



A Scoping Review on Artificial Intelligence-Based Control Strategies for Regenerative Braking Optimisation

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ABSTRACT

Global patronage of electric vehicles is increasing year by year. Amidst the adoption of this clean means of mobility lies the underlying issue of energy utilisation. The lower energy density of most battery storage systems results in limited driving range, and the prolonged charging time, among other factors, is a constraint impeding the full adoption of electric vehicles. This review seeks to investigate the various artificial intelligence control strategies currently implemented in the regenerative braking system of electric vehicles and provide insights for future study in the field. The study was conducted using the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) framework, and the research questions were formulated using the Population-Concept-Context (PCC) framework, as these guided the development of inclusion criteria and the literature search strategy. The study was conducted after a rigorous search of 2 databases (IEEE Xplore and Google Scholar), and the search was narrowed down to 9 articles through the identification and screening of various studies. Findings from the study identified 5 AI/ML control strategies applied in the regenerative braking system of electric vehicles, as the performance of electric vehicles is generally improved through the use of artificial intelligence optimisation strategies in the braking torque, predicting and managing the energy storage in real time, and adapting braking strategies, respectively. Future review should prioritise standardised benchmarking protocols as well as validating their findings using hardware-in-the-loop for real-world applications.

ARTICLE INFO

Article History

Received: November, 2025

Received in revised form: December, 2025

Accepted: January, 2026

Published online: March, 2026

KEYWORDS

Artificial Intelligence, Control, Machine Learning, Optimisation, Regenerative Braking

INTRODUCTION

The transportation industry has been one of the major contributors to greenhouse gas emissions, as over the years, about 20% of the world's CO₂ has been introduced to the atmosphere through the transportation industry [1]. The advent of electric vehicles has seen a plunge in the global greenhouse gas emission index [2], thanks to the favourable policies and advancement in the electric vehicle (EV) industry [3]. This has further led to creating a sustainable environment by mitigating against climate change [4]. When compared to traditional petrol or diesel-powered vehicles, the electric vehicle has a

shorter driving range. This has been one of the factors mitigating the adoption of electric vehicles, as such could potentially breed fear in the minds of drivers [5]. Although driving pattern is also a factor in determining the driving range of electric vehicles [6], hence the need for more adaptive control and optimisation techniques. The electric vehicles can become a substitute for fossil-powered vehicles if proper control and optimisation techniques are applied [7].

The regenerative braking system in electric and hybrid vehicles makes it possible for some of the kinetic energy that could have been wasted as heat due to friction to be converted to

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useful electrical energy in charging the battery for improved performance [8]. This is particularly critical in extending the driving range of electric vehicles. This is imperative for application in electric vehicles, following the high cost of battery packs and scarce supply of infrastructure for charging [6]. Although there has been an ongoing effort to improve the energy density of batteries for electric vehicle applications [9], it is still very important to have the proper control and optimisation strategies implemented for better performance.

There has been a transition from the traditional proportional integral derivative (PID) controllers to more predictive and adaptive approaches, as these new approaches have outperformed the PID controller in terms of improvement in the driving range, reduction in maintenance cost, extension in the service life of disk brake, and reduction in the emission of greenhouse gases [8], [10]. Through the use of artificial intelligence (AI) and machine learning (ML), all critical performance metrics, such as rise time, transient response, and control action, have proven AI and ML to be a better control and optimisation technique.

This review seeks to map and systematically synthesise existing studies on the artificial intelligence-based control techniques implemented in regenerative braking systems of electric vehicles, considering the AI and ML techniques, vehicle type, driving cycle, energy recovery improvement, and key limitations.

METHODOLOGY

Review Design

This review was carried out in line with the five-stage scoping review framework presented by Arksey and O'Malley [11] and further improved by Levac et al. [12]. This allows for proper mapping of novel discoveries, recognising gaps, and synthesising different literature with a great level of ease.

The review seeks to investigate the artificial intelligence-based control strategies for regenerative braking optimisation in electric

vehicles. This was done by answering the following research questions:

1. Which artificial intelligence control schemes are implemented in regenerative braking of electric cars?
2. How is the application of AI control schemes for regenerative braking done to improve performance?
3. What criteria and techniques are utilised to evaluate the effectiveness of artificial intelligence control schemes for regenerative braking?

