

Prediction-Oriented Fuzzy Logic Approach to Autonomous Braking Activation in Electric Vehicles under a Time Headway-Based Spacing Policy

Khairul Amri Tofrowaih^{1,2}, Muhammad Abdullah^{1*}, Siti Fauziah Toha³,
Syazarudin Md Said⁴, Salmiah Ahmad⁵

¹Department of Mechanical and Aerospace Engineering, Kuliyah of Engineering, International Islamic University, Gombak 53100, Malaysia

²Fakulti Teknologi dan Kejuruteraan Mekanikal, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia

³Department of Mechatronics, Kuliyah of Engineering, International Islamic University, Gombak 53100, Malaysia

⁴Department of Chemical and Environmental Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400, Selangor, Malaysia

⁵College of Engineering and Technology, University of Doha for Science and Technology, Doha, Qatar

ARTICLE INFO

Article history:

Received 12 February 2026

Revised 23 April 2026

Accepted 11 June 2026

Published 15 September 2026

Keywords:

Autonomous braking

Electric vehicle

Fuzzy logic

Regenerative braking

Time headway-based spacing policy

DOI:

10.24191/jmeche.v23i3.10761

ABSTRACT

Regenerative Braking Systems (RBS) in Electric Vehicles (EVs) generate electricity during coasting, yet energy recovery can be reduced when friction brakes are used prematurely. This paper investigates an autonomous braking control strategy for EVs based on Fuzzy Logic (FL) by incorporating a time-headway spacing policy to improve energy recovery during deceleration. Using relative distance and relative speed, a headway-based spacing rule is enforced to decide friction-brake activation. This rule is set to prioritise coasting and regenerative braking whenever possible. The control system is implemented in MATLAB/Simulink on an electric go-kart model and benchmarked against a baseline FL controller without safe-distance gating across three lead-vehicle scenarios. The first scenario is a constantly slower lead vehicle (with varying initial gaps); the second involves gradual deceleration, and the third involves sudden deceleration. Simulation results demonstrate that the proposed strategy reduces peak brake force, shortens total braking duration by over 50%, and often eliminates unnecessary friction-brake usage. Maximum deceleration also decreased by up to 46.1%, coasting distance increased by approximately 1.95%, and energy recovery improved by 21.7%. In genuine emergency braking situations, both controllers (with and without prediction) produce equivalent behaviour, demonstrating that energy-aware braking is achieved without compromising safety.

^{1*} Corresponding author. E-mail address: mohd_abdl@iiu.edu.my
<https://doi.org/10.24191/jmeche.v23i3.10761>

Introduction

Electric Vehicles (EVs) offer numerous benefits, including zero emissions, high energy efficiency, and low operating costs. Nevertheless, a common concern is range anxiety, due to their limited driving range and relatively long charging time (Gunasekaran et al., 2024; Madani et al., 2025; Tran et al., 2021). Even with fast-changing technology, an EV typically still requires at least 30 minutes to reach a usable battery level (Zentani et al., 2024; Zhiani et al., 2026). As a result, a wide range of strategies have been explored to overcome range limitations, such as optimisation of powertrain architectures, increased battery capacity, development of more effective battery management systems, and others (Zhang et al., 2025). Among these approaches, regenerative braking is considered one of the simplest and most direct methods for recovering additional energy without changing the overall vehicle's system configuration. This system recovers kinetic energy during deceleration by operating the motor in generator mode to recharge the battery. For a default setup, its efficiency depends on maximising coasting and minimising friction braking, which is difficult to control manually. This motivates the use of autonomous braking control to optimise energy recovery without compromising safety. In this context, Fuzzy Logic (FL) controllers are often used as they provide smooth driving conditions and can be tuned to local traffic behaviour.

Despite the widespread use of FL in autonomous braking, many existing controllers rely on relative distance and speed as input parameters (Ondoğan & Yavuz, 2019; Rizianiza & Shoodiqin, 2021). While these parameters describe basic car-following dynamics, they provide limited anticipative capability, particularly in dynamic or high-density traffic. Consequently, braking actions may be initiated prematurely, which can reduce energy efficiency or too late, which can affect passenger comfort. In EVs, this challenge becomes critical, as the timing and smoothness of braking directly affect the amount of energy that can be recovered through regenerative braking (Budijono et al., 2022; Faghihian & Sargolzaei, 2025; Patil et al., 2026). In addition, conventional FL controllers do not evaluate braking urgency using predictive indicators, such as Time-To-Collision (TTC) or safe distance thresholds. Thus, the system may engage friction braking unnecessarily.

In the literature, the integration of TTC or safe distance metrics within control algorithms is predominantly associated with Adaptive Cruise Control (ACC) (Liu et al., 2021) and Autonomous Emergency Braking (AEB) (Rani et al., 2019). In particular, the time gap, or spacing policy, between the ego and lead vehicle forms the core algorithmic component, with significant implications for traffic capacity and string stability (El-Baklish et al., 2025; Fiorani et al., 2008). Wu et al. (2020) categorised five principal spacing policies: 1) the constant spacing policy (also referred to as the Constant Distance Gap, CDG), 2) four variable spacing policies based on time headway (the most widely adopted and commonly referred to as the Constant Time Gap, CTG), 3) traffic flow stability, 4) constant safety factors (typically more conservative), and 5) human driving behaviour. It is noted that none of the spacing policies can simultaneously guarantee string stability, safety, and passenger comfort across all driving conditions (Song et al., 2019; Van Der Heijden et al., 2017). In practice, the choice of spacing policy therefore represents a compromise among these competing objectives rather than an optimal solution in all respects (Wu et al., 2020).

To address these trade-offs, several alternative spacing strategies have been proposed. Variable time-gap (VTG) policies were introduced to allow closer following at low speeds while preserving acceptable dynamic behaviour at higher speeds (Flores et al., 2017). Other researchers have explored hybrid formulations that combine multiple spacing concepts. For example, Massow et al. (2022) proposed a hybrid CTG–CDG spacing policy that blends time-headway-based and constant-distance-based rules to exploit the advantages of both, resulting in improved car-following behaviour. While these approaches improve flexibility, they do not fully eliminate the underlying trade-offs between stability, comfort, and safety. Many AEB algorithms continue to rely on safety-distance models coupled with TTC metrics, where braking is triggered once predefined distance or time-gap thresholds are violated. These include Constant Time Gap (CTG) strategy, as discussed by Zhang et al. (2023), and the Variable Time-Gap strategy (VTG) as

presented by Guo et al. (2020), hybrid distance time formulations such as CTG-CDG (Fu et al., 2024), and models derived from observed human driving behaviour (Lai et al., 2024). Although effective for collision avoidance, such threshold-based schemes are inherently reactive. Braking decisions are typically initiated only after safety margins have already been violated, leaving limited scope for anticipation of energy-aware deceleration. These limitations motivate the development of prediction-oriented autonomous braking strategies using FL that operate independently of conventional ACC architectures.

Although predictive braking concepts such as TTC-based AEB, rule-based deceleration control, and MPC based ACC have been widely investigated, many existing approaches remain either fundamentally reactive or tightly coupled to cruise-control structures with fixed or semi-adaptive spacing policies. TTC-based approach, in particular, relies on scalar thresholds that do not explicitly consider regenerative braking optimisation during non-emergency deceleration. MPC-based solutions, while more predictive, often incur a significant computational burden, which limits their suitability for real-time embedded implementation (Stanger & del Re, 2013; Ying & Solomon, 2017; Zhang & Zhuan, 2019). As a result, there remains a gap in the literature for autonomous braking frameworks that simultaneously incorporate prediction, energy-aware braking, and low-complexity inference while remaining independent of ACC systems.

A closely related method is TTC-based braking. For example, Bae et al. (2020) proposed a two-stage braking strategy that switches between partial and full braking based on TTC thresholds and validated the approach in a CarSim/Simulink environment, while considering both safety and ride comfort. However, in this work, a different triggering mechanism is proposed. Rather than predicting collision time, the proposed approach predicts the minimum safe following distance and initiates braking when the predicted gap falls below this threshold. This results in a fundamentally different control paradigm compared to TTC-based designs, where braking decisions are no longer triggered reactively but are instead initiated based on predicted safety margins. By doing so, braking decisions can be made more selectively, enabling greater utilisation of regenerative braking while preserving safety and ride comfort. In addition, unlike conventional ACC or AEB approaches, the proposed system operates during pedal-inactive states and modulates brake intensity through fuzzy-logic inference. By predicting the minimum safe following distance under a time-headway-based spacing policy, it enables anticipatory deceleration and strategically defers friction-brake engagement, achieving an improved balance between regenerative energy recovery, ride comfort, and safety in representative car-following scenarios. Table 1 summarises the key differences between the proposed method and representative existing approaches in terms of triggering mechanism, prediction capability, and energy-awareness.

Table 1. Comparison of autonomous braking approaches

Approach	System Type	Trigger Mechanism	Control Nature	Prediction Capability	Energy Aware	References
Variable Spacing Policy-Based ACC System	ACC	Spacing Control Objective	Continuous Control	Limited	No	(Wu et al., 2020)
CTG-Based AEB System	AEB	TTC	Reactive	No	No	(Zhang et al., 2023)
Two-Stage Braking Strategy	Autonomous Braking	TTC	Reactive	No	No	(Bae et al., 2020)
Proposed Method	Autonomous Braking	Predicted minimum safe distance	Anticipatory (Predictive)	Yes	Yes	This work

The main novelty of this study lies in the use of a minimum safe following distance prediction, rather than conventional Time-To-Collision (TTC) thresholds, as the primary braking trigger. This enables a more anticipatory and spatially aware braking response. In addition, the proposed method operates independently of standard ACC architectures, allowing flexible integration into existing vehicle platforms without reliance

on predefined spacing policies. Furthermore, a fuzzy-logic-based control framework is employed to modulate braking intensity with low computational complexity, making it suitable for real-time implementation. Unlike many existing approaches, the proposed strategy explicitly incorporates energy-aware braking by maximising the use of regenerative braking via prolonging the coasting period while maintaining safety and ride comfort. Therefore, this work contributes a unified framework that simultaneously addresses prediction capability, energy efficiency, and implementation simplicity, which remains underexplored in current literature.

