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*Review*

# Effect of Regenerative Braking on the Life of Battery

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**Abstract:** The automobile industry is often believed to be moving towards electric vehicles. Hybrid electric vehicles (HEVs) and electric vehicles (EVs) are anticipated to dominate the automotive industry. Regenerative braking is one of the modern approaches that recharge the battery by extracting the kinetic energy from the braking thus improving the vehicle range. However, the rate of current supplied by regenerative braking to the battery is a major concern as lithium-ion (Li-ion) is susceptible to failure due to the intensity of the charging-discharging rate, and operating temperature. So, this review article focuses on the effect of regenerative braking on the life of the battery and measures being taken to protect the battery from higher charging during regenerative braking. Various research articles are considered for observing the effect of regenerative braking on battery life. It is found that longer duration charging current obtained from regenerative braking that is irrespective of current intensity is the prominent factor of battery deterioration. If the SOC and the temperature are not in the optimal range, the Lithium plating rate increases. However, a higher level of regenerative braking increases the battery life even at high SOC and temperature by reducing the Depth of Discharge (DOD) and by using shorter recharging periods.

**Keywords:** Regenerative Braking; SOC; SOH; Battery Life; Charging and Discharging Characteristics; Ultracapacitor

## 1. Introduction

In urban driving situations, conventional braking systems discard the kinetic energy of the vehicle as heat in the braking system. A Regenerative Braking System (RBS) works by converting kinetic energy to electric energy / mechanical work, which is then stored in a Battery / Ultra Capacitor or in a Fly Wheel. RBS cannot substitute or replace the mechanical braking system in a vehicle, whereas it is used to decelerate the vehicle to certain level during which the energy can be taped. Based on the rate of application of brake (travel of brake pedal) the level of regenerative braking is decided by the controller. EVs use this harvested energy to accelerate the vehicle immediately after braking or for charging the battery pack or Ultracapasitor (UC) or Supercapasitors (SC). So, regenerative braking leads to an increase in the range of electric vehicles. Regenerative braking improves the driving range by 8 to 25 %. The maximum current that can be absorbed by the source (battery) is dependent on the input voltage, the speed of the motor and the internal resistance of the source and the armature resistance. Several regenerative braking systems (RBS) or kinetic energy recovery systems (KERS) studied by researchers for electric, hybrid or internal combustion engine vehicles, with different energy storage systems (mechanical, electrical, chemical, hydraulic), and suitable or not for retrofit application on current production vehicles. During urban driving, as much as one-third to one-half of the energy is wasted in braking. Figure.1 shows the conceptual diagram of regenerative braking system used in HEVs and EVs.

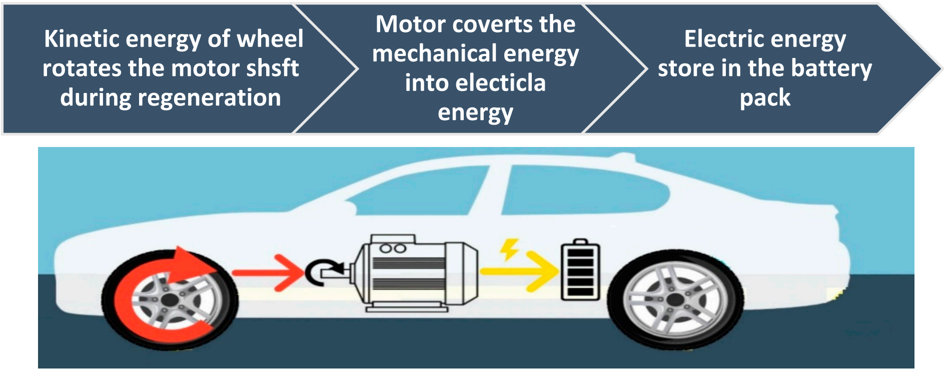


**Figure 1.** Conceptual diagram of regeneration of braking.

The voltage adaptation between the starter/generator and/or the battery is usually performed by suitable power converters able to guarantee a bidirectional flow of energy with high efficiency. In any case, the use of supercapacitor as unique storage solution in electric vehicles remains limited since their energy density cannot compete with batteries. Fly wheels which are pure mechanical systems are als used as energy recovery systems in trains and trucks and sports vehicles. When compared between SC or UC and flywheels as secondary energy storage system on a pure electric vehicle, the use of SC or UC is by far much more convenient than the use of a flywheel to manage extreme start-up and regenerative braking. Recently, supercapacitors have also been conceived in railway systems where it is appreciable the improvement of energy consumption efficiency and reducing peak power demand and costs of operation in railways substations.

The implementation of modern power electronic components like the ultracapacitor, DC-DC converter (Buck-Boost), and flywheel have improved the performance of the regenerative braking system. A flywheel is utilized to improve energy recovery mechanically through the car's wheel, while the Buck-Boost converter maintains power management in the regenerative braking system, for enhanced acceleration. [2]. The ultracapacitor improves the transient state of the car during start-start, provides a smoother charging characteristic for the battery and also enhances the overall performance of the EV system. Furthermore, this technology allows the vehicle to accelerate and decelerate faster with less energy loss and less degradation of the primary battery pack [8]. By using the ultracapacitors with a bidirectional IGBT DC-DC converter, an improvement in the efficiency of the vehicle can be achieved through regenerative braking.

Storing RBS energy or charging the battery depends on the State of Charge of the Battery, which indicates how much charge is remaining in a battery. Accurate measurement of SOC measurement leads to longer battery life and the prevention of premature battery failure. Additionally, a reliable and accurate SOC estimation is essential for effective EV operation. However, due to its reliance on various variables, including battery age, the surrounding environment, and numerous unknown elements, SOC estimation is a challenging process. The model-based and data-driven techniques are used in recent SOC estimate methods [32]. Model-based methods aim to model battery behaviour by including many aspects into complex mathematical equations to accurately estimate the SOC, whereas data-driven methods use complex algorithms to learn the battery’s behaviour from a vast quantity of measured battery data. The classifications of SOC such as the bookkeeping, adaptive, and hybrid method of estimation are explained in terms of drawbacks, and estimation error in [36].

Another important battery parameter that dictates the RBS energy recovery is the State of health (SOH) which is a very important parameter for estimating battery life. In an intelligent battery management system, state of health (SOH) prediction in Li-ion batteries is critical (BMS). The occurrence of the capacity regeneration phenomenon provides a significant obstacle in precisely estimating the battery SOH [62,73]. Batteries must be controlled more efficiently to maximize driving range, optimal power use, longevity, and battery performance, and to ensure safe operation. Improper battery management may result in safety-related concerns such as increased battery ageing and overheating, which might lead to an explosion. SOH refers to the current condition of an old battery’s ability to offer specified performance as compared to its ability to give specific performance when it was in its initial state. The SOH of a battery is calculated by dividing the actual capacity by the nominal capacity [71]. To predict the SOH for lithium-ion batteries these methods are implemented, direct assessment approach, adaptive approach, data-driven approach, and others [62,71].