The research follows the standard specified by Arksey and O'Malley's (2005) for formulating research questions, where we started from a broad question of investigating the artificial intelligence-based control strategies for regenerative braking optimisation in electric vehicles and then narrowed it down to the three aforementioned questions. The authors in this current review are researchers in the field of electric vehicles and strongly believe that these questions will provide a guide to a systematic review. The report of the results is then reported using the 2018 Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for scoping reviews guidelines (PRISMA-ScR) [13].

Search strategy & databases

The databases used for this study are Google Scholar and IEEE Xplore, with the given publication dates limited to 2021 – 2026 for recent journal articles in the field. The search terms used were in English ("regenerative braking optimisation") AND ("electric vehicle" OR "BEV" OR "EV") AND ("reinforcement learning" OR "deep learning" OR "neural network" OR "fuzzy logic"). All review articles, ranging from systematic, scoping, narrative and meta-analysis, were excluded from the search.

Eligibility criteria

The eligibility criteria were used in forming our basis for the selection and exclusion of articles in the artificial intelligence-based control strategies for regenerative braking optimisation.

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Inclusion criteria

1. Articles reporting evidence on artificial intelligence control schemes in regenerative braking of electric cars.
2. Articles reporting evidence on artificial intelligence-based control of regenerative braking performance.
3. Articles reporting evidence on the evaluation of the effectiveness of artificial intelligence control schemes.

Exclusion Criteria

1. Articles published before 2021
2. Review articles

Screening

The screening of the articles was done in 2 stages, first was the screening of the title to ensure it is in line with the study objectives, after

which the abstracts were then screened. The final selected articles were then exported to CSV.

Data extraction

We extracted data on the following: author and year, AI/ML technique, vehicle type, driving cycle, energy recovery improvement, and key limitation.

RESULTS AND DISCUSSION

Search Results

Our search result follows the PRISMA-ScR flow as shown in **Figure 1**. A total of 64 results were found following the Boolean string search from both databases. Among the searched 64 potential eligible articles, 2 duplicates were removed, and 62 were found to be potential articles for inclusion. We were able to have 9 articles included in the study after the entire screening process.

