively on onboard perception, Cooperative Adaptive Cruise Control (CACC) incorporates vehicle-to-vehicle (V2V) communication to significantly enhance safety, stability, and responsiveness in vehicle platooning scenarios [1]. By adopting cooperative strategies such as Predecessor Following (PF), CACC-enabled vehicles can receive real-time kinematic data from the immediately preceding vehicle. This direct data exchange allows for more accurate modeling of inter-vehicular dynamics and enables proactive control actions [1].

However, the design and tuning of CACC controllers present considerable challenges due to the need to balance multiple, often conflicting, performance criteria such as safety, comfort, responsiveness, and energy efficiency. In this context, multi-objective optimization algorithms offer a powerful solution, enabling simultaneous tuning of controller parameters across several performance metrics. These algorithms are particularly effective in handling trade-offs and finding Pareto-optimal solutions that ensure a more balanced system performance. This paper proposes CACCga (Collaborative Adaptive Cruise Control), a framework for the multi-objective optimization of CACC controller parameters using the NSGA-III algorithm. The primary aim is to evaluate whether this approach can reduce transient regime errors and improve overall control performance in cooperative driving scenarios.

II. RELATED WORK

Various studies like [6] and [7] propose cascaded architectures, where low-level controllers act on vehicle dynamics, while high-level controllers maintain a safe distance. Notably, [6] demonstrates that using V2V to anticipate the behavior of the preceding vehicle can significantly improve the system's transient performance.

In parallel, optimization algorithms have been successfully applied to the calibration of controller parameters. In [5] and [8], metaheuristic algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are employed to tune PID controller gains. These focus mainly on minimizing accumulated error, overlooking overshoot's impact on control performance. Similarly, [9] highlights multi-objective optimization and computational efficiency but does not directly address transient metrics like overshoot or accumulated error.

III. METHODOLOGY

A. Vehicle Dynamic Model

A moving vehicle is subject to multiple forces beyond those produced by its propulsion and braking mechanisms. By invoking Newton's second law, the longitudinal motion of the vehicle can be modeled using the following relation 1:

$$m\frac{d_u}{dt} = F_t - mg\sin(\theta) - mfg\cos(\theta) - 0.5\rho A C_d(u + u_w)^2 \quad (1)$$

Equation 1 can be analyzed under steady-state conditions—i.e., when $\frac{du}{dt} = 0$. At this equilibrium point, the traction force required to maintain constant speed is given by:

$$F_{t0} = mg\sin(\theta_0) - mfg\cos(\theta_0) - 0.5\rho A C_d(u_0 + u_w)^2 \quad (2)$$

To assess the system's dynamic behavior around the equilibrium point, a linearization of equation 1 can be performed via a first-order Taylor series expansion, yielding the following linearized model:

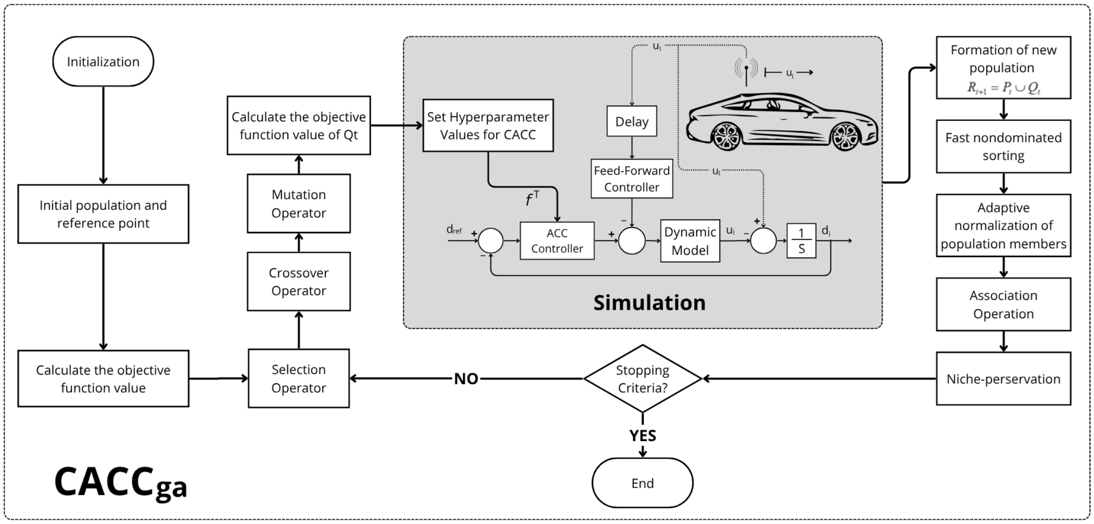

Fig. 1. Proposed Optimization Mechanism ($CACC_{ga}$)

