



IJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** VI **Month of publication:** June 2026

DOI: <https://doi.org/10.22214/ijraset.2026.83864>

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Inverter Modeling and Regenerative Braking, Speed Optimization Using a Fuzzy Logic Controller for Autonomous Vehicles Battery Power Management

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Abstract: *In order to improve battery power management and regenerative braking energy recovery in Connected Autonomous Vehicles (CAVs), this study proposes an intelligent control technique. During approach, cruising, and deceleration events, the suggested framework maximizes vehicle operating conditions. The system reduces needless braking, smoothness speed changes, and enhances energy flow into the regenerative braking system (RBS) by anticipating the driving situation. For co-simulation, a MATLAB/Simulink rule-based controller was created and connected with a vehicle simulation platform. Under ideal circumstances, the CAV decelerated from 15 m/s to 0 m/s after traveling around 100 meters in the evaluation scenario. The suggested control approach achieved a braking energy recovery of over 100 kJ by increasing effective RBS usage. Additionally, by lowering peak power demands, guaranteeing smoother torque distribution, and improving overall energy utilization, the technology enhanced battery power management. The controller outperformed the other solutions evaluated in terms of vehicle efficiency, battery energy optimization, regenerative braking efficacy, and safe operating behavior. The substantial potential of intelligent transportation technologies to improve the energy efficiency and operational sustainability of next-generation electric and driverless cars is highlighted by this work.*

Keywords—controlled autonomous vehicle, regenerative braking system, battery power management.

I. INTRODUCTION

Self-driving vehicles and connected auto technologies are gaining a lot of attention these days, and for good reason they have the potential to enhance our roadways' efficiency, safety, and environmental quality. These technologies include a range of sophisticated automobile features, entertainment systems, enhanced driving assistance, and communication systems that let cars talk to each other and the traffic infrastructure(1). Even though automation and connectivity have come a long way, there are still a lot of challenges to be solved before self-driving cars become commonplace. The technology needs to be more reliable, there are legitimate safety and security concerns, development costs are very high, and the regulatory framework is still being worked out(2). To solve these problems, businesses and researchers are working together to create standardized vehicle communication protocols. Things like IEEE 802.11p are improving traffic safety, efficiency, and entertainment services. Current research is primarily focused on improving sensors, navigation systems, and vehicle-to-vehicle communication to enable applications like coordinating traffic lights and warning drivers of potential collisions(3). Particularly for electric cars and other new energy vehicles, research on energy efficiency has increased dramatically. Regenerative braking is a great way to recover energy when you're slowing down, especially at traffic lights. The problem is that the majority of current car management systems significantly limit the amount of energy they can recover because they rely too much on driver behavior and are unable to anticipate traffic patterns(4). Vehicle-to-infrastructure (V2I) communication is one possible solution to this problem. It gives cars access to real-time traffic light information, which helps them make better decisions about speed and braking. Recent advances in optimization and machine learning have made it possible to manage energy in a number of ways without the need for incredibly accurate traffic or vehicle models. However, a lot of recent research ignores short-term traffic patterns, looks at simplistic scenarios, or concentrates on conventional gas cars rather than electric ones. These gaps show that new energy vehicles require more intelligent, predictive speed planning that balances energy recovery, traffic efficiency, and passenger comfort(5).

Because they increase pollution, traffic, and safety risks, traffic lights are a major source of annoyance in today's transportation networks. Vehicle-to-vehicle and vehicle-to-infrastructure communication enable connected and autonomous vehicle technologies to offer two potential solutions: eco-driving and cooperative cruise control.