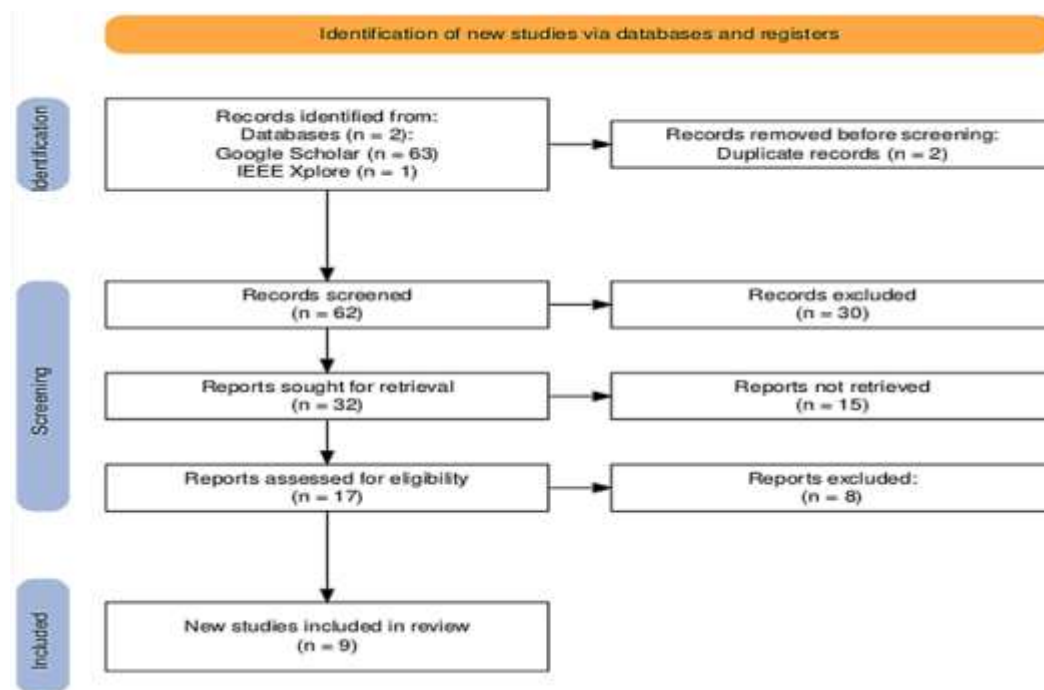


Figure 1. PRISMA-ScR flow [13]

Characteristics of included studies

The studies used in this review are presented in **Table 1**. All the included studies

reported evidence of regenerative braking and the use of AI/ML in electric vehicles. All of the 9 journal articles are peer-reviewed and published within the years 2021-2026. These reputable journals are IEEE Access, Scientific Reports, World

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Electric Vehicle Journal (MDPI), Journal of Advanced Computational Intelligence and Intelligent Informatics, Processes (MDPI), Symmetry (MDPI), Frontiers in Mechanical Engineering, and Pamukkale Universitesi Muhendislik Bilimleri Dergisi, respectively. The vehicle types covered in the articles include the Plug-in Hybrid Electric Vehicles (PHEV), Hybrid Electric Vehicles (HEV), Battery Electric Vehicles (BEV), dual-motor EVs, and electric buses (E-Bus), which shows the current areas in which AI/ML strategies have been implemented in the regenerative braking of electric vehicles.

The categorisation of the study is in three themes, namely: Fuzzy Logic Control Approaches (Section 4.3), Neural Network and Deep Learning Approaches (Section 4.4), and Reinforcement Learning and Evolutionary Optimisation Approaches (Section 4.5). MATLAB/Simulink software was utilised in the vast majority of the study, while 2 of the studies utilised real-world operational data.

Fuzzy Logic Control Approaches

One of the most used artificial intelligence techniques is that of fuzzy logic control in optimising energy from regenerative braking, as it has the ability to handle time-varying, non-linear models. Another interesting feature about the FLC is its ability to handle models with incomplete characteristics that are unique to braking conditions. In order to show its importance in the optimisation control, 2 of the studies utilised the FLC artificial intelligence technique as either the main mechanism or part of a hybrid control, hence depicting its importance in the AI/ML control and optimisation space for electric vehicle braking systems.

Fuzzy logic for front-axle braking

In the FLC strategy that was developed by [14], a distributive regenerative braking force is applied to the front wheel drive for electric vehicles. This approach was implemented in the MATLAB/Simulink environment, and the FLC was used to optimise the ratio of motor braking force to total front-axle braking force while addressing inherent pertinent issues such as time variability,

delay in response, non-linearity, and insufficient model information that characterises regenerative braking.

The study by [14] focused on 6 different drive cycles, which are: the New European Driving Cycle (NEDC), the World Harmonised Light-Duty Vehicle Test Cycle (WLTC), Federal Test Procedures 72 and 75 (FTP-72, FTP-75), the China Light-Duty Vehicle Test Cycle for Passenger Vehicles (CLTC-P), and the New York City Cycle (NYCC). Given the 6 different drive cycles, the proposed FLC energy saving strategy exceeded 15% in terms of performance efficiency. The performance efficiency of the FLC under the WLTC condition was 25%, and the drive cycle conditions of FTP-72, FTP-75, and CLTC-P reached 30%.

The drive cycle with the most energy savings is that of NYCC, which is 40%, this is due to the fact that the frequent braking action in densely populated urban areas. The findings from this study confirm the effectiveness and adaptability of FLC when implemented in various real-world driving conditions. Although the study highlights the various drive cycles and energy savings during regenerative braking, there is no testbed to validate the MATLAB/Simulink simulation. The study is also limited to electric vehicles that are solely front-wheel drive, hence limiting the generalizability of the findings.

