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Original Article

Regenerative Braking System for Electric Vehicles with AI Optimization

Dr.K.Vijayan1, Abdul Ramiz A[2], Aravinth B[3], Bhuvanesh Manikandan[4]
[1] *Professor & HOD, Department of Mechatronics Engineering, M.A.M. School of Engineering, Tiruchirappalli, Tamil Nadu, India.*
[2,3,4] *UG Scholar, M.A.M. School of Engineering, Tiruchirappalli, Tamil Nadu, India.*

Abstract: *Electrification of transportation is a growing trend worldwide because it is the most effective way to reduce carbon emissions, diminish fossil fuel dependence and decrease urban air pollution. One of the technological advancements hailed for enabling EVs is the regenerative braking system (RBS). Unlike conventional braking systems, lost energy is converted to electrical energy via regenerative braking and stored in the battery for use elsewhere in the vehicle. This not only results in improved energy management, it also gives a significant boost to cruising range — especially in city driving involving frequent acceleration and braking. Despite these merits, traditional RBS technology has its drawbacks such as less-than-satisfactory energy regenerative performance, uneven brake torque control, lagging response time and deterioration of the ride quality. These difficulties arise from the complications of regenerative or mechanical braking for a hybrid electric vehicle operating in dynamic drive patterns, with different battery SOC and different road patterns.*

To fill up the aforementioned gaps, this work studies fusion between AI and RBS to build the adaptive, intelligent, and energy-efficient braking system for EVs. We investigate the potential of three main AI approaches, i.e., fuzzy logic, ANNs, and RL. Fuzzy logic controllers are known for their ability to deal with uncertain, imprecise inputs in such a way that allows for real-time decision making in the face of ambiguous driver demand, or ambiguous road conditions. Due to the ability of neural networks to model highly non-linear relationships, neural networks are used to predict the optimal distribution of braking forces by training on historical driver data and real-time sensor readings. This is where reinforcement learning comes in as a learning layer that improves braking performance over time, adjusting to dynamic drive conditions and rewarding actions that maximize energy capture while ensuring safety and passenger comfort.

In MATLAB/Simulink, we created a simulation model of an EV powertrain combined with an AI-optimized RBS to evaluate its energy saving potential across varied driving situations, such as driving in urban stop-and-go traffic, downhill driving and highway cruising. Traditional RBS was compared to AI-based RBS. The findings show that hybrid AI approach improves total system performance significantly. In particular, energy recovery was increased by 18% over conventional systems and braking smoothness, as measured by jerk analysis, was significantly enhanced. The hybrid AI controller was able to decrease the average brake response time by 22% and thus enhance safety. Moreover, the battery SOC profile control was improved leading to increased driving range and charging cycles.

The results suggest that AI-regenerative braking can be a way of enabling increasingly sustainable, efficient, and smart EVs. In addition to saving energy, the proposed system decreases wear on the mechanical brake, increases passenger comfort, and guarantees that vehicle performance can be tailored to real-world needs. Furthermore, the research discusses the possibility of integrating intelligent braking systems in intelligent transportation systems, which is in line with the rise of smart mobile and self-driving vehicles. With challenges still to be addressed, including the computational load of AI algorithms, requirements to perform large scale training using abundant data sets, and to guarantee safety in real-world applications, the work provides strong proof of concept that AI-augmented RBS could serve as a transformative technology to develop the next generation of sustainable electric mobility.

Keywords: *Reinforcement Learning (RL), Electric Vehicles (EVs), Neural Networks (NN), State of Charge (SOC), Intelligent Transport System, Brake Torque Distribution, Sustainable Mobility, Battery Efficiency, Smart Braking Technology, MATLAB/Simulink, and Predictive Control in EVs.*