Real life is more complex due to numerous intersections and mixed traffic, even though prior research has demonstrated benefits in fully connected traffic or at single crossroads(6).Recent research has extended these ideas by developing cooperative eco-driving and cruise control systems that operate in partially connected traffic and longer road segments. Simulations show that these tactics can greatly improve traffic flow, lower energy use, and boost urban driving safety.Numerous studies have focused on optimizing deceleration to improve regenerative braking in electric vehicles. Energy-optimal deceleration systems have been developed in response to the shortcomings of traditional eco-driving techniques in dynamic traffic. These systems frequently use real-time acceleration data, vehicle-to-everything communication, and dynamic programming or predictive control techniques to determine the ideal speed and brake profiles (7).Tests using actual plug-in hybrid electric vehicles have shown that these methods can significantly improve regeneration energy recovery and travel economy when compared to human driving. Regenerative braking is difficult to simulate accurately because manufacturers often hide their special methods. To get around this, data-driven methods like reinforcement learning have been created that use real driving data to directly learn regenerative braking behavior. Techniques like Batch Fuzzy Q-Learning can estimate regenerative braking behavior without requiring prior knowledge of the internal control schemes in order to build models that can be used in traffic simulators for energy optimization across various electric vehicle platforms(8).In addition to energy management, perception and sensing technologies are critical for safe autonomous driving. Single-sensor systems are often not reliable enough due to environmental factors or individual sensor flaws. To improve perception, researchers are combining a variety of sensors, including cameras and radar. Recent studies have proposed fusion techniques that outperform traditional rule-based methods and eliminate the need for expensive sensors like LiDAR. These techniques improve awareness of the surroundings and provide a solid foundation for autonomous navigation in difficult driving situations(9).Passenger comfort is a key consideration when building regenerative braking systems. Energy conservation is usually prioritized over comfort in conventional regenerative braking techniques. To address this trade-off, comfort-aware regenerative braking systems have been developed. These systems incorporate human comfort requirements while regulating speed changes and braking force using learning models. Simulations suggest that these technologies could successfully balance energy efficiency and passenger comfort, making them appropriate for autonomous electric vehicles (10).

II. LITERATURE REVIEW

Recent studies on autonomous vehicles (AVs) and intelligent transportation systems have primarily focused on perception, communication, energy efficiency, and passenger comfort. RasheedHussain et.al.(1).Looked into the development of autonomous driving systems using LiDAR and camera sensors in conjunction with vehicular communication based on IEEE 802.11 standards and Vehicular Ad Hoc Networks (VANETs). Their study found that deep residual networks performed better on perception tasks than other convolutional neural network (CNN) architectures. While the results confirmed the effectiveness of deep learning for autonomous perception, they also highlighted problems with practical application and communication latency.In an effort to increase passenger comfort and driving efficiency, cars' ability to communicate with their environment, including traffic signals and road equipment, has received a lot of attention.Yuchuan Zhanget.al.(2). and his research team created a system that uses this car-to-infrastructure communication to enhance energy management by using some intelligent learning techniques that are capable of independent decision-making.Future smart cars could be revolutionized by enabling autonomous learning and adaptation. They tested this in both computer simulations and real world experiments, and they saw some pretty obvious gains in how much energy they could save back, how well traffic moved, and how comfortable the ride was. In similar work, Ziran Wanget.al.(3).and colleagues built what they call a cooperative eco-driving system that brings together adaptive cruise control with data from multiple sources - including the car's own diagnostics, radar systems, and cameras. When they put this to the test, both in simulations and out on real roads, they found it really cut down on how much energy the vehicles used and how much pollution they put out, especially when cars were all connected and talking to each other.There has also been a lot of talk about how cars can slow down more efficiently and enhance their braking energy recovery. Dohee Kim and the team created a system that they installed in a Hyundai IoniqHybrid et.al.(4).To save the most energy. When and how to slow down was part of the system's design. When real drivers tested the setup, it was evident that it improved the vehicle's overall energy efficiency by using the timing of traffic signals to recover as much energy as possible during braking.Ricardo Maia et.al.(5).and his research group took on the tricky problem of how to model regenerative braking systems effectively. They came up with a learning approach that could figure out the unique braking patterns from different car manufacturers just by looking at real driving data.