Hierarchical fuzzy control enhanced by particle swarm optimisation

The fuzzy logic control was further advanced [15] by presenting the hierarchical fuzzy control strategy. This novel strategy was meant to complement the Particle Swarm Optimisation (PSO) algorithm. The study by [15] proffered a solution to address the inherent issues with battery energy storage systems, which are: limited driving range, extended charging cycle, and limited energy density. Their solution implemented rule base for flexibility across the various speed and braking conditions of electric vehicles. Also, the PSO algorithm was improved to optimally assign boundaries between hydraulic and motor braking forces, thereby boosting energy recovery.

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Findings from the study show that the improved PSO strategy is more advantageous when compared to the traditional PSO, as it converged faster with better accuracy, having a loss factor of just 10-5, which happens to be the lowest amongst all the studied literature. An energy recovery rate of 16.8% was recorded, as it extended the driving range by 35 KM with a 0.71-second reduction in the braking time response. The results from [15] show clearly that the hybridisation of FLC and PSO yields a better output as opposed to the standalone FLC technique, which is evident in the improved stability, energy recovery, and responsiveness. Comparing the findings by [15] and [14], one clear distinction is in the lack of the use of drive cycles by [15] in the implementation of the hybrid strategy, thereby constraining the direct comparison of both studies. The use of FLC in both control strategies shows how relevant it is in the regenerative energy of electric vehicles.

Neural Network and Deep Learning Approaches

These artificial intelligence approaches are capable of real-time deployment and adaptive weight optimisation. The need for deep learning applications in the electric vehicle space is seen in 2 of the 9 studies, as neural network models were applied as the primary technique. These journal articles were published in 2025, indicating the trajectory of deep learning in the field of regenerative braking optimisation of electric vehicles.

Long Short-Term Memory Networks for Supercapacitor Current Prediction

The strategy proposed by [16] presents a novel LSTM machine learning approach in the prediction of the current reference in a supercapacitor. The main objective was to optimize the distribution of energy between the supercapacitor and battery in both hybrid battery electric vehicles (BHEV) and battery electric vehicles (BEV). The MATLAB/Simulink environment was used in the simulation, where real-world drive cycle data were trained and imported for training of the LSTM neural network.

Furthermore, the study was validated using the Nissan Sakura electric vehicle, where the extra-urban driving cycle (EUDC) and the IM240 cycle respectively.

When subjected to the EUDC drive cycle, 21.3% reduction was achieved in the battery peak current, as well as a reduction in peak power demand of 18.1%. Furthermore, a 5.75% reduction in battery energy consumption was recorded. In the IM240 cycle, the performance improved as 33.5% was recorded in peak battery current, 31.6% drop in peak power demand, and a reduction in battery energy consumption of 12.36%. It can be deduced that LSTM-based adaptive current management performs better under conditions warranting constant acceleration and braking actions.

The study by [16] contributes to existing literature through the implementation of the ONNX export framework, as this addresses the gap in electric vehicle regenerative braking AI/ML literature. Although the study is limited to a single vehicle model, there was no testbed or prototype for proper validation. Furthermore, the study did not factor in computational complexity and thermal resilience of the ONNX-based LSTM algorithm under actual embedded controller conditions, which is one area where future research should be headed.

Hybrid crow search algorithm and recurrent elephant neural network

A novel controller comprising a bio-inspired Crow Search Algorithm (CSA) with a Recurrent Elephant Neural Network (RERNN) was proposed by [17]. The hybrid algorithm was designed for the control of high-performance electric vehicle drives. The weights of RERNN are tuned by the CSA, where it acts as an optimiser. This approach is novel as it introduces the fusion of a recurrent neural architecture along with a bio-inspired search algorithm.

The performance of the CSA-RERNN controller showed superior performance in comparison with traditional controllers in regard to overall drive efficiency, torque response, and speed drive efficiency. The capability of the recurrent elephant neural network for adaptive



temporal learning makes it possible for the controller to perform optimally under various driving load profiles, as the CSA component of the hybrid approach ensures the convergence to global optimal weights. The aforementioned capabilities make it relevant in the control and optimisation of regenerative braking in real time. The study by [17] provided a conceptual contribution to existing literature through the CSA-RERNN framework, quantitative performance metrics were not included in the study. The CSA-RERNN strategy is underexplored as not much study has been done in this field, and this provides future direction for AI/ML regenerative braking research.