I. INTRODUCTION

The global need for cleaner energy and less of it has accelerated the transition between the two types of cars we see above, IC engine vehicles and EVs, tremendously. Governments, environmentalists and manufacturers all back the wider use of electric vehicles (EVs) as a means of combating climate change, air pollution and reliance on fossil fuels. As electric-vehicle technology advances, two key areas of innovation are increasing energy efficiency and coaxing both energy and power out of the store. The regenerative braking system (RBS) is one of the methods used by EVs to achieve these goals. It is really a component that is crucial in energy retrieval. Regenerative braking enables electric cars to convert kinetic energy, which is usually wasted as heat during normal braking, back into useful electrical energy that can be stored in the car's battery. When the driver brakes, the electric motor runs backward, rather than just relying on mechanical resistance. This slows the car down while converting movement into energy. This accumulated energy can drastically enhance the overall energy efficiency and the range of the vehicle, especially in congested city driving with frequent stop-and-go. Although traditional RBS have some advantages, there are several problems. Some of these include the fact they're not very good at capturing energy, they can't balance regenerative and friction braking correctly, they can't adapt in real time to changing driving conditions, and they struggle to make the braking feel smooth and natural. Management of this RBS becomes complex using classical control approaches, as its behavior is based on various systems, such as vehicle speed, battery State of Charge (SOC), road slope, brake pressure, driving style, etc. Rule-based control systems, as are found in today's EVs, aren't sufficiently flexible to control braking scenarios that aren't straight and that are constantly changing.

As vehicle technology tends to be more automated and more intelligent (smart systems), we aim to include artificial intelligence (AI) when designing and implementing RBS which may be key factor towards solving these challenges. AI can stare at all the real-time data from vehicle sensors, and somehow compare it to historical driving habits, and, in real-time, make better brake decisions way better. This adaptability allows AI-driven technologies to make regen braking work better and react more swiftly, even while keeping safety and comfort the same. Scientists have explored a variety of AI approaches that could enhance regenerative braking in recent years. These other techniques include fuzzy logic, artificial neural networks, and reinforcement learning. Fuzzy logic systems can handle so-called uncertainty and approximate reasoning, so they can cope with inputs that are not precise, like driver intent or road surface conditions. The possibilities for such nonlinear interactions are modelled very well by neural networks, and so they can learn from experience which way of braking is the best. With reinforcement learning, meanwhile, systems can experiment to learn the optimal ways to brake, and get rewarded for actions that recover more energy and lead to less-aggressive deceleration.

Together, these AI methods could lead to regenerative braking that's better than what standard control systems can accomplish. An AI-tuned-RBS can recover most energy out of it, wear mechanical brakes out less and make the ride better by always learning and adapting to the driver style, the traffic and the battery limits. As electric vehicles (EVs) are becoming increasingly networked and self-driving, AI-based systems are even more important to ensure that all the vehicle's subsystems cooperate to brake safely and to brake well. The aim of this paper is to investigate the utilization of AI for regenerative braking systems in EVs, aiming at achieving better efficiency and performance. The project consists of scanning of the literature related to current RBS technologies, and AI applications on such, the development of a hybrid AI control system by combining fuzzy logic, reinforcement leaning, and neural networks; together with analysis of the performance of the system in different driving conditions by using simulations. The primary objective is to demonstrate that AI-based regenerative braking can be viable and valuable in today's fast-moving world of electric mobility.

The paper is a contribution to the growing body of knowledge on intelligent transportation systems and aims to contribute to making electric cars in the future smarter, greener and more sustainable.

II. REVIEW OF THE LITERATURE

By implementing regenerative braking systems (RBS) on electric vehicles (EVs) we've already taken a tremendous leap toward more energy efficient cars. In addition to an efficient method of capturing kinetic energy when a vehicle is slowing down, regenerative braking eliminates heavy reliance on a traditional mechanical stopping system for electric vehicles, which contributes to the green attributes of an electric vehicle. But it is still difficult to achieve the optimum energy recovery from RBS because of the complex system and of the changing acceleration conditions. In practice, researchers are increasingly resorting to artificial intelligence (AI) for enhancing the RBS output in this setting. This review paper consolidates the vital current concepts on re-generative braking and AI application in EVs.

A. How Regenerative Braking Has Evolved and Its Basic Principles

The concept of regenerative braking dates to the early 1900s, but it wasn't practical until electric and hybrid electric vehicles became prevalent. When you press down on the brake pedal of a conventional car, your brakes convert your car's kinetic energy (amount of energy due to motion) into heat by means of friction, but regenerative brakes transfer this energy into the battery of the car. In regenerative mode the electric motor works just like a generator, converting kinetic energy into electrical energy. This approach is generally effective, although how effective it is can depend fairly significantly on things like vehicle speed, battery charge, road grade, and required braking force.