Methodology

This work employs a simulation-based analysis based on the mathematical modelling of vehicle longitudinal dynamics for a developed electric Go-Kart system (refer to Fig. 1). The model uses actual physical parameters derived from the Go-Kart and was originally developed by Matlab (2023). Although the model has not yet undergone formal experimental validation, it is appropriate for the present study, which aims to evaluate the control logic and decision-making behaviour of the proposed autonomous braking strategy rather than to provide absolute vehicle performance predictions. The use of a physics-based longitudinal model enables consistent and repeatable comparison of competing control strategies under identical conditions, thereby allowing the isolated assessment of control effectiveness without influences from hardware variability or sensor noise. While experimental validation and hardware implementation are planned as future work, the current simulation framework is sufficient to demonstrate the feasibility, safety preservation, and relative performance benefits of the proposed prediction-oriented braking approach. This section is organised into four parts: a brief overview of the mathematical model, a description of the proposed control strategy, an FL-based algorithm, and the simulation setup with key assessment parameters used for performance evaluation.



Fig. 1. Converted electric Go-Kart.

Simulation plant

The simulation plant adopted in this study is based on a physics-based longitudinal vehicle model previously developed and reported in the article by Tofrowaih et al. (2025). As the focus of the present work lies in the design and evaluation of the proposed autonomous braking control strategy rather than detailed vehicle model development, a concise description of the simulation plant is provided to support

the control implementation and performance assessment. The model is based on a simplified longitudinal vehicle dynamics formulation, with key governing equations and parameters presented in Equations 1 – 5 and Table 2. These formulations capture the essential relationships between traction force, braking force, and vehicle motion required for control evaluation. Using this model allows the simulated scenarios to be evaluated under consistent and repeatable conditions, which is essential for a fair comparison of different control strategies. The overall simulation plant has five interconnected subsystems, namely vehicle body dynamics, traction motor dynamics, driveline dynamics, brake dynamics, and battery state-of-charge (SOC) estimation module. These subsystems are implemented within the Simulink environment. Fig. 2 illustrates the corresponding block diagram and the signal flow between the individual components, providing an overview of the longitudinal vehicle dynamics and energy-related states in the simulation.

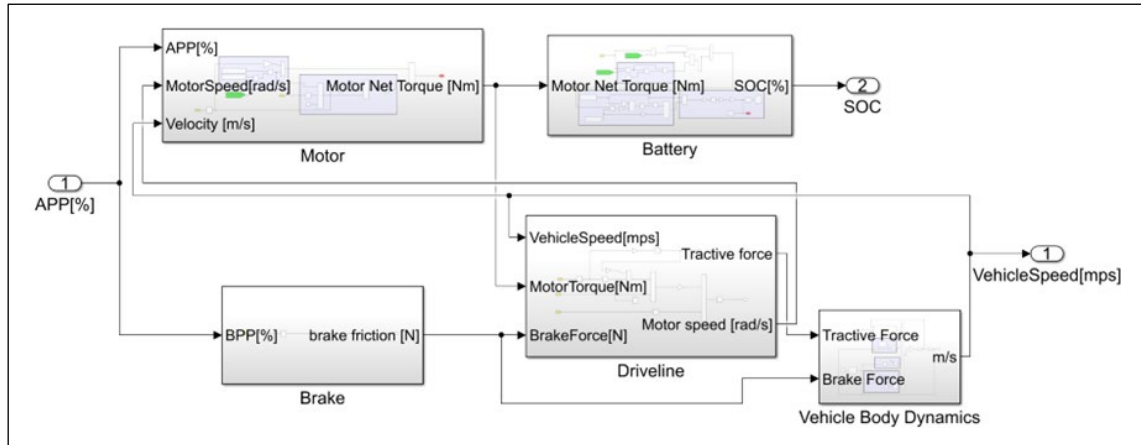


Fig. 2. Simulink block diagram of vehicle plant.

The main inputs to the model are throttle and brake pedal positions, expressed as percentages (0–100%), which simulate driver or controller commands. The primary outputs include vehicle velocity, acceleration, and battery SOC, depending on the simulation objectives. Each subsystem is governed by its mathematical formulation based on simplified physical laws, which can be represented in a simplified form as in Equation 1 to Equation 5 below:

$$T_{m,net} = T_m + T_{rbs} \quad (1)$$

$$F_t = \frac{G_r}{r_w} (T_{m,net} - T_{loss}) \quad (2)$$

$$F_b = k_b x_b \quad (3)$$

$$V(t) = f(x_t, x_b, \rho, C_d, A_f, v^2, \mu_k, m, g, \theta) \quad (4)$$

$$SOC = -\frac{1}{3600 * 1000 * C} (\int I \cdot V_{oc} dt) \quad (5)$$

where $f(\cdot)$ represents the combined longitudinal vehicle dynamics, and all variables in Equations 1–5 are defined in Table 2. The equations represent a simplified longitudinal vehicle model used for control-oriented simulation.

Table 2. List of symbols for Equation 1 – Equation 5

Symbol	Description	Values	Unit
$T_{m,net}$	Net torque produced by traction motor	Scenario-dependent	N.m
T_m	Traction motor torque	Scenario-dependent	N.m
T_{rbs}	RBS torque	Scenario-dependent	N.m
T_{loss}	Estimated mechanical torque loss encountered by the driveline	Scenario-dependent	N.m
F_t	Traction force	Scenario-dependent	N
b	Torque damping coefficient	0.004	-
G_r	Gear ratio between output gear and input gear	6.1935	-
r_w	Wheel radius	0.15	m
F_b	Brake force	Scenario-dependent	N
k_b	Brake gain	100	-
x_b	Brake pedal pressing	Controller input (0–100%)	%
x_t	Throttle pedal pressing	Driver input (0–100%)	%
$V(t)$	Vehicle speed	Time varying	m/s
ρ	Air density	1.2250	kg/m ³
C_d	Drag coefficient	0.2	-
A_f	Vehicle frontal area	0.66	m ²
μ_k	Rolling resistance coefficient	0.015	-
m	Vehicle load mass	150	kg
g	Gravitational acceleration	9.81	m/s ²
θ	Vehicle inclination angle	0	degree
SOC	State of charge	Scenario-dependent	%
I	Supplied current	Scenario-dependent	A
V_{oc}	Open circuit voltage	48	V
C	Battery energy capacity	5	kWh

Note: Scenario-dependent values vary according to the operating conditions and controller outputs.

Proposed control strategy

The braking algorithm is designed as an autonomous intervention system that activates only during pedal-inactive states, i.e., when neither the accelerator nor brake pedal is engaged by the driver. The control logic is implemented using an FL controller, which evaluates the traffic situation and determines an appropriate braking force based on a set of input conditions. The key objective is to ensure safe deceleration while maximising energy recovery through regenerative braking for EV operation.

Fig. 3 shows the driving scenario of the ego car (the controlled car) and the lead vehicle, and Fig. 4 presents the flow chart of the control logic for the autonomous braking strategy that is designed to activate only when the throttle pedal is released, indicating a transitional driving state where the driver is neither accelerating nor actively braking. This design ensures that the system complements the driver's intent, intervening only when necessary and avoiding conflicts with manual input. The first decision checks whether the ego vehicle is moving faster than the lead vehicle ($v_{ego} > v_{lead}$). This condition ensures that braking is only considered if the ego vehicle is closing the gap and potentially approaching the lead vehicle.

If the ego vehicle is slower or travelling at the same speed, there is no immediate collision risk, and thus, no braking force is applied ($F_b = 0$).

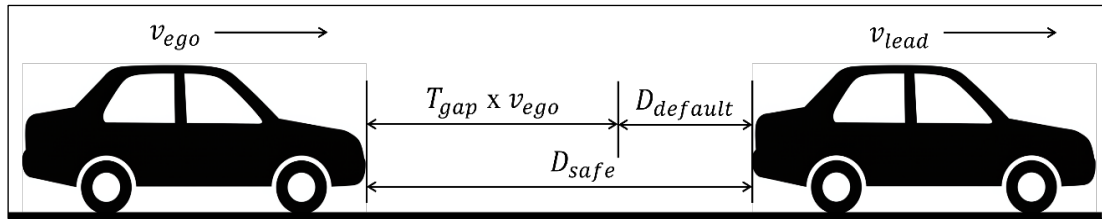


Fig. 3. Car following application.

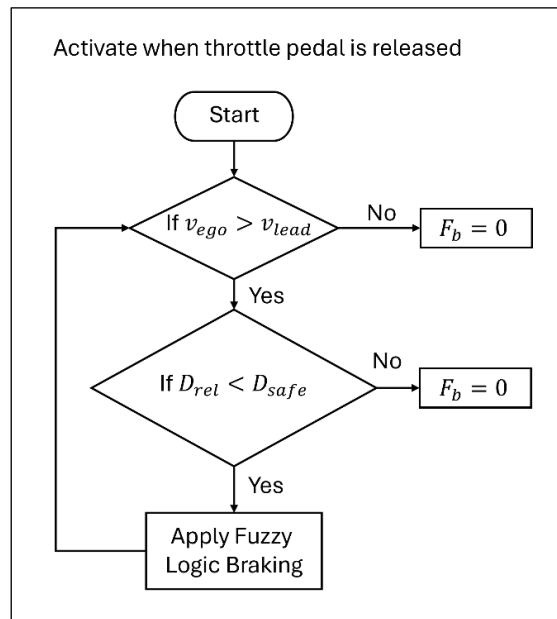


Fig. 4. Control logic of proposed autonomous braking system.

