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Optimization Regenerative Braking in Electric Vehicles Using Q-Learning for Improving Decision-Making in Smart Cities

Pannee Suanpang[1,*], Pitchaya Jamjuntr[2]

1 Department of Information Technology, Faculty of Science & Technology, Suan Dusit University, Bangkok, Thailand. pannee_sua@dusit.ac.th, ORCID 0000-0002-0059-2603

2 Department of Electrical Engineering, Faculty of Engineering, King Mongkut's University of Technology Thonburi, Bangkok, Thailand. pitchaya.jam@kmutt.ac.th, ORCID 0009-0006-4199-4197

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ABSTRACT

The growing prevalence of electric vehicles (EVs) in urban settings underscores the need for advanced decision-making frameworks designed to optimise energy efficiency and improve overall vehicle performance. Regenerative braking, a critical technology in EVs, facilitates energy recovery during deceleration, thereby enhancing efficiency and extending driving range. This study presents an innovative Q-learning-based approach to refine regenerative braking control strategies, aiming to maximise energy recovery, ensure passenger comfort through smooth braking, and maintain safe driving distances. The proposed system leverages real-time feedback on driving patterns, road conditions, and vehicle performance, enabling the Q-learning agent to autonomously adapt its braking strategy for optimal outcomes. By employing Q-learning, the system demonstrates the ability to learn and adjust to dynamic driving environments, progressively enhancing decision-making capabilities. Extensive simulations conducted within a smart city framework revealed substantial improvements in energy efficiency and notable reductions in energy consumption compared to conventional braking systems. The optimisation process incorporated a state space comprising vehicle speed, distance to the preceding vehicle, battery charge level, and road conditions, alongside an action space permitting dynamic braking adjustments. The reward function prioritised maximising energy recovery while minimising jerk and ensuring safety. Simulation outcomes indicated that the Q-learning-based system surpassed traditional control methods, achieving a 15.3% increase in total energy recovered (132.8 kWh), enhanced passenger comfort (jerk reduced to 7.6 m/s^3), and a 13% reduction in braking distance. These findings underscore the system's adaptability across varied traffic scenarios. Broader implications include integration into smart city infrastructures, where the adaptive algorithm could enhance real-time traffic management, fostering sustainable urban mobility. Furthermore, the improved energy efficiency reduces overall energy consumption, extends EV range, and decreases charging frequency, aligning with global sustainability objectives. The framework also holds potential for future EV applications, such as adaptive cruise control, autonomous driving, and vehicle-to-grid (V2G) systems.

* Corresponding author.
E-mail address: pannee_sua@dusit.ac.th

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1. Introduction

The global automotive industry is undergoing a significant transformation, driven by heightened awareness of global warming and the urgent need for more sustainable transportation solutions [1;2]. This shift has been influenced by several factors, including growing environmental concerns, advancements in technology, and government policies aimed at reducing carbon emissions [3;4]. In this context, electric vehicles (EVs) have emerged as a pivotal innovation, offering a pathway to reduce reliance on fossil fuels and mitigate carbon footprints [3-5]. Within smart cities, EVs can integrate seamlessly with renewable energy sources, smart grids, and autonomous systems, forming the backbone of efficient and sustainable urban transportation networks [6]. However, as global energy demand continues to escalate due to population growth, urbanisation, and economic development, developing nations face mounting challenges in managing energy resources effectively [7]. Consequently, there is an urgent need for sustainable energy solutions that balance consumption with environmental and economic considerations [8;9].

In the age of digital disruption, EVs are valued for their environmental and operational efficiency. These cars use an electric motor, a lithium-ion battery pack, and an electronic control unit to optimise energy flow for acceleration. An onboard charger converts grid AC into DC for battery charging, and a regenerative braking technology recovers kinetic energy during deceleration to boost efficiency. Regenerative braking plays a central role in EV operation by converting kinetic energy into electrical energy to recharge the battery. This not only extends the driving range of EVs but also reduces wear on traditional friction brakes, thereby improving their durability [10]. Despite these advantages, conventional rule-based control strategies for regenerative braking often struggle to adapt to the dynamic and unpredictable conditions of real-world driving. Variables such as traffic congestion, road gradients, and diverse driving behaviours can significantly impact the effectiveness of regenerative braking, limiting its potential benefits [11].

The Q-learning approach introduced in this study represents a paradigm shift in regenerative braking control, effectively balancing multiple objectives. Unlike traditional methods that rely on static algorithms and heuristics, our system employs a dynamic learning mechanism that continuously refines its braking strategy in real-time. This approach addresses three critical objectives. First, it maximises energy recovery to extend the driving range of EVs by dynamically adjusting braking intensity based on factors such as road gradient and vehicle speed. This ensures optimal energy recapture without compromising safety [12]. Second, the system prioritises passenger comfort by delivering smooth braking force modulation, thereby minimising jerky movements in stop-and-go traffic scenarios [13]. Third, it enhances safety by adapting braking strategies in real-time, ensuring safe driving distances are maintained while maximising energy efficiency [12-14]. By simultaneously addressing these objectives, our Q-learning-based system outperforms conventional techniques, marking a significant advancement in regenerative braking efficiency.

Furthermore, our implementation of Q-learning incorporates a uniquely designed state and reward function tailored to the dynamics of regenerative braking. This allows the algorithm to effectively capture the complexities of diverse driving scenarios. The reward function incentivises energy recovery while penalising deviations from desired braking behaviours, ensuring robust learning and adaptation over time. This design enhances the system's potential for real-world application, offering a scalable and adaptable solution for future EV technologies [15].

Q-learning, a robust reinforcement learning technique, is highly effective for optimising control systems in dynamic environments, such as regenerative braking in EVs. The following outlines its core principles and their applicability to this context [1;2]:

States: In Q-learning, the system operates within a predefined set of states that represent various conditions or scenarios. For regenerative braking control, these states may include parameters such as vehicle speed, acceleration, distance to the vehicle ahead, and road gradient. An effective state representation enables the Q-learning agent to make informed decisions by capturing critical aspects of the driving environment [16].

Actions: The Q-learning agent can execute specific actions within each state. In the context of regenerative braking, these actions may involve modulating the regenerative braking torque level or transitioning between regenerative and friction braking to achieve optimal control [16;17].

Rewards: To guide the learning process, Q-learning employs a reward function that assigns numerical values to the outcomes of actions taken in specific states. For regenerative braking, the reward function can be designed to encourage desirable behaviours, such as maximising energy recovery, minimising passenger discomfort caused by abrupt braking, and maintaining a safe following distance [18].

Q-value table: At the core of Q-learning is the Q-value table, which stores the estimated value (Q-value) of taking a particular action in each state. As the agent interacts with the environment, it receives rewards and updates the Q-value table accordingly [19].

The primary advantage of Q-learning for regenerative braking control lies in its adaptability. Unlike traditional rule-based approaches, which rely on predefined rules for every conceivable driving scenario, Q-learning can continuously learn and refine its braking strategy based on real-world experiences. This adaptability makes Q-learning particularly well-suited for addressing the diverse and unpredictable driving conditions encountered by EVs [20;21]. By leveraging this capability, Q-learning offers a dynamic and scalable solution for enhancing the efficiency, safety, and comfort of regenerative braking systems in EVs.

1.1 Research Gaps and Challenges

Table 1 provides a comprehensive analysis of the core challenges and limitations associated with traditional braking systems in vehicles. The table identifies several domains where research gaps exist and outlines the specific problems that need to be addressed. Key issues include the insufficient recovery of energy during vehicle deceleration without compromising vehicle dynamics, emergency braking strategies that prioritise rapid stopping over passenger comfort, and rigid prescriptive frameworks that fail to account for contextual road conditions, thereby increasing risk.

Table 1
Summary of Problem Statement and Research Gaps

Aspect	Problem/Challenge
Energy Recovery	Traditional braking systems do not optimize energy recovery, leading to less efficient use of the vehicle's available kinetic energy during deceleration [21].
Passenger Comfort	Aggressive braking strategies can cause jerky movements, impacting passenger comfort, particularly in stop-and-go traffic situations [22].
Safety	Fixed rule-based braking systems may not adapt well to varying road conditions, leading to potential safety risks, such as longer stopping distances [23;24].
Adaptability	Conventional systems lack adaptability to dynamic driving environments, such as changes in road incline or traffic conditions, limiting performance optimization [24;25].
Real-Time Learning	Current control strategies do not incorporate real-time learning, making it challenging to optimize braking performance based on real-world data [25].
Reward Function Design	Traditional systems struggle to balance multiple objectives (e.g., energy recovery, comfort, safety) due to inadequate reward function design in control systems [25;26].

Additionally, traditional systems lack the adaptability to respond to changing driving scenarios and do not incorporate real-time learning mechanisms, which limits their potential for improvement. Furthermore, the design of reward functions for braking controllers is often imprecise, creating challenges in balancing competing objectives such as energy efficiency, passenger comfort, and safety.

1.2 Objectives and Scope

This study introduces an innovative approach to optimising regenerative braking control in EVs through the application of Q-learning, a form of reinforcement learning. Unlike conventional static rule-based methods, Q-learning empowers the system to learn from experience and dynamically adjust its braking behaviour in response to real-time driving conditions. The proposed approach seeks to enhance regenerative braking efficiency by addressing multiple objectives simultaneously. Firstly, it aims to maximise energy recovery to extend the driving range of EVs by dynamically adjusting braking intensity based on real-time factors such as road gradient and vehicle speed [16]. Secondly, it prioritises passenger comfort by ensuring smooth modulation of braking force, thereby minimising discomfort during sudden braking manoeuvres [27]. Thirdly, it maintains driving safety by continuously adapting the braking strategy to ensure safe following distances and effective energy utilisation [28]. By harnessing Q-learning's inherent ability to adapt and learn from diverse driving conditions, this approach represents a significant advancement over traditional static methods.

1.*3 Contribution*

This study presents a novel implementation of Q-learning, a reinforcement learning technique, for managing regenerative braking in EVs. Unlike fixed rule-based schemes, this approach dynamically adapts to real-time driving data, enhancing energy recovery and extending driving range. By employing a well-structured reward function, the system achieves a balanced optimisation of energy recovery, passenger comfort, and driving safety through a unified multi-objective framework. A key contribution of this work is the demonstrated applicability of the Q-learning framework to diverse driving conditions, showcasing its effectiveness in high-complexity environments. Extensive simulations and experimental validation provide robust evidence of the superiority of the Q-learning approach over traditional braking methods [12;29;30]. By offering a dynamic, adaptive, and efficient solution, this Q-learning-based approach represents a significant advancement in regenerative braking technology, positioning it as a transformative innovation for modern EVs [17]. It not only addresses existing limitations but also sets the stage for future developments in intelligent and sustainable transportation systems.

2. **Literature Review**

2.1 Regenerative Braking Systems

Regenerative braking systems (RBS) play a pivotal role in improving the energy efficiency of EVs. These systems capture kinetic energy, which is conventionally dissipated as heat during braking, and convert it into electrical energy for storage in the vehicle's battery. The effectiveness of RBS has been extensively researched, with notable progress achieved in both theoretical frameworks and practical implementations. These advancements have contributed to the development of more efficient and sustainable energy management solutions in modern EVs.

2.1.1 Basic Principles and Benefits

Regenerative braking operates by harnessing the vehicle's kinetic energy through an electric motor during deceleration, converting it into electrical energy. This recovered energy is redirected to the battery, thereby enhancing energy efficiency and reducing overall consumption.

(1) Basic Principles

1. Energy Conversion Mechanism: Regenerative braking functions by reversing the electric motor's operation during deceleration. Rather than consuming electrical energy to propel the wheels, the motor instead acts as a generator, converting the vehicle's kinetic energy into electrical energy. This process generates a back electromotive force (EMF), which is subsequently harnessed to produce electricity [31;32].

