

Original Research Article

Research on new energy vehicle control technology based on genetic algorithm and fuzzy control

Cenglin Yao

School of Artificial Intelligence and Big Data, Wuhan Business University, Wuhan, Hubei, 430056, China

Abstract: This study develops a genetic-algorithm-optimized fuzzy proportional-integral-derivative (GA-fuzzy PID) controller for longitudinal speed tracking of new energy vehicles. A nonlinear simulation model includes aerodynamic, rolling, and grade resistance, actuator lag, force saturation, rate limitation, and measurement noise. A two-input fuzzy system adjusts the PID gains online, while a real-coded genetic algorithm optimizes baseline gains, modulation amplitudes, and input scaling factors. The controller is compared with conventional PID, expert fuzzy PID, and fixed-gain GA-PID under nominal, disturbance, and parameter-variation conditions. In the parameter-variation case, GA-fuzzy PID reduces RMSE, maximum error, and overshoot by 8.5%, 13.2%, and 23.5% relative to GA-PID. Across 100 independent randomized simulations, mean RMSE, maximum error, and overshoot decrease by 6.4%, 13.4%, and 13.6%, respectively, and the composite score improves in 97% of cases. The mean force-variation penalty is only 0.5%. Results support fuzzy gain scheduling as a transparent robustness enhancement, but all evidence is simulation-based and requires hardware or vehicle validation.

Keywords: new energy vehicle; genetic algorithm; fuzzy PID; longitudinal control; robust speed tracking

1. Introduction

Accurate longitudinal control is essential for electric and hybrid vehicles because payload, road grade, drag, rolling resistance, and actuator delay vary during operation. Fixed-gain PID control is simple and inexpensive, but gains optimized for one condition may lose robustness elsewhere^[1-3]. Fuzzy PID control adapts the gains from the speed error and its rate, whereas genetic algorithms (GAs) reduce dependence on subjective tuning^[4-6]. This work combines offline GA optimization with online fuzzy gain scheduling and evaluates whether adaptation adds value beyond an equally optimized fixed-gain GA-PID controller.

2. Vehicle model and control method

The controlled plant is a lumped longitudinal model, whose force balance is given by Equation (1):

$$m \frac{dv}{dt} = F_t - \frac{1}{2} \rho C_d A v^2 - mg C_{rr} \cos \theta - mg \sin \theta - F_d \quad (1)$$

In Equation (1), m is mass, v is speed, F_t is the delivered traction or braking force, θ is road angle, and F_d is an external disturbance. Nominal values are $m = 1650$ kg, $C_d = 0.29$, $A = 2.25$ m², $C_{rr} = 0.012$, and an actuator time constant of 0.22 s. Traction and braking are limited to 5200 and -7200 N, and the force-rate limit is 18,000 N/s.

The online controller schedules the PID gains according to Equation (2):

$$K_j(t) = K_{j0} [1 + s_j u_j(e_n, \dot{e}_n)], \quad j \in \{p, i, d\} \quad (2)$$

In Equation (2), K_{j0} is a baseline gain, s_j is its modulation amplitude, u_j is a normalized fuzzy output, and e_n and $\dot{e}_n$ are clipped normalized inputs. Five linguistic sets (NB, NS, Z, PS, PB) and a 25-rule Mamdani-type rule base increase proportional action for large errors, strengthen integral action near persistent small errors, and add derivative damping during rapid transients^[7]. Anti-windup and filtered differentiation are applied.

A real-coded GA uses 54 chromosomes and 75 generations. For GA-fuzzy PID, eight decision variables

define three baseline gains, three modulation amplitudes, and two input scales. The objective combines RMSE, mean absolute error, maximum error, positive overshoot, and force total variation over three deterministic scenarios. GA-PID optimizes only the three fixed gains, providing an optimization-only ablation. **Figure 1** summarizes the architecture.