When the ego vehicle approaches the lead vehicle, the control logic evaluates the proximity risk associated with the lead vehicle using the safe distance criteria. Rather than relying on a single indicator, the controller compares the measured relative distance with a dynamically defined safety threshold ($D_{rel} < D_{safe}$) which reflects spatial separation and the urgency of interaction. This combined assessment improves robustness by preventing incorrect braking actions, such as unnecessary braking when the lead vehicle is moving away or delayed intervention when the gap is large but rapidly closing. The approximation of D_{safe} is given in Equation 6.

$$D_{safe}(k) = D_{default} + [T_{gap} \times v_{ego}(k)] \quad (6)$$

This algorithmic structure reflects a context-aware braking strategy that prioritises energy efficiency (by favouring coasting), driving comfort, and safety. This characteristic is especially relevant for EVs, as unnecessary braking degrades ride comfort while simultaneously reducing the opportunity for regenerative energy recovery. Moreover, by activating only in the absence of driver input, the system maintains driver authority and avoids intrusiveness, which are the key aspects of effective semi-autonomous driving systems.

Fuzzy logic design

The membership-function (MF) families were selected based on their suitability for representing the system dynamics and ensuring smooth control response. A trapezoidal MF was used for the relative distance input (0-25 m) to effectively capture boundary conditions between safe and critical regions. A Gaussian MF was adopted for the relative speed input (0-15 m/s) to provide smooth transitions under dynamic conditions, while a triangular MF was selected for the braking-intensity output (0-100 %) for its simplicity and computational efficiency. These selections ensure a balance between interpretability, control smoothness, and real-time implementation feasibility. A Mamdani-type fuzzy inference system (mamfis) with max–min composition and centroid defuzzification was employed. The overall FLC architecture is shown in Fig. 6, whereas the corresponding MF ranges and rule base are explicitly provided in Table 3 to ensure reproducibility of the proposed controller. The rule base was constructed from heuristic driving insights and iteratively tuned using scenario playback in the Simulation 3D viewer via Unreal Engine. A total of 25 fuzzy rules were implemented to cover all operating conditions, as shown in Table 4.

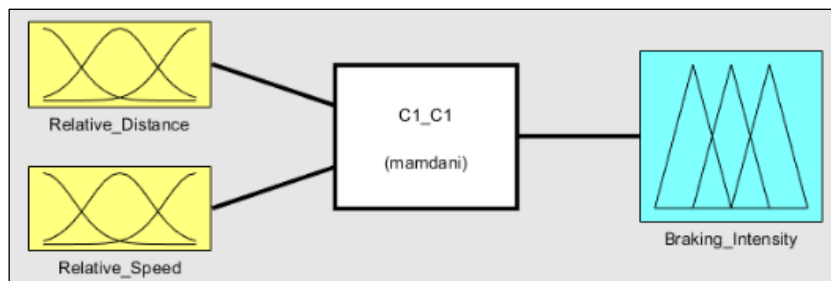


Fig. 6. Fuzzy logic design.

Table 3. MF ranges and linguistic labels

Relative Distance (trapmf, m)	MF Parameters	Relative Speed (gaussmf, m/s)	MF Parameters	Braking Intensity (trimf, %)	MF Parameters
Very Close	[0.4 2.6 5.3 7]	Very Slow	[1.21 1.575]	No Braking	[0 0 0]
Close	[5 8.5 11.5 15]	Slow	[1.274 4.5]	Light Braking	[-20 -10 10]
Medium	[10 13.5 16.5 20]	Moderate	[1.274 7.5]	Moderate Braking	[5 25 45]
Far	[15 18.5 21.5 25]	Fast	[1.274 10.5]	Strong Braking	[40 60 80]
Very Far	[20 23.5 26.5 30]	Very Fast	[0.7007 13.43]	Emergency Braking	[75 100 125]

Note: For trapezoidal membership functions (trapmf), parameters are defined as [a, b, c, d], while Gaussian (gaussmf) parameters are given as [σ , c], and triangular (trimf) parameters as [a, b, c]. Negative values in the braking intensity output indicate low or negligible braking commands within the control scaling.

Table 4. Fuzzy rules applied

Relative Speed	Relative Distance				
	Very Close	Close	Medium	Far	Very Far
Very Slow	LB	NB	NB	NB	NB
Slow	LB	LB	NB	NB	NB
Moderate	MB	LB	NB	NB	NB
Fast	MB	LB	NB	NB	NB
Very Fast	SB	LB	NB	NB	NB

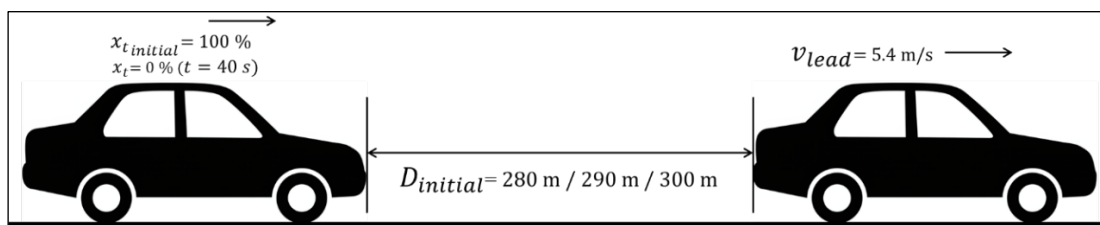
Legend: NB = No Braking; LB = Light Braking; MB = Moderate Braking; SB = Strong Braking

Simulation setup and parameters

The proposed autonomous braking algorithm was evaluated in a closed-loop simulation of a longitudinal electric go-kart model under driver-inactive conditions (accelerator and brake pedals released by the human driver). The objective was to assess how the fuzzy-logic controller, augmented with safe-distance logic, manages car-following across representative traffic situations. Three scenarios were considered as shown in Fig. 7: (a) a constant-lower speed lead vehicle (Scenario 1), (b) a gradually decelerating lead vehicle (Scenario 2), and (c) a suddenly decelerating lead vehicle (Scenario 3). In all scenarios, the ego vehicle's accelerator pedal position (APP) command was stepped from 100% to 0% at $t = 40$ s to create a repeatable pedal-inactive entry condition, prompting the controller to assume longitudinal authority.

In Scenario 1 (constant-speed case), the lead vehicle travels steadily at 5.4 m/s, which is slower than the ego vehicle's 15 m/s, while the initial ego–lead spacing is varied parametrically at 280 m, 290 m, and 300 m. These values were chosen to cover the range where prior calibration showed the proposed controller to be most effective. For initial spacings below 300 m, the ego vehicle consistently closes the gap to the lead vehicle within the simulation horizon, ensuring meaningful interaction to occur. At substantially larger initial distances, however, the lead vehicle remains beyond the effective influence of the ego vehicle, and the resulting interaction becomes negligible. The longitudinal actuation dynamics of the lead vehicle are modelled using a first-order lag $1/(s+1)$ as shown in Fig. 8(a).

In Scenario 2 (gradual deceleration), the lead vehicle speed is commanded from 4 m/s to 0 m/s at $t=39$ s and filtered by a slower first-order lag $1/(5s+1)$ to emulate a gentle, driver-like slowdown as shown in Fig. 8(b); the initial spacing is 400 m to permit a prolonged coasting response by the ego vehicle before any potential brake request. In Scenario 3 (sudden deceleration), the lead vehicle speed is likewise stepped from 4 m/s to 0 m/s at $t = 39$ s, but with a faster first-order lag $1/(s+1)$ to represent an abrupt stop as shown in Fig. 8(c); the initial spacing is set to 350 m to ensure a meaningful closure while preserving a safety margin for collision avoidance. Across all scenarios, the differing time constants distinguish gradual over sudden deceleration profiles, while the offset in step times (lead at 39 s, ego APP release at 40 s) guarantees a convergent approach that activates the controller's decision logic.



(a)

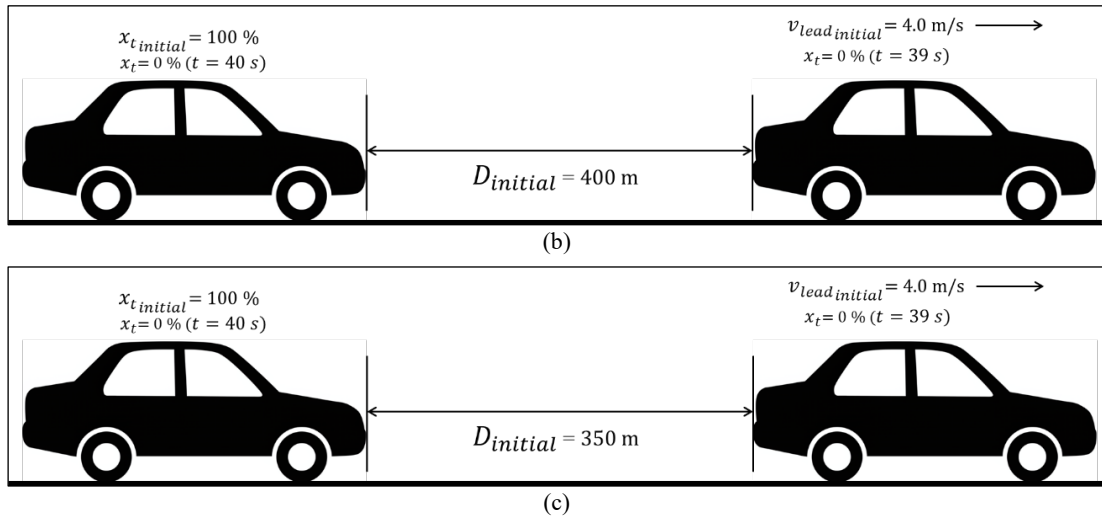


Fig. 7. Scenario illustration (a) constant lower speed lead vehicle, (b) gradually decelerating lead vehicle and (c) sudden decelerating lead vehicle.