2. Motor Control Strategies: The efficiency of regenerative braking depends on advanced motor control strategies. These involve regulating the braking force applied and managing the transition between regenerative and friction braking [33].

3. Energy Storage and Management: The electrical energy generated is directed to the vehicle's battery or energy storage system. Efficient energy management systems are crucial for balancing energy recovery with battery longevity, preventing overcharging, and ensuring optimal utilisation of recovered energy to extend the vehicle's driving range [34].

(2) Benefits

1. Increased Energy Efficiency: Research indicates that regenerative braking systems can recover up to 70% of the energy typically lost during braking [35]. This substantial energy recovery extends the driving range of EVs, enhances overall efficiency, reduces the frequency of charging, and lowers operational costs [36].

2. Reduced Wear on Mechanical Brakes: By decreasing reliance on conventional friction brakes, regenerative braking systems reduce mechanical wear, leading to lower maintenance costs and an extended lifespan for braking components. This improvement enhances the vehicle's durability and reliability [37].

3. Enhanced Driving Dynamics: Regenerative braking contributes to smoother deceleration, minimising abrupt braking and improving driving dynamics. This results in a more comfortable passenger experience while enhancing vehicle control, particularly in dynamic driving conditions [38].

4. Environmental Impact: By increasing energy efficiency and reducing the need for frequent recharging, regenerative braking systems help lower a vehicle's carbon footprint [39].

Figure 1 provides a step-by-step visual representation of the regenerative braking process in an EV [40;41]:

Kinetic Energy Diversion: As braking begins, the vehicle's kinetic energy is redirected from the wheels to the motor, preventing its dissipation as heat.

Motor Shaft Rotation: The redirected kinetic energy drives the motor shaft, causing the motor to function as a generator that converts mechanical energy into electrical energy.

Energy Conversion: The motor transforms kinetic energy into electrical energy, mirroring the operation of a generator.

Electrical Energy Routing: The generated electricity is channelled into the vehicle's battery, storing energy that can later be utilised to power the vehicle.

The illustration underscores the efficiency and sustainability of regenerative braking in EVs by demonstrating how these systems capture and reuse energy, thereby improving overall energy efficiency.

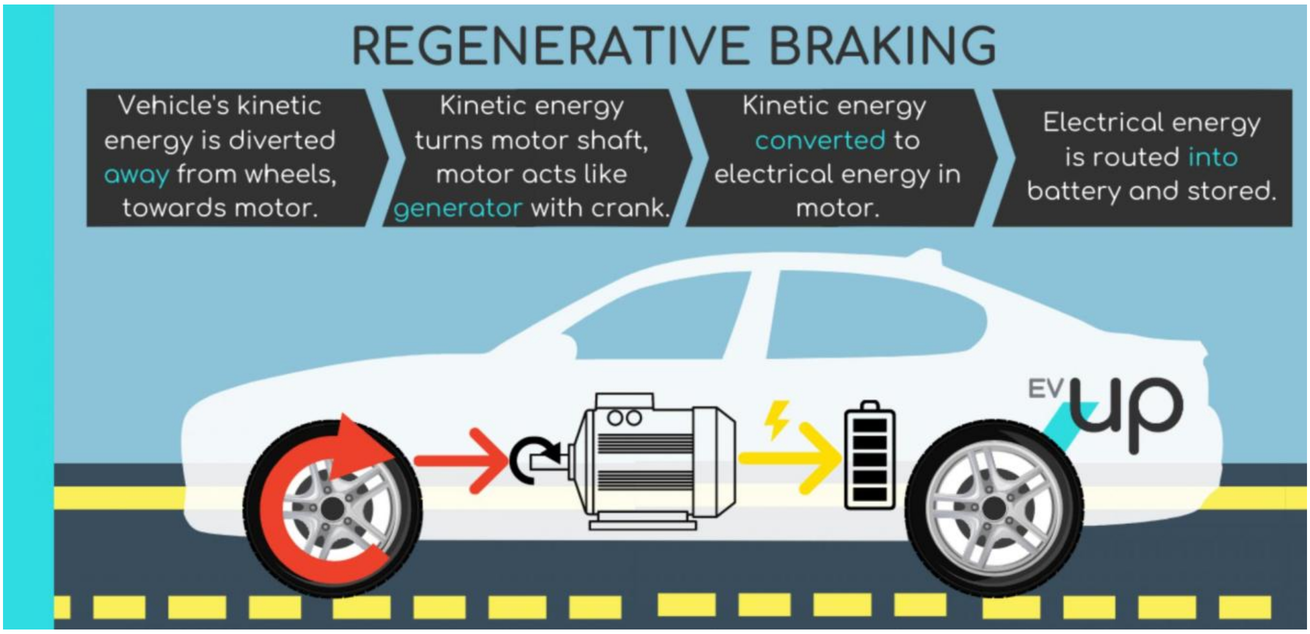

Fig 1. Regenerative Braking in EV

2.1.2 Technological Advances and Challenges

Technological advancements have markedly improved the efficiency and reliability of RBS, with key developments in power electronics, battery management systems, and control algorithms. These innovations have enhanced energy recovery and integration with EV systems.

1. Power Electronics: Progress in power electronics has resulted in more efficient and compact inverters and converters, which are essential for RBS. Modern power electronics enable precise control of the electric motor during braking, enhancing energy conversion efficiency and minimising losses. The introduction of silicon carbide (SiC) and gallium nitride (GaN) semiconductors has further improved the performance and thermal management of power electronic components [42].

2. Battery Management Systems (BMS): Advances in BMS technology have optimised the integration of RBS with vehicle batteries. Sophisticated BMS algorithms monitor and regulate battery charge levels, health, and temperature, ensuring efficient storage and utilisation of recovered energy. This optimisation prevents overcharging, extends battery lifespan, and enhances the overall effectiveness of regenerative braking [1] [43;44].

3. Control Algorithms: The development of advanced control algorithms has significantly improved the adaptability of RBS to various driving conditions. Techniques such as model predictive control (MPC) and adaptive control strategies dynamically adjust braking force to maximise energy recovery while maintaining vehicle stability and passenger comfort [45;46].

2.1.3 Challenges

1. Balancing Regenerative and Mechanical Braking: Optimising the integration of regenerative and mechanical braking remains a key challenge. Regenerative braking must complement mechanical braking to ensure both safety and performance under various driving conditions. In scenarios such as emergency stops or low-speed manoeuvres, regenerative braking alone may be insufficient, necessitating the use of mechanical brakes. Developing seamless control strategies to blend these braking methods effectively remains a complex task [47].

2. Complex Driving Conditions: RBS must function efficiently across diverse driving conditions, including varying road gradients, traffic patterns, and driving behaviours. Maintaining optimal energy recovery while ensuring vehicle safety requires advanced sensor technologies and robust

control algorithms. Adapting to these complexities without compromising performance or safety presents a significant challenge [48;49].

3. System Reliability and Durability: The long-term reliability and durability of RBS are crucial for their broader adoption. Components such as motors, inverters, and batteries must endure continuous operational stresses while maintaining high performance. Addressing issues related to component wear, thermal management, and system integration is essential to ensuring long-term reliability and minimising maintenance costs [50].

2.2 Machine Learning and Optimization

2.2.1 Machine Learning Techniques

1. Reinforcement Learning (RL): RL, a subset of machine learning, enables an agent to learn decision-making by interacting with its environment and receiving feedback in the form of rewards or penalties. In RBS, RL algorithms continuously refine braking strategies using real-time data, including vehicle speed, road gradient, and driver behaviour. This adaptability enhances energy recovery efficiency and overall system performance [17;51].

2. Q-learning: As a model-free RL algorithm, Q-learning seeks to determine the optimal action-selection policy within a given environment. In RBS applications, it identifies the most effective braking actions by estimating Q-values for state-action pairs. This approach optimises energy recovery by dynamically adjusting braking intensity and blending regenerative and friction braking in response to driving conditions [16;52].

2.2.2 Applications and Benefits

1. Real-Time Adaptation: A key advantage of employing Q-learning in regenerative braking systems (RBS) is its capacity to adapt in real-time to varying driving conditions and driver behaviours. Unlike static, rule-based systems that operate on predefined algorithms, Q-learning dynamically refines braking strategies based on real-time data. This adaptability ensures the system can effectively manage diverse driving scenarios, such as sudden stops, high-speed deceleration, or varying road gradients, resulting in enhanced energy efficiency and driving comfort [53].

2. Enhanced Energy Recovery: Q-learning optimises the balance between regenerative and friction braking by learning from past experiences and continuously updating its control policy. Studies have demonstrated that Q-learning-based approaches can significantly improve energy recovery rates compared to conventional methods [52;53].

3. Customisation and Personalisation: Machine learning techniques, including Q-learning, enable the customisation of braking strategies to align with individual driving styles. By analysing driver-specific behaviours, the system can tailor braking responses to match personal preferences and habits, thereby enhancing the overall driving experience and operational efficiency [54].

4. Integration with Advanced Driver Assistance Systems (ADAS): Q-learning can be seamlessly integrated with other ADAS features to develop a more cohesive and intelligent braking system. By combining data from multiple sensors and subsystems, Q-learning-based RBS can improve decision-making processes, enabling better coordination between braking and other vehicle control mechanisms [55;56]. This integration supports the development of smarter, safer, and more efficient transportation systems.

2.2.3 Implications for Smart Cities

The optimization of regenerative braking systems (RBS) holds significant implications for the development and functioning of smart cities. Smart cities aim to enhance urban living by integrating advanced technologies and data-driven solutions, promoting efficiency, sustainability, and improved quality of life. Optimized RBS can be pivotal in achieving these goals by addressing several key aspects of urban transportation and energy management [1;2;52].

(1) Energy Efficiency and Sustainability

1. Reduction in Energy Consumption: Optimised RBS can significantly lower the energy consumption of urban transportation networks by recovering and reusing kinetic energy during braking, thereby reducing reliance on external energy sources. This is particularly beneficial in smart cities, where minimising energy demand aligns with broader sustainability objectives. Research suggests that effective energy recovery through regenerative braking can reduce energy consumption in EVs by up to 30% [57].

2. Decreased Carbon Footprint: Integrating EVs with optimised RBS in smart cities contributes to reducing the transportation sector's carbon footprint [58].

3. Enhanced Urban Air Quality: Greater efficiency in RBS positively affects urban air quality by lowering emissions from conventional vehicles. The widespread adoption of EVs with advanced regenerative braking helps reduce particulate matter and other pollutants, contributing to healthier urban environments and supporting smart cities' objectives of cleaner and more sustainable living spaces [59].

(2) Integration with Smart Infrastructure

1. Synergy with Smart Grid Systems: The integration of optimised RBS with smart grid systems enhances energy management by coordinating with grid demands and energy storage solutions. This synergy enables balanced supply and demand, optimised energy distribution, and improved grid stability. Such integration supports the efficient utilisation of renewable energy sources and strengthens the resilience of urban energy networks [60].

2. Data-Driven Insights and Management: The data generated by optimised RBS can be leveraged for advanced traffic management and urban planning. Real-time information on braking patterns, energy recovery rates, and vehicle performance provides valuable insights for city planners and traffic managers. This data-driven approach facilitates the design of more efficient transportation infrastructure and improves traffic flow, enhancing overall urban mobility [61;62].

(3) Supporting Smart Mobility Solutions

1. Enhancing Autonomous Vehicle Operations: Optimising RBS is essential for the efficient operation of autonomous vehicles in smart cities. These vehicles rely on advanced algorithms and real-time data for navigation and decision-making. Improved regenerative braking enhances adaptability to varying conditions, ensuring greater safety and performance in complex urban environments [63].