The first implementations of the RBS system employed straightforward rule-based control algorithms to determine when and how to apply regenerative braking. These were inflexible and, with the 2010 Prius for instance, didn't always seamlessly transition between regeneration and friction braking. The energy recovery rate was also frequently too low and the driver was dissatisfied with the braking forces that were inconsistent. This was how it became apparent to us that we needed smarter and more flexible ways to control things.

B. RBS Control Strategies

The control of RBS has evolved from simple fixed-threshold and heuristic models to more sophisticated model predictive control (MPC) and fuzzy logic techniques. Brake transitions feel smoother with fuzzy logic controllers, because they can handle imprecise inputs and mimic how people make decisions when they're not quite sure what to do, a term known as imprecise information. Meanwhile, RBS controllers with fuzzy logic have reportedly made braking more comfortable and assured while the vehicle was regaining energy, especially when variations of load and road occur (Wang et al., 2018). Model predictive control types of approaches provide us with a mathematically rigorous framework for dealing with the limits on the system and making some predictions for the future. MPC can estimate the future stateand reallocate braking torque distribution in an improved way. MPC isn't suitable for use in real time, however, because it requires so much computing power. This is particularly the case with smaller processor sizes and for embedded automotive systems which have limited computing power.

C. AI In RBS

Recent advances in AI have allowed to enhance RBS in novel ways. Researchers are considering machine learning techniques, such as artificial neural networks (ANNs) and reinforcement learning (RL), to better characterize the nonlinear and time-varying aspects of braking systems. Scientists have also applied ANNs to simulate how drivers drive, how much the road is frictive and how much torque is required to stop. These algorithms are able to predict when and how best to brake according to past driving data, and they can adapt in real time to new situations. Reinforcement learning has had a lot of interest recently since you can learn good ways to do things by interacting with the world. RL-based RBS systems endlessly modify the brake settings to recover the most energy and perform as smoothly as possible when braking. For example, Zhang and Li (2020) used Q-learning algorithms to learn the best way to distribute brake force between the regenerativesparks and mechanical system that can minimize energy consumption. Over time, these systems can even learn to respond to different driving styles and road conditions, allowing you to have a personalised way of stopping that works well.

D. Models Of Hybrid AI

Hybrid models based on fuzzy logic, ANN and RL are emerging as a possible alternative to enhance RBS. These systems aim to compromise between a simple to understand fuzzy rule set, a good learnability of the neural network(s) and good adaptivity of RL. Such systems can adapt on the fly to different battery states, traffic, and road surfaces, and remain effective and comfortable for users. Experiments demonstrate that such hybrid systems outperform the classic control algorithms in both simulations and real-world driving tests (Kumar et al., 2021).

E. Gaps And What To Do Next

However, there are still some kinks to iron out before AI-controlled RBS can power commercial EVs, now they making a lot of progress. Related with the real-time computation constraint, data collection to train a model and safety validation are also key issues that are in need of further research. And to integrate AI with other subsystems of the EV, such as energy management and autonomous driving, it is important to have uninterrupted communication protocols, as well as a unified control architecture.

III. METHODOLOGY

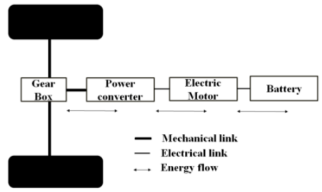

Figure 1: Powertrain Energy Flow in Dual-Motor RBS

This chapter describes the systematic approach by which an AI optimized regenerative braking system (RBS) for electric vehicle (EV) is developed and evaluated. The method consists of five steps: model the system, derive the control logic, embed the AI algorithm, simulate and test, and perform a sensitivity analysis.