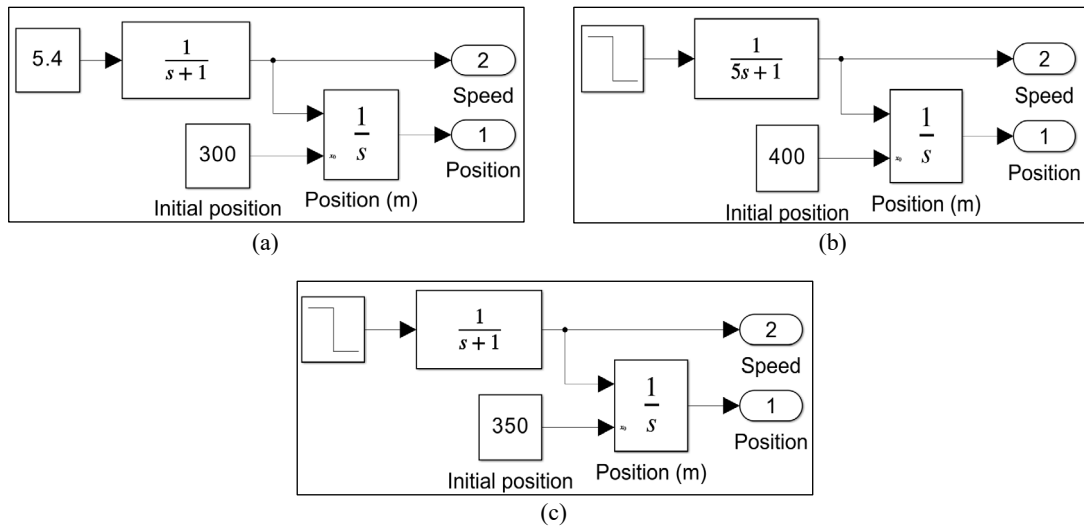


Fig. 8. Longitudinal actuation dynamics of the lead vehicle in (a) Scenario 1, (b) Scenario 2 and (c) Scenario 3.

The principal parameters governing each simulated interaction are presented in Table 5. The table lists the APP step inputs for the ego and lead vehicles, the first-order dynamic model used for the lead vehicle, and the initial separation distance.

Table 5. Summary of test-scenario parameters for car-following simulations

Test Scenarios	Ego vehicle APP step input parameter	Lead vehicle speed step input parameter	Lead vehicle Acceleration / Deceleration Dynamics	Lead Vehicle Initial Distance (m)
Constant Slower Speed Lead Vehicle	Initial Value: 100% Final Value: 0% Step time: 40s	Initial Value: 5.4 m/s Final Value: 5.4 m/s	$\frac{1}{s+1}$	280, 290, 300
Decelerating Lead Vehicle (gradual)	Initial Value: 100% Final Value: 0% Step time: 40s	Initial Value: 4 m/s Final Value: 0 m/s Step time: 39s	$\frac{1}{5s+1}$	400
Decelerating Lead Vehicle (sudden)	Initial Value: 100% Final Value: 0% Step time: 40s	Initial Value: 4 m/s Final Value: 0 m/s Step time: 39s	$\frac{1}{s+1}$	350

Performance is quantified using maximum brake force, brake duration, distance travelled by the ego vehicle over a fixed 100 s horizon, minimum relative distance, estimated SOC gain, and maximum (negative) acceleration, capturing safety, following quality, energy recovery, and ride comfort in a controller-agnostic manner. While such performance requirements in automotive studies are often benchmarked against established standards, no standardised criteria exist for go-kart platforms. Accordingly, the evaluation parameters in Table 6 are employed as relative measures of system behaviour, enabling meaningful comparison of controller performance across these key dimensions.

Table 6. System performance evaluation parameters

Metric, unit	Description
Maximum Brake Force, N	To measure the controller's peak friction-brake intervention
Brake Duration, s	To measure the controller's coasting ability
Distance Travelled by Ego vehicle after 100 s, m	To quantify longitudinal progress and coasting effectiveness over a fixed time horizon (100 s)
Minimum Relative Distance, m	To ensure the collision avoidance margin is maintained
Estimated SOC Gain, %	Change in battery SOC before and after braking event
Maximum Deceleration, m/s ²	To estimate the ride comfort of the vehicle experience

Results and Discussion

This section presents the simulation results for the fuzzy logic-based autonomous braking system. Three representative driving scenarios were analysed to assess braking performance, following ability, energy recovery through regenerative braking, and passenger comfort. The results compare the proposed fuzzy controller enhanced with safe distance logic (denoted as “with prediction”) against a baseline fuzzy controller without safe distance check (denoted as “without prediction”).

Constant speed lead vehicle

Figs. 9 to 11 summarise the braking behaviour of the baseline and prediction-enhanced controllers for constant lower speed car-following under three initial spacings (300 m, 290 m, and 280 m), respectively.

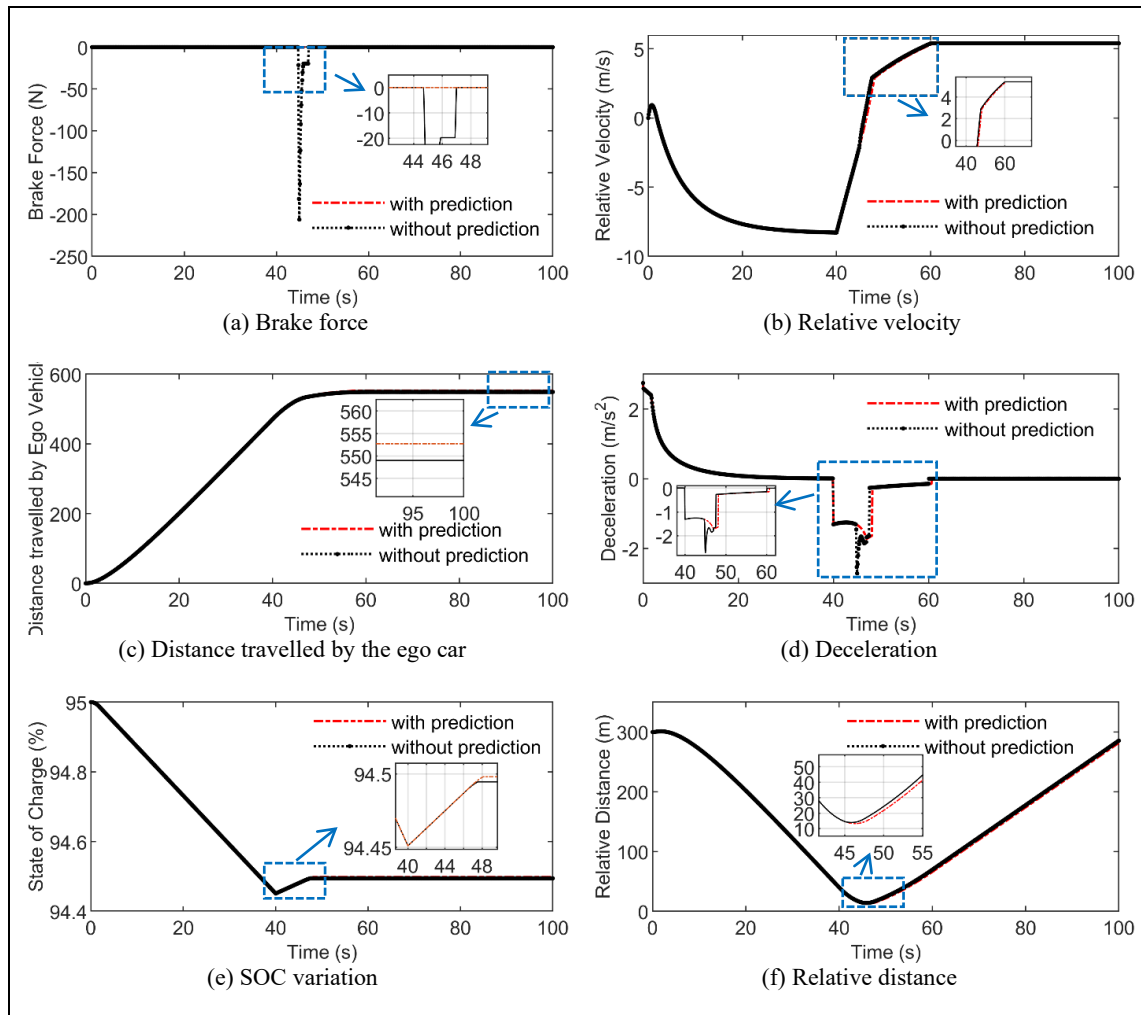


Fig. 9. Graph of (a) brake force, (b) relative velocity, (c) distance travelled by ego car, (d) deceleration, (e) SOC variation, and (f) relative distance over 100 s period for Scenario 1 (300 m initial separation distance).