$$\tau \dot{u}' + u' = K(F' + w) \tag{3}$$

Here, the variables are expressed as perturbations from their nominal values:

$$\tau = \frac{m}{\rho C_d A(u_0 + u_w)} \qquad K = \frac{1}{\rho C_d A(u_0 + u_w)} \tag{4}$$

The resulting linearized vehicle dynamics can also be described in the frequency domain using a transfer function:

$$G(s) = \frac{K}{\tau s + 1} \tag{5}$$

B. Controller Design (CACC)

Consider the design of a controller to maintain a desired headway. The state plant model of vehicle i for the ACC controller is obtained using the transfer function in the equation 5 and adding a double integrator and it results as:

$$\dot{x_1} = -x_2 + v_l, \tag{6}$$

$$\dot{x_2} = -\frac{x_2}{\tau_i} + \frac{K_i}{\tau_i}(u + w_i) \tag{7}$$

$$\dot{x_2} = d_i^{ref} - d_i \tag{8}$$

$$\dot{x_4} = x_3 \tag{9}$$

where $x_1 = d_i$, $x_2 = v_i$, x_3 is the integral of control error and x_4 the double integral of error. The state based controller yields:

$$u = -F_1 x_1 - F_2 x_2 - F_3 x_3 - F_4 x_4 = f^T x \tag{10}$$

where $f^T = -\begin{bmatrix} F_1 & F_2 & F_3 & F_4 \end{bmatrix}$ is the vector of gains and $x = -\begin{bmatrix} x_1 & x_2 & x_3 & x_4 \end{bmatrix}^T$ is the vector of states.

According to [6], we can add the feed-forward controller G_{ff} for rejecting the measurable disturbance, the ideal feed-forward controller is determined by taking the inverse of the vehicle dynamics, but this inverse is not realizable and an approximation has to be used. Thus, the inverse of the transfer function can be approximated with:

$$G_{ff}(s) = \frac{1 + s\tau_i}{K_i(1 + \frac{s\tau_i}{N})} \tag{11}$$

C. Proposed Optimization Mechanism ($CACC_{ga}$)

To minimizing tracking error and overshoot, we propose using the Nondominated Sorting Genetic Algorithm III (NSGA-III) for automatic hyperparameter optimization, termed Collaborative Adaptive Cruise Control genetic optimization ($CACC_{ga}$), illustrated in Figure 1.

The pseudo-code for the proposed optimization mechanism ($CACC_{ga}$) follows:

1) **Initial population and reference point**: The vector f^t represent the genes on the chromosome. The population initialization is done by:

$$x_{ik} = x_k^{min} + (x_k^{max} - x_k^{min}) \cdot rand \tag{12}$$

where, $i = 1, 2, ...N$ (N is the population size = 40). x_{ik} is the k-th ($k = 1, 2, 3, 4$) represents k-th gene of the i-th individual, and x_k^{min} and x_k^{max} are the lower and upper bounds. $\begin{bmatrix} -10000 & 10000 \end{bmatrix}$.
2) **The objective functions calculation**: Calculate/Simulate objectives on the CACC vehicle dynamic model for all individuals:
3) **Selection Operator**: Apply tournament selection to choose parents for crossover.
4) **Crossover Operator**: Generate offspring q_i using differential evolution:

$$q_{ik} = p_{ok} + F \cdot (p_{ik} - p_{sk}), \tag{13}$$

where F is the evolution parameter.

5) **Mutation Operator**: Mutate genes with probability 0.5:

$$q'_{ik} = q_{ik} + \beta \cdot (q_k^{max} - q_k^{min}) \cdot \mathcal{N}(0,1) \quad \text{para } k \in K \tag{14}$$

with $\beta = 0.1$.