Today, RBS for most of the electric vehicles is based on batteries, the optimal energy management of the storage systems. This review article introduces the RBS and majorly concentrates on storing the recuperated energy in Lithium-ion battery and the effect of rate of storage of this energy on life of the battery pack. So the parameters like SOC, SOH are explained in detail for the effective storage of the energy. Figure.2 shows the layout of this paper

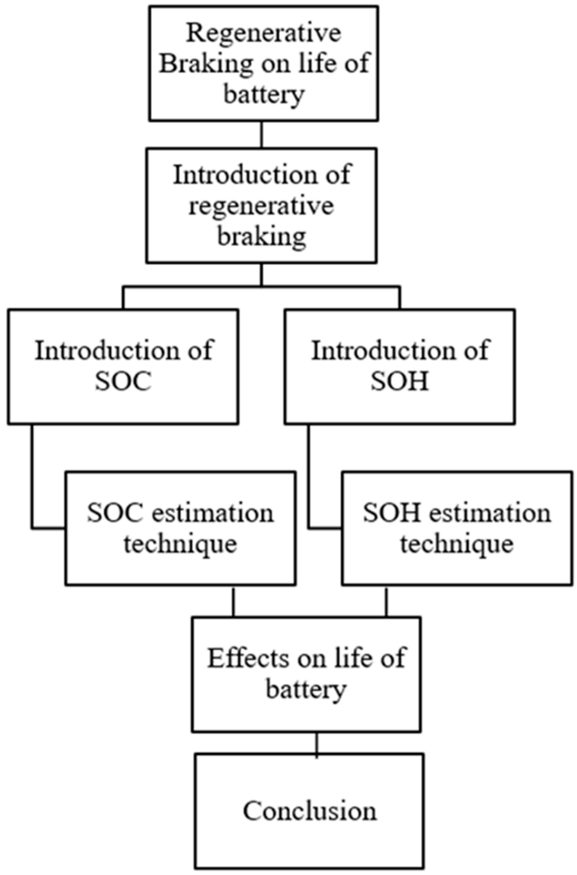


**Figure 2.** Layout of the paper.

## 2. Literature Review

### *2.1. Regenerative Braking*

#### 2.1.1. Different Regenerative Braking Strategies

A regenerative Braking System (RBS) is discussed by Cikanek and Bailey [3] for Parallel Hybrid Electric Vehicles (PHEV) which perform energy recovery based on vehicle attributes. The RBS algorithm is modelled using an analogue MATRIXx algorithm and then discretized by developing the code using MATRIXx Autocode. They first created a connection between hydraulic brake pressure and electric brake torque for that, and using slopes and intercepts, they calculated the maximum front and rear brake forces. The available regenerative braking torque's magnitude is finally calculated as a function of motor speed against torque. The engine is detached from the drive wheels during braking to reduce engine frictional losses. Regenerative braking is carried out using a high-efficiency, single-gear, direct-drive transaxle. The removal of regenerative brake torque at the drive wheels, this improved energy recovery and braking performance. In another similar simulation study on HEV, the results of baseline (without RBS) and proposed regenerative braking strategies are compared in terms of HEV system behavior such as overall fuel economy, and emissions characteristics [22]. The results showed improved performance, efficiency and reliability at less payback time.

Gao et al. [1] assumed that for ideal wheel braking distribution, deceleration should be less than 0.1g then regenerative is only applied on the front wheels otherwise the ideal braking force curve is to be followed. In braking with optimal energy recovery, the optimal regenerative energy can be recovered by distributing the braking forces on the front and rear axles to avoid locking either of the axles. The maximum deceleration is equal to the adhesive coefficient when the deceleration (j/g) is greater than or equal to the adhesive coefficient of the tire-ground contact (μ). According to the required braking force and the quantity of available regenerative braking, the front axle either receives combined regenerative and mechanical braking force or just regenerative braking. For this strategy, more braking force is allocated to the front wheels considering that the front wheels are never locked earlier than the rear wheels. The braking distribution is divided according to the r-lines and f-lines where both lines depict the ground braking forces on the front and rear wheels when the rear and front wheels are locked respectively [6].

Only regenerative braking is used in parallel braking when the required deceleration is less than 0.1 g, and only mechanical braking is used when the required deceleration is larger than 0.7 g. Both the mechanical and regenerative brake systems are operable between 0.1 and 0.7 g. Only the regenerative braking forces must be controlled by the electric motor controller in accordance with the vehicle's motor speed and deceleration. Again, in the latest paper [6], parallel hybrid braking is described when the wheel speed is lower than the given threshold, and total mechanical braking takes place.

Figures 3 and 4 shows the graphical representation of the series and the parallel regeneration braking and it is denoting the relation between the braking torque demand versus delivery. When the wheel speed is above the threshold and the desired vehicle deceleration is less or above than required value, total electric regenerative braking or combined mechanical and regenerative braking takes place respectively. Furthermore, Gao et al. [6] presented a new optimal braking performance strategy (2007), when the required total braking force is less or more than the capacity of the electric motor then total regenerative braking or both electric and mechanical braking are applied respectively. The total mechanical braking is applied by following the specified I-curve in the given graph. This could lead to a 12% reduction in fuel usage for HEV powertrains [23].

