Comparative Analysis of Human Braking Behavior and Automated Regenerative Braking Systems in Electric Vehicles

1st Hamed Faghihian
Department of Mechanical Engineering
University of South Florida
Tampa, United States
hfaghihian@usf.edu

2nd Seckin Ozkul
Muma College of Business
University of South Florida
Tampa, United States
sozkul@usf.edu

3rd Arman Sargolzaei
Department of Mechanical Engineering
University of South Florida
Tampa, United States
a.sargolzaei@gmail.com

***Abstract*—Electric vehicles (EVs) utilize regenerative braking systems (RBS) to recover a portion of the vehicle's kinetic energy, making RBS an essential component for improving energy efficiency and extending vehicle range. However, the efficiency of energy recovery in RBS is significantly influenced by driver behavior in human-operated vehicles or by control algorithms in automated vehicles (AVs). Although existing studies acknowledge the dependence of RBS performance on driver behavior, there is a notable lack of research focusing on quantifying this impact or understanding its patterns. This paper addresses this gap by analyzing data from an EV operated by human drivers and compares the influence of braking behavior on energy recaptured with an automated RBS. The results reveal that braking patterns play a critical role in determining the amount of energy recaptured, offering insights into the variability introduced by human drivers. This study demonstrates that an automated braking system can achieve, on average, a 15.86% higher energy recapture compared to human drivers, with even greater improvements observed in specific scenarios. These findings are essential for refining driver training, improving vehicle energy efficiency, and advancing the development of automated braking systems for EVs.**

***Index Terms*—Electric vehicle; Energy efficiency; Human braking behavior; Automated regenerative braking system;**

I. INTRODUCTION

The shift to EVs is driven by environmental and economic goals, but full market adoption faces significant challenges [1, 2]. Key barriers include limitations in charging infrastructure and range anxiety [3]. Increasing battery capacity to address range issues presents a trade-off, as it raises concerns about environmental impacts and carbon emissions associated with larger batteries [4]. Concurrently, with the growing adoption of EVs, improving their energy efficiency has become imperative. Enhanced energy efficiency not only addresses the range limitations of EVs but also contributes to sustainability, which is critical for the widespread integration of EVs into modern transportation systems.

EVs' energy efficiency increasing can be achieved through various approaches, including advancements in battery technology, driver training [5], improvements in power electronics, and optimization of vehicle control systems [6]. Also, some methods are studied in the literature to increase EV energy efficiency by increasing the efficiency of electric motors, as highlighted in [7]. Similarly, approaches to enhance efficiency through battery thermal control are discussed in [8]. Other works propose solutions such as improving power electronic components and semiconductors [9], or achieving better efficiency by optimizing vehicle routes [10]. Another approach to improving EV efficiency, as explored in [11], involves optimizing energy consumption through energy management strategies under different driving cycles. With the recent advancements in connected and automated vehicle (CAV) technologies [12, 13], higher energy efficiency can be achieved by the adoption of CAV features as discussed in [1].

Although extensive research has been conducted on energy efficiency technologies, many of these methods are not entirely suitable for EVs, as they were originally developed for vehicles with internal combustion engines. Two key differences in energy consumption differentiate EVs and ICEVs. First, the efficiency maps of electric powertrain are fundamentally different from those of internal combustion engines [14]. Second, EVs have the unique ability to utilize electric motors as RBS, offering significant potential for energy recovery. The braking system is a major contributor to energy dissipation in vehicles, responsible for up to 50% of total traction power losses [15] which can be saved through RBS. Recent advancements in RBS technologies have notably improved their efficiency and effectiveness [16], attracting considerable interest from the automotive industry [17].

The effectiveness of RBS in recapturing dynamic energy depends significantly on how braking torque is applied, as brake controllers balance hydraulic braking and RBS to ensure sufficient braking while maintaining energy recovery efficiency . Also, the energy efficiency of the motor in generator mode varies with braking torque and speed [18]. To evaluate the effectiveness of RBS, the study in [19] incorporated real-world driver data to measure the Vehicle regeneration efficiency (VRE), defined as the ratio of regenerated energy stored to total braking energy, with reported values ranging from 59% to 69%. Despite these efforts, none of the studies directly investigated how variations in human driver behavior influence RBS effectiveness in energy recovery under real-world braking scenarios.