6) **Formation of new population**: Merge parents and offspring ($R_t = P_t \cup Q_t$) to form a 2N-sized pool.
7) **Fast nondominated sorting**: Identify nondominated solutions for Pareto ranking ($F_1, F_2, ...$).
8) **Adaptive normalization of population individuals**: TNormalize objective values using the ideal point and extreme points defined by the Achievement Scalarizing Function (ASF).
9) **Association Operation**: Assign individuals to uniformly distributed reference points in the objective space using perpendicular distance metrics.
10) **Niche-preservation operation**: If ($S_t < N$, fill remaining spots in P_{t+1} by selecting individuals associated with the least represented reference points.
11) **Stop Criterion**: When the number of iteration is reached ($i = 50$), stop and the optimized parameters of f^t are output, otherwise return to step 3.

This method enhances population diversity and approximates the Pareto front effectively. Table I lists the adopted NSGA-III parameters.

TABLE I
NSGA-III PARAMETERS FOR $CACC_{ga}$

Parameters	Values	Parameters	Values
Population size (N)	40	Crossover Percentage	0.5
$MaxIter$	50	Mutation Percentage	0.5
Evolution parameter (F)	0.02	Reference Points (h)	10

D. Objective Functions

1) **Accumulated Error**: it is the sum of errors over time, defined by:

$$e(t) = \int_{t=0}^{T} (c_l(t) - c_{i-1}(t)) * d(t) \tag{15}$$

2) **Overshoot**: it is the maximum peak value of the response curve, measured from the reference signal, defined by:

$$M_p = \frac{c(t_p) - c(\infty)}{c(\infty)} \tag{16}$$

IV. RESULTS

The proposed design approach for the CACC system was evaluated through simulations conducted in the MATLAB/Simulink environment. For the test executions, a delay of 100 ms was considered, as indicated in [6] the parameter values were adopted according to [6]. Additionally, since the controller depends on communication between the vehicles, a delay of 100 ms was considered, as indicated in [6].

A. Proposed Optimization Analysis

The NSGA-III algorithm was implemented to optimize the gains of a CACC controller, with the goal of achieving a transient response that effectively balances system stability and response time. Figure 2 illustrates the Pareto front resulting from the multi-objective optimization performed by $CACC_{ga}$.

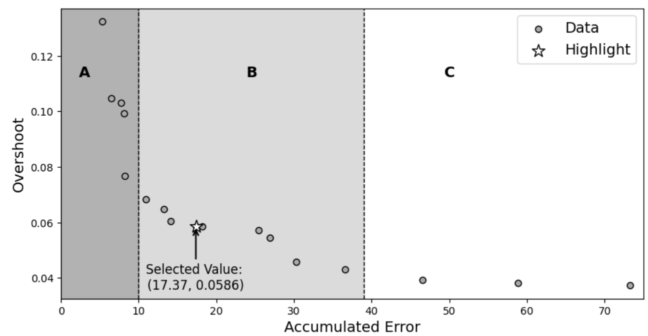

Fig. 2. Pareto front of Accumulated Error vs. Overshoot metrics

The graph is divided into three distinct regions, labeled A, B, and C:

- Region A: is characterized by solutions with low accumulated error but high overshoot. This region represents system responses that are fast, but exhibit significant oscillations.
- Region B: encompasses solutions that strike a more favorable balance between accumulated error and overshoot, potentially representing the optimal trade-off between control stability and precision.
- Region C: contains solutions with high accumulated error and low overshoot, indicating more conservative approaches where stability is prioritized.

The points presented in the figure represent the solutions obtained by $CACC_{ga}$, forming the Pareto front. A specific solution was highlighted with a marker and a label indicating its coordinates: the point (17.37, 0.0586). The accumulated error is moderate, while the overshoot is relatively low. The parameter values for the selected point are $f^T = \begin{bmatrix} -12288 & 4909 & -5079 & -1093 \end{bmatrix}$.

B. Evaluation

Figure 3 illustrates the follower vehicle's behavior in a simulation. The controller from [7] demonstrates the slowest stabilization, with delayed responses to leader speed changes and notable overshoot, which may affect passenger comfort and increase collision risk.