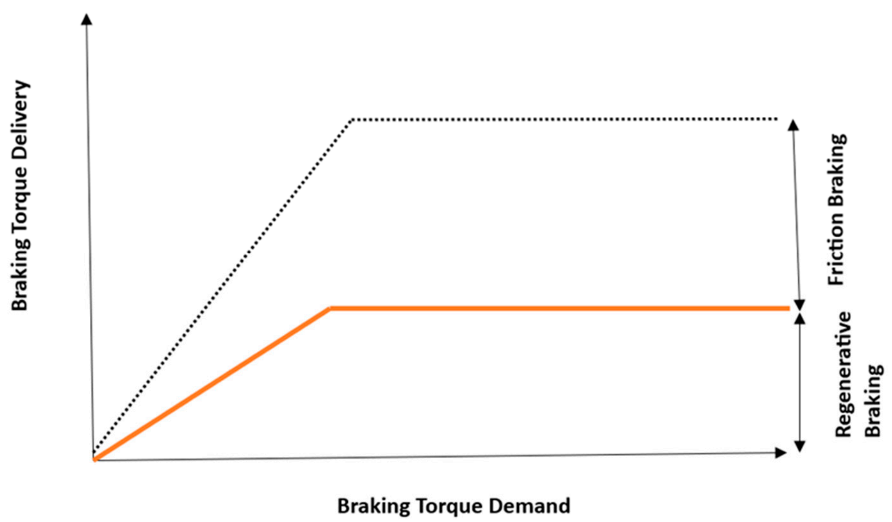


**Figure 3.** Parallel regeneration braking.

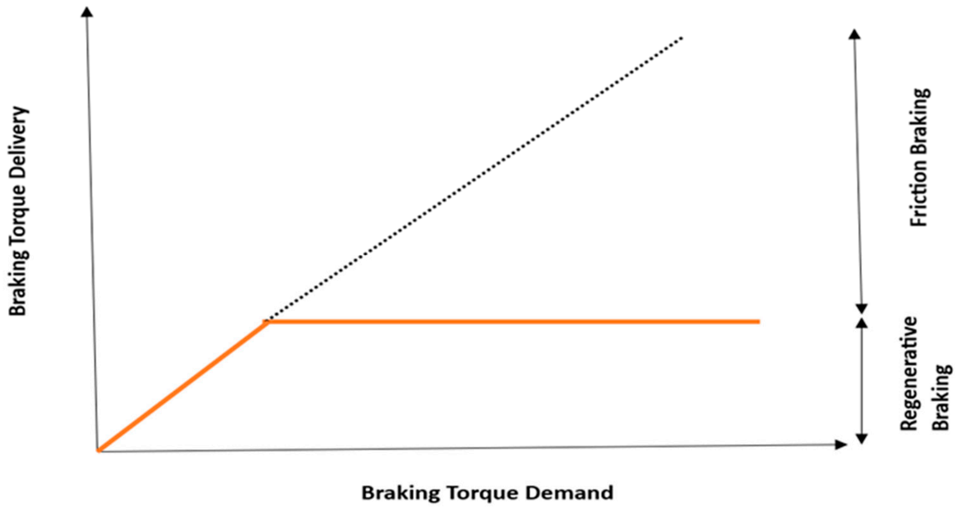


**Figure 4.** Series regeneration braking.

Figure 5 is a layout that represents the methods of regeneration of braking. An integrated braking system is introduced that combines regenerative braking, automatic control force distribution and ABS in which the braking strategy is applied according to the vehicle speed and maximum motor torque [4]. If the braking torque is less than the maximum motor torque then regenerative braking is applied and if it is greater than the maximum motor torque then combined regenerative braking and mechanical braking takes place i.e. parallel hybrid braking strategy [6] by considering terms of motor braking torque. The simulation results showed that more than 60% of braking energy can be recovered when only front wheels are available for regenerative braking. In a panic-stop situation, a regenerative ABS reaction is preferable. An enhanced hybrid ABS solution for electrified powertrain applications might be obtained by assessing the reliability, cost, and sizing issues of electric drives and the required energy storage device for regenerative ABS [15]. Different strategies of RBS are compared to maintain vehicle stability and energy recovery. A basic regenerative braking approach is presented according to the battery and motor's charge and discharge characteristics. The strategy considered the required braking torque, the motor's rated braking torque, and the braking torque limit, and it can maximize the motor's braking torque. The proposed method is stated to generate more energy than a parallel technique that enhanced the battery state of charge (SOC) and regenerates energy efficiency [9]. By using the optimal CVT speeds ratio control algorithm for regenerative braking, an increase of 8% in recuperation energy for the federal urban driving schedule is observed [21]. Qiu et al. [19] aimed at the EV control method for regenerative braking for safety-critical driving circumstances. The appropriate braking torque for ABS control of an electric vehicle is computed using phase plane theory after presenting the RBS strategy. Then, an allocation control is proposed, in which the required optimal brake torque is divided into two halves and distributed between the mechanical and regenerative brakes. Furthermore, two metrics for measuring the contribution of regeneration braking energy efficiency during the deceleration braking process are known as 'serial control strategy' which is similar to optimizing braking performance strategy [6]. The findings of the ice road test indicate that the serial control approach increased energy efficiency has a contribution ratio to stable and dynamical breaking energy efficiency of up to 58.56% and 69.74%, respectively.

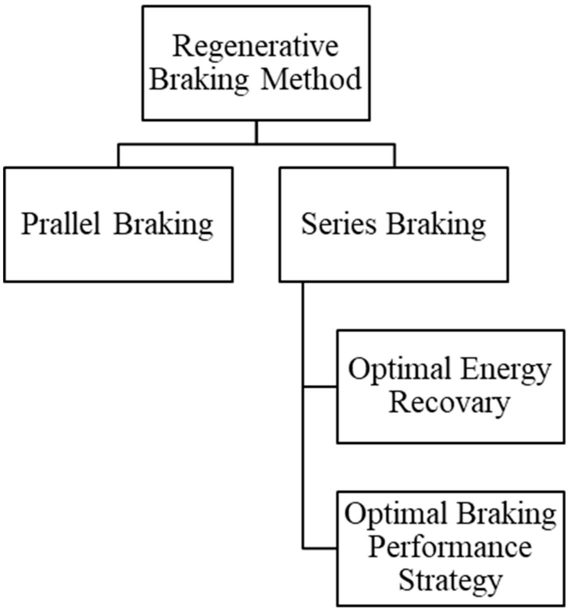


**Figure 5.** Regenerative Braking Methods.

2.1.2. Combined Regenerative Braking and Fuzzy Logics System

Nian et al. [5] used proportional-integral-derivative (PID) control for the brushless direct-current (BLDC) motor, and fuzzy logic control for the distribution of braking force to make RBS adaptive to the BLDC motor. From this, the distribution of the braking force and BLDC motor control is made easier. The state of charge (SOC), and braking force, are currently used for producing the braking torque as input variables of the fuzzy control and simulated in the Simulink. By simulating, the performance of RBS is determined that are similar to the practical results and so the system optimized the regenerative braking and extended the driving distance. However, in terms of steady-state tracking error and response speed, experimental results reveal that H∞ robust control that is actuated by a permanent DC motor outperforms typical PID control [27]. Also, H∞ can be optimized process by integrating the sliding phase and the hitting phase creating the parameter of the sliding mode controller. Furthermore, the system's gain matrix ensures the system's robust stability and disturbance rejection specifications [28]. The regenerative braking controller comprises a back propagation neural network (BPNN), a radial basis function NN (RBFNN), and a sliding mode controller (SMC or NNSMC). To avoid whippings, the BPNN is employed to modify the switching gain of the SMC online adaptively. The RBFNN is used to identify and predict parameters in a system. The experimental results show that NNSMC further outperforms standard SMC in terms of response speed, steady-state tracking error, and regenerative-braking disturbance resistance. It can also recover more energy, extend battery life, and boost driving range by around 6% [29]. If NN based PID controller is used, then the driving range is increased by 5.3% [31]. NN-based switching reluctance motor (SRM) drive control technique is also developed to meet regenerative braking requirements. However, iron loss at high rotor speed has resulted in lower energy recovery efficiency at lower braking torque [30].

Xu et al. [7] implemented the concept of fuzzy logic in the RBS system for reducing energy consumption. To prevent cars from experiencing wheel lock and slip while braking, the ideal energy recovery distribution curve distributes braking power between the front and rear wheels [6]. The allocation of friction braking force and regenerative braking force is then calculated to maximise energy recovery efficiency using a fuzzy RBS that incorporates the driver's braking force command, vehicle speed, SOC [25], and battery temperature. Experiments on an FWD- LF620 prototype EV confirmed the feasibility, controllability and effectiveness of fuzzy RBS [26]. The maximum driving range increased by 25.7 % as compared to non-RBS systems. Also, the fuzzy RBS saved an additional 11% of the battery capacity energy thus resulting in a 22% increase in overall energy efficiency. Peng

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et al. [10] presented a combined braking control strategy (CBCS) that synchronized hydraulic and regenerative braking systems according to HEV braking torque distribution. The control system meets the criteria of a vehicle's longitudinal braking performance while also recharging the battery with greater regenerative energy. A logic threshold control strategy (LTCS) and fuzzy logic control strategy (FCS) adjusted the hydraulic braking torque and regenerative braking torque respectively in real-time conditions. The control strategy ensured high regenerative efficiency and good braking performance, even when emergency braking is necessary on roads with low adhesion coefficients. Based on the calculation of the μ and using a fuzzy logic estimation approach, Paul et al. [20] proposed a Brake Force Distribution (BFD) strategy for an all-wheel-drive (AWD) electrified vehicle with a single electric motor. The suggested method takes into account motor efficiency and available speed reduction ratios to find the ideal BFD that maximises regenerative power while braking for a specific vehicle speed and deceleration need. Preliminary test findings with a prototype car serve as confirmation for simulation evaluations showing the suggested tire-road friction estimation-based BFD optimisation technique greatly increases braking energy recovery.