This turned out to work really well and showed they could apply it to all kinds of electric vehicles, not just one specific brand. Self-driving cars need to be able to see and identify objects in their surroundings in order to be safe. Changsuk Oh et al. (6) and to see how well systems combining cameras and LiDAR could recognize objects, the researchers tested some cutting-edge algorithms like YOLO and Faster R-CNN.

What they found was very straightforward: you basically had to choose between having a system that is very precise or one that doesn't require a lot of processing power. Xu Dong et al. (7) and colleagues furthered the field by combining radar and cameras in a novel way and using a technique called AssociationNet to make the two work flawlessly. Their method, which was highly effective at identifying and tracking objects using either radar or video data, showed that combining multiple types of sensors may be very helpful in difficult driving scenarios. Scientists have recently focused on creating more sophisticated methods for regenerative braking and enhancing perception systems. Yunyun Song et al. (8) team created a system that integrates cameras and millimeter-wave radar using YOLOv5. It was able to be both fast enough to operate in real time and incredibly accurate at object detection exactly what you need for autonomous driving to be dependable. Ning Li et al. (9) and the research team looked into ways to enhance regenerative braking performance by using a specific type of motor along with some clever optimization techniques and technology that allows vehicle communication. They found that by setting the cars speed at specific times during simulations, they could achieve noticeably higher energy efficiency. Myeong Hwan Hwang et al. (10) and the team created what they call a Comfort Regenerative Braking System using neural networks and ISO comfort standards. Passengers would be more comfortable when braking, according to testing simulations, but the device was still able to efficiently recover energy rather than waste it.

III. PROBLEM IDENTIFICATION

Regenerative braking system (RBS) focuses on two key hardware factors: the battery state of charge (SOC) and vehicle travel distances between 103 and 112 km. The study employed reinforcement learning (RL) methods, specifically fuzzy Q-learning (BFQL), for system modeling and simulation. The experimental evaluation revealed a Root Mean Square Error (RMSE) of 13.59%, demonstrating the usefulness of the recommended approach. The main objective of the work was to develop flexible RBS models that could be applied to various electric vehicle (EV) platforms. The authors also mentioned potential future improvements, like optimizing the number of fuzzy rules and improving the accuracy of the Radial Basis Function (RBF) model. Although reinforcement learning-based regenerative braking techniques have been thoroughly studied in prior research, the application of the proposed strategy to hybrid electric vehicles (HEVs) is not investigated in this paper. This is a major disadvantage because, because of their different designs and control strategies, regenerative braking techniques intended for EVs might not be directly applicable to HEVs. A barcode-based method that identifies and classifies objects using data from LiDAR and camera sensors. Several object detection techniques and an Intersection over Union (IOU) threshold of 0.5 were used to assess the performance of the proposed system. The trial data showed that YOLO had the highest mean Average Precision (mAP) of 63.4%, followed by Faster R-CNN with 59.9%, while SSD performed significantly worse with a mAP of 6.9%. Using an 18-layer ResNet architecture, one processing module in the simulation scenario achieved an accuracy of 2.8%. The dataset was split into training and testing subsets in a 70:30 ratio, and the experiments were carried out utilizing two core processing modules and trained for 200 iterations. Enhancing decision-making skills in autonomous driving applications was the study's main objective. In order to further improve system performance and reliability, the scientists also recommended future enhancements, such as the incorporation of shape-based characteristics and signal information.