Reinforcement Learning and Evolutionary Optimisation Approaches

In this study, 5 out of the 9 studies addressed the implementation of reinforcement learning (RL), evolutionary optimisation algorithms, and ML-based driving behaviour analysis. This shows that the vast majority of the research tends to move in this direction.

Reinforcement Learning Integrated with Graph Attention Networks

The methodological approach proposed by [18] appears to be the most sophisticated as it presents a multi-modal RL-based framework for the optimisation of EV energy consumption through the integration of driver behaviour patterns, road conditions, and environmental factors. The study by [18] utilised a real-world dataset of 3,395 charging sessions, which was extracted from 85 electric vehicles. The framework by [18] achieved an improvement averaging 17.3% in energy efficiency when compared to baseline methods among different driving cycles. The strategy introduced by [18] is very critical, especially in the development of contextual regenerative braking controllers.

There was no actual benchmark for standardized driving cycle, constraining the direct comparison with other studies. Another limitation of the study by [18] is that the dataset utilised for the study was based on a workplace charging

environment, hence limiting its geographical generalizability.

Genetic Algorithm-Based Torque Distribution for Dual-Motor EVs

A Genetic Algorithm (GA)-based regenerative braking torque distribution strategy was proposed by [19]. The strategy was designed for dual-motor EVs and involves addressing the existing challenge faced in the simultaneous optimisation of braking stability and energy recovery in dual-motor EVs. The optimisation strategy utilised 3 key variables, namely, vehicle speed, state of charge (SOC), and braking intensity.

When compared with the traditional rule-based approach, the energy recovery improvement by GA-RBD was 22.8% and a braking stability of 4.8%. With an increase in braking speed came a corresponding increase in the performance of the GA-RBD strategy. This points to the fact that genetic algorithms can be useful, especially during global optimisation under demanding conditions. The multi-objective improvement by the GA-RBD strategy tackles both the maximisation of energy and the dynamic control of electric vehicles. This differentiates the GA-RBD strategy from single-objective fuzzy logic control and PSO, respectively.

Since the study by [19] was based on simulation, it constrains its application in the real world. Also, the dual-motor architecture implementation in the study makes it impossible to apply to a single-motor architecture. Lastly, the study did not address the computational intensity that comes with the genetic algorithm, as this could potentially impede the seamless real-time implementation.

Particle Swarm Optimisation for PI Controller Tuning

The PSO was used in tuning the proportional integral (PI) controller; these parameters are the K_p and K_i , respectively [20]. The main purpose was to optimise the speed regulation of a brushless direct current (BLDC) motor in electric vehicles. The study was carried out using MATLAB/Simulink, as shown in Figure

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Machine Learning-Based Traffic-Aware Energy Modelling for Electric Buses

A high-resolution, traffic-aware energy modelling framework for electric buses was presented by [21]. The strategy utilised regenerative braking of electric bus (E-Bus), traffic congestion metrics, vehicle dynamics, and ML-based driving behaviour in their analysis. One of the key Findings from the study showed that in order to achieve optimal driving range, 78.32% of the entire braking energy must be recovered through regenerative braking. Furthermore, findings from the study further showed that through autonomous driving, the total reduction in energy consumption was 11%–14% while regenerative braking utilisation was increased by 9%–12%.

Intelligent Friction Coefficient Estimation for Adaptive Braking Control

The existing limitation in the regenerative braking controller was addressed by [22]. In their study, an intelligent regenerative braking control system that works with AI-based friction coefficient estimation for HEV was presented, as shown in Figure 3. This allowed for the dynamic adaptation of the braking force distribution to the prevailing surface of road conditions.

Just as in the study by [17], the study by [22] did not provide specific quantitative performance metrics. Nonetheless, the friction estimation framework presented by [22] could potentially contribute to the implementation of AI-optimised regenerative braking systems in electric vehicles.