#### 2.1.3. Other Regenerative Braking System Strategies

The three different strategies i.e., the maximum regeneration-efficiency strategy, the good-pedal-feel strategy and the coordination strategy are also introduced by Zhang et al. [11] for an EV passenger car. MATLAB/Simulink models of the EV car's regenerative and frictional blending brakes are created and examined the control effects and regeneration efficiency of the control schemes in a typical deceleration process. The practical and modelling results show that the maximum-regeneration-efficiency method is compromised with brake comfort and safety. In terms of brake comfort and regeneration efficiency, the good-pedal-feel approach and coordination strategy outperform the first strategy. For the ECE driving cycle, the developed regenerative braking technology increased fuel economy by more than 25%. Ahn et al. [12] propounded the incorporation of an electronically controlled brake subsystem that independently distributes the braking forces to all four wheels for HEV electro-mechanical brake (EMB) systems. The internal combustion (IC) engine, electric motor, battery, and transmission are all modelled as part of the HEV powertrain to simulate the RBS performance in MATLAB/ Simulink. The EMB system's control performance is assessed by simulating the HEV's regenerative braking under various driving circumstances. Li et al. [13] studied the HEV with an automated manual transmission (AMT). The methodology of AMT downshifting is analyzed, and the features of regenerative braking are determined using various gear locations and different downshifting strategies. based on which two types of downshifting strategies are offered based on rule and dynamic programming (DP) algorithms. Finally, hardware-in-the-loop (HIL) tests are conducted, with results indicating that the energy conservation of the regenerative braking process with downshifting can be raised by 10.5–32.4% as compared to without downshifting systems. By using HIL testing, Junzhiet al. [16] compared a 'modified control strategy' i.e., maximum regenerative efficiency strategy with a control strategy termed 'baseline control strategy'. Simulation and HIL tests revealed that the updated control approach has a regeneration efficiency of 47% in normal deceleration braking i.e., 15% greater than the baseline control strategy. Furthermore, the energy economy is increased for EV operating for ECE driving cycle by greater than 10% with an updated strategy which is 3% higher i.e., total energy regenerated increased by 37%. The dual ABS/Traction Assist Regenerative Braking (ATR) system also analyzes fast dynamics and enables Software-in-the-loop (SIL) testing before the addition of ATR hardware to the loop [24]. The cooperative control algorithm for a hydraulic brake system and regenerative braking is presented based on hydraulic brake system characteristics. The cooperative control algorithm completed the demanded braking force by conducting cooperative control between regenerative and friction brakingIf the pedal stroke is shorter than the threshold value, only the front wheels will brake, either solely through regenerative braking or through a mix of friction and regenerative braking. Regenerative braking or combined regenerative and friction braking at the front wheel and friction braking at the rear wheel were used to brake the vehicle if the pedal stroke exceeded the threshold amount. More braking force is transmitted to the front wheels, improving the energy recovery of

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regenerative braking, when the required braking force gradient against pedal force is increased up to a particular limit. Otherwise, driving comfort is compromised. The necessary brake force gradient is influenced by the driver's braking abilities, regenerative braking energy, and comfort while driving. [18].

Chen et al. [14] discussed the mechanism for evaluating the contribution of regenerative braking to the development of EV energy efficiency. The energy flow of an electric car is studied, including energy regeneration braking energy. Then, the regenerative brake's contribution to vehicle energy efficiency is introduced. Two evaluation measures, namely the contribution ratio to energy efficiency improvement and the driving range extension, are proposed based on the energy flow examined. Vehicle testing is conducted on a chassis dynamometer using three different control techniques and typical driving cycles. For the NEDC driving cycle, regenerative braking enhanced the energy efficiency improvement criteria by 11.18% and driving range extension by 12.58% respectively. Similarly, the 'serial 2 control strategy' is also introduced that is compared with two control strategies namely 'parallel control strategy' and 'serial 1 control strategy'. The contribution ratio to regenerative braking energy transfer efficiency improvement i.e., serial 2 strategies and the contribution ratio to regenerative driving range i.e., serial 1 strategy are two new evaluation measures. On the road tests, it is found that the serial 2 control technique outperforms the parallel and serial 1 control strategies for regeneration efficiency. The results under the China typical city regenerative driving cycle (CTCRDC) show that regenerative braking increases up to 41.09% and 24.63% for energy transfer efficiency and regenerative driving range, respectively [17].

### *2.2. State of Charge (SOC) of Battery*

#### 2.2.1. Types of SOC Estimation Techniques

State of Charge (SOC) is the measurement for understanding the remaining battery capacity of the user. Figure 6 shows the state of charge of the battery through the regeneration and the figure 7 shows the numerical expression of the State of Charge and Health. This knowledge is very important because many systems are sensitive to deep discharging and overcharging.

$$SoC = \frac{C_{RemainingCharge}}{C_{Design}} (\%) \text{ ----- } (1)$$

$$SoH = \frac{C_{FullCharge}}{C_{Design}} (\%) \text{ ----- } (2)$$

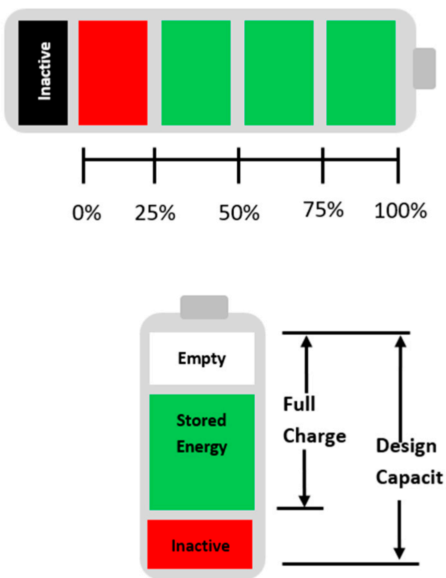


**Figure 6.** State of charge.

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This knowledge is very important because many systems are sensitive to deep discharging and overcharging. Very low or extremely high SOC can lead to damage to the battery [32]. Full SOC can define as the battery currently being constant for 2 h at constant charge and temperature (according to DIN 43539) [33]. Typically, the battery's level of charge should be kept within acceptable parameters (between 20% to 95%). As a result, being able to estimate the state of charge of the battery is critical to keeping the state of charge within safe limits [34]. SOC estimation under various discharging situations has different characteristics. Therefore, four types of estimating mathematical approaches are as follows:

(a). Direct measurement: This method takes advantage of physical battery features such as voltage and impedance.

(b). Book-keeping estimation: To calculate the SOC, this approach takes the discharging current as input and integrates it over time.

(c). Adaptive systems: The adaptive systems are self-designing and can modify the SOC for various discharging situations automatically. Adaptive methods for SOC estimation have been created in a variety of ways.