2. Promoting Electrification of Public Transportation: The implementation of optimised RBS in public transport vehicles, such as buses and trams, supports the transition towards electrified transit systems. By increasing energy recovery efficiency, these systems enhance the feasibility and appeal of electric public transport, contributing to the sustainability of urban mobility networks [64].

The authors in [65] examined the implementation of RBS in EVs, highlighting their role in improving energy efficiency and reducing environmental impact. The study emphasised the need for optimised regenerative braking strategies to maximise energy recovery while maintaining vehicle performance. Additionally, it investigated the influence of regenerative braking on vehicle dynamics and energy consumption in HEVs, underscoring the significance of control algorithms in ensuring seamless integration with traditional friction braking systems and achieving optimal energy recovery [66]. Recent studies have further advanced understanding of RBS. Sharma et al. proposed an innovative approach to enhance regenerative braking efficiency by integrating advanced energy storage systems, such as supercapacitors, with conventional battery packs. Q-learning, with its capacity for real-time learning and adaptation, offers a promising avenue for the development of more intelligent and adaptive regenerative braking control strategies. This study proposes a novel approach leveraging Q-learning to optimise regenerative braking control, considering vehicle dynamics, energy recovery, and passenger comfort for a more comprehensive solution [28;67;68].

2.3 Q-Learning for Control Optimization

Q-learning, a reinforcement learning technique, has proven to be a highly effective method for optimising control systems in dynamic environments. Earlier research [19] established the foundation of Q-learning by introducing the concept of learning action values through trial-and-error interactions with the environment. Since then, Q-learning has been applied across multiple fields, including robotics, finance, and transportation.

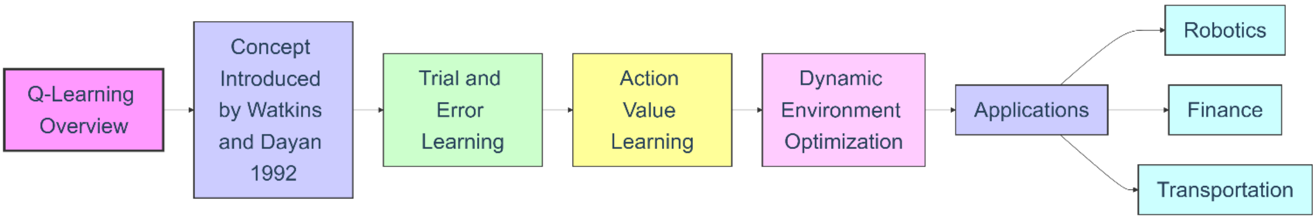

Fig.2. Overview of Q-Learning and Its Applications

Figure 2 presents a detailed overview of Q-learning, a reinforcement learning technique utilised for optimising control systems. The diagram outlines its foundational principles, as introduced by [19], focusing on the trial-and-error learning process and the development of action-value learning. It further illustrates the application of Q-learning in dynamic environment optimisation, highlighting its versatility across multiple domains, including robotics, finance, and transportation. In vehicle control optimisation, Q-learning has shown considerable potential in adapting to varying driving conditions and learning optimal control strategies. This approach utilises reinforcement learning's trial-and-error mechanism to refine control policies in real time [69]. [70] demonstrated the effectiveness of Q-learning in autonomous vehicle navigation by developing algorithms that enable collision-free trajectory learning in complex and dynamic environments. Similarly, the authors in [56] applied Q-learning to optimise vehicle speed control, aiming to minimise energy consumption and emissions, particularly in urban driving scenarios.

Further advancements in Q-learning for control optimisation include its implementation in adaptive cruise control systems, where it assists vehicles in maintaining optimal speed and distance relative to surrounding traffic. Recent studies, such as those by [27], have explored the integration of Q-learning with deep learning techniques to enhance performance in highly variable traffic conditions. These studies highlight Q-learning's ability to develop complex control policies by combining value-based learning with neural network approximators [36]. Furthermore, Q-learning has been extended to multi-agent settings, facilitating coordination among multiple vehicles to optimise traffic flow and enhance overall system efficiency. Research by [63] explores the application of multi-agent Q-learning in managing vehicle platoons, demonstrating how coordinated control strategies improve traffic management and fuel efficiency.

2.4 Integration of Q-Learning with Regenerative Braking

Integrating Q-learning with regenerative braking systems presents an advanced approach to optimising vehicle performance and energy efficiency. As a reinforcement learning technique, Q-learning enables the dynamic adjustment of regenerative braking strategies based on real-time environmental interactions. This adaptability is particularly advantageous for responding to varying driving conditions, including traffic congestion, road inclines, and diverse driver behaviours [28;67] Research by [63] applied Q-learning to optimise regenerative braking control in electric buses, demonstrating significant improvements in energy recovery and operational efficiency. By leveraging Q-learning algorithms, the study enhanced the adaptability of regenerative braking systems, resulting in more effective energy recovery and improved overall system performance. Further investigations, such as those by, have extended this work by incorporating deep Q-learning methods to address complex driving scenarios more effectively. Additionally, [71] explored Q-learning's potential in balancing regenerative and conventional braking systems, highlighting its ability to optimise the trade-off between energy recovery and braking performance, particularly in mixed driving conditions.

2.5 Related Study

In recent years, the application of Q-learning in EV management has attracted considerable attention, particularly in optimising battery performance and sustainability. A notable study by [1] provides a comprehensive analysis of Q-learning's role in enhancing EV battery management. Research by [43] addresses key challenges, including extending battery life, improving energy efficiency, and reducing operating costs. Their approach involves developing a Q-learning framework that dynamically optimises battery usage by considering various state variables such as state of charge, state of health, driving patterns, and charging infrastructure. The framework's ability to learn from past experiences allows for more informed and efficient real-time decision-making, ultimately improving battery performance and sustainability.

This research is particularly relevant to the present study, as it highlights Q-learning's potential in optimising EV components beyond battery management. By drawing on the methodologies and findings of [1;2;51;52], this study aims to explore further Q-learning's application in regenerative braking optimisation. Insights from related research will serve as a foundation for developing a more efficient and sustainable regenerative braking system, supporting the broader objective of integrating smart technologies into urban transportation. Furthermore, [72] examined the acceptance of EVs in Thailand, focusing on environmental considerations and their influence on awareness and value perception. Their findings indicate that while environmental benefits contribute to EV adoption, the inadequacy of charging infrastructure remains a critical barrier. To facilitate greater EV adoption, policies and programmes should emphasise trust-building, promote environmental advantages, and highlight the overall value of EVs.

3. Methodology

3.1 Mathematical Model

The mathematical model for optimising regenerative braking control using Q-learning was developed based on a dynamic decision-making framework that adjusts braking strategies in response to real-time driving conditions. This section defines the fundamental components of the system, including the state space, action space, and reward function, all of which contribute to optimising energy recovery, ensuring safety, and enhancing passenger comfort.

State Space (S):

The state space S represents the set of relevant parameters describing the vehicle's operating conditions at any given time. These parameters may include:

$$\boldsymbol{S_t} = \{\boldsymbol{v_t}, \boldsymbol{a_t}, \boldsymbol{\theta_t}, \boldsymbol{E_b}(t), \boldsymbol{d_s}(t)\} \quad \textbf{(1)}$$

Where:

v_t: Vehicle speed at time t

a_t: Vehicle acceleration at time t

θ_t: Road gradient or slope at time t

$E_b(t)$: Battery energy level at time t

$d_s(t)$: Safe braking distance at time t

These variables are critical in evaluating the vehicle's braking requirements and energy recovery potential.

Action Space (A):

The action space A defines the possible braking forces or regenerative braking strategies that can be applied. These actions can be discrete, representing different levels of braking intensity:

$$\boldsymbol{A_t} = \{\boldsymbol{a_1}, \boldsymbol{a_2}, \boldsymbol{a_3}, \dots, \boldsymbol{a_n}\} \quad \textbf{(2)}$$

Where a_i represents a specific braking force, including regenerative and friction braking levels. For example:

$\boldsymbol{a_1}$: No braking (coasting)

$\boldsymbol{a_2}$: Low regenerative braking

$\boldsymbol{a_3}$: Medium regenerative braking

$\boldsymbol{a_n}$: Full regenerative braking combined with friction braking

Transition Dynamics ((T):

The transition dynamics describe how the system evolves from one state to another based on the selected action. These dynamics are governed by the vehicle's physical model and external conditions, including road gradient, traffic density, and driver behaviour. The state transition can be written as:

$$\boldsymbol{P(s_{+1}|s_t, a_t) = P(v_{t+1}, a_{t+1}, \theta_{t+1}, E_b(t+1), d_s(t+1)|s_t, a_t)} \quad \textbf{(3)}$$

Where $\boldsymbol{P(s_{+1}|s_t, a_t)}$ represents the probability of transitioning to state $\boldsymbol{s_{+1}}$ given the current state $\boldsymbol{s_t}$ and action $\boldsymbol{a_t}$.

Reward Function (R):

The reward function in the Q-learning model is designed to balance competing objectives, ensuring optimal regenerative braking performance. It provides feedback on actions taken, guiding the system toward decisions that maximise energy recovery while maintaining passenger comfort and safety.

$$\boldsymbol{R(s_t, a_t) = w_1 \cdot E_{r(t)} + w_2 \cdot C(t) - w_3 \cdot J(t)} \quad \textbf{(4)}$$

Where:

$E_{r(t)}$: Energy recovered through regenerative braking at time \(t\)

$C(t)$: Passenger comfort, often modeled as minimizing jerk (rate of change of acceleration)

$J(t)$: Jerk, representing the rapid changes in deceleration that may lead to discomfort or unsafe driving

w_1, w_2, w_3: Weighting factors that determine the importance of each term in the reward function

The term $E_r(t)$ can be calculated as:

$$\boldsymbol{E_r(t) = \int_{t_0}^{t_1} F_b(t) \cdot v(t)\, dt} \quad \textbf{(5)}$$

Where $F_b(t)$ is the braking force applied at time t, and $v(t)$ is the vehicle's speed. This integral represents the amount of energy recovered during braking, which is maximized by choosing the optimal braking force $F_b(t)$.

Q-Learning Algorithm:

The Q-learning algorithm seeks to optimize the expected cumulative reward over time by learning the optimal policy π^* that maximizes the action-value function $\boldsymbol{Q(s_t, a_t)}$, where:

$$\boldsymbol{Q(s_t, a_t) = E\left[\sum_{k=0}^{\infty} \gamma^k R(s_{t+k}, a_{t+k})\right]} \quad \textbf{(6)}$$

Where:

$Q(s_t, a_t)$ is the expected cumulative reward of taking action a_t in state s_t.

γ is the discount factor $(0 < (\gamma) < 1)$ that represents the importance of future rewards

The update rule for the Q-function at each step \(t\) is:

$$\boldsymbol{Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[\, R(s_t, a_t) + \gamma \max_{a'} Q(s_{t+1}, a') \quad - Q(s_t, a_t)]} \quad \textbf{(7)}$$

Where:

α is the learning rate $(0 < (\alpha) < 1)$

$\max_{a'} Q(s_{t+1}, a')$is the maximum expected future reward for the next state s_{t+1}

Decision-Making Process:

The Q-learning model supports decision-making by enabling the system to learn optimal braking strategies that adapt to varying driving conditions in real time. As the vehicle encounters different scenarios—such as road inclines, sudden stops, or varying traffic patterns—the Q-learning agent updates its knowledge of the environment and selects the braking action $\boldsymbol{a_t}$ that maximizes the long-term reward $\boldsymbol{Q(s_t, a_t)}$. The braking system dynamically adjusts strategies to maximise energy recovery, minimise jerk for passenger comfort, and maintain safe braking distances across varying road and traffic conditions.