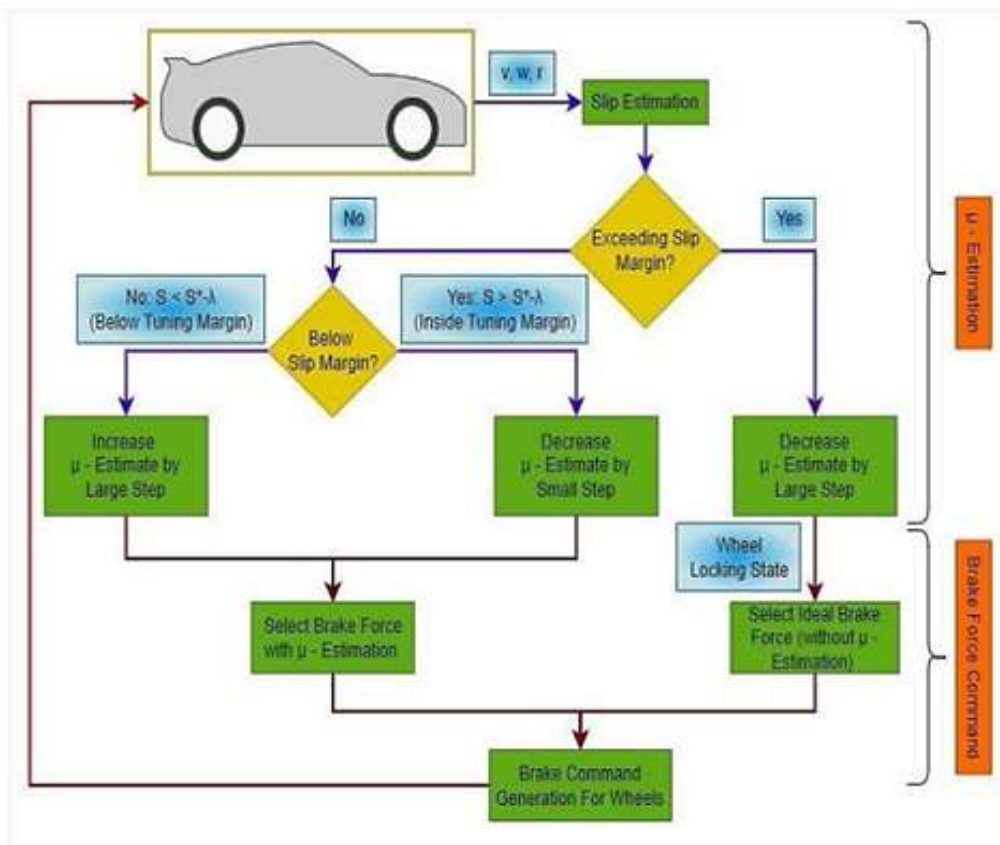


Figure 2. Proposed μ -estimation logic [22]

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Table 1. Comparative summary table of all studies

S/N	Author(s) & Year	AI/ML Category	Vehicle Type	Driving Cycle(s)	Key Improvement
1	[17]	Hybrid Neural Network (CSA + RERNN)	EV (electric drives)	Not reported	Improved drive control (full-text required for metrics)
2	[18]	Reinforcement Learning + GAT + Contrastive Learning	BEV	Real-world urban data	+17.3% energy efficiency
3	[16]	LSTM Neural Network + ONNX	BEV / HBEV	EUDC, IM240	EUDC: -5.75% energy; IM240: -12.36% energy
4	[19]	Genetic Algorithm (GA-RBD)	Dual-Motor EV	Custom (90 km/h, intensity 0.3)	+22.8% energy recovery; +4.8% stability
5	[21]	ML-based driving behaviour analysis	Electric Bus (E-Bus)	Real-world urban route (1 Hz data)	Autonomous: -11-14% energy; +9-12% regen utilisation
6	[20]	Particle Swarm Optimisation (PSO)	HEV / PHEV / EV	Custom (1,300 s simulation)	+6% travel distance; +14.57% speed efficiency
7	[15]	Fuzzy Logic + Improved PSO	EV (motor + hydraulic)	Not specified	16.8% energy recovery; +35 km range; 150 Wh/km
8	[14]	Fuzzy Logic Control	Front-wheel-drive EV	NEDC, WLTC, FTP-72, FTP-75, CLTC-P, NYCC	>15% (NEDC); 25% (WLTC); ~30% (FTP); >40% (NYCC)
9	[22]	Intelligent AI friction coefficient estimation	HEV	Not reported	Improved braking performance (full-text required for metrics)