To investigate how human driver behavior influences the effectiveness of RBS, studies such as [20] have tested the impact of different driving styles model on the amount of recaptured energy. Similarly, [21] modeled various human

SoutheastCon 2025 | 979-8-3315-0484-7/25/$31.00 ©2025 IEEE | DOI: 10.1109/SOUTHEASTCON56624.2025.10971603

driving behaviors, demonstrating in experiments that braking behavior can influence energy recovery by up to 16.32% under different models of human drivers braking behavior. However, while these studies modeled human driver braking behavior, none incorporated real-world human drivers in tests, and they did not analyze how driver input patterns impact instantaneous vehicle power consumption.

To minimize the impact of human drivers on braking and maximize energy recovery, automated braking systems by using CAV features have been proposed in various studies. For instance, [22, 23] introduced an automated braking planning system utilizing a dynamic programming-based energy-efficient deceleration strategy to enhance regenerative energy recovery. Also, in the work reported in [24] an automated braking system aimed at maximizing RBS effectiveness. However, these studies did not compare their results with human braking behavior. Although studies such as [25] modeled average driver braking behavior, they do not account for interactions with EVs, and do not provide any insight on comparisons between human and automated braking performance. Therefore, our investigation reveals a lack of studies that incorporate real human driver braking patterns over time, analyze how driver input patterns impact instantaneous vehicle power consumption or timely energy recapture, and compare them with automated braking systems designed to maximize energy recovery. To bridge this gap, it is necessary to develop and utilize metrics that effectively relate human driver performance in recapturing energy to the performance of automated braking systems which designed to maximize energy recovery.

The methodology of this paper involves collecting real-world braking data from human drivers operating an EV. To address the lack of comparative studies in the literature, we introduced two metrics to quantify RBS performance. The metrics compare RBS effectiveness between human drivers and an automated braking system, designed to maximize energy recovery, were evaluated under identical conditions to establish a baseline for comparison. This approach brings a systematic evaluation of how human braking behavior influences energy recovery. The findings highlight the variability introduced by human behavior and the potential of automation to maximize energy recovery.

The structure of this paper is outlined as follows: Section II presents the methodology of the study, including the fundamental principles of energy recovery systems in EVs equipped with RBS, as well as the procedures for data collection from the test vehicle. In addition, metrics are presented to evaluate the effectiveness of the RBS and the methodology for comparing driver performance with an automated braking system. Section III discusses the results, analyzing how variations in driver behavior and vehicle speed influence energy recovery efficiency, and examining the distribution of recapture metrics between human drivers and the automated braking system. Finally, Section IV summarizes the findings, provides recommendations, and suggests future research based on findings.

II. METHODOLOGY

This section introduces the energy principles of vehicles and the basic concepts of RBS. It also outlines the test procedures, metrics for evaluating RBS effectiveness, and the methodology for comparing automated and human-driven braking systems.

A. Energy Principles and Evaluating Metrics

The total energy consumption of a vehicle can be expressed as

$$E_c = E_{air} + E_{roll} + E_{acc} + E_g, \tag{1}$$

where $E_{air} \in \mathbb{R}$ accounts for aerodynamic drag, $E_{roll} \in \mathbb{R}$ for energy to overcome the rolling resistance force, $E_{acc} \in \mathbb{R}$ for energy to accelerate the vehicle, and $E_g \in \mathbb{R}$ for the energy being used for elevation changes. Among these, $E_{acc} \in \mathbb{R}$ is the most directly controllable parameter, while the others depend on external conditions. For EVs and HEVs, regenerative braking allows the recovery of energy that would otherwise be lost. Subtracting the recovered energy, $E_{rb} \in \mathbb{R}$, from the total consumption yields

$$E_c = E_{air} + E_{roll} + E_g + E_{acc} - E_{rb}. \tag{2}$$

Maximizing E_{rb} significantly improves vehicle efficiency by increasing the energy returned to the battery. However, in practice, it is impossible to recover all of a vehicle's kinetic energy through the RBS due to limitations in braking torque. The RBS torque alone may be insufficient in for some braking demands,therefore, the braking controller combine RBS torque with hydraulic braking torque.