(d). Hybrid methods: In hybrid models, the benefits of each SOC estimate strategy are merged to produce an estimation performance that is globally optimal. The literature indicates that hybrid strategies provide accurate SOC estimation as compared to individual methodologies [35].

Some of these approaches operate well when the discharging current is fixed, whereas others perform better when the discharging current is changed. Because the existing ones are utilized with various battery sizes and discharge circumstances, it is hard to compare how well they work. In battery applications like BMS in hybrid electric vehicles, many SOC estimating methods are probably beneficial [36]. There has been a lot of research into the use of model-based and data-driven estimating methods. In SOC estimation, both the model-based and data-driven approaches have generated significant results. A model-based strategy is theoretically the optimum approach from the standpoint of statistical performance if the system model is known a priori, according to the rigorous review. The data-driven method, on the other hand, outperforms model-based solutions if the system is not well understood [37,38].

**Table 1.** Overview of SOC Estimation Methods:.

| Category | Model | Characteristics |
|---|---|---|
| Direct measurement [39–43] | (i) Open circuit voltage method<br>(ii) Terminal voltage method<br>(iii) Impedance method<br>(iv) Impedance spectroscopy method | • Easy to implement<br>• Low accuracy<br>• Accuracy depends on sensors measurement<br>• Depends on battery characteristics<br>• Not suitable for real-time measurement |
| Book-keeping estimation[44–48] | (i) Coulomb counting method<br>(ii) Modified Coulomb counting method | • Average precision<br>• Easy to implement<br>• It has cumulative errors<br>• Accuracy depends on sensor measurement |
| Adaptive systems[41,49] | (i) BP neural network<br>(ii) RBF neural network<br>(iii) Support vector machine<br>(iv) Fuzzy neural network<br>(v) Kalman filter<br>(vi) Model-based | • High accuracy<br>• Hard to implement<br>• Accuracy depends on the training data<br>• Can implement on any type of battery<br>• Need extensive domain knowledge<br>• A lot of experimental data is required |

| | | |
|---|---|---|
| Hybrid methods[50–53] | (i) Coulomb counting and EMF combination<br>(ii) Coulomb counting and Kalman filter combination<br>(iii) Per-unit system and EKF combination | • Good precision.<br>• Easy to implement<br>• Less Cumulative error compared with bookkeeping estimation<br>• Accuracy depends on sensor measurement |

2.2.2. SOC Estimation Technique in Modern Vehicle

In modern vehicles, the SOC estimation method based on coulomb counting with an extended Kalmon-filter is used. When compared to the Coulomb counting approach, EKF-based methods have better tracking performance but higher processing and complexity. Better results are obtained using the traditional coulomb counting approach, which is occasionally corrected by EKF tracking with a predetermined battery model [54]. An adaptive nonlinear observer design that corrects for nonlinearity and improves estimation accuracy is also effective. It is shown that a fixed feedback gain cannot sufficiently tolerate wide ranges of SOC fluctuations during charge/discharge operations [55–58]. SOC estimation accuracy can be significantly improved by using the calculated SOC to alter the feedback gain. SOC estimates are extremely susceptible to voltage and current measurement disturbances, resulting in estimate bias and volatility. To reduce the influence of measurement disturbances on SOC estimates, a two-time-scale signal processing approach is used [59,60]. The Kalman filter method is utilized in the Kalman Ah method to make the approximate initial value converge to the true value. The SOC is then estimated using the Coulomb counting method for the prolonged operating period. The SOC estimation inaccuracy is 2.5 percent when compared to the actual SOC obtained from a discharge test. This has a favourable comparison to an estimating error of 11.4% when using the Coulomb counting method [61].

*2.3. State of Health (SOH) of Battery:*

Venugopal et al. [62] assessed that the usable battery's capacity should not fall below 80% of its original capacity because of its exponential degradation below 80 percent. Estimating battery SOH is challenging as many unknown and unpredictable aspects influence the battery's health. To estimate the SOH of Li-ion batteries utilized in EV applications, the Independently recurrent neural network (IndRNN)-based SOH estimation model was used.

The deep learning-based data-driven technique is used to estimate SOH. Because of its ability to capture complicated non-linear properties of batteries by avoiding the gradient problem and allowing the neural network to learn long-term relationships among capacity degradations, the IndRNN has been used [79,82]. Shi et al. [63] said in a battery management system, an online state of health (SOH) estimate is critical for lithium-ion batteries. Therefore, various measures linked to internal resistance have been offered as SOH estimate indicators. Figure 7 shows the flow chart of State of Health and its methods. The reduction of temperature disturbances and the elimination of the state of charge (SOC) disturbances are considered. The suggested indicators and estimation approach were estimated with a maximum error of 2.301 %, demonstrating its dependability and practicality. The most common method for calculating SOH is to use the battery capacity. However, capacity estimate in EVs is challenging to accomplish online. This work proposes measurable SOH indicators from ECM based on statistical analysis [88]. Xu et al. [64] described the battery parameters and used current, charge depth, and charge frequency to determine charge behaviour and charge capacity. The K-Means clustering technique is used to investigate various charging habits and the findings demonstrate that there are clear distinctions between the various groups. The charge behaviour characteristics, of which the charge current has the most impact on the state of health of the battery, are connected to the attenuation rate of the vehicle's lithium battery capacity. The frequency of charge is the second most critical element impacting battery health, and it gives a theoretical framework for us to investigate alternative charge habits and offer excellent charge behaviour suggestions [89,90].