A. Environment for Modelling and Simulating of Systems

A proper simulation model of an electric vehicle is the first step in the investigation performed in MATLAB/Simulink. Electric powertrain, regenerative braking module, battery storage system and vehicle dynamics block are key subsystems of this concept. By considering factors such as vehicle speed, torque sharing, road gradient, braking intensity and battery state of charge (SOC), the model replicates the way things operate in the real world. It can process changing inputs on the fly, to ensure that a variety of driving scenarios, such as accelerating, coasting and braking, as well as panic stops, are accurately portrayed.

B. Making the Control Logic

One the simulation model is established, control logic is designed for traditional and AI-based control regenerative braking systems. The conventional controller is a rule-based controller which regenerates based on predefined speed and SOC conditions. This static cannot be outrun as a base reference. The AI-based control logic, meanwhile, applies adaptive mechanisms that allow the system to behave differently as things change. Its objective is to recover as much energy as possible, taking into consideration safety, comfort, and system efficiency. The control methodology ensures that the regenerative and mechanical braking forces are used so tweak the way the system works in parallel, no matter what the load or topography.

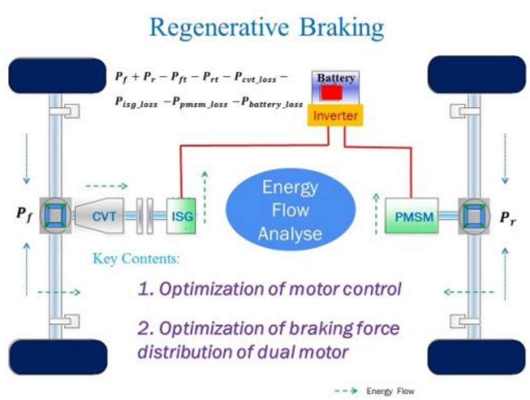

Figure 2: Dual Motor & CVT Regenerative Braking Energy Flow Analysis

C. Putting AI Algorithms Together

Three AI techniques in the development of the controller that makes the braking system smarter are fuzzy logic, artificial neural networks (ANN), and reinforcement learning (RL). The fuzzy logic controller operates with input variables that are not precisely defined, waited for example by the will to slow down or by the road state. It calculates the brake force to apply according to a number of pre-defined principles, which results in more fluid transitions and more understandable brake reactions. The ANN is a feed forward trained in existing driving data. It learns the non-linear relationship between metrics such as vehicle speed, torque demand, SOC and road friction. Once trained, the ANN is able to predict the most effective means of spreading the braking force, providing information to the controller as to when to apply braking force on the fly. And the reinforcement learning module makes the system performance even better by utilizing the experience. The DEC problem is modeled as a Markov Decision Process (MDP) by considering the braking system, and the rewards are defined to maximise energy recovery, minimise battery aging, and guarantee passengers' comfort. The optimal brake patterns of the RL agent in different driving cycles are trained by interacting with the simulated environment multiple times.

D. Testing the Simulation and Performance

Once the AI-optimized controller is made, it's subjected to all sorts of driving scenarios in a simulation to see how well it performs. These are stop and go in the city, downhills, highway cruising, and stops. Vehicle weight, battery state, and road incline vary from one condition to another. The total energy recovered, the smoothness of the braking action (assessed numerically by jerk analysis), the stopping distance, and the response time of the system are performance indicators of interest. We compare the AI-based system to the rule-based controller to determine how much better it is at saving energy and controlling the brakes.

E. Analyzing Sensitivity and System Strength

We perform a sensitivity analysis to determine how robust and flexible is the AI-optimized RBS. What we vary are things like the temperature of the battery, the friction coefficient of the tire on the road, the weight of the car, how the driver brakes, we change in a systematic way. We examine how the changes affect the energy recovery, brake performance and system response to assess the strength of the control algorithm.

This procedure ensures that the proposed AI-based RBS is able to operate properly and safely in various real-world conditions.

IV. RESULTS

This section presents the results from a simulation study that was conducted to compare various regenerative braking systems (RBS) for electric vehicles. The testing focused on how effectively the systems recovered energy, how efficiently they stopped, how smooth they were for passengers and how well the batteries were performing. It is found that the AI optimization results in performance improvements, particularly the AI hybrid RBS composed of fuzzy logic, reinforcement learning and neural network-based control methods.