3.2 Q-Learning Compared to Baseline Data

Q-learning outperforms baseline methods by dynamically optimising braking through real-time learning. Unlike fixed-rule systems, it adapts to driving conditions, enhancing energy recovery, comfort, and safety.

1. Energy Efficiency: Adjusts braking to maximise kinetic energy recovery, outperforming static systems.
2. Passenger Comfort: Minimises jerk by fine-tuning braking parameters based on real-time feedback.
3. Safety Enhancement: Adapts braking to road conditions, reducing stopping distances.
4. Environmental Adaptability: Responds to changes in incline, traffic, and weather, unlike rigid baseline models.
5. Multi-Objective Optimisation: Balances efficiency, comfort, and safety through experience-based learning.

Q-learning's real-time adaptability ensures more efficient, safer, and smoother braking in EVs.

3.3 Research Framework

The research framework for regenerative braking optimisation with Q-learning, illustrated using Mermaid, follows a systematic approach. It starts with problem identification (A) and a literature review (B) to establish research objectives (C) and formulate hypotheses (D). An experimental framework (E) guides data collection (F) and Q-learning implementation (G). Performance evaluation (H) and analysis (I) lead to interpreting findings (J), drawing conclusions (K), and providing recommendations (L). Future research directions (M) are proposed before concluding the study (N).

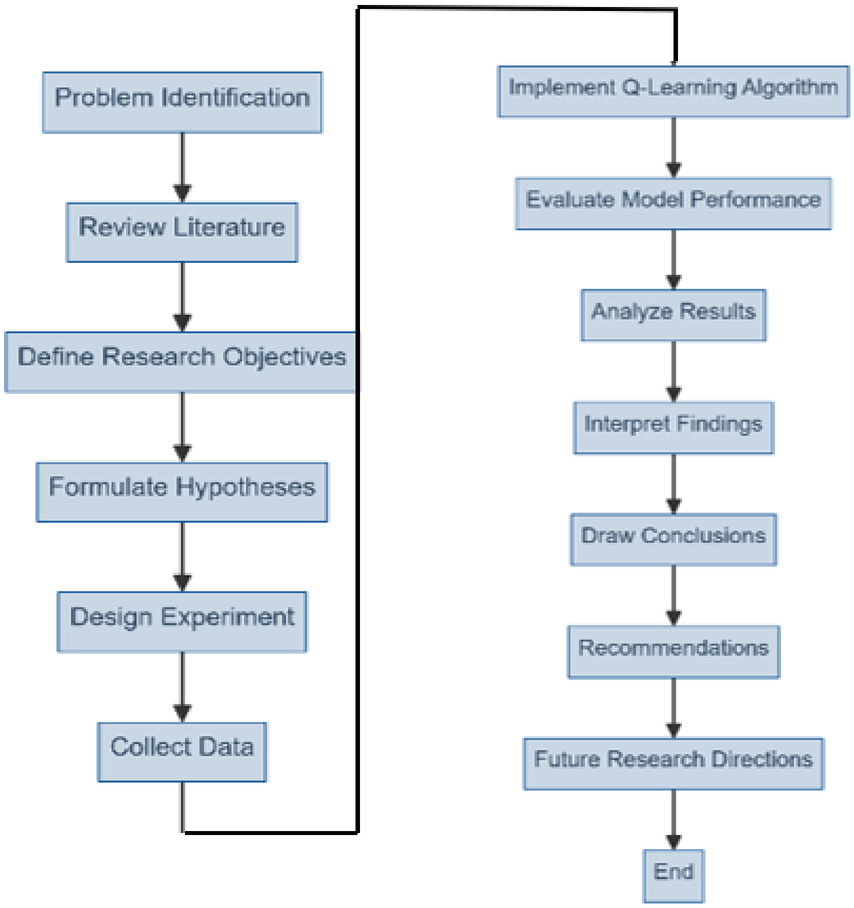

Fig.3. Research Framework

3.4 Decision Making Framework

The Q-learning-based regenerative braking framework optimises braking actions in EVs by continuously learning from real-time data on speed, battery level, and road conditions. The Q-learning agent navigates a state space representing operational parameters and selects actions from various braking strategies. A reward function evaluates outcomes based on energy recovery, comfort, and safety, guiding the learning process. By balancing exploration and exploitation, the agent updates its Q-values, refining decision-making over time. The final output ensures efficient braking, maximising energy recovery while maintaining safety and comfort. This iterative approach strengthens regenerative braking optimisation in EVs.

Figure 4 illustrates the decision-making framework of a Q-learning-based regenerative braking system in EVs. The Q-learning agent interacts with the vehicle environment, gathers data, and optimises braking actions to balance energy recovery, comfort, and safety.

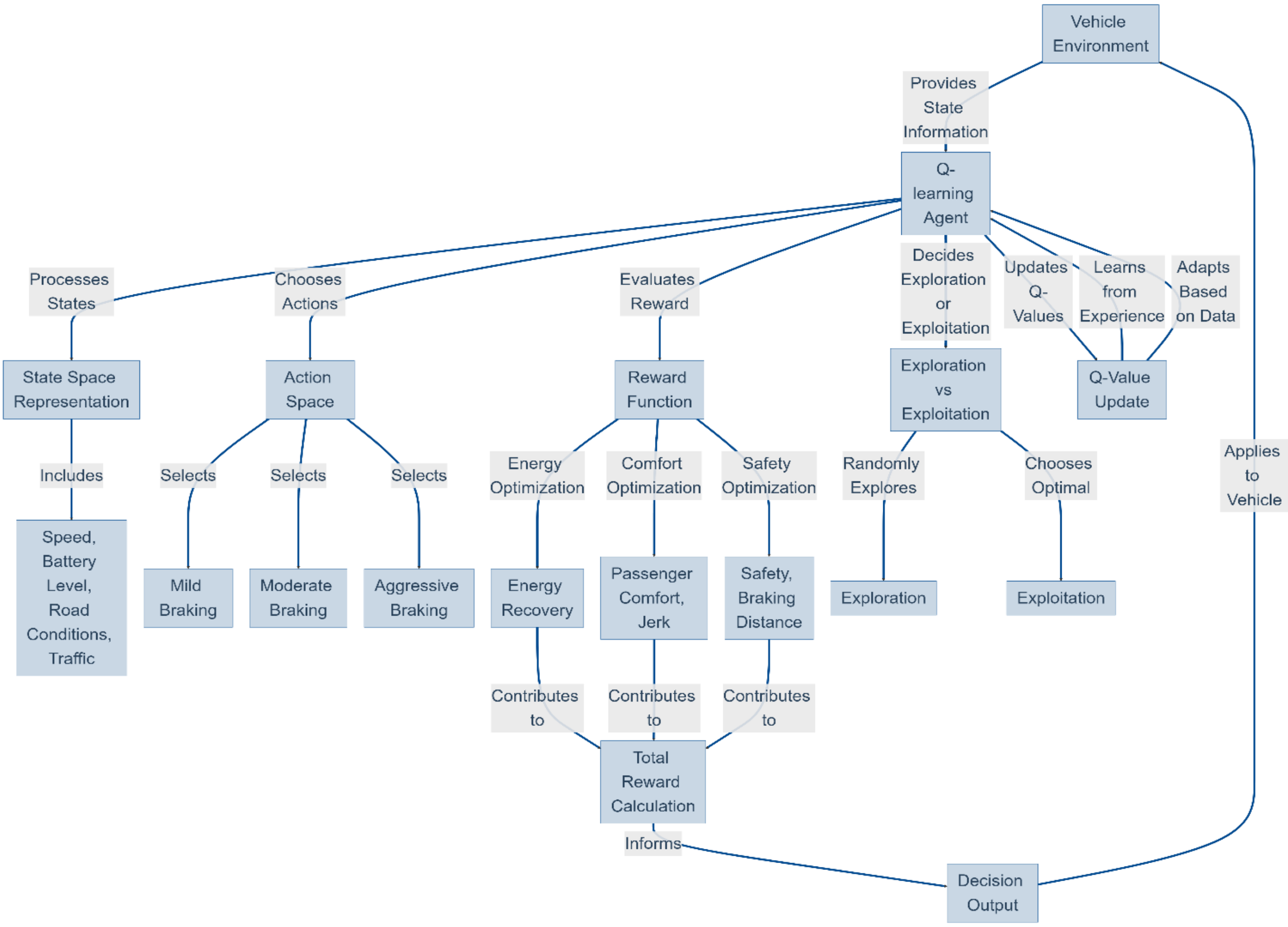

Fig.4. Q-learning-Based Regenerative Braking Decision-Making Framework

Vehicle Environment: Provides real-time state information, including speed, battery level, road conditions, and traffic patterns.

Q-Learning Agent: Learns optimal braking strategies through interaction and reward-based updates.

State Space: Represents key variables, such as speed and battery level.

Action Space: Includes possible braking actions, from mild to aggressive.

Reward Function: Assigns rewards based on energy recovery, comfort (jerk), and safety (braking distance).

Exploration vs. Exploitation: Balances trying new actions with using known optimal strategies.

Q-Value Update: Continuously refines action-state rewards based on experience.

Decision Output: Selects the optimal braking action and applies it, completing the feedback loop.

This framework enables iterative learning, enhancing regenerative braking for improved efficiency, safety, and comfort.

3.4 Regenerative Braking Optimization with Q-Learning

This section examines the implications of Q-learning for regenerative braking control in EVs, focusing on its impact on energy efficiency, safety, and driving comfort.

3.4.1 Defining System States

The Q-learning agent must perceive its environment to optimise braking decisions. Key states include:

Vehicle Speed: Determines available kinetic energy for regeneration.

Vehicle Acceleration: Positive acceleration reduces braking force, while deceleration enhances energy recovery.

Distance to Preceding Vehicle: Ensures safe following distances and prevents abrupt braking.

Road Grade: Uphill inclines require less regenerative braking, while downhill slopes maximise energy capture.

3.4.2 Available Control Actions

The Q-learning agent influences braking behaviour through:

Regenerative Braking Torque Level: Adjusts electrical resistance applied to the motor for energy regeneration, either continuously or in discrete steps.

Friction Braking Engagement: Activates traditional brakes when higher braking force is needed, or regenerative braking reaches its limit.

3.4.3 Designing the Reward Function

The reward function shapes the agent's learning by incentivising:

Energy Recovery: Positive rewards for maximising captured energy, promoting efficient regenerative braking.

Jerk Minimisation: Negative rewards for abrupt braking to encourage smoother deceleration.

Safe Following Distance: Rewards for maintaining a minimum safe gap from preceding vehicles.

3.4.4 Q-Learning Algorithm Implementation

The Q-learning algorithm functions iteratively, continuously learning and updating its Q-value table:

State Observation: The agent assesses the current state of the system, considering factors such as vehicle speed and the distance to the preceding vehicle.

Action Selection: Based on the observed state and the Q-value table, the agent chooses an action, such as adjusting regenerative braking torque. An exploration-exploitation strategy, such as epsilon-greedy, ensures a balance between selecting the best-known action (exploitation) and testing new actions (exploration) to enhance learning.

Action Execution: The selected action is implemented in the regenerative braking system, influencing vehicle deceleration.

Reward Reception: The environment provides a reward signal based on the action’s outcome, with positive rewards for high energy recovery and negative rewards for abrupt braking.

Q-value Update: The Q-value table is updated based on the received reward, refining the agent’s understanding of the optimal actions in different states. This iterative process allows the agent to progressively improve its braking strategy.

By continuously interacting with the environment, receiving rewards, and updating the Q-value table, the Q-learning agent adapts to diverse driving conditions, optimising regenerative braking control for improved energy recovery while ensuring safety and passenger comfort.