IV. METHODOLOGY

A. PROPOSED RBS MODELING APPROACH

Regenerative braking in self-driving cars aims to extend battery life. Instead of wasting braking energy like traditional cars do, this technique gathers it and recharges the battery. The entire idea revolves around projecting future developments. When the car senses that it needs to slow down or stop, it can prepare and apply the smart braking system at the right time. This technology works perfectly when you're driving normally, whether you're speeding, slowing down, or approaching anything. It's like having a co-passenger who knows exactly when to apply regenerative brakes. It is truly remarkable how well it balances efficiency, safety, and comfort. Without engaging in risky braking or sudden stops, your energy recovery has improved. It just seems natural. The system avoids using the conventional mechanical brakes whenever possible. Instead of wasting energy as heat, regenerative braking captures it. Smooth speed changes are a key focus. The descent is slow, deliberate, and comfortable; there are no sudden stops or startling lurches. When it comes to braking torque distribution, this technology is clever. It efficiently distributes the exact amount of braking force needed by each wheel.

The goal is to lessen the battery's workload during peak hours. Instead of putting sudden, high demands on the battery, it more evenly distributes the power consumption. In general, this approach leads to more effective energy collection. The battery captures all of the kinetic energy it is capable of storing electrical energy.

B. BRAKING SUBSYSTEM

Electric motors can also be used as generators by transforming kinetic energy into electrical energy. This feature is especially useful in electric vehicles because it improves overall braking performance. When the vehicle slows down, some of the lost mechanical energy can be returned to the battery to regenerative torque. However, the electric motor alone is unable to produce enough torque to handle all braking situations. As a result, the braking force is carefully divided between the mechanical and electric brakes by the regenerative braking system (RBS).

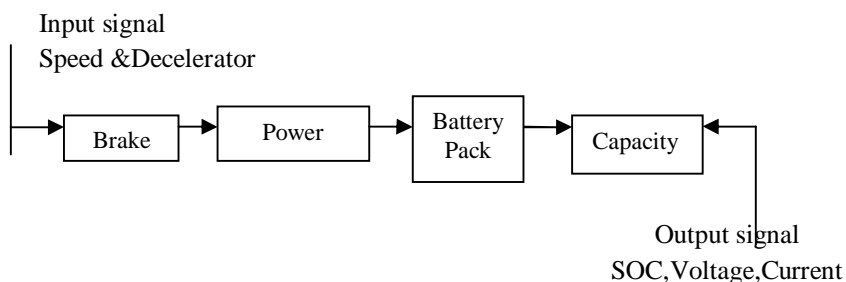


Fig.1. Work flow in a CAV vehicle with regenerative braking

The system fig.1 receives input signals about the vehicle's speed and whether braking is required. The brake unit is activated by this input, which also coordinates it with an optimizer that determines the optimal distribution of braking power. The optimizer prioritizes regenerative braking to optimize energy recovery while maintaining safe braking performance. The recovered electrical energy is then stored in the battery pack, depending on its capacity. Finally, the system outputs critical battery characteristics like voltage, current, and state of charge for continuous monitoring and control.

The vehicle has a starting speed of 20 m/s and weighs 1200 kg. When a regenerative braking torque of 100 Nm is applied, a wheel with a radius of 0.3 m experiences a braking force of about 333 N. This braking force results in a slight slowdown of about 0.28 m/s². During the 10-second braking phase, the vehicle's speed is reduced by about 2.78 m/s. As a result shown in tab.1 the car's speed drops to roughly 17.2 m/s, and regenerative braking is insufficient to stop it completely. At the starting speed, the wheels rotate at about 66.7 rad/s. This results in a mechanical regeneration power of about 6.67 kW. With 60% efficiency, about 4 kW of this power is recovered as electrical energy. Approximately 40 kJ, or 0.011 kWh, of energy was recovered during the entire 10 second braking period.