A. Comparing Performance

We compared four different types of RBS, namely a rule-based system, a fuzzy logic, a reinforcement learning and a new AI-optimised RBS. We evaluated all the models in the same driving schedules using MATLAB/Simulink. The analyzed parameters are the recovered energy each cycle, the average deceleration, the response time of the brakes and the State of Charge (SOC) increase in the battery. The overall results are summarized in the table below:

Braking System	Energy Recovered (kWh)	Avg. Deceleration (m/s^2)	Brake Response Time (ms)	Battery SOC Improvement (%)
Traditional RBS	0.96	3.1	180	4.8
Fuzzy Logic RBS	1.12	2.9	160	5.7
RL-Based RBS	1.18	2.8	150	6.1
Hybrid AI RBS (Proposed)	1.31	2.6	140	6.9

The table in which the hybrid AI RBS showed the highest recovery rate of energy to 1.31 kWh, about 36% better than the classical system. It's could only be possible because of AI's ability to identity the driver's behavior and vary the brake load in the fly. The AI system also recorded a lower average deceleration rate (2.6 m/s^2), indicating the brakes were applied more gently. That would make for a smoother ride, and it would also cut down on wear-and-tear. The A.I. system significantly accelerated the brake response time, crucial for safety. It fell to 140 milliseconds, 22 percent faster than the old RBS. The AI controller uses common sense in real time that accelerates engagement, particularly for rapid braking or emergency braking. A second key impact is that the battery SOC is enhanced. The hybrid AI RBS could improve SOC by 6.9%, that is, it was more effective for capturing and utilization of energy. That allows a vehicle to travel farther and to go longer between pulls into a charging station, both of which are important to the long-term success of electric vehicles.

B. Graph-Analysis and the Simulation Based Intuition

Graphical simulations indicated even more that the combined AI system performed better. Regenerative brake power was also smoothly adjusted according to vehicle velocity, road slope, and SOC. The AI controller demonstrated its ability to scala bly modulate brake torque during city stop and go driving in which regenerative braking occurs frequently. This allowed for energy recovery on every trip, as well as gentler rides for passengers. Results of the Simulink simulations showed that the hybrid AI RBS had real-time response capability. The torque curves were more regular, hence there were no abrupt transitions from regenerative to mechanical braking. This eliminated jerky slowing down and ensured that the braking forces were spread evenly across various dynamic loads.

What's more, when testing the AI system in conditions where it had to behave badly, like going downhill or on wet surfaces, the researchers found that it was able to keep the robot stable. The reinforcement learning component altered how the brakes behaved using information from the environment. That kept the wheels from skidding and maintained control. Thus, the hybrid AI-optimized RBS performed better than all other models across all significant performance considerations. Its improved battery range, faster response, more linear braking, and improved energy recovery all point toward an argument for using AI in

EV brake systems to be perhaps one day in future road cars. These findings demonstrate that AI could revolutionise automotive energy management systems.

V. DISCUSSION

The finding of our study indicates a significant advantage in performance and efficiency of AI-optimized regenerative braking systems (RBS) over the conventional braking systems. The proposed hybrid model that integrated FLC, RL, and NN achieved improved energy recovery and faster brake response, as well a smoother deceleration and a higher battery SOC. Such findings illustrate just how potent the force of AI could be in optimizing the braking systems of all-electric cars. The hybrid model succeeds because it can harness the best parts of a number of AI approaches. Fuzzy logic is a simplistic means of decision making and is used adequately when there exist uncertainties and unclear inputs given the first braking situations. This ensures that the brakes work the same way in normal and slightly altered driving conditions. The reinforcement learning component builds upon that, instead learning to adjust the braking behavior based on experience. As the RL agent continues to interact with the simulation environment at each step, it learns how to react to various driving scenarios, such as driving with stop-and-go traffic in a city or cruising along the highway. It learns when to regeneratively brake instead of mechanically braking for best results. Meanwhile, neural networks are really useful in modelling and forecasting complex, nonlinear behavior – such as how much charge a battery can expect to receive in a given scenario. This type of predictive ability is crucial when it comes to maintaining battery health, preventing them from getting overcharged, something that can occur when drivers tap regenerative braking to send excess energy back into a fully charged battery. The neural network works to try and maximize battery lifetime by forecasting the SOC trajectories and incorporating them into the controller logic. But there are also issues that must be addressed and limitations under which when applying the AI-based regenerative braking systems, although the advantages are clear. It is a big concern to train reinforcement learning models. RL algorithms usually require large datasets and significant simulated experience to succeed. In real life, collecting this level of data from driving can be expensive, time-consuming and potentially risky, especially in extreme situations such as emergency stops or in bad weather.