At the largest initial distance (300 m), the prediction-enhanced controller completely suppressed friction-brake activation, with the deceleration demand being satisfied through coasting and regenerative braking, as shown in Fig. 9(a). This result is attributed to the sufficiently long spacing, which allows gradual speed reduction within the regenerative braking capacity of the electric drivetrain. Under this condition, peak deceleration was reduced by 36.4%, as shown in Fig. 9(d), while a safe minimum separation was maintained throughout the manoeuvre, as shown in Fig. 9(f). This outcome indicates that, under favourable spacing conditions, the required deceleration can be achieved entirely through regenerative means. In practical terms, friction braking may still be required under more demanding conditions, such as shorter initial distances or higher deceleration demands. Furthermore, similar to other ADAS functions, the proposed control strategy can be overridden by manual driver intervention if the driver is not confident in the system's response. Nevertheless, the result demonstrates the potential of the proposed control strategy to significantly reduce reliance on mechanical braking, which is expected to lower brake pad wear and improve long-term maintenance efficiency. By comparison, the baseline controller-initiated braking earlier despite the availability of sufficient headway, resulting in avoidable energy dissipation

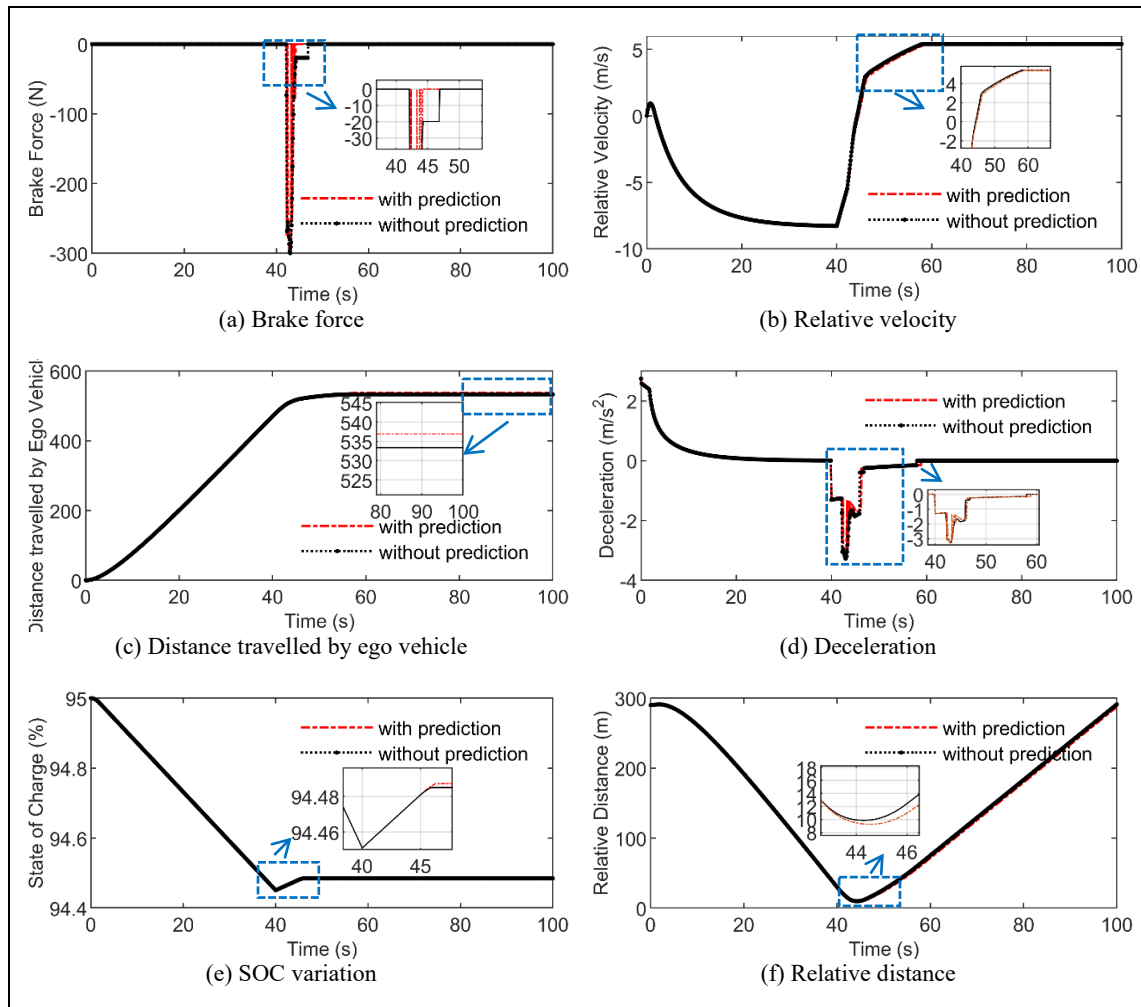


Fig. 10. Graph of (a) brake force, (b) relative velocity, (c) distance travelled by ego car, (d) deceleration, (e) SOC variation, and (f) relative distance over 100 s period for Scenario 1 (290 m initial separation distance).

At intermediate and shorter initial spacings (290 m and 280 m), friction braking became necessary for both controllers. Even so, the prediction-enhanced strategy consistently reduced braking duration by more than 50%, as shown in Fig. 10(a) and Fig. 11(a). Differences in peak brake force were relatively small at these shorter gaps. However, the shortened braking intervals allowed longer coasting phases to develop. As a result, the ego vehicle travelled a greater distance over the fixed simulation horizon as shown in Fig. 10(c) and Fig. 11(c). This effect was most evident in the 280 m case, where the distance gain (+1.12%) was nearly twice that observed at 300 m (+0.62%) and 290 m (+0.67%). The larger gain reflects more effective use of the available headway during car-following. These observations align with earlier findings that regenerative braking systems benefit most from extended coasting, during which kinetic energy is recovered gradually rather than dissipated through abrupt friction-brake engagement (Ji et al., 2020).

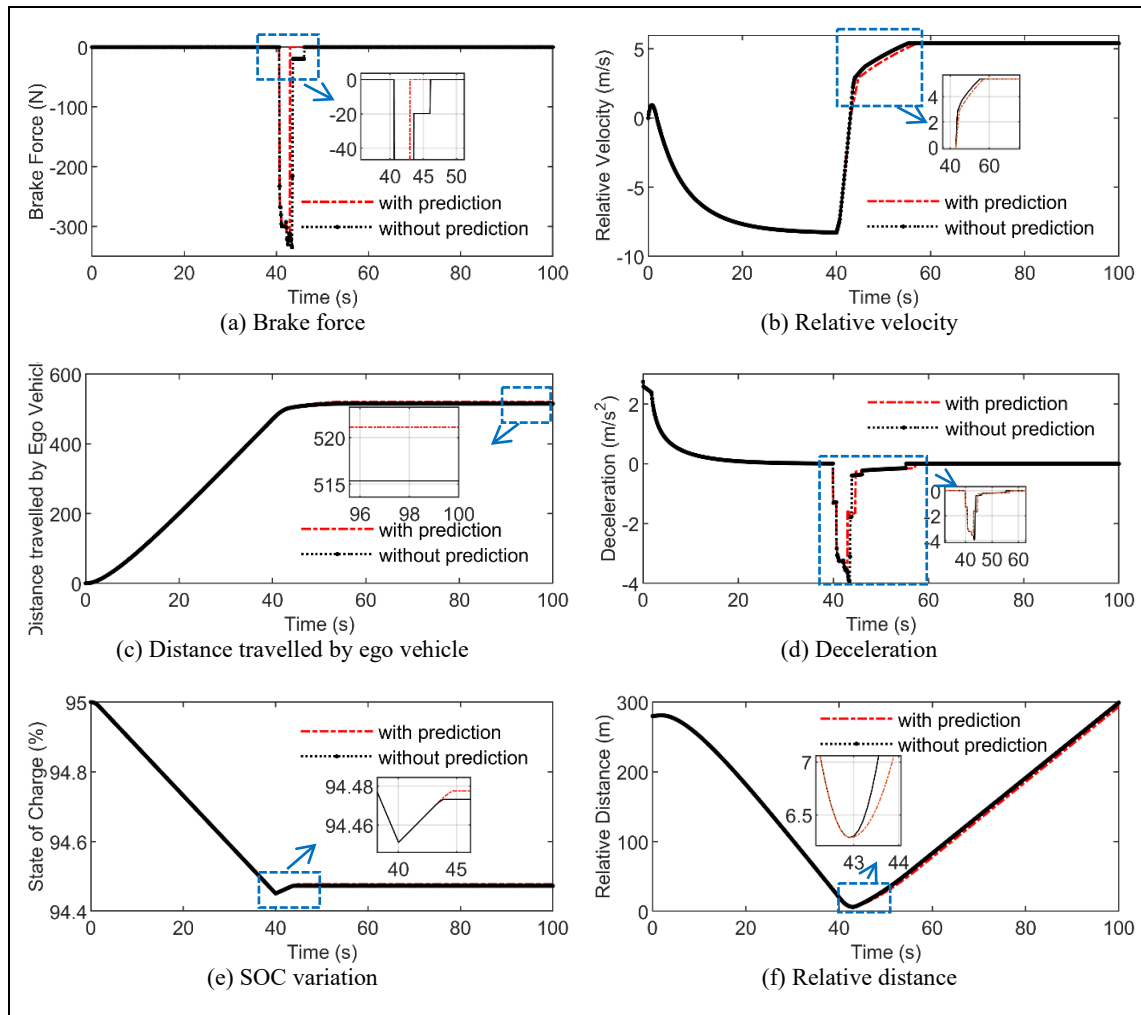


Fig. 11. Graph of (a) brake force, (b) relative velocity, (c) distance travelled by ego car, (d) deceleration, (e) SOC variation, and (f) relative distance over 100s period for Scenario 1 (280 m initial separation distance).