The energy recovered through the RBS depends on the EV's powertrain efficiency in regeneration mode, which is almost identical to its efficiency map in acceleration. Therefore, we introduce the following measure to represent RBS overall effectiveness in a drive cycle as

$$\eta_{rc} = \frac{E_{\text{recaptured}}}{E_{\text{charged}}}, \tag{3}$$

where $E_{\text{recaptured}} \in \mathbb{R}$ represents the total amount of energy recovered through regenerative braking in a certain part of a cycle, $E_{\text{charged}} \in \mathbb{R}$ is the total energy supplied to the vehicle through battery in the same part of a cycle, and η_{rc} denotes the recapture-to-charge efficiency in that part of a driving cycle, Since as complete energy recovery during braking is not feasible, ensuring $0 \leq \eta_{rc} < 1$.
To evaluate the effectiveness of RBS during a braking scenario from an initial speed v_0 to a complete stop, we define the braking efficiency as

$$\eta_{br} = \frac{E_r}{E_{K0}}, \tag{4}$$

where $E_r \in \mathbb{R}$ denotes the net energy recaptured and charged to the battery during braking (excluding vehicle auxiliary systems consumption), $E_{K0} \in \mathbb{R}$ represents the total kinetic energy available at the start of braking, and η_{br} is introduced as net RBS efficiency. Analyzing the distribution of this parameter provides insights into how different drivers' interactions with EVs influence energy recovery.

B. Test procedure

The Ford Mustang Mach-E, shown in Figure 1, selected for this study because of its RBS capabilities and its compatibility with the necessary sensors for real-time data collection. Although the methodology is applicable to other EV models, as they utilize similar underlying dynamics, powertrain systems, and RBS principles. Thirty participants were asked to drive the experiment vehicle with time provided for familiarization before data collection. To ensure natural driving behavior, the test objectives were not disclosed to participants. The driving test took place on a circuit replicating urban conditions (Figure 2), featuring a designated stop location and endpoint. All tests were conducted under similar environmental conditions Participants completed the circuit twice: once under crowded-zone speed limitations and once without restrictions to assess variations in driving behavior.

The vehicle's onboard sensors collected data, which were subsequently used to analyze how driver behavior impacts the recapture-to-charge efficiency.

C. Compare with automated braking

To evaluate performance of human driver behavior in recapturing power, we used automated braking system specifically designed to maximize energy recovery, as detailed in [24] as a baseline. A simulation conducted using the modeled EV parameters outlined in Table I, with energy efficiency map in [26]. Although environmental factors can influence the results, we conducted our experiments under conditions closely aligned with the idealized assumptions used in modeled EV. By minimizing variations in environmental conditions, such as temperature, road surface, and wind, we minimized this impact. The use of a normalized net RBS efficiency metric ensures that the comparison remains valid, enabling a meaningful evaluation of energy recapture performance across both human-driven and automated braking scenarios.

This automated braking system use the efficiency map described in Figure 3 to find the optimum braking torque, $T_{eff} \in \mathbb{R}$ and use the following equation for finding braking torque, $T_b \in \mathbb{R}$

$$T_b = \max\{T_{eff}, T_{necs.}\}. \tag{5}$$

Fig. 1: The RANCS lab EV, equipped with sensors for real-time data collection.

Fig. 2: Circuit map designed for the test procedure.