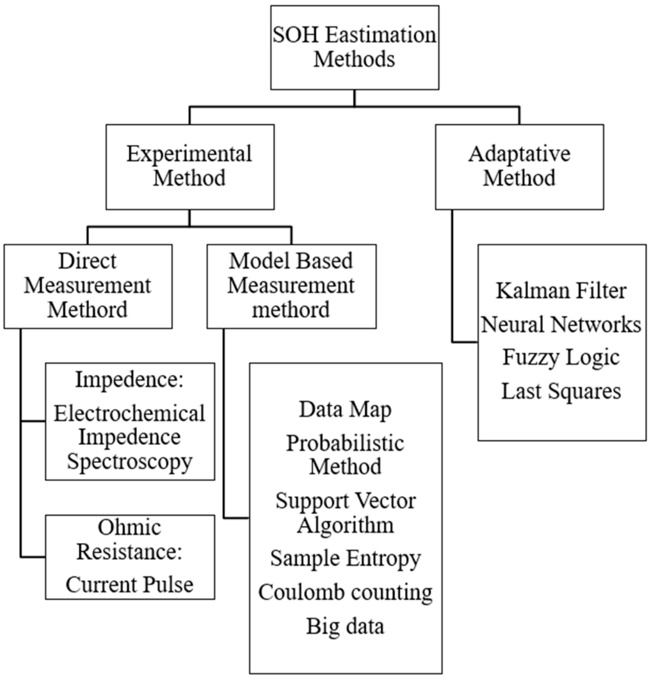


**Figure 7.** Flow chart of SoH Estimation Methods.

Lin et al. [65] estimated SOH without utilizing the whole battery profile, incremental capacity analysis can increase estimation efficiency. A robust cubic smoothing spline approach to generate an incremental capacity curve is used, which is superior to traditional filters that need trial-and-error window size tweaking. A robust cubic smoothing spline approach for obtaining the IC curve, with the key benefit of being able to identify the smoothing value via cross-validation rather than subjective trial and error parameter adjustment. The suggested technique estimated the SOH even without full charge or discharge data. Gabriel et al. [66] said that in the 0 to 50 °C range, the discharge capacity of LiCoO2 (LCO) batteries charged at one temperature and discharged at another is investigated for the low and high status of health (SOH) batteries. A discharge capacity dependency on relative charge-discharge temperatures is discovered. The surface self-temperature of the battery is tested at varied charging and discharging currents in 0.2C to 2C C-rates, and the surface heat is practically constant with the charging C-rates. In the battery discharges, however, a considerable surface temperature rise is observed, which corresponded to the battery SOH dependency. The temperature at which LCO batteries are charged and discharged in the 0-50 °C range, as well as the battery's SOH, affects their performance. When charging or discharging temperatures are loaded, the amount of charge stored or supplied decreases as well, and this decline is particularly pronounced at 0 °C. At any temperature, the coulombic efficiency of an L battery is always lower than that of an H battery. Diao et al. [67] elaborate on the current maximum available energy (MAE) to the rated total energy is proposed and defined as the energy SOH for a battery pack. In comparison to the capacity and power of SOH, this technique is more suitable and accurate in reflecting the real status of the battery pack. The superiority of this strategy is demonstrated by comparison and study in several ways. The energy SOH model for a battery pack incorporates capacity and internal resistance inconsistencies. The data from LiCoO2 and LiFePO4 batteries are used to analyse the cases. It demonstrates that both deterioration and irregularity influence the battery pack's SOHE [84,91].

Battery energy storage is a key enabling technology for electric vehicles and renewable energy sources, according to Moura et al. [68]. Using parabolic PDEs and nonlinearly parameterized output functions, the state of health is estimated as a parameter to pinpoint the problem. The elements influencing the battery's life degradation are depicted in Figure 8. The swapping identification strategy for unidentified parameters is applied to the diffusion partial differential equation (PDE). The availability of full-state measurements is a key premise in this investigation. By creating a signal-only parametric model, this assumption is relaxed. This makes it possible to create an adaptive observer that estimates states (SOC) and parameters (SOH) at the same time. We also wish to investigate the theoretical and practical performance of the state estimator/parameter identifier structure. Cacciato et al. [69] stated to allow the exact construction of the control algorithms for Energy Storage Systems (ESS), detailed information on the battery pack's SOC and SOH is required. A new method for estimating SOC and SOH has been proposed. It is based on the creation of a battery circuit model as well as a technique for adjusting model parameters. Accurate ESS modeling is critical because it helps power electronics systems to improve their control strategies. In the field of main electrochemical technologies, a unique approach for ESS state estimation has been devised. The core component of the technique is a PI-based observer system, in which the SOC and SOH values are calculated via an appropriate algorithm. Hatzell et al. [70] stated the literature on Lithium-ion battery characterization, control, and optimization is reviewed in this work. It looks at the basic degrading mechanisms in cycled cells before highlighting the difficulties in managing them. This necessitates determining how batteries fail and building fundamental models of their failure that are control-oriented. Impedance spectroscopy is a powerful method for identifying battery health models, as well as for online health estimation, prognostics, and diagnostics. Health-conscious battery control is a very interesting study subject, especially if the community can get rid of the limitations imposed by "conventional" battery control systems such as CCCV charging/discharging and rigorous cell-to-cell balance. Lipu et al. [71] observed electric vehicles with lithium-ion batteries have a hard time predicting their health and remaining useful life. The SOH and RUL of the battery are analyzed using traditional procedures, model-based approaches, and algorithms. The construction of an adequate model for calculating SOC while taking into consideration different model disruptions and uncertainties must be investigated. A thermal management module should be implemented inside the BMS to decrease the impact of thermal runaway. Cuma et al. [72] stated estimating methodologies help with battery management, vehicle energy management, and vehicle control by completing several duties. To estimate the capacities and instantaneous resistance that is the major indications of SOH. For lead-acid batteries Sample entropy (SE), Subspace parameter (SP), Equivalent circuit parameter (ECP) etc. methods are proposed with their percentage of error. For lithium-ion batteries, Genetic algorithm (GA), Model-based, Dynamic Impedance, Dynamic Bayesian network (DBN) etc. methods are employed with their accuracy. Qin et al. [73] propounded an intelligent battery management system, state of health (SOH) prediction in Li-ion batteries is critical (BMS).The occurrence of capacity regeneration events, on the other hand, presents a significant barrier in precisely estimating the battery SOH. From the raw SOH time series of the present battery, the global deterioration of n trend and regeneration phenomena (defined by regeneration amplitude and regeneration cycle number) is derived. The present battery's global deterioration trend and regeneration phenomena are prospected and then combined to produce overall SOH prediction values. The historical battery's regeneration threshold is calculated using particle swarm optimization (PSO).The global deterioration trend is forecasted using a Gaussian process (GP) model, while the regeneration amplitude and cycle number of each regeneration zone are forecasted using linear models. Yeon Lee et al. [74] stated a lithium-ion battery's state of health (SOH) is crucial in deciding how long it will last. Before developing a suitable SOH estimation model, consider the factors that cause battery deterioration. Multiple regression models with selected parameters are developed to account for the effects of deterioration. The reduction in battery capacity and increase in resistance are used as signs that the battery is getting older. Multiple regression analysis is used to examine the complicated impacts of factors on lithium-ion battery degeneration [87].

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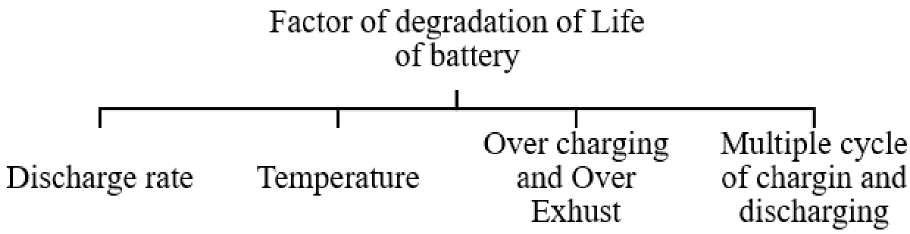