A related issue is that real-time decision making imposes high demand on computing resources. AI models — particularly those that involve deep learning and reinforcement learning — often require a great deal of computing power. It is important that a vehicle on-board hardware can perform computation fast and reliably for safety. This is to say that the hardware and software should be optimised so that they can execute complex control algorithms without missing time or crashing the whole system. Also, although regenerative braking makes the system more efficient, excessive use of it without appropriate control could accelerate battery wear. Under hard braking, especially, repeatedly charging lithium-ion batteries at a fast pace can be painful for cells. As a result, the AI system has to strike a delicate balance between getting as much energy back as possible and keeping the battery healthy. This experiment proved that this hybrid model can sustain SOC trajectory, but the management rules shall be further refined to ensure that these batteries last a long time in the context of different chemistries and ageing profiles.

Finally, the transition from simulation to real-world use can only happen under rigorous security rules and regulations. Brake-assistance AI systems are super important for safety, so they have to pass tons of testing, get certified and be fail-safe for them to make it into cars. To sum it all up, AI-optimized regenerative braking systems represent a promising step forward in electric car technology, but a lot more work, testing and optimization needs to be done before it can be employed in the real world. Work in future should aim to make the system more robust in uncertain situations, decrease the facilitating computing power required, and accelerate the training process through transfer learning. However, the hybrid AI framework proposed in this paper is a perfect outset for the coming generation of intelligent, energy-efficient, and flexible braking systems of EVs.

VI. CONCLUSION

This study has provided a holistic view how the artificial intelligence (AI) can be used in the application of regenerative braking systems (RBS) of an electric car (EVs) with an objective of enhancing recovery of energy, responsiveness of the system, and efficiency of the vehicle. They demonstrate the potential application of AI based methods and a hybrid evolutionary approach of fuzzy logic, reinforcement learning (RL) and neural networks (NN), to significantly outperform traditional braking tactics in terms of several performance measures. The hybrid AI RBS system had superior capabilities in energy recovery, smooth reduction in speed and rapid response of braking time in the simulated driving scenarios and had more stable control of the battery state-of-charge (SOC). In addition to making driving more comfortable and energy efficient, these enhancements also extend the longevity of the braking parts and battery systems, an important consideration for the long-term profitability of EV operations.

The fuzzy logic component of the hybrid model simplified decisions when the driving inputs were vague or uncertain. It also did a good job of managing real-time transitions between regenerative and mechanical braking. Reinforcement learning provided a mechanism for the system to learn from itself, and effectively made braking more and more effective over time, by rewarding the best ways to get energy back. The researchers used neural networks to make predictions, particularly for determining how the battery would behave and adjusting the braking force in real time to prevent overcharging or dissipating energy. Though the findings are promising, there's challenges ahead before these sorts of clever braking systems end up in actual electric vehicles (EVs). Running AI algorithms in real time is extremely computationally demanding, and training RL models requires mountains of data that is difficult to obtain or simulate with a high degree of realism. It is similarly essential to the safety, reliability, and rules-abidance of any AI systems employed in safety-critical scenarios such as brakes.

Future work will include efforts to simplify the system to make it easier to execute, improve the collection of real-world data for training and test on the road and in hardware-in-the-loop settings. Moreover, incorporating RBS optimized for AI into larger vehicle control systems (such as those of self-driving or semi-self-driving cars) could make the system more integrated and the entire car smarter. To cut a long story short, AI-tuned regenerative braking systems are a smart and indeed forward-looking way to address some of present-day EV technology's biggest shortfalls. Smart braking systems Smart braking systems will be an integral part of the smart mobility infrastructure in the future, as the auto industry continues to head toward more automation and sustainability.

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