Interestingly, the 280 m initial-distance scenario also produced the highest estimated SOC gain (+21.74%) despite representing the most severe braking conditions. As shown in Fig. 11(e) and Table 7, this scenario involved the largest brake force demand, the longest braking duration, the highest peak deceleration, and the smallest minimum relative distance. Together, these factors indicate a higher kinetic energy level before braking, consistent with the relationship proportional to $\frac{1}{2}mv^2$. When combined with the proposed headway-based predictive strategy, a larger portion of this available kinetic energy was recovered regeneratively rather than dissipated through friction braking. Although both controllers initiate braking at a similar time, as demonstrated in Fig. 11(a), the prediction-based controller releases braking earlier, thereby extending coasting duration and enhancing energy recovery. This behaviour suggests that predictive brake modulation is particularly effective in high-energy, short-gap car-following situations, where purely reactive strategies tend to sacrifice regenerative potential. This finding contrasts with the genetic algorithm (GA)-based regenerative braking force distribution approach proposed by Taleghani et al. (2018), where the lowest SOC improvement was reported under the US06 drive cycle, which represents aggressive driving behaviour characterised by high speeds and rapid acceleration. This difference can be

attributed to the predictive, distance-based triggering mechanism employed in the present study, which releases friction braking earlier to prolong the coasting phase, unlike optimisation-based strategies that react primarily to instantaneous braking demand. Across all tested initial spacings, the minimum relative distance remained above the safety threshold as illustrated in Fig. 9(f), Fig. 10(f), and Fig. 11(f). This confirms that the observed improvements in energy recovery and braking behaviour were achieved without compromising collision avoidance.

Table 7. Summary of results for Scenario 1

Metric, unit	Initial Distance: 300 m		Initial Distance: 290 m		Initial Distance: 280 m	
	Without prediction	With prediction	Without prediction	With prediction	Without prediction	With prediction
Maximum brake force, N	-206.09	0.00 (-100.00 %)	-300.00	-300.00 (0.00 %)	-335.02	-330.02 (-1.49 %)
Brake duration, s	2.30	0.00 (-100.00 %)	4.30	2.00 (-53.49 %)	5.40	2.40 (-55.56 %)
Distance travelled by ego car at 100s, m	549.00	552.38 (+0.62 %)	533.41	536.97 (+0.67 %)	515.35	521.12 (+1.12 %)
Minimum relative distance, m	13.93	13.26 (-4.83 %)	9.85	9.25 (-6.16 %)	6.28	6.28 (0.00 %)
Estimated SOC gain, %	0.046	0.050 (+8.70 %)	0.036	0.038 (+5.56 %)	0.023	0.028 (+21.74 %)
Maximum deceleration, m/s ²	-2.72	-1.73 (-36.41 %)	-3.28	-3.27 (-0.23 %)	-3.92	-3.59 (-8.47 %)

Note: Negative values indicate braking operation, where both brake force and deceleration are defined in the opposite direction of vehicle motion based on the adopted sign convention.

Overall, the results indicated that augmenting fuzzy logic control with a Time Headway-based spacing policy enhances both braking performance and energy efficiency. The advantages are most apparent at intermediate and shorter following distances, where the prediction enables smoother, earlier, and more energy-efficient deceleration.

Gradual deceleration of lead vehicle

In the gradual deceleration scenario (Fig. 12 and Table 8), the benefit of incorporating prediction is particularly evident. The baseline controller, which operates without prediction, engaged friction braking for 3.7 s and reached a peak braking force of -234 N. In contrast, the prediction-enhanced controller avoided friction braking altogether as observed in Fig. 12(a). Therefore, the maximum deceleration was reduced by 46.1% as presented in Fig. 12(d), resulting in a smoother deceleration response while maintaining collision-free operation. It should be noted that the minimum relative distance serves both as a safety constraint and a traffic efficiency indicator, depending on the driving scenario. In previous Scenario 1, the nearly identical values (6.28m) confirm that a safe separation distance is consistently maintained, as observed in Fig. 11(f). However, in scenarios involving gradual deceleration of the lead vehicle, the proposed prediction-enhanced strategy enables a significant reduction (-76.02%) in inter-vehicle spacing while still maintaining safety as depicted in Fig. 12(f). This reduction improves road space utilization and has the potential to enhance traffic flow efficiency. Therefore, the proposed method achieves a balance between safety preservation and traffic capacity optimization.

The elimination of friction braking also allowed a longer coasting phase to develop, increasing the distance travelled by the ego vehicle by 1.95% and producing a small but consistent SOC improvement as observed in Fig. 12(c) and (e). Taken together, these results suggest that under low-to-moderate risk conditions, predictive safe-distance gating is effective in suppressing unnecessary braking. This, in turn, enables the fuzzy controller to make better use of regenerative braking compared with purely reactive strategies.

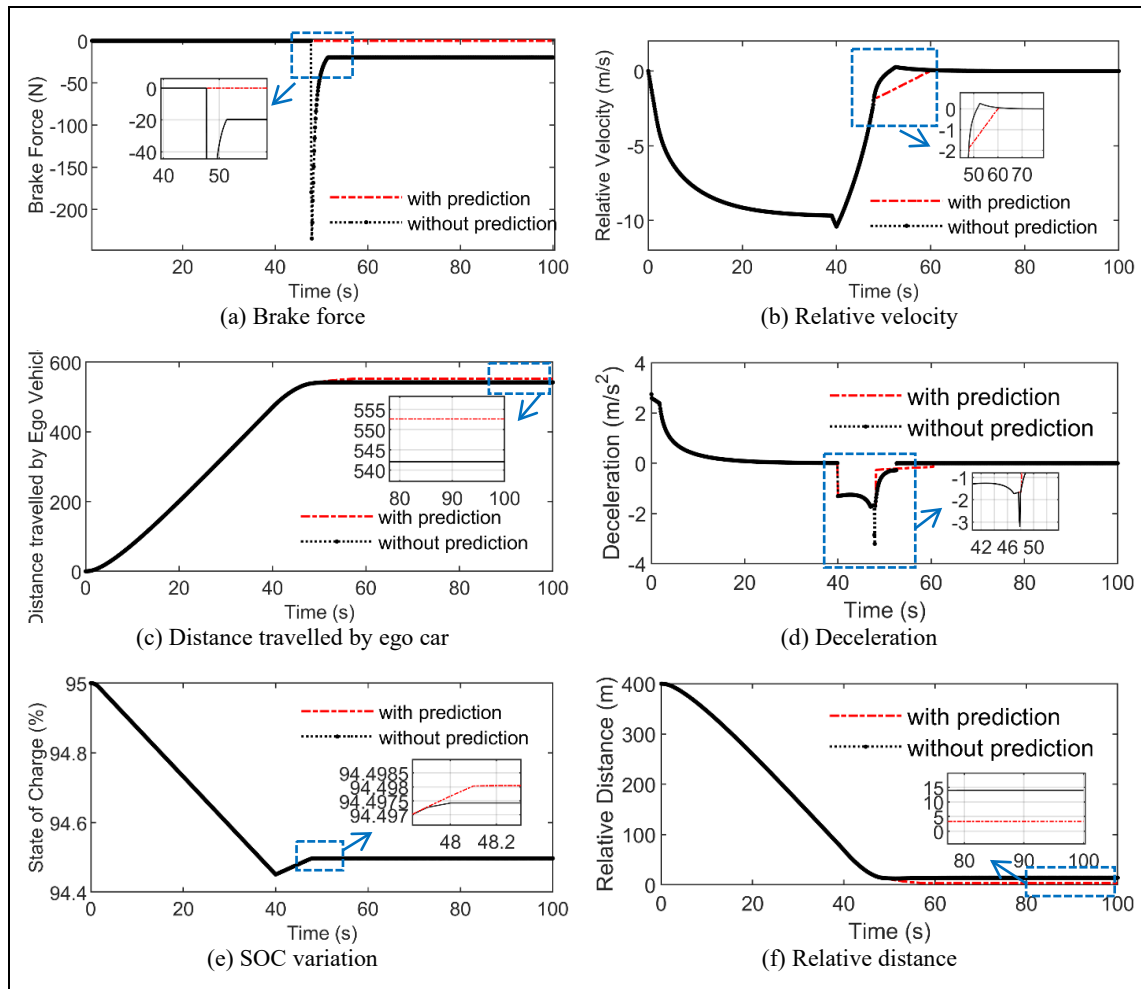


Fig. 12. Graph of (a) brake force, (b) relative velocity, (c) distance travelled by ego car, (d) deceleration, (e) SOC variation, and (f) relative distance over 100 s period for Scenario 2.

Table 8. Summary of results for Scenario 2

Metric, unit	Without prediction	With prediction
Maximum brake force, N	-234.341	0 (-100 %)
Brake duration, s	3.7	0 (-100 %)
Distance travelled by ego car at 100 s, m	542.078	552.662 (+1.95 %)
Minimum relative distance, m	13.9216	3.33809 (-76.02 %)
Estimated SOC gain, %	0.049	0.050 (+2.04 %)
Maximum deceleration, m/s ²	-3.20541	-1.72781 (-46.10 %)

Note: Negative values indicate braking operation, where both brake force and deceleration are defined in the opposite direction of vehicle motion based on the adopted sign convention.

<https://doi.org/10.24191/jmeche.v23i3.10761>

Sudden deceleration of lead vehicle

Under sudden lead-vehicle deceleration (Fig. 13 and Table 9), both controllers exhibited identical performance across all evaluated metrics, including peak brake force, braking duration, stopping distance, minimum relative distance, SOC gain, and maximum deceleration. This outcome indicates that, in genuine emergency scenarios, the control logic prioritises immediate safety over energy optimisation, regardless of predictive enhancement. A minor qualitative difference was observed in brake release behaviour, where the prediction-enhanced controller disengaged braking slightly earlier once a safe distance was re-established, as shown in Fig. 13(a).