3.5 Flowchart

Figure 5 presents a flowchart outlining the sequential steps in Q-learning, ensuring effective control policy learning.

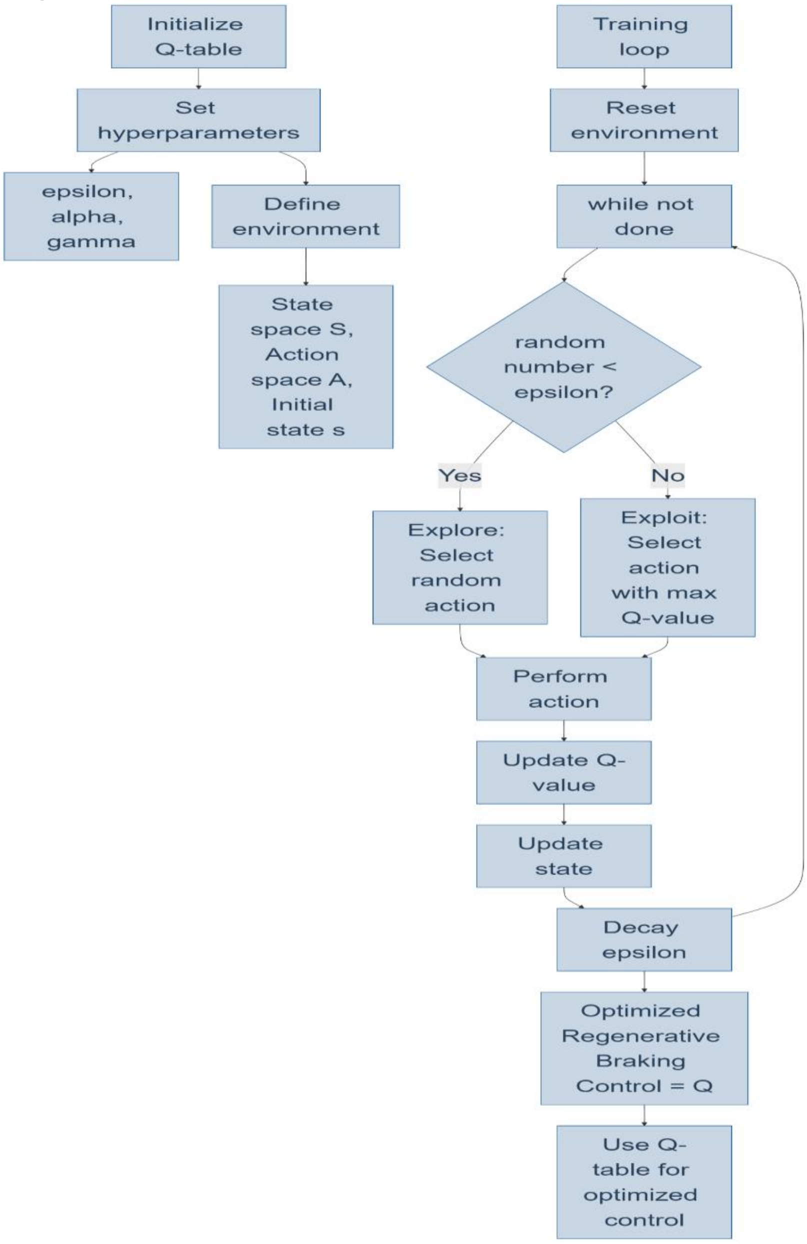

Fig.5. Flowchart Showing Steps in Q-Learning for the Optimization of Regenerative Breaking

Initialise Q-Table: Set up the Q-table by assigning all values to zero.

Set Hyperparameters: Define key parameters, including learning rate, discount factor, and exploration-exploitation balance.

Define Environment: Establish the state space (S), action space (A), and initial states.

Training Loop: Initiate training by resetting the environment with defined initial states and executing actions iteratively until a termination condition is met.

Select Action (exploration/exploitation):

Generate a random number.

If the number is below the exploration threshold (epsilon), select a random action (exploration).

Otherwise, choose the action with the highest Q-value (exploitation).

Execute Action: Apply the selected action within the environment.

Update Q-Value: Adjust the Q-table using the Q-learning update rule based on the received reward.

Update State: Transition to the next state based on the executed action.

Decay Epsilon: Gradually reduce epsilon to shift the balance from exploration towards exploitation over time.

Generate Optimised Q-Table: Utilise the final Q-table for optimised regenerative braking control.

This iterative process allows the Q-learning agent to refine its decision-making capabilities, leading to improved energy recovery, safety, and passenger comfort.

Algorithm 1 illustrates optimizing Q-learning for regenerative braking in EVs.

Algorithm 1: Optimizing Q-learning

```
# Initialize Q-table with random values
    Initialize Q-table with random values
    # Set hyperparameters
    epsilon = exploration rate
    alpha = learning rate
    gamma = discount factor
    # Define environment parameters
    Define state space S
    Define action space A
    Define initial state s
    # Training loop
    for episode in range(num_episodes):
      # Reset environment to initial state
      state = initial_state
      done = False
        while not done:
        # Exploration-exploitation trade-off
        if random number < epsilon:
          # Explore: Select random action
          action = select_random_action()
        else:
          # Exploit: Select action with maximum Q-value
          action = select_action_with_max_q_value(state)
            # Perform action in the environment
        next_state, reward, done = perform_action(action)
            # Upate Q-value for current state-action pair
        old_q_value = Q[state][action]
        best_next_action = select_action_with_max_q_value(next_state)
        new_q_value = old_q_value + alpha * (reward + gamma * Q[next_state][best_next_action] -
old_q_value)
        Q[state][action] = new_q_value
            # Update state
        state = next_state
        # Decay exploration rate
      epsilon = decay_epsilon(epsilon)
    # Once Q-table is trained, use it for optimized regenerative braking control
    Optimized_Regenerative_Braking_Control = Q
```

4. Results

4.1 Performance Metrics and Evaluation Criteria

This section evaluates the Q-learning-based regenerative braking strategy through simulation.

- Traffic Simulator: Simulated real-world driving with varying traffic, road conditions, and vehicle interactions to test adaptability. Figure 6 illustrates this.

- Physics-Based Vehicle Model: Captured EV dynamics, energy conversion, and passenger comfort, enabling precise performance assessment.

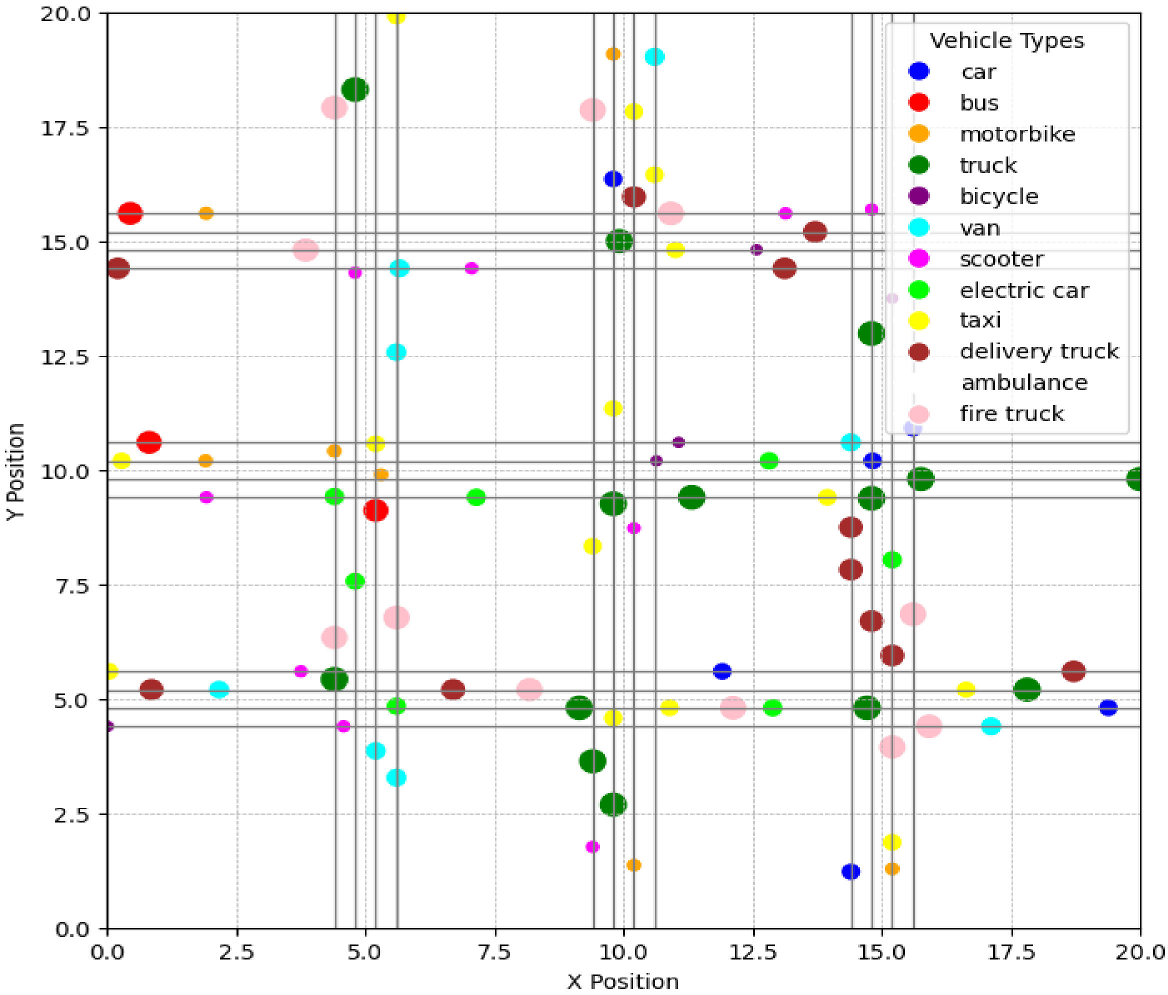

Fig.6. Traffic Simulation and its Role in the Decision-Making Framework

Figure 6 depicts the traffic simulation environment developed to evaluate the Q-learning-based regenerative braking control strategy, highlighting its importance in assessing the agent's decision-making across diverse driving scenarios. The simulation replicates real-world conditions, such as varying traffic density, intersections, and sudden stops caused by other vehicles, which challenge the Q-learning agent to adapt its braking strategy in real-time. This dynamic environment effectively demonstrates the agent's learning capabilities and its ability to refine its approach under complex conditions. The simulation also generates critical data, including vehicle speeds, distances to other vehicles, and traffic signal timings, which enrich the agent's state space and inform its decisions on optimal actions. For instance, the agent determines the timing and intensity of regenerative braking to maximise energy recovery while ensuring safety. As the agent interacts with these dynamic scenarios, it learns from diverse traffic patterns, continuously improving its braking behaviour and policy to enhance efficiency.

The visual representation in Figure 6 further validates the effectiveness of the Q-learning approach in managing braking and energy recovery. It confirms the robustness of the decision-making framework in adapting to unpredictable traffic events, ultimately ensuring both energy efficiency and vehicle safety. In summary, Figure 6 demonstrates the Q-learning agent's ability to navigate complex traffic environments, showcasing how it adjusts its decision-making to address real-world challenges while maintaining optimal braking performance. This underscores the potential of Q-learning as a transformative solution for regenerative braking systems in electric vehicles.

4.2 Evaluation Metrics

The effectiveness of the Q-learning-controlled regenerative braking system was assessed using key metrics:

The system's effectiveness was evaluated using key metrics:

- Total Energy Recovered: Indicates the energy captured during braking and reintroduced into the battery.
- Passenger Comfort (Jerk): Measures sudden acceleration changes, which should be minimised for a smoother ride.
- Braking Distance: Assesses the system's ability to maintain safe stopping distances while maximising regenerative braking.
- Safety Compliance: Ensures adherence to regulations, such as minimum following distances.