TABLE I: Modeled vehicle characteristics

Parameter name	Values	Unit
mass	1500	kg
drag coefficient	0.3	-
vehicle frontal area	2	m^2
battery capacity	400	Ah
battery response time	30	s
initial SOC	60	%
stator phase resistance	0.73	Ω
BLDC torque constant	1.8	-
BLDC rotary inertia	0.034	kgm^2
Wheel radius	32.1	cm
Gear ratio	8.193	-

where $T_{necs.} \in \mathbb{R}$ is the minimum necessary torque calculated as

$$T_{necs.} = \frac{mV^2}{2d}\frac{R}{G}, \tag{6}$$

where $d \in \mathbb{R}$ is the detected distance to the final stop location, $V \in \mathbb{R}$ is the vehicle speed at the time braking procedure starting, $m \in \mathbb{R}$ is the vehicle mass, $R \in \mathbb{R}$ is the vehicle wheel radius, and $G \in \mathbb{R}$ is the gear ratio.

The experimentally measured η_{br}, representing the recapture efficiency for human drivers, was compared against the simulated $\eta_{br-automated}$, which reflects the optimal performance of the automated RBS. This comparative analysis provides insights into how human driving behavior influences regenerative braking performance. The comparison method illustrated in Figure 4. As shown, the initial speed and the distance to the

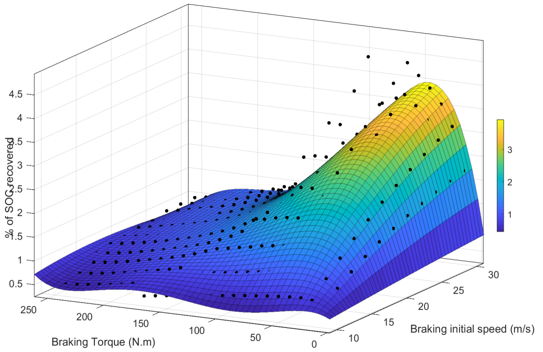


Fig. 3: The efficiency map for finding braking torque maximizing recovered energy [24].

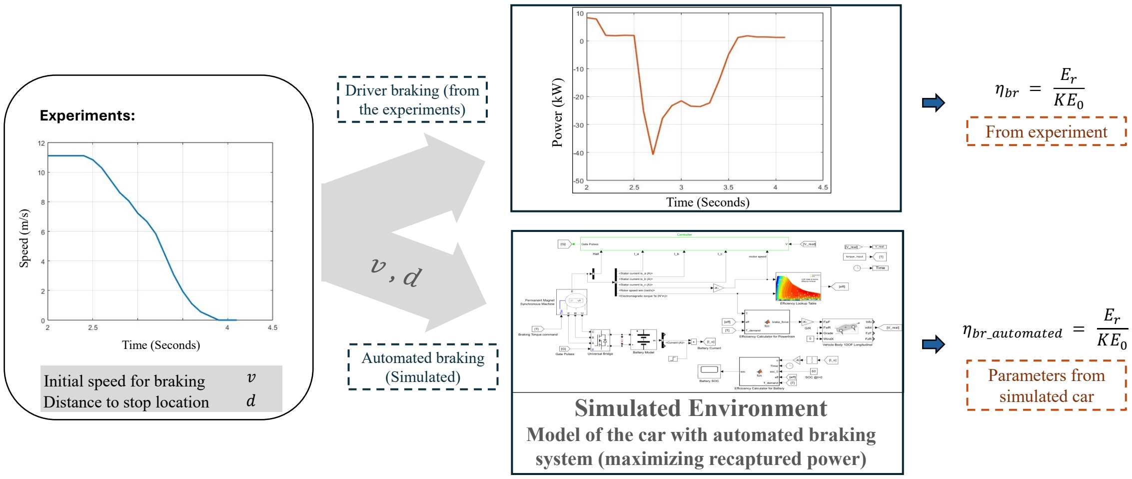


Fig. 4: The scenario for the comparison between human driver and automated braking controller.

stop location for each driver used as the input parameters of the automated braking controller and values of the RBS efficiency for automated braking and the human driver braking derived.