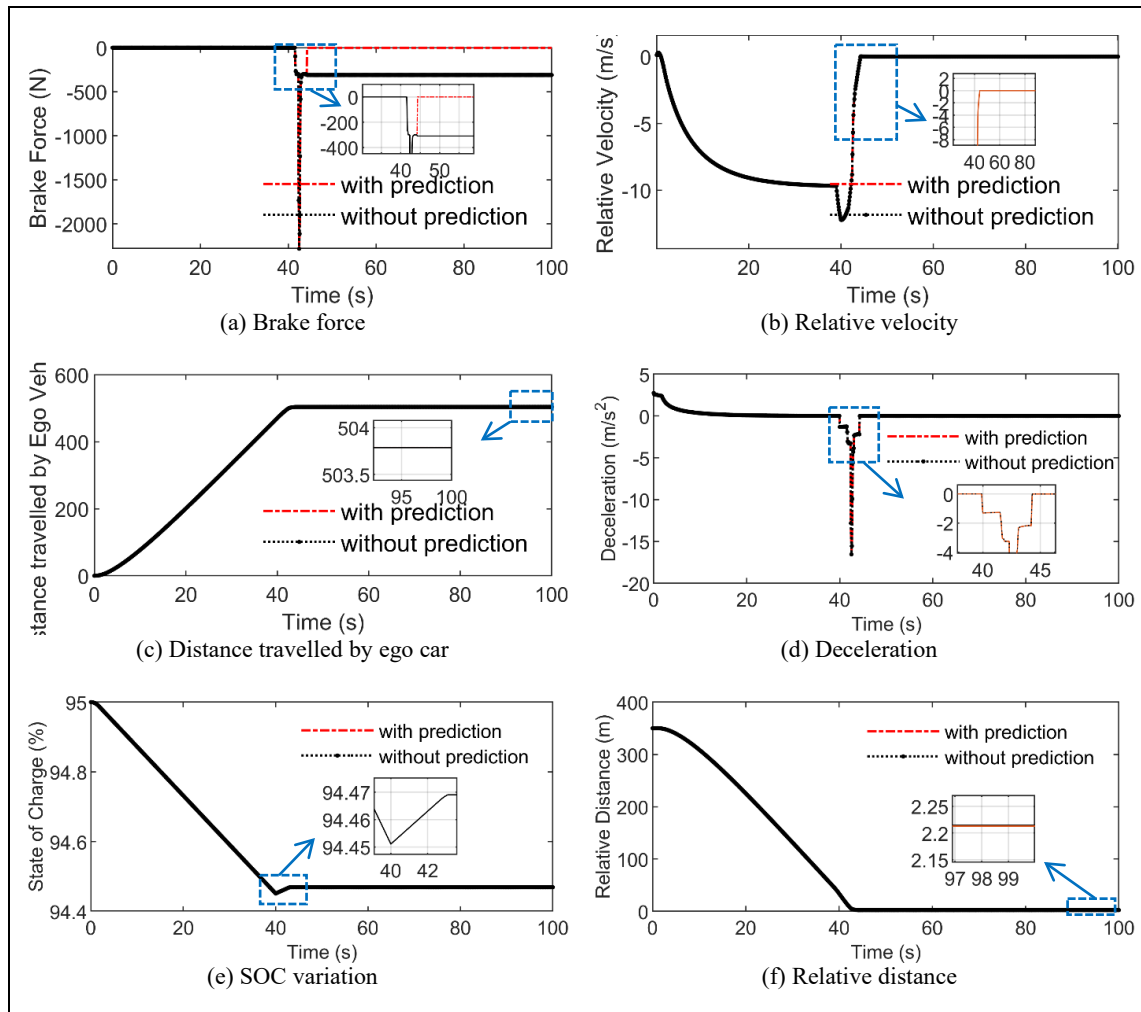


Fig. 13. Graph of (a) brake force, (b) relative velocity, (c) distance travelled by ego car, (d) deceleration, (e) SOC variation, and (f) relative distance over 100 s period for Scenario 3.

Table 9. Summary of results for Scenario 3

Metric, unit	Without prediction	With prediction
Maximum brake force, N	-2,282.04	-2,282.04
Brake duration, s	Saturated at $t = 44.3$ s	2.8
Distance travelled by ego car at 100 s, m	503.786	503.786
Minimum relative distance, m	2.21421	2.21421
Estimated SOC gain, %	0.019	0.019
Maximum deceleration, m/s^2	-16.5357	-16.5357

Note: Negative values indicate braking operation, where both brake force and deceleration are defined in the opposite direction of vehicle motion based on the adopted sign convention.

This behaviour can be attributed to the prediction module's consideration of time headway-based spacing policies even during short-duration braking events. By integrating safe distance evaluation, the predictive system can recognize when the critical threat has subsided and transition into a cruising state more efficiently. Although the benefit in this scenario is minimal, such responsiveness may contribute to long-term improvements in energy efficiency and brake wear over repeated stop-go cycles in urban environments, as could be observed in Scenario 1 (constant lower speed lead vehicle) and Scenario 2 (gradual deceleration of lead vehicle).

Although the predictive enhancement does not provide a measurable benefit in extreme emergency scenarios, it exhibits more refined brake release behaviour once the critical event has passed, suggesting potential advantages during transitional driving states.

Summary of results

The most noticeable advantages of incorporating prediction are observed in non-emergency car-following (constant lower speed lead vehicle) and in scenario involving gradual deceleration. In these cases, the safe-distance gating mechanism frequently delays or suppresses unnecessary braking actions. As a result, braking interventions are shorter, deceleration profiles are smoother, coasting phases are extended, and higher SOC recovery is achieved, all while maintaining safe inter-vehicle headways. In contrast, under genuine emergencies (Sudden decelerating lead vehicle), the predictive and baseline controllers exhibit essentially identical behaviour, reflecting the dominance of collision avoidance over maximising energy recovery. A summary of these cross-scenario observations is provided in Table 10. It is important to recognise that the reported findings are based on step-input simulations rather than a representative driving cycle. Therefore, the reported SOC gains should be interpreted as indicative trends rather than absolute performance measures. This limitation arises primarily from the absence of a standardised go-kart driving cycle within the MATLAB/Simulink environment. Even so, the results underline the importance of appropriately calibrating safe-distance profiles to maximise coasting opportunities while preserving safety margins. By avoiding or shortening friction-brake events, the proposed approach not only improves regenerative energy recovery but is also expected to lower brake pad wear, offering potential lifecycle benefits in addition to improved ride comfort, particularly under urban stop-and-go driving conditions.

Table 10. Cross-scenario synthesis table

Scenario	Key Benefit of Prediction	Safety Impact	Energy Impact	Deceleration Impact
Constant-speed lead vehicle	Brake suppression	No degradation	+6 to 22% SOC	Lower peak deceleration
Gradual deceleration	Full brake elimination	Safe gap preserved	+2% SOC	-46% deceleration
Sudden deceleration	No difference	Identical	Neutral	Neutral

Conclusion

This study investigated the effect of prediction-based autonomous braking on the performance of an electric go-kart, with particular emphasis on the balance between safety, ride quality, and energy recovery. Three representative scenarios were examined using MATLAB/Simulink, namely (i) a slower lead vehicle at constant speed with initial separations of 280 m, 290 m, and 300 m, (ii) gradual lead-vehicle deceleration, and (iii) sudden lead-vehicle deceleration. The behaviour of a baseline fuzzy logic (FL) controller was compared with a predictive FL controller augmented with a safe-distance gating mechanism. Across the non-emergency scenarios, the predictive strategy consistently reduced peak brake force and, in some cases, avoided friction-brake use entirely. When friction braking was not required, total brake duration was more than 50% shorter than that produced by the baseline controller. Peak deceleration was reduced by up to 46.1%, resulting in smoother longitudinal responses, while coasting distance increased by up to 1.95% and estimated SOC recovery improved by as much as 21.74%, while retaining safe headways. The largest energy recovery gain was observed under short-gap conditions, where higher kinetic energy was available, and braking could be released earlier through predictive modulation. Under genuine emergency deceleration, both controllers exhibit comparable behaviour, confirming that safety remained the overriding priority. The observed improvements can be attributed to the controller's ability to anticipate lead-vehicle behaviour and defer friction braking when sufficient margin exists. This allows a greater proportion of kinetic energy to be recovered regeneratively while reducing friction brake usage. Nevertheless, the present study is limited by its reliance on simulation and simplified input assumptions, and the absence of experimental validation means that the reported magnitudes should be interpreted as indicative rather than absolute. Despite these limitations, the results demonstrate that incorporating prediction through safe-distance gating can improve energy efficiency and drivability without compromising safety. Future work should validate the model with instrumented testing and apply realistic drive cycles for parameter calibration and external validation.

Acknowledgements/ Funding

The first author gratefully acknowledges the financial support provided by the Ministry of Higher Education Malaysia and Universiti Teknikal Malaysia Melaka (UTeM) for enabling the pursuit of further studies. The authors thank the Ministry of Higher Education Malaysia for the research grant FRGS23-318-0927 Optimal Deceleration Formulation Based on Reinforcement Deep Learning for Energy Generation from Regenerative Braking Mode of an Electric Motorcycle. This support has been instrumental in the successful completion of this research.

Conflict of Interest Statement

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

Authors' Contributions

The authors confirm their contribution to the paper as follows: study conception and design: Muhammad Abdullah, Siti Fauziah Toha; data collection: Khairul Amri Tofrowaih; analysis and interpretation of results: Muhammad Abdullah, Siti Fauziah Toha, Syazarudin Md Said, Salmiah Ahmad; draft manuscript

preparation: Khairul Amri Tofrowaih, Muhammad Abdullah. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Generative AI in the Writing Process

During the preparation of this work, the author(s) used ChatGPT (Open AI) in order to improve the readability and language quality of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Data Availability/ Supplementary Materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics Statement

The authors declare that this research did not involve human or animal subjects. All experimental procedures were performed following the institutional Safety, Health, and Environmental (HSE) protocols of International Islamic University Malaysia.