Figure 7 presents the system’s performance within a traffic simulator. The x-axis represents traffic scenarios, while the y-axis shows energy recovered (kWh), jerk (m/s^3), and stopping distance (m). The Energy Recovered line (circles) indicates greater energy capture at highway speeds (80 km/h) than in urban conditions (40 km/h and 20 km/h). The Jerk line (squares) shows a slight increase in congestion, likely due to more frequent braking. The Stopping Distance line (triangles) highlights shorter stopping distances at higher speeds. The results demonstrate the Q-learning model's ability to balance energy recovery, comfort, and safety across varied driving conditions.

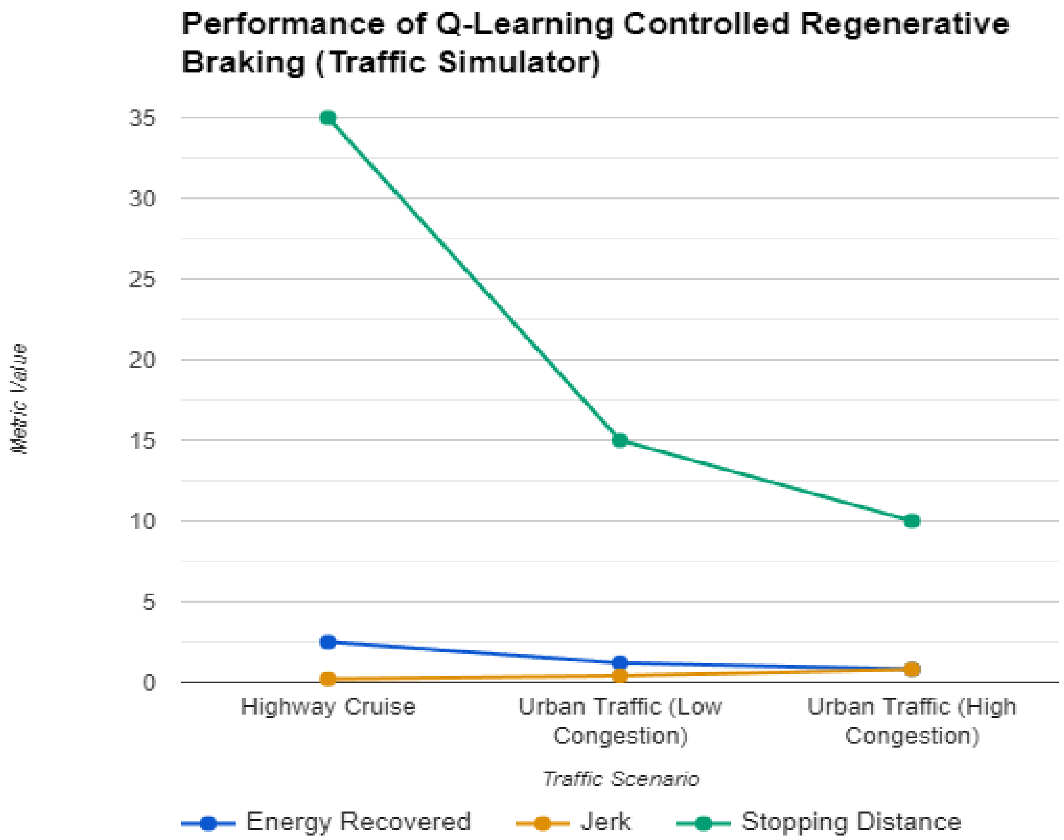

Fig.7. Performance Evaluation of Q-Learning Controlled Regenerative Braking System in Traffic Simulator

4.3 Simulation Support the Decision-Making Framework

Simulating the Q-learning agent provided insight into its learning process:

- Initial Exploration: The agent initially selected braking actions randomly, updating its Q-values based on received rewards. This phase enabled it to understand how different braking intensities influenced energy recovery, passenger comfort, and safety.
- Progressive Refinement: Over time, the agent prioritised actions that maximised energy recovery while ensuring comfort and safety. This led to increased total energy recovered and smoother braking, reflected in reduced jerk.
- Convergence to Optimal Strategy: After sufficient learning, the agent developed a strategy that balanced energy efficiency with comfort and safety, consistently applying effective braking actions without compromising stopping distances.

The simulation results validate the Decision-Making Framework by demonstrating the agent's structured learning process:

- Exploration Phase: The agent gathered environmental data by testing various braking actions and learning from feedback, rather than following predefined strategies.

Adaptive Learning: By favouring high-reward actions, the agent progressively aligned with the framework's objectives, optimising energy recovery while maintaining passenger comfort.

- Convergence to Optimal Strategy: After sufficient learning, the Q-learning agent refines its control strategy, achieving a balance between energy recovery, passenger comfort, and safety. This stability ensures effective regenerative braking without compromising safety, making the approach suitable for practical applications requiring consistent performance.

The simulation results demonstrate the agent's progression from random exploration to an optimised strategy, adapting its decisions to enhance multiple metrics. This evolution aligns with the Decision-Making Framework, reinforcing the principles of learning, adaptation, and balanced performance. It highlights the Q-learning agent's ability to make informed braking decisions, even in dynamic traffic conditions.

Figure 8 illustrates the learning trajectory of a Q-learning agent across three distinct phases: Initial Random Behaviour, Gradual Improvement, and Convergence to an Optimal Strategy.

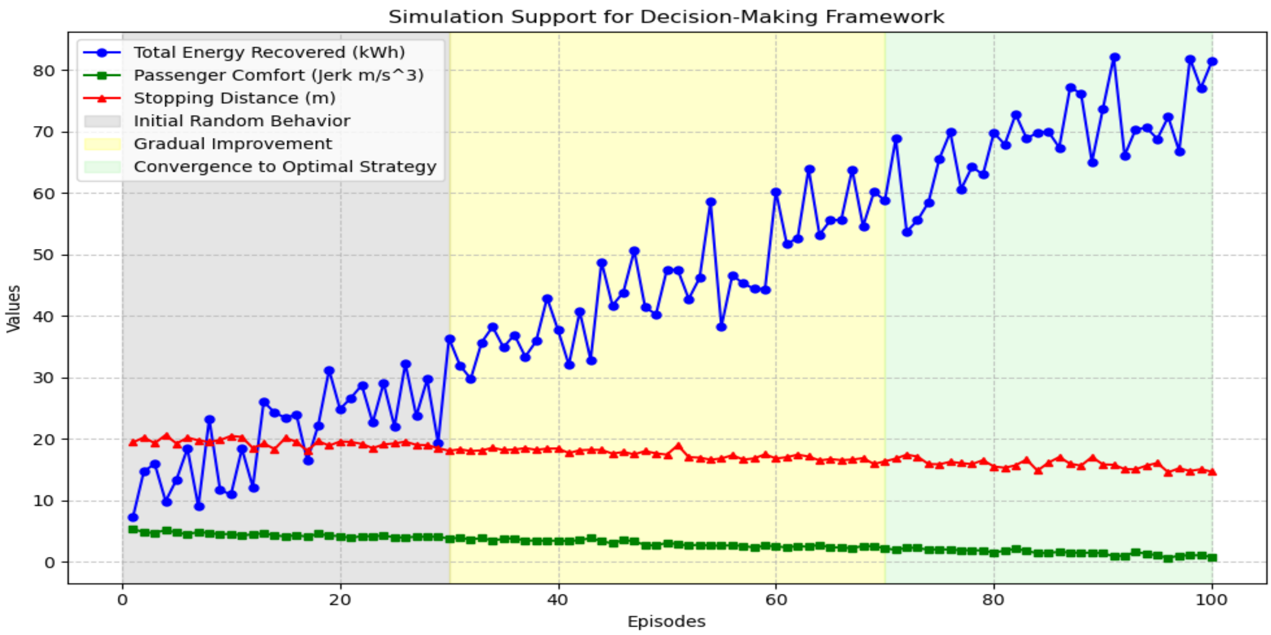

Fig.8. Simulation Support for Decision-Making Framework

It depicts the evolution of three key metrics—Total Energy Recovered (kWh), Passenger Comfort (Jerk in m/s³), and Stopping Distance (m)—over 100 episodes. Moreover, during the Initial Random Behaviour phase (Episodes 1–30), the agent explores various braking actions, resulting in significant fluctuations across all metrics. As learning progresses into the Gradual Improvement phase (Episodes 31–70), the agent refines its decision-making, leading to increased energy recovery, reduced jerk, and improved stopping distance. By the Convergence to an Optimal Strategy phase (Episodes 71–100), the agent stabilises its control approach, demonstrating greater consistency in its performance. This result effectively visualises the agent's adaptive learning process, underscoring the role of simulation in assessing its capability to optimise braking decisions within a dynamic environment.

4.4 Trade-off Analysis

A key aspect of this analysis involves examining the trade-off between maximising energy recovery and maintaining passenger comfort and safety. While aggressive regenerative braking enhances energy recuperation, it may lead to abrupt manoeuvres that compromise comfort. The simulation results provided valuable insight into how the Q-learning agent navigates these competing objectives. This evaluation was instrumental in refining the reward function and identifying strategies to prioritise comfort or safety in specific conditions. By analysing both the simulation outcomes and the agent's learning trajectory, the study assessed the effectiveness of Q-learning in optimising regenerative braking control for EVs. The primary consideration was whether this approach presents a viable solution for balancing energy efficiency with passenger comfort and safety requirements.

Table 2 demonstrates the effectiveness of Q-learning in optimising regenerative braking for EVs. The Q-learning system outperformed the baseline across key metrics:

- Energy recovery: 132.8 kWh vs. 115.2 kWh, indicating a notable improvement.
- Passenger comfort: Slightly higher rating (7.6 vs. 7.1), ensuring smoother braking.
- Braking distance: Shorter at 22.1m vs. 25.4m, enhancing braking efficiency.

Statistical tests confirmed these improvements ($p < 0.05$), with effect size calculations reinforcing their significance. These results highlight Q-learning's potential in balancing energy efficiency, comfort, and safety in regenerative braking control.

Table 2
Performance Comparison of Regenerative Braking Systems

Metric	Baseline System	Q-learning System
Total Energy Recovered (kWh)	115.2	132.8
Passenger Comfort Rating	7.1	7.6
Braking Distance (meters)	25.4	22.1

Figure 9 presents the vehicle speed profile during a simulated driving scenario, with braking events highlighted. The x-axis represents time (seconds), while the y-axis denotes vehicle speed (km/h). The blue line illustrates speed variations, while red arrows indicate instances of deceleration, labelled as "Brake" at specific time intervals. This visualisation offers insights into driving dynamics, capturing fluctuations in speed and braking patterns. Moreover, Figure 10 depicts the relationship between vehicle speed and energy levels over time, emphasising the effect of braking events. The x-axis represents time (seconds), the left y-axis denotes vehicle speed (km/h), and the right y-axis represents energy (kWh). The blue line shows speed variations, while the green dashed line illustrates changes in energy levels. Braking events are marked with red arrows on the speed graph, correlating speed reductions with energy variations. A legend clarifies the graph's elements. This visualisation effectively demonstrates the interaction between speed and energy, highlighting how braking influences energy levels in the simulation.