Proposed control architecture

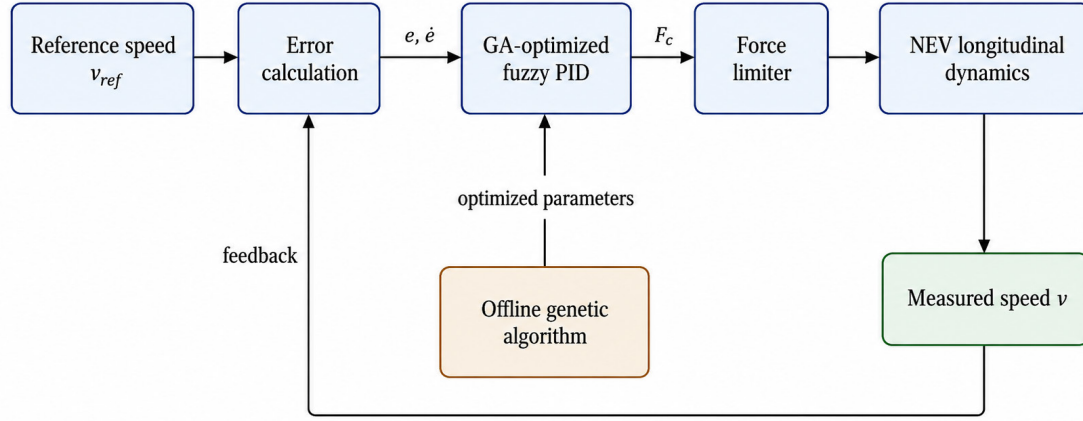


Figure 1. GA-optimized fuzzy PID longitudinal-control architecture.

3. Simulation design

A 180 s reference cycle contains stops, accelerations, decelerations, and plateaus up to 30 m/s. The nominal case uses standard parameters; the disturbance case changes mass, resistance, actuator lag, grade, and external force; and the parameter-variation case applies larger simultaneous deviations. Final evaluation uses a 0.05 s step. Robustness is further tested on 100 out-of-sample cases generated with seed 2026. Mass, drag, rolling resistance, actuator lag, three grade segments, disturbance amplitude, and noise phase are independently sampled from bounded uniform distributions. None of these random cases is used for GA tuning.

4. Results

The optimized GA-PID gains are $K_p = 797.071$, $K_i = 280$, and $K_d = 0$. The GA-fuzzy PID solution uses $K_{p0} = 627.626$, $K_{i0} = 240.399$, and $K_{d0} = 1.005$, with proportional, integral, and derivative modulation amplitudes of 0.950, 0.415, and 0.628. **Table 1** reports the most informative comparisons. GA-PID has slightly lower nominal RMSE, but GA-fuzzy PID produces smaller peak error, overshoot, and force variation. Under parameter variation, fuzzy scheduling provides clear robustness gains.

Table 1. Selected deterministic and monte carlo results. Positive change denotes improvement of GA-fuzzy PID.

Condition / metric	GA-PID	GA-fuzzy PID	Change
Nominal RMSE (m/s)	0.112	0.116	−3.6%
Nominal max error (m/s)	0.337	0.324	+3.9%
Parameter-variation RMSE (m/s)	0.286	0.261	+8.5%
Parameter-variation max error (m/s)	0.767	0.666	+13.2%
Parameter-variation overshoot (m/s)	0.712	0.544	+23.5%
Monte Carlo mean RMSE (m/s)	0.1939	0.1815	+6.4%
Monte Carlo mean max error (m/s)	0.6590	0.5705	+13.4%
Monte Carlo mean force TV (kN)	35.1359	35.3169	−0.5%

In the disturbance case, GA-fuzzy PID reduces RMSE from 0.171 to 0.164 m/s and maximum error from 0.551 to 0.413 m/s. In the 100 randomized cases, it wins in 93% of cases for RMSE, 98% for maximum error, and 96% for overshoot. Holm-adjusted Wilcoxon tests indicate significant paired differences

for all five reported metrics, although the force-variation difference is practically small. **Figure 2** shows that the largest distributional improvements occur in maximum error and overshoot.