Reference

- Bae, J. J., Lee, M. S., & Kang, N. (2020). Partial and full braking algorithm according to time-to-collision for both safety and ride comfort in an autonomous vehicle. *International Journal of Automotive Technology*, 21(2), 351–360. <https://doi.org/10.1007/s12239-020-0033-8>
- Budijono, A. P., Sutantra, I. N., & Pramono, A. S. (2022). Friction losses during slip conditions in regenerative braking of electric vehicles. *Journal of Mechanical Engineering*, 11(1), 95–108. <https://doi.org/10.24191/jmeche.v11i1.23591>
- Dong, J., Wang, J., Chen, L., Gao, Z., & Luo, D. (2021). Effect of adaptive cruise control on mixed traffic flow: a comparison of constant time gap policy with variable time gap policy. *Journal of Advanced Transportation*, 2021(1), 3745989. <https://doi.org/10.1155/2021/3745989>
- El-Baklish, S. K., Kouvelas, A., & Makridis, M. A. (2025). Driving towards stability and efficiency: a variable time gap strategy for adaptive cruise control. *Transportation Research Part C: Emerging Technologies*, 174, 105074. <https://doi.org/10.1016/j.trc.2025.105074>
- Faghihian, H., & Sargolzaei, A. (2025). A novel energy-efficient automated regenerative braking system. *Applied Energy*, 390, 125746. <https://doi.org/10.1016/j.apenergy.2025.125746>
- Fiorani, M., Mariani, M., Minin, L., & Montanari, R. (2008). Monitoring time-headway in car-following task. CHI '08 Extended Abstracts on Human Factors in Computing Systems Proceedings (pp. 2143–2146). Association for Computing Machinery. <https://doi.org/10.1145/1358628.1358646>
- Flores, C., Milanés, V., & Nashashibi, F. (2017). A time gap-based spacing policy for full-range car-
<https://doi.org/10.24191/jmeche.v23i3.10761>

- following. 20th International Conference on Intelligent Transportation Systems (pp. 1-6). IEEE Publisher. <https://doi.org/10.1109/ITSC.2017.8317793>
- Fu, X., Wan, J., Wu, D., Jiang, W., Ma, W., & Yang, T. (2024). Research on vehicle AEB control strategy based on safety time–safety distance fusion algorithm. *Mathematics*, 12(12), 1905. <https://doi.org/10.3390/math12121905>
- Gunasekaran, R., Manjunatha, B., Anand, S., Pareek, P. K., Gupta, S., & Shukla, A. (2024). Prediction of electric vehicle charging demand using enhanced gated recurrent units with RKO based graph convolutional network. *Discover Applied Sciences*, 6(11), 605. <https://doi.org/10.1007/s42452-024-06326-x>
- Guo, L., Ge, P., & Sun, D. (2020). Variable time headway autonomous emergency braking control algorithm based on model predictive control. *Chinese Automation Congress* (pp. 1794–1798). IEEE Publisher. <https://doi.org/10.1109/CAC51589.2020.9327238>
- Ji, F., Pan, Y., Zhou, Y., Du, F., Zhang, Q., & Li, G. (2020). Energy recovery based on pedal situation for regenerative braking system of electric vehicle. *Vehicle System Dynamics*, 58(1), 144–173. <https://doi.org/10.1080/00423114.2019.1567927>
- Lai, F., Liu, J., & Hu, Y. (2024). An automatic emergency braking control method for improving ride comfort. *World Electric Vehicle Journal*, 15(6), 259. <https://doi.org/10.3390/wevj15060259>
- Liu, Z., Yuan, Q., Nie, G., & Tian, Y. (2021). A multi-objective model predictive control for vehicle adaptive cruise control system based on a new safe distance model. *International Journal of Automotive Technology*, 22(2), 475–487. <https://doi.org/10.1007/s12239-021-0044-0>
- Madani, S. S., Shabeer, Y., Allard, F., Fowler, M., Ziebert, C., Wang, Z., Panchal, S., Chaoui, H., Mekhilef, S., Dou, S. X., See, K., & Khalilpour, K. (2025). A comprehensive review on lithium-ion battery lifetime prediction and aging mechanism analysis. *Batteries*, 11(4), 127. <https://doi.org/10.3390/batteries11040127>
- Massow, K., Radusch, I., & Shorten, R. (2022). A numerical study on constant spacing policies for starting platoons at oversaturated intersections. *IEEE Access*, 10, 43766–43786. <https://doi.org/10.1109/ACCESS.2022.3167424>
- Matlab. (2023). System-level battery electric vehicle (BEV) model. <https://www.mathworks.com/help/sps/ug/system-level-battery-electric-vehicle-model.html#BEVSystemLevelExample-3>
- Ondoğan, A., & Yavuz, H. S. (2019). Fuzzy logic based adaptive cruise control for low-speed following. 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (pp. 1-5). IEEE Publisher. <https://doi.org/10.1109/ISMSIT.2019.8932776>
- Patil, L. N., Toke, L. K., & Agrawal, V. K. (2026). Experimental investigation on electric vehicle braking system using fuzzy rule-based control strategy. *World Journal of Engineering*, 23(3), 615–627. <https://doi.org/10.1108/WJE-01-2025-0019>
- Rani, M. F. H., Abu Bakar, S., Hashim, M. S. M., Harun, A., Razlan, Z. M., Wan, W. K., Zunaidi, I., Ibrahim, I., Afendi, M., Efi, N. E., Dalib, M., & Mat Rudin, S. S. (2019). Calculating the brake-application time of AEB system by considering maximum deceleration rate during a primary accident in Penang's urban road. *Journal of the Society of Automotive Engineers Malaysia*, 3(3), 320–332. <https://doi.org/10.56381/jsaem.v3i3.130>
- Rizianiza, I., & Shoodiqin, D. M. (2021). Automatic braking system using fuzzy logic method. *Journal of* <https://doi.org/10.24191/jmeche.v23i3.10761>

- Physics: Conference Series, 1833, 012005. <https://doi.org/10.1088/1742-6596/1833/1/012005>
- Song, X., Lou, X., & Meng, L. (2019). Time-delay feedback cooperative adaptive cruise control of connected vehicles by heterogeneous channel transmission. *Measurement and Control*, 52(5–6), 369–378. <https://doi.org/10.1177/0020294019837997>
- Stanger, T., & del Re, L. (2013). A model predictive cooperative adaptive cruise control approach. *American Control Conference* (pp. 1374–1379). IEEE Publisher. <https://doi.org/10.1109/ACC.2013.6580028>.
- Taleghani, H., Hassan, M. K., Abdul Rahman, R. Z., & Che Soh, A. (2018). Improving regenerative braking strategy using genetic algorithm for electric vehicles. *Journal of Mechanical Engineering*, 6(1), 121–130.
- Tofrowaih, K. A., Abdullah, M., Toha, S. F., & Rahman, M. A. (2025). Longitudinal dynamics modeling of an electric go-kart and analysis of regenerative braking under various braking profiles using MATLAB simulink. *International Journal of Automotive and Mechanical Engineering*, 22(3), 12586–12602. <https://doi.org/10.15282/ijame.22.3.2025.5.0962>
- Tran, M. K., Bhatti, A., Vrolyk, R., Wong, D., Panchal, S., Fowler, M., & Fraser, R. (2021). A review of range extenders in battery electric vehicles: current progress and future perspectives. *World Electric Vehicle Journal*, 12(2), 54. <https://doi.org/10.3390/wevj12020054>
- Van Der Heijden, R., Lukaseder, T., & Kargl, F. (2017). Analyzing attacks on cooperative adaptive cruise control (CACC). *IEEE Vehicular Networking Conference* (pp. 45–52). IEEE Publisher. <https://doi.org/10.1109/VNC.2017.8275598>
- Wu, C., Xu, Z., Liu, Y., Fu, C., Li, K., & Hu, M. (2020). Spacing policies for adaptive cruise control: a survey. *IEEE Access*, 8, 50149–50162. <https://doi.org/10.1109/ACCESS.2020.2978244>
- Ying, Y., & Solomon, O. O. (2017). Research on adaptive cruise control systems and performance analysis using Matlab and Carsim. *5th International Conference on Mechanical, Automotive and Materials Engineering* (pp. 249–253). IEEE Publisher. <https://doi.org/10.1109/CMAME.2017.8540177>
- Zentani, A., Almaktoof, A., & Kahn, M. T. (2024). A comprehensive review of developments in electric vehicles fast charging technology. *Applied Sciences*, 14(11), 4728. <https://doi.org/10.3390/app14114728>
- Zhang, L., Yu, Z., Xu, X., & Yan, Y. (2023). Research on automatic emergency braking system based on target recognition and fusion control strategy in curved road. *Electronics*, 12(16), 3490. <https://doi.org/10.3390/electronics12163490>
- Zhang, Q., Shang, Y., Li, Y., & Zhu, R. (2025). A concise review of power batteries and battery management systems for electric and hybrid vehicles. *Energies*, 18(14), 3750. <https://doi.org/10.3390/en18143750>
- Zhang, S., & Zhuan, X. (2019). Study on adaptive cruise control strategy for battery electric vehicle. *Mathematical Problems in Engineering*, 2019(1), 7971594. <https://doi.org/10.1155/2019/7971594>
- Zhiani, M., Moslemi, M., Jamali, M., & Gharibi, H. (2026). Impact of fast-charging protocols and state-of-charge windows on the performance and cycle life of commercial lithium-ion batteries. *Journal of Power Sources*, 678, 239975. <https://doi.org/10.1016/j.jpowsour.2026.239975>



© 2026 by the authors. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY-NC-SA) license (<https://creativecommons.org/licenses/by-nc-sa/4.0/>)