III. RESULT

This section presents the results and discusses the findings. As mentioned in Section II-B, test data were collected from various drivers completing laps around the circuit. In Figure 5 a sample of speed and power data for one lap of a driver is shown. The probability density function (PDF) used to evaluate the results, offering a statistical representation of the likelihood of a variable taking on specific values. This analysis provides insights into the distribution and variability of metrics [27]. The PDF effectively visualizes how data points are distributed across the range of data, highlighting the impact of drivers and automated braking systems on RBS performance.

A. RBS efficiency in complete round

This section presents the results of the energy analysis for a complete round using the recapture-to-charge efficiency. As shown in Figure 6 this metrics varies among drivers, indicating its dependency on individual driving behavior. The average η_{rc} across all participants was 20.2% when drivers were asked to drive with the lower speed, and 29.9% in the higher-speed scenario. This suggests that participants achieved better energy recapture performance when driving at higher speeds. While driver speed influences energy-saving, the results indicate that attaining higher total recapture efficiency does not necessarily require precise and cautious driving, which can be achieved more in lower speed scenario.

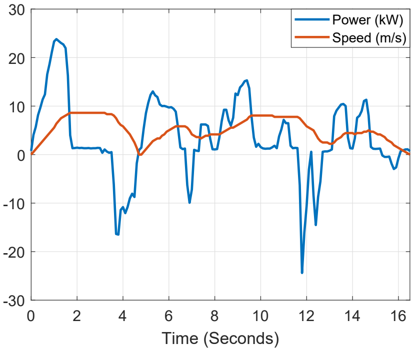
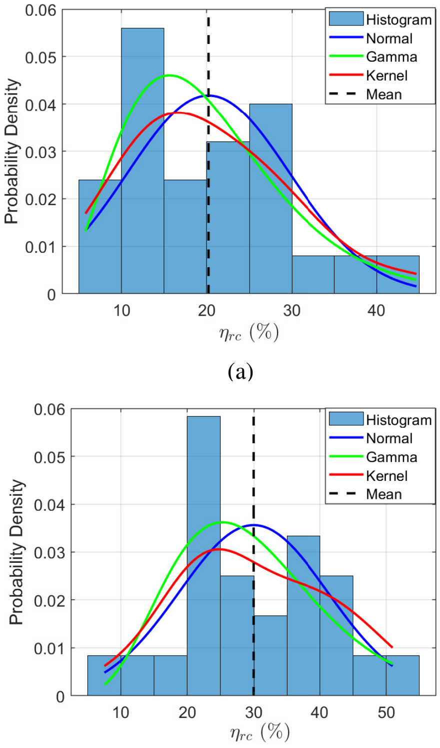


Fig. 5: A sample of speed and power graph collected

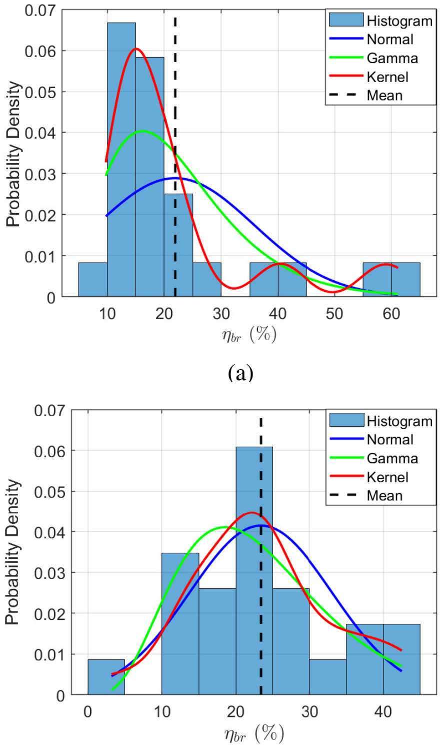


(a)

(b)

Fig. 6: PDF of recapture-to-charge efficiency, η_{rc}, for: (a) low-speed scenarios (average top speed = 7.3 m/s). (b) high-speed scenarios (average top speed = 9.8 m/s).