CONCLUSION AND RECOMMENDATION

The review identified 5 AI/ML control strategies applied in the regenerative braking of electric vehicles. These are fuzzy logic control, hybrid fuzzy-PSO control, LSTM-based neural networks, hybrid bio-inspired neural networks (CSA-RERNN), reinforcement learning integrated with graph attention networks, genetic algorithms, particle swarm optimisation, ML-based driving behaviour analysis, and intelligent friction coefficient estimation.

The performance of electric vehicles is improved with the use of artificial intelligence through the optimisation of the braking torque, predicting and managing the energy storage in real time, and adapting braking strategies. With the use of a membership function, the fuzzy logic

controller has been able to control periodic speeding and braking intensity, saving up 40% in urban driving conditions. Through the use of a genetic algorithm (GA), energy recovery and braking stability were improved by 22.8% and 4.8%, respectively. LSTM neural networks improved the performance of electric vehicles by reducing battery peak current demand by 33.5% and the overall energy consumption by 12.36%, while Reinforcement learning improved performance through adapting the driver's behaviour and environmental inputs, achieving as it achieved a 17.3% energy improvement.

The effectiveness of the AI/ML strategies was measured using the following metrics: energy recovery rate, energy consumption reduction, braking stability index,

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driving range extension, standardised driving cycles, and real-world operational data. Future reviews should give priority to standardised benchmarking protocols as well as validating their findings using hardware-in-the-loop for real-world applications.

REFERENCES

- [1] U. Azhar, S. Yaseen, M. Arif, M. Babar, and M. Sagir, "Emission of greenhouse gases from transportation," in *Advances and Technology Development in Greenhouse Gases: Emission, Capture and Conversion*, Elsevier, 2024, pp. 147–163. doi: 10.1016/B978-0-443-19231-9.00016-8.
- [2] Z. Gao *et al.*, "Electric vehicle lifecycle carbon emission reduction: A review," *Carbon Neutralization*, vol. 2, no. 5, pp. 528–550, Sep. 2023, doi: 10.1002/cnl2.81.
- [3] A. E. Airoboman *et al.*, "Advancing the Implementation of E-mobility for Safer Climate and Energy Resilience in Developing Economy," in *2024 IEEE 5th International Conference on Electro-Computing Technologies for Humanity (NIGERCON)*, Ado Ekiti, Nigeria: IEEE, Nov. 2024, pp. 1–6. doi: 10.1109/NIGERCON62786.2024.10927152.
- [4] A. Desrevaux, A. Bouscayrol, R. Trigui, E. Hittinger, E. Castex, and G. M. Sirbu, "Accurate energy consumption for comparison of climate change impact of thermal and electric vehicles," *Energy*, vol. 268, p. 126637, Apr. 2023, doi: 10.1016/j.energy.2023.126637.
- [5] I. Miri, A. Fotouhi, and N. Ewin, "Electric vehicle energy consumption modelling and estimation—A case study," *Int. J. Energy Res.*, vol. 45, no. 1, pp. 501–520, Jan. 2021, doi: 10.1002/er.5700.
- [6] R. Mao *et al.*, "Understanding the Determinants of Electric Vehicle Range: A Multi-Dimensional Survey," *Sustainability*, vol. 17, no. 10, p. 4259, May 2025, doi: 10.3390/su17104259.
- [7] A. M. Al-Ghaili, H. Kasim, H. Aris, and N. M. Al-Hada, "Can electric vehicles be an alternative for traditional fossil-fuel cars with the help of renewable energy sources towards energy sustainability achievement?," *Energy Inform.*, vol. 5, no. S4, p. 60, Dec. 2022, doi: 10.1186/s42162-022-00234-3.
- [8] S. Vasiljević, B. Aleksandrović, J. Glišović, and M. Maslač, "Regenerative braking on electric vehicles: working principles and benefits of application," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 1271, no. 1, p. 012025, Dec. 2022, doi: 10.1088/1757-899X/1271/1/012025.
- [9] C. Yang, "Running battery electric vehicles with extended range: Coupling cost and energy analysis," *Appl. Energy*, vol. 306, p. 118116, Jan. 2022, doi: 10.1016/j.apenergy.2021.118116.
- [10] L. N. Patil, L. K. Toke, and V. K. Agrawal, "Experimental investigation on electric vehicle braking system using fuzzy rule-based control strategy," *World J. Eng.*, Apr. 2025, doi: 10.1108/WJE-01-2025-0019.
- [11] H. Arksey and L. O'Malley, "Scoping studies: Towards a methodological framework," *Int. J. Soc. Res. Methodol.*, vol. 8, no. 1, pp. 19–32, 2005.
- [12] D. Levac, H. Colquhoun, and K. K. O'Brien, "Scoping studies: Advancing the methodology," *Implement. Sci.*, vol. 5, no. 1, p. 69, 2010.
- [13] N. R. Haddaway, M. J. Page, C. C. Pritchard, and L. A. McGuinness, "PRISMA2020: An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and Open Synthesis Campbell Systematic Reviews," vol. 18, 2022.
- [14] Z. Yin, X. Ma, R. Su, Z. Huang, and C. Zhang, "Regenerative Braking of Electric Vehicles Based on Fuzzy Control Strategy," *Processes*, vol. 11, no. 10, p. 2985, Oct. 2023, doi: 10.3390/pr11102985.
- [15] J. Zuo, Q. Chai, J. Zuo, and G. Li, "Control strategy of electric vehicle regenerative braking integrating fuzzy control and PSO," *Front. Mech. Eng.*, vol. 11, p. 1697447, Nov. 2025, doi: 10.3389/fmech.2025.1697447.