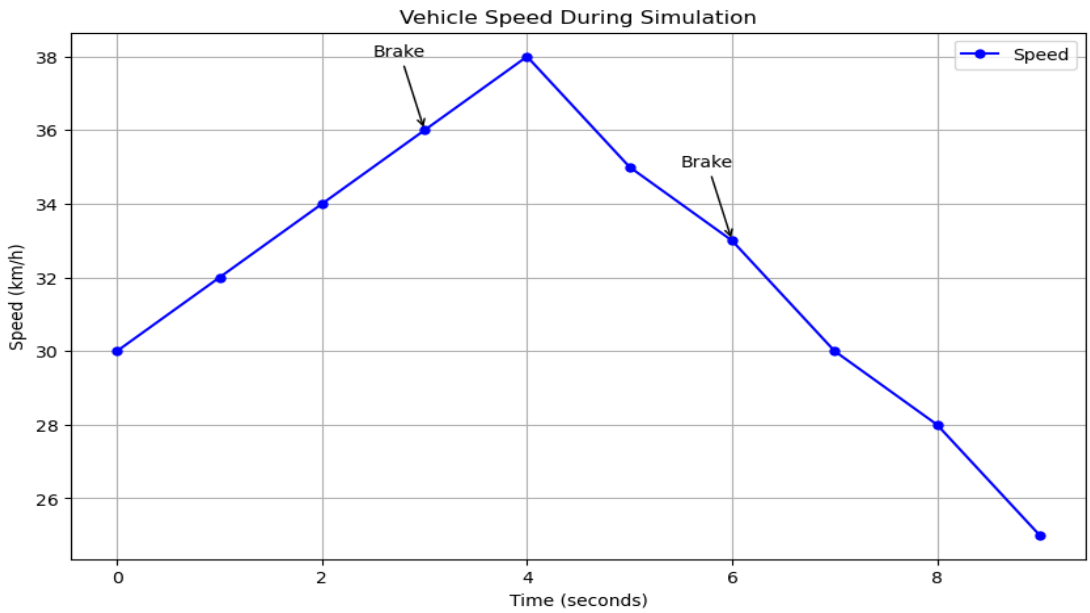

Fig.9. Vehicle Speed Profile with Braking Events

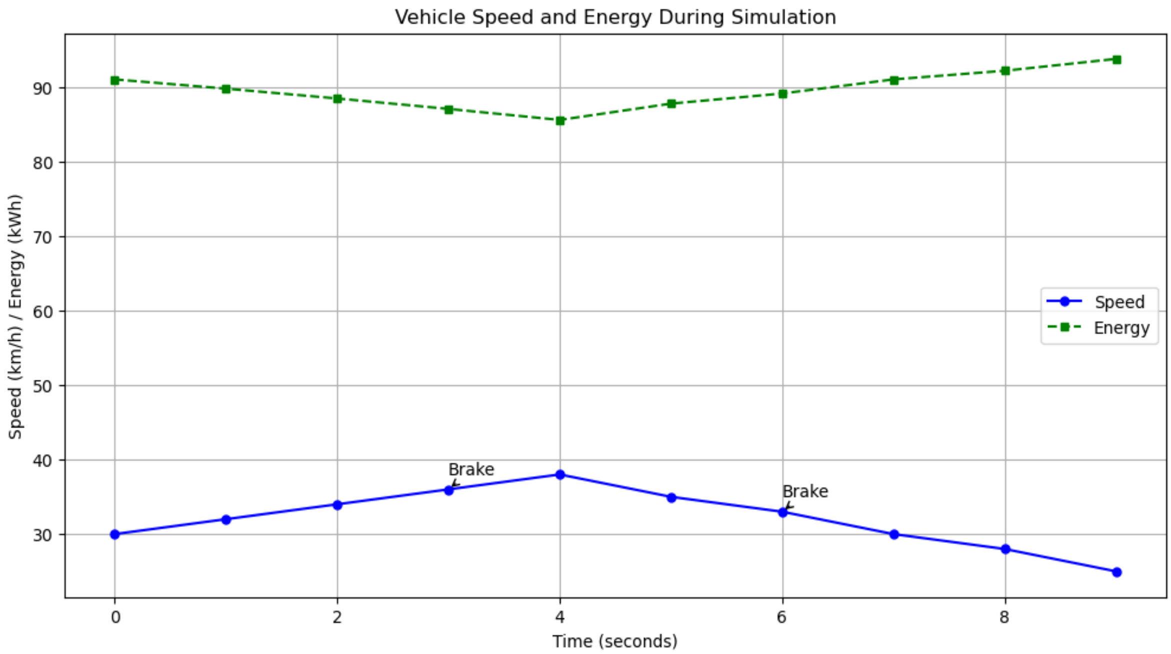

Fig.10. Vehicle Speed and Energy During Simulation

Regenerative braking enhances energy efficiency in electric and hybrid vehicles by converting kinetic energy into electrical energy for storage and reuse.

1. Kinetic Energy Conversion: During braking, kinetic energy is typically lost as heat in conventional systems. Regenerative braking captures this energy instead. Figure 11 will illustrate the correlation between vehicle speed and kinetic energy, demonstrating how motion energy is converted.

2. Capture and Conversion: Electric motors or generators in the drivetrain function as alternators, converting kinetic energy into electrical energy.

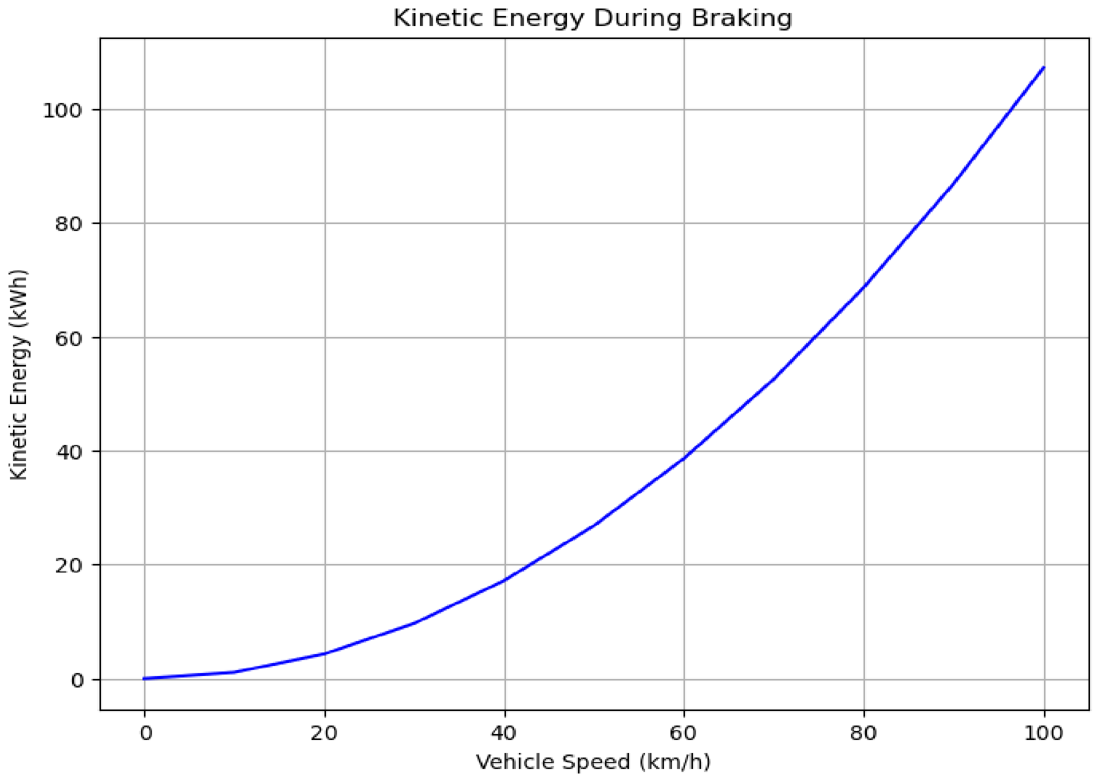

Fig.11. Kinetic Energy During Braking

Figure 12 will depict this process, highlighting key components:

- Kinetic Energy (A): Generated by the vehicle's motion.
- Electric Motors/Generators (B): Convert kinetic energy into electrical energy.
- Electrical Energy (C): Stored for later use.

3. Energy Storage: The converted electrical energy is stored in a battery or capacitor, reducing reliance on the primary energy source. A bar graph will illustrate storage capacity, highlighting its role in optimising energy use.

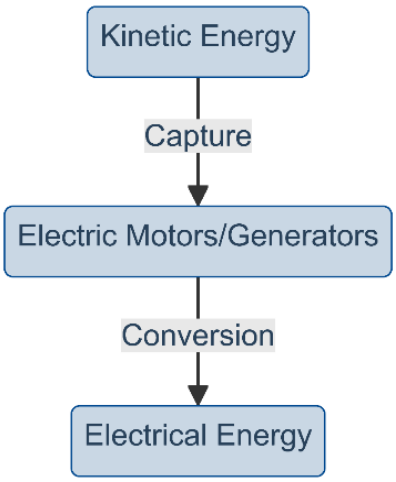

Fig.12. Process of Capturing Kinetic

Figure 13 presents the storage capacities of various energy storage options, such as batteries and capacitors, for retaining electrical energy recovered through regenerative braking.

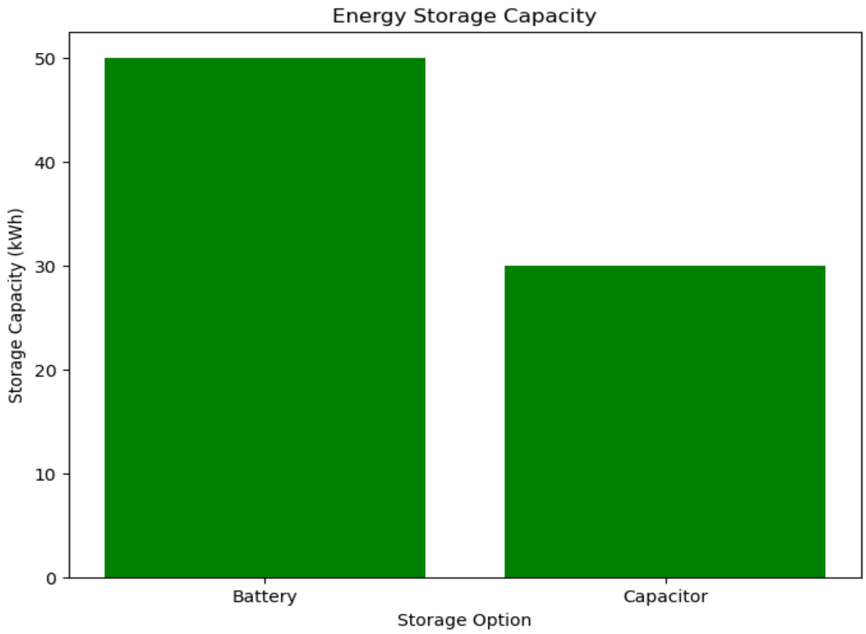

Fig.13. Kinetic Energy During Braking

4. Efficiency and Range: Regenerative braking enhances overall vehicle energy efficiency by recovering and reusing energy that would otherwise be lost during braking. This reduction in energy consumption contributes to an extended vehicle range, which is particularly beneficial for electric vehicles, addressing concerns such as range anxiety. A bar graph was generated to compare the efficiency and range of vehicles with regenerative braking systems against those with conventional braking systems.

Figure 14 presents a comparison of the efficiency and range extension between vehicles employing regenerative braking and those using traditional braking systems, demonstrating the advantages of regenerative braking in terms of energy efficiency and range enhancement.