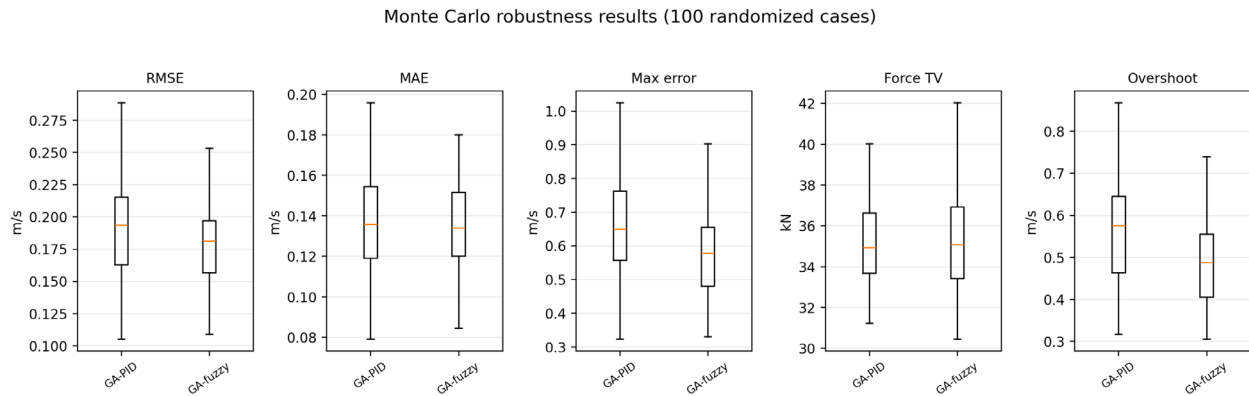


Figure 2. Performance distributions across 100 out-of-sample Monte Carlo simulations.

5. Discussion

The comparison separates the benefit of online adaptation from that of offline optimization. Aggressive fixed gains give GA-PID a small nominal RMSE advantage, whereas the fuzzy controller lowers its baseline proportional gain and increases it only when the error state requires stronger action. This mechanism suppresses peak deviations under large uncertainty without materially increasing actuator activity. The method remains interpretable and inexpensive enough for real-time implementation, but its validity is limited by the synthetic plant, assumed lower-level force tracking, simplified tire behavior, and absence of battery, regenerative-braking, and communication models.

6. Conclusion

GA-optimized fuzzy PID control improves robustness and peak-error suppression in the simulated NEV longitudinal-control problem. It does not dominate fixed-gain GA-PID in every nominal metric, but it performs better under parameter variation and randomized uncertainty. The next step is repeated optimization with multiple seeds, followed by hardware-in-the-loop, dynamometer, and road testing.

Declarations

Data availability: No external dataset was used; all values were generated by the numerical simulations described above. Funding: None. Conflict of interest: None. Ethics approval: Not applicable.

About the author

Cenglin Yao, wuhanycl@163.com.

References

- [1] R. Rajamani, *Vehicle Dynamics and Control*, 2nd ed. Springer, 2012.
- [2] M. Ehsani et al., *Modern Electric, Hybrid Electric, and Fuel Cell Vehicles*, 3rd ed. CRC Press, 2018.
- [3] A. Mahmood et al., "Comparison of GA-PID, LQR, and fuzzy controllers for cruise control," *World Electric Vehicle Journal*, vol. 15, p. 351, 2024.
- [4] H. Qin et al., "Fuzzy adaptive PID coordination control based on particle swarm optimization," *Energies*, vol. 17, p. 5311, 2024.
- [5] T. L. Sime et al., "GA-tuned adaptive fuzzy fractional-order PID speed control for EV PMSM," *Discover Applied Sciences*, vol. 6, p. 505, 2024.
- [6] S. Zhang et al., "GA-optimized fuzzy PID for air-suspension ride comfort," *Applied Sciences*, vol. 14, p. 7787, 2024.
- [7] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, pp. 338-353, 1965.
- [8] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addison-Wesley, 1989.