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- [16] T. Paulraj and Y. P. Obulesu, "Machine learning-based approach for reduction of energy consumption in hybrid energy storage electric vehicle," *Sci. Rep.*, vol. 15, no. 1, p. 29303, Aug. 2025, doi: 10.1038/s41598-025-11330-1.
- [17] J. Prabhakaran, P. Thirumoorthi, M. Mathankumar, and S. P. Mangaiyarkarasi, "Development of intelligent controller for high performance electric drives with hybrid CSA and RERNN technique," *Sci. Rep.*, vol. 15, no. 1, p. 14020, Apr. 2025, doi: 10.1038/s41598-025-98704-7.
- [18] J. Wang, H. Zhang, B. Wu, and W. Liu, "Symmetry-Guided Electric Vehicles Energy Consumption Optimization Based on Driver Behavior and Environmental Factors: A Reinforcement Learning Approach," *Symmetry*, vol. 17, no. 6, p. 930, Jun. 2025, doi: 10.3390/sym17060930.
- [19] T. Wu, F. Wang, and P. Ye, "Regenerative Braking Strategy of Dual-Motor EV Considering Energy Recovery and Brake Stability," *World Electr. Veh. J.*, vol. 14, no. 1, p. 19, Jan. 2023, doi: 10.3390/wevj14010019.
- [20] W. S. Chai *et al.*, "Regenerative Braking Optimization Using Particle Swarm Algorithm for Electric Vehicle," *J. Adv. Comput. Intell. Intell. Inform.*, vol. 26, no. 6, pp. 1022–1030, Nov. 2022, doi: 10.20965/jaciii.2022.p1022.
- [21] Y. E. Ekici, "Traffic Aware 1 Hz Energy Modeling and Regenerative Braking Analysis of E-Bus Operations Using Real-World Data," *Pamukkale Üniversitesi Mühendis. Bilim. Derg.*, no. Advanced Online Publication, Apr. 2026, doi: 10.65206/pajes.1865497.
- [22] G. Gupta *et al.*, "Intelligent Regenerative Braking Control With Novel Friction Coefficient Estimation Strategy for Improving the Performance Characteristics of Hybrid Electric Vehicle," *IEEE Access*, vol. 12, pp. 110361–110384, 2024, doi: 10.1109/ACCESS.2024.3440210.

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