**Figure 8.** Degradation of battery life.

Anselma et al. [75] explained the fundamental problem in the design of hybrid electric cars is achieving a sufficient high-voltage battery lifespan while maintaining fuel efficiency. While there have been various battery state-of-health (SOH) sensitive control techniques for HEVs proposed in the literature, they have seldom been empirically verified. This work intends to demonstrate an optimum, multi-objective battery SOH sensitive off-line HEV control strategy based on dynamic programming (DP), which has been empirically tested in terms of battery lifetime prediction capabilities. Cells with present characteristics are aged for three distinct expected lifespan instances in an experimental campaign. By incorporating the influence of temperature and updating the empirical ageing characterization curve, the battery ageing model's predicted accuracy is increased [85,86]. Yang et al. [76] analyse the existing characteristic parameters for defining battery SOH at the cell and pack levels. The factors used to define SOH, including capacity, impedance, and ageing-mechanism parameters, are utilized to categorize SOH estimating techniques. Limiting the SOH definition to battery capacity or impedance estimation makes it difficult to characterize the battery's ageing status completely. An emphasis on pack-level SOH is also created in addition to the cell-level SOH definition. The capacity to distribute energy and cell-to-cell variances is taken into account when defining pack-level SOH. Internal deterioration types, data accessibility, and the aims of chosen SOH-related characteristics. The current SOH prognosis approaches mostly consisted of short-term state estimate and long-term RUL prediction, which judges' battery retirement point and ignore the instructional value of the battery ageing process [81]. M Dalal et al. [77] stated the battery's life can be estimated on dynamic properties using a lumped parameter battery model, including non-linear open-circuit voltage, current, temperature, cycle number, and time-dependent storage capacity. The remaining usable life (RUL) of the system was estimated using statistical estimations methods. With a particle filtering framework & sequential significance resampling approach to estimate the battery's EOL and EOD for individual discharge cycles & the battery cycle life. With the help of developed methods (RUL) estimation can be done [80]. Sarikurt et al. [78] presented to estimate of the number of battery pulse-width the ECE 15 driving cycle. A new approach for obtaining the SOH of a battery using the cycle number is also shown. An analytical SOH estimate approach is provided in which the usable capacity of a battery depends on its cycle count. The usable capacity of a battery decreases when its cycle number increases [83].

Interventionary studies involving animals or humans, and other studies that require ethical approval, must list the authority that provided approval and the corresponding ethical approval code.

### *2.4. Effect of Regenerative Braking on the Life of Battery:*

Keil and Jossen [92] prospected that a high charging current by using regenerative braking deteriorates the battery life. So, they conducted a cycle life study on the Li-ion battery by using different driving load profiles for different regenerative braking values.

The different regenerative braking conditions are applied to Li-ion cells at different temperatures and states of charge (SOCs). It is found that cells cycled at 25 °C provide a good compromise between calendar and cyclic aging. Further, on evaluating the battery ageing in EVs based on driving load profile, they revealed that calendar ageing diminishes as the temperature drops, and cycle ageing increases and becomes more sensitive to load profile changes. Cycling over 200,000 km demonstrated that regenerative braking extends the battery life by reducing the cycle depth. Figure 9 represents the layout of the energy recovery due to integrated regenerative and neural network methods. This significantly reduces capacity fade and increases resistance. The evaluation of different levels of regenerative braking has shown that short-duration recharging times during braking do not enhance battery degradation for a typical driving load profile- even at low battery temperatures of 10° C. Higher degrees of regenerative braking inhibit degradation, particularly at high SOC and low temperature, which are prime conditions for lithium plating. The lower degradation is due to the battery's reduced DOD when partially refilled by using shorter recharging periods during braking moments [92]. The amount of charge refilled at the charging station appears to have a greater impact on capacity fade than the overall charge flow. As a result, an EV is benefitted from a high level of regenerative braking but only low recharging currents are used [96].

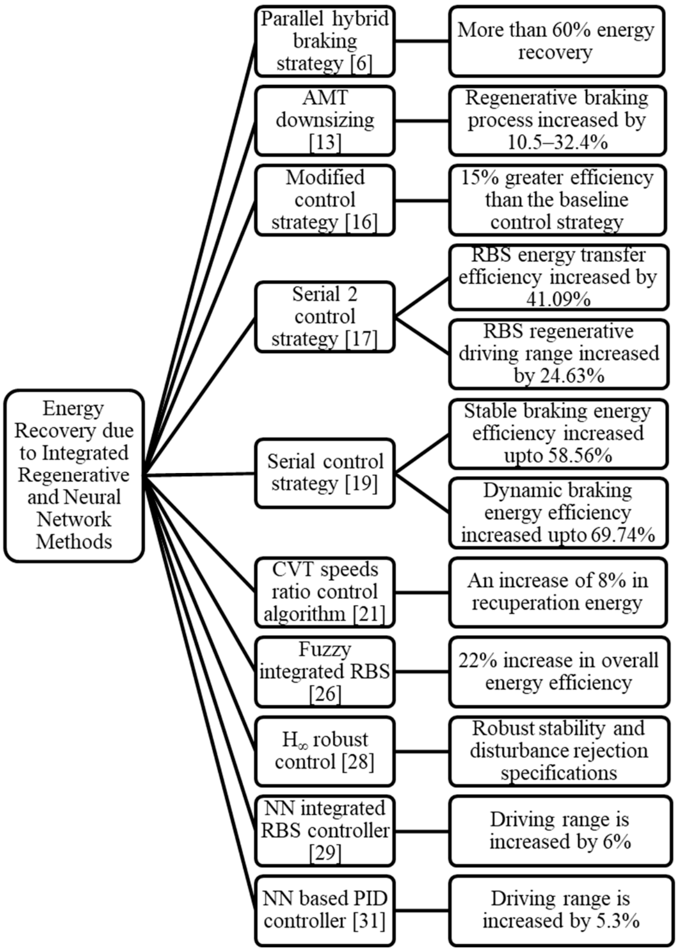


**Figure 9.** Flow chart of combined energy recovery of regeneration.

Jingying et al. [93] revealed that regenerative braking increases the temperature of the Li-ion battery. They proposed a control method subjected to braking safety regulation and adjusted the regenerative braking ratio by using a fuzzy controller. It is found that by modifying the charge current due to regenerative braking, the proposed control strategy suppresses the rise in the battery temperature. It is also observed that the real-time battery SOC and temperature, the fuzzy logic controller adjust the regenerative braking ratio. Carrilero et al. [94] examined the above C/2 charging regimes. When more than 90% of the effective capacity can be recharged in 15 minutes or less over the course of the cell's life (more than 5000 cycles) without experiencing a significant loss in power capability, it is determined that the cell's overall performance is suitable for fast-charging. Asif et al. [95] introduced an RBS used in HEV to give backup power in deceleration mode that made HEV drive longer but moreover also increased the battery life cycle by charging of ultra-capacitor. Without using a buck or boost system, the improved regenerative braking system has lower power losses between the BLDC motor and ESS. In RBS mode, energy is increased by using an induction motor in winding and the inverter's H-bridge switching approach to transfer it to ESS with the fewest possible losses. Through the fuzzy logic controller, pulse width modulation (PWM) is used to operate these switches. As a result, battery life and working time will both increase. Wu et al. [97] presented a hierarchical control technique by considering battery aging. The up-level controller's control objectives are to increase energy recovery and decrease battery aging while ensuring vehicle braking safety in emergency braking mode. The low-level controller, which takes instructions from the up-level controller (EM), manages the pneumatic braking system and the electric motor. Maximum EM torque and battery charging power have been defined for the protection of the EM and battery. The real-time calculation performance is assessed using controller-in-the-loop testing and the control efficacy of the suggested method. For both control strategies, the braking distance, vehicle speed, wheel speed, and slip ratio are nearly identical (with or without battery aging consideration). When battery aging is taken into account, the EM motor is reduced in size considering EM torque. Long et al. [98] analyzed the hybrid power supply system made up of ultracapacitors and batteries that can increase the EV's one-time charging driving mileage and energy recovery efficiency. A design technique for $H\infty$ [27,28] is proposed based on stability and dynamic responsiveness. The experimental results show that a vehicle can gain approx. 5.3% braking energy when utilizing the suggested energy-management scheme and the recommended $H\infty$ than when using a regular PID controller under the same conditions. To protect the battery from damage brought on by an excessive charging current during regenerative braking, Cao et al. [99] suggest a control strategy that uses the charging current as a control object. The weighted mixed-sensitivity issue is used to model the design of regenerative braking controllers. In order to guarantee the robustness of the closed-loop system in the presence of uncertainties, such as parameter perturbation during the period and unidentified model dynamics, the H robust controller for regenerative braking is created together with a DC-DC converter. It also minimizes the effect of disturbance, battery voltage variation, state of the road, and driving profile of the vehicle. In terms of steady-state tracking error, response speed and energy recovery the experimental results revealed that the $H\infty$ robust controller outperforms the typical PI controller.