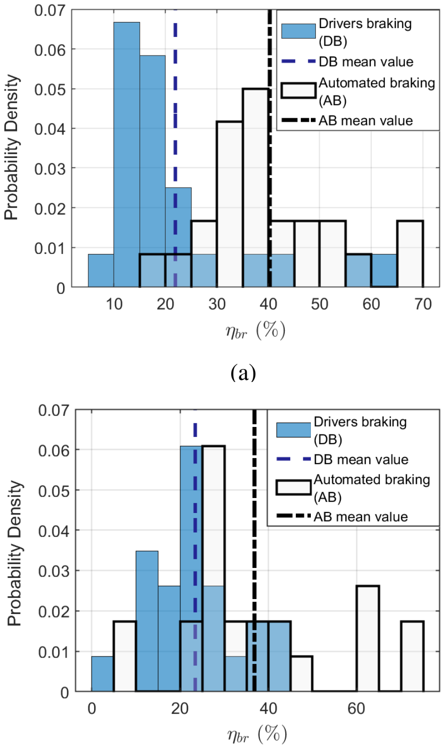
The graphs show that although different drivers utilize RBS with varying effectiveness, the variation in energy recapture among different drivers does not increase with higher speeds. These findings suggest that both driving habits and speed of an individual driver significantly influence the recapture-to-charge efficiency over a complete driving cycle.



(a)

(b)

Fig. 7: PDF distribution of net RBS efficiency at a stop location during: (a) slow-speed scenarios (average top speed = 7.3 m/s). (b) high-speed scenarios (average top speed = 9.8 m/s).



(a)

(b)

Fig. 8: comparison of PDF of net RBS efficiency distribution and mean value of net RBS efficiency at for braking to stop (a) slow-speed scenarios. (b) high-speed scenarios.

B. RBS efficiency in stopping scenarios

To analyze how different drivers affect the effectiveness of the RBS for braking to a full stop, the comparison of net RBS efficiency for different drivers shown in Figure 7. The average value of η_{br} among different drivers in the braking scenario was 21.9% when drivers were asked to perform at lower speeds, while it increased to 23.4% when they were asked to perform at higher speeds. However, while the average values of η_{br} are quite similar across different speed scenarios, at lower speeds, some drivers exhibited braking patterns that resulted in exceptionally high η_{br} values. This variation indicates that their braking habits allowed the RBS to operate more efficiently. However, the majority of drivers did not demonstrate this behavior.

This finding is crucial in understanding how training or improving braking habits, particularly at lower speeds where drivers have more time and space, can enhance energy recapture. This suggests that drivers at lower speeds potentially can achieve better efficiency as they have greater control and more time to optimize the braking process. These results emphasize the stronger impact of driver braking behavior on efficiency at lower speeds compared to higher speeds.

C. Comparison of Human Drivers and Automated Braking for Enhanced RBS Efficiency

This section provides results of the comparison method based on Figure 4. As shown in Figure 8, the automated braking system significantly improves net RBS efficiency, demonstrating its potential to enhance energy recovery. Each driver created a unique scenario with different initial speeds and distances to the stop location.

The mean value of η_{br} in slow driving scenarios increased from 21.9% for human driver braking to 40.2% with the automated braking system, while in higher-speed scenarios, the automated braking system increased this mean value from 23.4% for human driver to 36.8%. By comparing the mean values across these scenarios, we observe that an automated braking system, or a well-trained driver capable of following a similar braking pattern, can substantially improve net RBS efficiency with ensuring that no other parameters in the driving pattern are affected, particularly at lower speeds. At these speeds, the braking process can be extended over a longer duration, minimizing reliance on hydraulic braking and maximizing energy recovery efficiency.

IV. CONCLUSION

This study provides a comprehensive analysis of human driving behavior and its impact on the RBS performance, with a comparative evaluation against an automated braking system designed to maximize energy recovery. By introducing novel metrics, such as the recapture-to-charge efficiency and the net RBS efficiency.