TABLE I. Regenerative braking parameters

Parameters	Values
Initial speed	20m/s
Vehicle mass	1200kg
Regenerative torque	100nm
Wheel radius	0.3m
Efficiency	60%
Braking time	10s

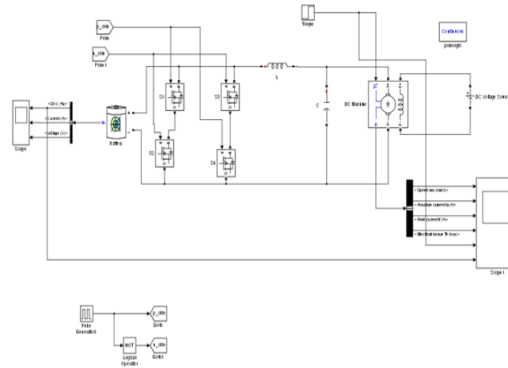


Fig.2. Regenerative braking with Simulink model

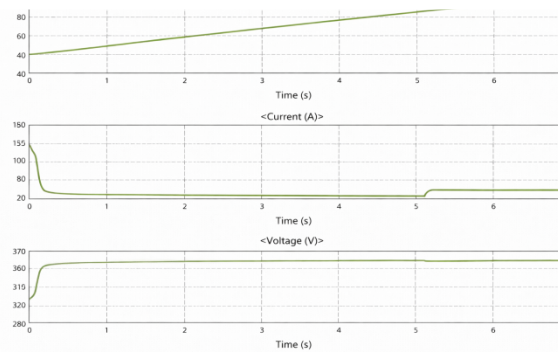


Fig.3. Battery energy recovered during regenerative braking

The MATLAB simulation results fig.2 show that regenerative braking helps recover energy and store it in the vehicle’s battery as the car slows down. When braking is applied, the vehicle decelerates smoothly, allowing the electric motor to function like a generator. As time progresses, the amount of recovered electrical energy steadily increase, showing that braking energy is reused instead of being wasted. By the end of the braking phase, about 37–38 kJ of energy is successfully stored in the battery. This gradual and consistent increase in recovered energy demonstrates the effectiveness of the regenerative braking approach and its ability to enhance overall energy efficiency in electric and autonomous vehicles.

C. FUZZY LOGIC BASED SOC ESTIMATION

This algorithm estimates the battery state of charge using a fuzzy inference system. In control systems where exact mathematical models are hard to come by, fuzzy logic controllers, are frequently employed. Instead of using precise calculations, they use membership functions and linguistic conventions to mimic human reasoning. This study develops a Mamdani-type Fuzzy Logic Controller that uses decelerator and speed inputs to estimate the State of Charge (SOC).

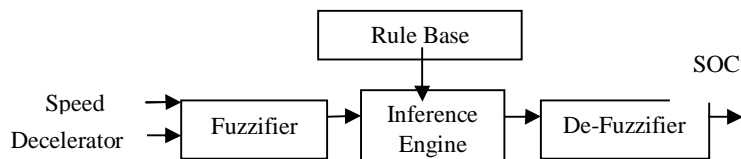


Fig.4. Fuzzy logic membership function

Each crisp input x is mapped to membership values $\mu_{A_i}(x)$ for linguistic sets A_i . For triangular membership functions (MF), the degree of membership is:

$$\mu_a(x) \begin{cases} 0, & x \leq a \text{ or } x \geq c \\ \frac{x-a}{b-a} & a < x \leq b \\ \frac{c-x}{c-b} & b < x < c \end{cases} \quad (1)$$

Here, a, b, and c represent the lower limit, peak point, and upper limit of the triangular membership function, respectively. The membership value increases linearly from zero to one between points a and b, and then decreases linearly from one back to zero between points b and c. Rule R_K IF Speed is A AND Decelerator is B THEN SOC is C. The firing strength of this rule, denoted by α_K , quantifies the degree to which the rule is activated. It is computed using the minimum operator, which implements the logical AND operation in fuzzy logic. The firing strength α_K is calculated by:

$$\alpha_K = \min(\mu_K(\text{Speed}), \mu_B(\text{Decelerator})) \quad (2)$$

Once the firing strength has been determined, the corresponding output membership function $\mu_{C_K}(Z)$ is modified through a clipping operation. Specifically, the output membership function is truncated at the height defined by Each rule's output membership function μ_{C_K} is clipped at height α_K : $\mu_K(z) = \min(\mu_{C_K}(Z), \alpha_K)$ To obtain a single combined output fuzzy set, all clipped output membership functions from the activated rules are aggregated using the maximum operator. The aggregated output membership function is expressed as:

$$\mu_{agg}(Z) = \max_x \mu_K(Z) \quad (3)$$

The final step of the fuzzy inference process is defuzzification, which converts the aggregated fuzzy output into a single crisp numerical value. In this work, the centroid or center-of-gravity method is employed, as it provides a balanced and widely accepted representation of the output distribution. The crisp output SOC is calculated as the centroid of the aggregated MF:

$$\text{SOC} = \frac{\int Z \mu_{agg}(Z) dz}{\int \mu_{agg}(Z) dz} \quad (4)$$

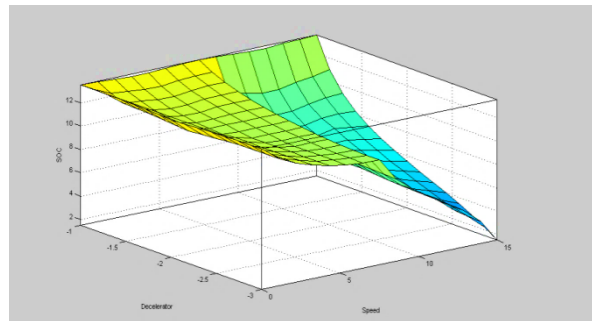


Fig.4.SOC Estimation Using FLC MATLAB Output

where z is the SOC output variable Speed=15Km/h, Decelerator=-3 m/s² Membership degrees $\mu_{High}(15)=1$, $\mu_{Low}(-3)=1$, $\alpha_3 = \min(1,1)=1$ De-fuzzified output centroid of membership N is approximately, SOC= 0.5=50%. A Mamdani-based Fuzzy Logic Controller (FLC) for State of Charge (SOC) estimation has been designed and analysed. The controller effectively combines vehicle speed and deceleration data using well established language principles to produce a smooth and understandable SOC output. The controller's consistent behaviour with expected physical intuition is confirmed by surface analysis and simulation results. All things considered, the recommended Mamdani FLC consistently estimates SOC by combining speed and deceleration inputs, providing consistent, fluid, and understandable control responses that are perfect for battery management and vehicle control applications.

TABLE II. The final SOC results

Speed	15 km/h
Energy Recovery	100KJ
SOC	50%
Battery capacity	37-38 KJ

The results of the MATLAB/Simulink model and the fuzzy logic controller approach roughly match the numbers above. At a vehicle speed of 15 km/h, the simulation indicates an energy recovery of about 100 kJ, which helps to achieve a battery state of charge of nearly 50%. The battery effectively stores about 37–38 kJ of this recovered energy. These findings demonstrate that the fuzzy logic controller successfully regulates battery power flow and regenerative braking and are in good agreement with the MATLAB/Simulink results.

V. CONCLUSION

In this paper, using a fuzzy logic controller to maximize regenerative braking and battery power management in autonomous cars.

- 1) The findings show that under various driving circumstances, the suggested control method successfully recovers braking energy and preserves an enhanced battery state of charge. The system accomplishes an energy recovery of around 100 kJ at a vehicle speed of 15 km/h, resulting in a battery state of charge of roughly 50% with approximately 37–38 kJ of energy effectively stored in the battery. The controller minimizes needless energy losses and guarantees smooth energy flow by cleverly controlling speed and deceleration inputs.
- 2) These advancements support dependable and stable battery management in autonomous vehicle systems and contribute to increased energy efficiency. Additionally, the close agreement between the fuzzy logic controller outputs and the MATLAB/Simulink results validates the accuracy and robustness of the suggested method, confirming its suitability for real-world vehicle energy management applications.

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