To improve the braking efficiency and regenerative energy of front-drive electric vehicles (EVs) powered by switched reluctance motors (SRM), Zhu et al. [100] proposed a regenerative braking control approach based on multi-objective optimisation of the switched reluctance generator (SRG) drive system. The partition brake force distribution approach is developed while simultaneously taking safety and braking energy into account. The SRG drive system model is constructed based on low and high-speed scenarios. The mechanic braking system, SRG drive system model, and partition braking force distribution system were all included in the braking system model of a front-drive vehicle propelled by a four-phase 8/6 SRM. Regenerative braking was then proposed as a control strategy to enhance braking efficiency and regenerative energy of the vehicle based on multi-objective optimisation of the SRG drive system, with output, generated power, torque smoothness, and current smoothness selected as optimisation objectives to enhance driving range, braking comfort, and battery lifetime, respectively. Naseri et al. [101] introduced a Hybrid Energy Storage System, and the complementary qualities of batteries and ultracapacitors may be efficiently employed (HESS). The usage of the HESS in electric cars (EVs) has a number of advantages, including quicker acceleration, more effective regenerative braking, and improved battery safety. An innovative RBS based on the utilisation of HESS is suggested for EVs with BLDC motors. During regenerative braking and/or energy regeneration, the ultracapacitor utilises the appropriate switching pattern of the inverter to store the vehicle's kinetic energy. Power electronics interfaces are therefore no longer necessary. The MLP-ANN controller is used to control how much braking power is applied to the front and rear wheels of the EV. Furthermore, the PI controller is employed to control the PWM duty cycle. Dixon et al. [102] stated through the interplay of the other aforementioned factors, such as the vehicle speed and the state of charge of the battery, the capacitor voltage is regulated by the IGBT PWM (insulated-gate bipolar transistor) technique used in the Buck-Boost Converter. For an electric car, a simulated ultracapacitor bank was constructed. The purpose of this device is to allow the vehicle to accelerate and decelerate more quickly with less energy loss and main battery pack degradation. An IGBT Buck-Boost converter controlled the system by monitoring the battery voltage, SOC, automobile speed, instantaneous currents at both terminals (load and ultracapacitor), and the ultracapacitor's actual voltage. Carteret et al. [103] stated to hybridize battery EVs and reduce peak battery currents, ultracapacitors can be employed. Extending the life of a battery has the potential to enhance total propulsion efficiency, increase range, and reduce life cycle costs. They constructed a programmable control strategy that can be altered to satisfy various objectives. When employed in a hybrid vehicle system, ultracapacitors may provide high burst power even when the battery capacity is low due to the low SOC, allowing the vehicle to keep its acceleration performance. Ultracapacitors can be employed in an EV hybrid battery/ultracapacitor system. Extending the life of the battery can improve total propulsion efficiency, boost range, and lower life cycle costs.

## 3. Conclusions

The following conclusions can be drawn as follows:

1. Various regenerative braking techniques have been introduced to extract the energy from the braking phenomenon. Two basic techniques are implemented i.e., the parallel hybrid braking system and the fully controllable hybrid braking system. The fully controllable hybrid braking system further included sub-strategies like optimal braking performance and optimal braking energy recovery which is based on the braking distribution of the vehicle.
2. Based on this, many authors have compared these strategies and stated their pros and cons. Moreover, the conventional regenerative braking is merged with the ABS and CVT offered maximum performance. Higher regenerative braking efficiency was also achieved by downsizing the AMT as more energy loss is observed by lowering the braking torque. The high speed of the rotor caused iron loss which reduced energy recovery efficiency due to regenerative braking.
3. A combined H∞ controller is implemented in the RBS which used the fuzzy logic systems to provide optimal performance while considering the SOC of the battery. The H∞ controller was further combined with PID and SMC to further improve the braking process.
4. In the field of SOC estimation, there has been a lot of research into the use of model-based and data-driven estimating methods. In SOC estimation, both model-based and data-driven approaches have shown significant results. A model-based strategy is theoretically the best approach but it has high complexity compared to other methods.
5. The conventional coulomb counting method and occasionally corrected by EKF tracking with pre-defined battery model gives better results as well as an adaptive nonlinear observer design that compensates for nonlinearity and achieves better estimation accuracy.
6. SOH is related to battery ageing; various methods are developed to estimate the accurate SOH. From the estimation, it can be determined when the battery should be replaced. In EVs regenerating barking is used to improve the battery life. A higher level of regeneration can reduce battery ageing.
7. It is found that if the temperature is too low or high, the battery life further deteriorates due to the current occurring due to the regenerative braking. It is stated that 25 °C provides optimal conditions which slow down the battery ageing process due to the RBS.
8. It has been also found that the Li-plating increases with the higher SOC, higher charging currents and low temperature. Therefore, at low temperatures, the ageing of the battery increases and becomes susceptible to changes in the load profile.
9. Also, the battery is prominently deteriorated because of the charging current for longer periods even having the low current intensity that promotes the Li-plating.
10. A higher degree of regeneration braking ameliorates the battery life by reducing the battery's DOD by using shorter and lower recharging currents. It also reduces the battery life degradation even at high SOC and high temperature. So, only a high level of regenerative braking for low recharging currents is preferred for battery life.
11. It has also been found that regenerative braking increases the internal resistance of the battery which eventually increases the temperature of the Li-ion battery.

12. Therefore, many control strategies have been introduced that included a fuzzy logic controller. The fuzzy controller adjusted the regenerative braking ratio by observing real-time battery SOC and temperature to prevent the battery temperature rise.
13. The RBS system is also used with an ultracapacitor to increase the battery life. Furthermore, the H-bridge switching technique and fuzzy logic based PWM controller is used to transfer energy to ESS.
14. The electric motor torque and battery charging power have also been taken into account in the hierarchical control while adjusting the regenerative braking ratio. For preventing battery ageing, motor size is optimized or reduced to a certain extent.
15. The H∞ controller also protected the battery from parameter perturbation and excessive charging current obtained during the regenerative braking. SRG drive system improved regenerative recovery energy while keeping the smoothness in the charging current and improving the battery lifetime.
16. The ultracapacitors allowed quick vehicle acceleration and deceleration with minimum energy loss while keeping the main battery safe. The ultracapacitors are used to reduce the peak current which reduces the battery life. Besides that, ultracapacitors provide high burst power when the battery's SOC is low.

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## 4. Future Work

There are very few works done which signify the effect of the regenerative braking on the SOH of the battery. However, much work has been done for the incorporation of ultracapacitors in regenerative braking as they support the battery in storing the charge for a long time. So, this work can be further extended by analyzing the effect of supercapacitors on the storage of charge and thus charging of the battery.

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