This research findings reveal that driver behavior strongly influences RBS performance, with better efficiency observed at higher speeds for complete driving cycles and at lower speeds during braking scenarios. This underscores the variability in energy recovery caused by individual driving styles. Furthermore, the comparison with an automated brake system demonstrates the potential for substantial improvements in energy recovery through optimized braking strategies. The automated system can save more energy than human drivers, particularly at lower speeds, where extended brake durations allowed for more efficient energy recapture.

These results emphasize the importance of optimizing braking strategies to enhance energy recovery in EVs and provide actionable insights for the development of advanced braking algorithms and driver-assistance systems. These findings can inform the design of training programs for human drivers and support the integration of automated regenerative braking technologies. Also, it shows the need for enhanced driver training and the development of advanced braking algorithms to maximize RBS effectiveness. Future research should explore real-world implementation scenarios and investigate additional factors influencing RBS efficiency, including different road conditions, more versatile driving scenarios, and the effects of weather. Additional future study can investigate emergency braking, long-term driver adaptation, and safety trade-offs, such as stopping distances, and compare with this framework.

ACKNOWLEDGMENT

Partial support for this research was provided by the National Science Foundation under Grant No. ECCS-EPCN-2241718. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the sponsoring agency.

REFERENCES

[1] H. Faghihian and A. Sargolzaei, “Energy efficiency of connected autonomous vehicles: A review,” *Electronics*, vol. 12, no. 19, p. 4086, 2023.

[2] S. Statharas, Y. Moysoglou, P. Siskos, G. Zazias, and P. Capros, “Factors influencing electric vehicle penetration in the eu by 2030: A model-based policy assessment,” *Energies*, vol. 12, no. 14, p. 2739, 2019.

[3] A. Ajanovic and R. Haas, “Electric vehicles: solution or new problem?,” *Environment, Development and Sustainability*, vol. 20, no. 1, pp. 7–22, 2018.

[4] C. R. Hung, S. Völler, M. Agez, G. Majeau-Bettez, and A. H. Strømman, “Regionalized climate footprints of battery electric vehicles in europe,” *Journal of Cleaner Production*, vol. 322, p. 129052, 2021.

[5] H. Faghihian, J. Holland, and A. Sargolzaei, “Chapter 1 - introduction to autonomous vehicles,” in *Handbook of Power Electronics in Autonomous and Electric Vehicles* (M. H. Rashid, ed.), pp. 1–16, Academic Press, 2024.

[6] A. M. Çolak and E. Irmak, “Electric vehicle advancements, barriers, and potential: A comprehensive review,” *Electric Power Components and Systems*, vol. 51, no. 17, pp. 2010–2042, 2023.

[7] L. Shao, A. E. H. Karci, D. Tavernini, A. Sorniotti, and M. Cheng, “Design approaches and control strategies for energy-efficient electric machines for electric vehicles—a review,” *IEEE Access*, vol. 8, pp. 116900–116913, 2020.

[8] V. Mali, R. Saxena, K. Kumar, A. Kalam, and B. Tripathi, “Review on battery thermal management systems for energy-efficient electric vehicles,” *Renewable and Sustainable Energy Reviews*, vol. 151, p. 111611, 2021.

[9] R. T. Yadlapalli, A. Kotapati, R. Kandipati, and C. S. Koritala, “A review on energy efficient technologies for electric vehicle applications,” *Journal of Energy Storage*, vol. 50, p. 104212, 2022.

[10] C. De Cauwer, W. Verbeke, T. Coosemans, S. Faid, and J. Van Mierlo, “A data-driven method for energy consumption prediction and energy-efficient routing of electric vehicles in real-world conditions,” *Energies*, vol. 10, no. 5, p. 608, 2017.

[11] K. Sayed, A. Kassem, H. Saleeb, A. S. Alghamdi, and A. G. Abo-Khalil, “Energy-saving of battery electric vehicle powertrain and efficiency improvement during different standard driving cycles,” *Sustainability*, vol. 12, no. 24, p. 10466, 2020.