By contrast, the controller in [6] responds faster to speed variations but exhibits the highest overshoot, causing unwanted oscillations. When communication is integrated into this controller, performance improves notably—delivering quick responses with reduced overshoot and promoting a smoother, safer ride. The proposed $CACC_{ga}$ controller achieves the best results, with faster, more accurate reactions and minimal oscillation during both acceleration and braking, enhancing stability and precision in following the lead vehicle.

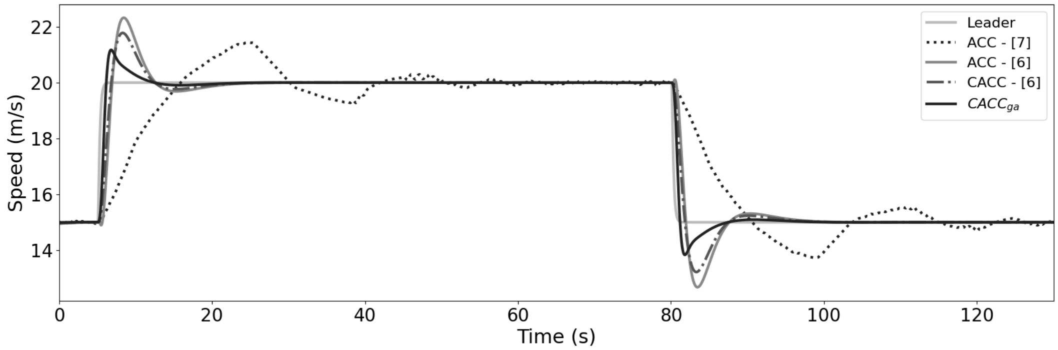

Fig. 3. Speed Follower Vehicle

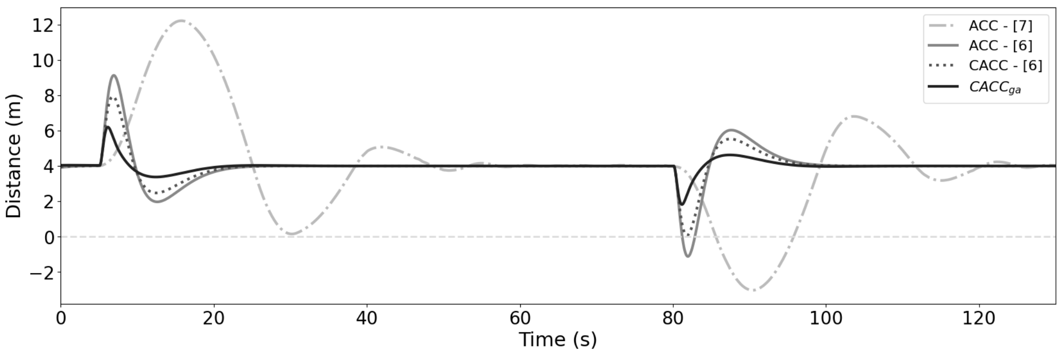

Fig. 4. Distance Analysis

The proposed $CACC_{ga}$ controller achieves the best results, with faster, more accurate reactions and minimal oscillation during both acceleration and braking, enhancing stability and precision in following the lead vehicle. Figure 4 shows how the distance between leader and follower evolves, highlighting the impact of each controller on tracking stability. During acceleration, all controllers guide the follower toward the 4m target distance with varying degrees of efficiency.

However, during deceleration, ACC controllers without communication perform poorly, often reducing the distance dangerously or even producing negative values—indicating potential collisions. Although the CACC from [6] avoids crashes, it still allows unsafe proximity. In contrast, the proposed CACC consistently maintains a safer gap and minimizes oscillations.

V. CONCLUSIONS

The results highlight that proper hyperparameter tuning is vital for optimizing CACC performance, enhancing stability and safety in distance control. The proposed $(CACC_{ga})$ achieved an accumulated error of 17.37 and an overshoot of 5.86%, outperforming the controllers in [7] and [6]. This optimization framework can also be extended to refine feedforward controller parameters and integrate models considering road inclines for further performance gains.

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