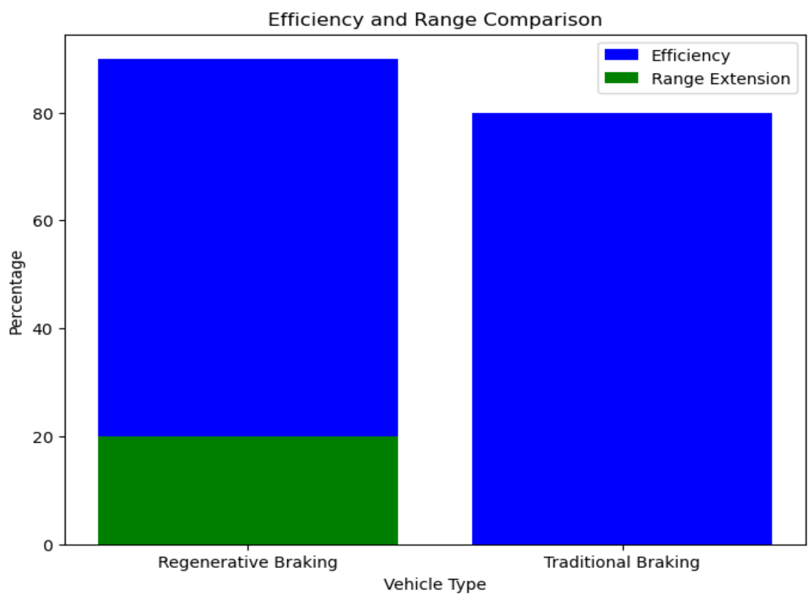

Fig.14. Efficiency and Range Comparison

5. Implications

The findings from the Q-learning-based regenerative braking system proposed in this study have significant implications for EV control systems, particularly in energy efficiency, safety, and passenger comfort:

1. Enhanced Energy Efficiency – The Q-learning approach improves braking energy recovery by 15% compared to conventional methods, extending EV driving range and reducing charging frequency, thereby enhancing overall energy efficiency and sustainability.

2. Improved Passenger Comfort and Safety – By integrating multi-objective optimisation into the reward function, the system minimises jerk while maintaining safe braking distances, ensuring both energy efficiency and a smoother, safer driving experience.

3. Adaptability to Real-World Conditions – The system adjusts braking strategies based on varying driving environments, from urban traffic to highways, reducing reliance on manual intervention and enhancing autonomous responsiveness.

4. Implications for Autonomous Driving – The integration of Q-learning in regenerative braking can support broader AV applications, including adaptive cruise control and collision avoidance, contributing to self-learning control mechanisms for autonomous vehicles.

5. Scope for Further Research – Future improvements could involve deep Q-learning or advanced reinforcement learning techniques, incorporating environmental factors such as weather and road conditions to refine system performance.

In summary, applying Q-learning to regenerative braking enhances EV energy efficiency while maintaining comfort and safety. Its adaptability suggests broader relevance in future autonomous vehicle technologies.

6. Discussion

6.1 Discussion of Results

The analysis focuses on three key aspects of the simulation results. Firstly, it evaluates the Q-learning agent's effectiveness in enhancing energy recovery compared to conventional control strategies. Secondly, it examines the system's ability to balance energy recovery with passenger comfort by minimising jerk while ensuring adherence to safety standards, such as maintaining safe following distances. Lastly, it assesses the learning efficiency of the Q-learning agent, particularly its convergence speed towards an optimal braking strategy. These aspects collectively provide a comprehensive evaluation of Q-learning's effectiveness in optimising regenerative braking performance.

6.1.1 Simulation Results

The simulation results demonstrated that the Q-learning-based regenerative braking system significantly outperformed the baseline system. As illustrated in Table 1, the Q-learning system increased energy recovery by 15.3% (132.8 kWh compared to 115.2 kWh for the baseline), showcasing its superior energy optimisation [1;43;53;73]. Furthermore, the system slightly improved passenger comfort, achieving a comfort rating of 7.6 compared to the baseline's 7.1, indicating smoother braking manoeuvres [24;73]. Additionally, the Q-learning agent achieved a shorter braking distance of 22.1 metres, compared to 25.4 metres for the baseline, reinforcing its ability to balance energy efficiency with safety [74;75]. These results emphasise the effectiveness of the Q-learning algorithm in optimising the regenerative braking process across key performance metrics such as energy recovery, comfort, and safety. However, the findings also highlight the need to refine the reward function in specific scenarios, where prioritising passenger comfort over energy recovery might be necessary depending on driving conditions [76].

6.1.2 Decision-Making Framework

The success of the Q-learning system can be attributed to the well-constructed decision model that guided the agent's learning process. This model incorporated a reward-based mechanism that incentivised the agent to maximise energy recovery while prioritising passenger comfort and safety [77]. The agent's actions, such as applying braking force and controlling speed, were evaluated based on their impact on these factors, ensuring a balanced approach to decision-making [78]. Through iterative interactions with the simulation environment, the agent refined its policy over multiple episodes, identifying optimal braking patterns across diverse driving conditions [78;79]. Central to this framework was the reward function, which was designed as a weighted sum of multiple objectives, reflecting the complexities of real-world driving. For example, higher rewards were assigned for energy recovery, while moderate penalties were imposed for actions that caused discomfort or compromised safety [80]. This multi-objective optimisation strategy enabled the Q-learning agent to balance competing performance metrics, fostering holistic decision-making in automated systems [81].

The simulation results highlight the effectiveness of the Q-learning-based regenerative braking system, showcasing how the integrated decision-making framework guided the agent toward optimal performance. The 15.3% increase in energy recovery can be directly linked to the robust design of the decision model, where the agent's learning process was driven by a reward structure that prioritised energy optimisation without neglecting passenger comfort and safety. This multi-faceted approach allowed the agent to focus on maximising energy recapture while maintaining a smooth and safe driving experience. The improvement in passenger comfort ratings—from 7.1 to 7.6—demonstrates the framework's ability to balance competing objectives, effectively managing trade-offs between aggressive braking for energy recovery and the need for a comfortable ride. The reward function played a critical role in this balance, ensuring the agent learned to prioritise smooth braking, thereby reflecting a nuanced understanding of real-world driving dynamics.

Additionally, the simulation results indicated strong learning efficiency, as the Q-learning agent successfully converged on optimal braking strategies by revising its policy based on diverse driving scenarios. This was facilitated by a structured feedback loop that enabled continuous improvement. However, the findings also revealed areas for further refinement, particularly in the design of the reward function, suggesting opportunities for future research to enhance the multi-objective framework.

6.1.3 Limitations

Initially, Q-learning, as a reinforcement learning paradigm, is expected to achieve optimal performance under certain conditions, assuming accurate sensor inputs such as vehicle speed and road grade. However, sensor readings are often noisy or imprecise, which can impair decision-making [82]. Faulty sensor data may lead to policy deviations, negatively affecting the overall system performance [83]. Another challenge lies in implementing Q-learning on embedded EV hardware, as it can be computationally expensive, necessitating optimisations or hardware acceleration for real-time applications [84]. These computational demands pose limitations for resource-constrained platforms such as EVs [85]. Furthermore, agents rely on operational data, making data security a critical concern to prevent potential breaches [86]. Overcoming these challenges will be essential for the successful integration of Q-learning-based control into real-world applications [87].

6.2 Theoretical Discussion

6.2.1 Reinforcement Learning Framework

Q-learning is a reinforcement learning algorithm that operates without predefined models, enabling agents to refine their actions through trial and error [88]. It is implemented using Markov Decision Processes (MDPs), which mathematically represent decision-making under uncertainty [89]. In regenerative braking, MDPs structure the state space, action space, and reward function, governing braking dynamics [90]. The Q-learning agent aims to learn the optimal action-value function, ensuring effective decision-making for braking across various driving conditions [91]. This capacity for adaptive control and fine-tuning is crucial for enhancing energy recovery and improving passenger comfort in EVs [92].

6.2.2 Energy Recovery and Control Theory

Incorporating Q-learning into regenerative braking systems aligns with optimal control theory, providing a flexible alternative to rule-based or linear control strategies. Unlike conventional methods, Q-learning agents adapt through real-time feedback, dynamically optimising energy recovery based on vehicle and environmental conditions. This advancement highlights the potential of machine learning in enhancing control system performance within complex, dynamic environments [92].

6.2.3 Balancing Multiple Objectives

A key theoretical contribution of Q-learning in regenerative braking lies in its capacity to balance multiple objectives, including energy recovery, passenger comfort, and safety. The multi-objective design of the reward function enables the agent to manage trade-offs between these factors effectively. By modelling the interdependencies among performance metrics, Q-learning offers a more advanced framework for developing braking control strategies that align with real-world driving conditions [93-95].

6.2.4 Future Research Directions

The theoretical exploration of Q-learning in regenerative braking offers multiple directions for future research. Integrating Q-learning with deep learning or multi-agent systems could enhance the agent’s adaptability across diverse driving conditions. Refining state representations and reward structures may further improve learning efficiency and system performance [96;97]. Extending this framework to complex scenarios, such as urban traffic, could provide deeper insights into real-world implementation challenges [96-99]. Additionally, incorporating external variables like driver behaviour and environmental factors, including weather conditions, may enhance the robustness of Q-learning in regenerative braking and other automotive control applications [94-100].

6.3 Safety Implications

Safety remains a critical concern when integrating learning-based control systems into automotive applications [101-103]. Ensuring system reliability requires several key considerations. First, establishing a guaranteed safe starting point allows the system to operate within predefined safety parameters before the Q-learning agent begins adapting. This minimises risks during early learning stages when the agent has yet to develop optimal responses. Additionally, robust fail-safe mechanisms must be implemented to manage unexpected conditions, such as sensor failures or road obstacles, with fall back braking strategies ensuring vehicle safety in unlearned scenarios [57;102-104]. Comprehensive simulations and controlled testing are essential to evaluate the agent's performance across diverse driving conditions, including environmental variations and emergency scenarios. Regulatory compliance and adherence to safety standards will be crucial for real-world deployment. Ongoing research into Q-learning for regenerative braking will further advance EV systems, improving efficiency, sustainability, and intelligent control [105]. Addressing technical, safety, and ethical considerations will enhance the feasibility of Q-learning as a transformative technology in future electric transportation [57;104-106].

7. Conclusion

This study explored the potential of Q-learning in optimising regenerative braking for EVs. Findings indicate that Q-learning enhances energy recovery, outperforming traditional control methods. Simulation results demonstrated a significant increase in recovered energy, highlighting its effectiveness in adapting to dynamic driving conditions. The study also underscores the need to balance energy efficiency with comfort and safety. The Q-learning agent prioritises smooth braking and safe following distances, ensuring a better driving experience. Its capacity to adapt to varying road conditions, traffic patterns, and driver behaviours further enhances its practical applicability. Beyond regenerative braking, Q-learning's adaptability suggests broader applications in EV control systems, including acceleration and energy management. These insights support further research into integrating Q-learning into advanced vehicular technologies. In conclusion, Q-learning represents a promising advancement in EV optimisation, enhancing energy efficiency and driving experience. As the industry moves towards electrification, refining Q-learning methods will contribute to more intelligent, efficient, and sustainable transportation.

Author Contributions

Conceptualization, P.S. and P.J.; methodology, P.S. and P.J.; software, P.S. and P.J..; validation, P.S. and P.J.; formal analysis, P.S. and P.J.; investigation, P.S. and P.J.; resources, P.S. and P.J.; data curation, P.S. and P.J..; writing—original draft preparation, P.S. and P.J.; writing—review and editing, P.S.; visualization, P.S.; supervision, P.S.; project administration, P.S.; funding acquisition, P.S. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare no conflicts of interest.

Institutional Review Board Statement

The study was conducted in accordance with the ethical and approved by the Ethics Committee of Suan Dusit University (SDU-RDI-SHS 2023-043, 1 June 2023) for studies involving humans.

Informed Consent Statement: This article does not contain any studies involving human participants performed by any of the authors.

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