[12] P. A. Bonab and A. Sargolzaei, “A nonlinear control design for cooperative adaptive cruise control with time-varying communication delay,” *Electronics*, vol. 13, no. 10, p. 1875, 2024.

[13] P. Ansari-Bonab, J. C. Holland, J. Cunningham-Rush, S. Noei, and A. Sargolzaei, “Secure control design for cooperative adaptive cruise control under false data injection attack,” *IEEE Transactions on Intelligent Transportation Systems*, 2024.

[14] M. Ehsani, Y. Gao, S. Longo, and K. M. Ebrahimi, *Modern electric, hybrid electric, and fuel cell vehicles*. CRC press, 2018.

[15] A. T. Hamada and M. F. Orhan, “An overview of regenerative braking systems,” *Journal of Energy Storage*, vol. 52, p. 105033, 2022.

[16] J. Ko, S. Ko, H. Son, B. Yoo, J. Cheon, and H. Kim, “Development of brake system and regenerative braking cooperative control algorithm for automatic-transmission-based hybrid electric vehicles,” *IEEE Transactions on Vehicular Technology*, vol. 64, no. 2, pp. 431–440, 2014.

[17] M. Panagiotidis, G. Delagrammatikas, and D. Assanis, “Development and use of a regenerative braking model for a parallel hybrid electric vehicle,” *SAE transactions*, pp. 1180–1191, 2000.

[18] F. Sangtarash, V. Esfahanian, H. Nehzati, S. Haddadi, M. A. Bavanpour, and B. Haghpanah, “Effect of different regenerative braking strategies on braking performance and fuel economy in a hybrid electric bus employing cruise vehicle simulation,” *SAE International Journal of Fuels and Lubricants*, vol. 1, no. 1, pp. 828–837, 2009.

[19] S. Van Sterkenburg, E. Rietveld, F. Rieck, B. Veenhuizen, and H. Bosma, “Analysis of regenerative braking efficiency—a case study of two electric vehicles operating in the rotterdam area,” in *2011 IEEE vehicle power and propulsion conference*, pp. 1–6, IEEE, 2011.

[20] Z. Xu, “Research on regenerative braking energy recovery strategy of electric vehicle based on driving style,” in *International Conference on Electronics, Electrical and Information Engineering (ICEEIE 2024)*, vol. 13445, pp. 222–231, SPIE, 2024.

[21] Q. Chengqun, X. Wan, N. Wang, S. Cao, X. Ji, K. Wu, Y. Hu, and M. Meng, “A novel regenerative braking energy recuperation system for electric vehicles based on driving style,” *Energy*, vol. 283, p. 129055, 2023.

[22] D. Kim, J. S. Eo, and K.-K. K. Kim, “Service-oriented real-time energy-optimal regenerative braking strategy for connected and autonomous electrified vehicles,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 11098–11115, 2021.

[23] D. Kim, J. S. Eo, and K.-K. K. Kim, “Parameterized energy-optimal regenerative braking strategy for connected and autonomous electrified vehicles: A real-time dynamic programming approach,” *IEEE Access*, vol. 9, pp. 103167–103183, 2021.

[24] H. Faghihian, M. Sarkar, and A. Sargolzaei, “A novel energy-efficient regenerative braking system for electric vehicles,” in *SoutheastCon 2024*, pp. 1300–1305, IEEE, 2024.

[25] M. Da Lio, A. Mazzalai, K. Gurney, and A. Saroldi, “Biologically guided driver modeling: The stop behavior of human car drivers,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 8, pp. 2454–2469, 2017.

[26] T. Burress, “Benchmarking state-of-the-art technologies,” in *Oak Ridge National Laboratory (ORNL), 2013 US DOE Hydrogen and Fuel Cells Program and Vehicle Technologies Program Annual Merit Review and Peer Evaluation Meeting*, 2013.

[27] J. L. Devore, “Probability and statistics,” *Pacific Grove: Brooks/Cole*, 2000.