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Emilia SZUMSKA
Adriana SKUZA

Combustion Engines
Polish Scientific Society of Combustion Engines

Enhancing regenerative braking efficiency in electric vehicles through urban driving pattern analysis

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Electric vehicles offer a sustainable alternative to internal combustion engine vehicles, significantly reducing emissions and improving energy efficiency. A key feature is the regenerative braking system, which recovers kinetic energy during braking. This study examines how braking parameters affect energy recovery in EVs under urban conditions, combining real-world data with simulation. The research involved two stages: data collection from 60 urban trips using a Hyundai Kona Electric, followed by AVL Cruise simulations. Statistical analysis (correlation and K-Means clustering) assessed the relationship between braking parameters (number of events, average braking speed, deceleration, maximum braking force) and recovered energy. Results showed a strong correlation (r = 0.9) between the number of braking events and recovered energy, highlighting the importance of frequent urban braking. Clustering identified four driving patterns. Cluster C4, with the highest number of braking events (84–158) and moderate intensity, achieved the greatest energy recovery efficiency (23.16%). Cluster C1, with fewer events (26–76) and smoother driving, showed the lowest efficiency (18.45%). The average efficiency across all trips was 21.47%, consistent with the literature. Findings suggest that frequent, moderate braking in dense urban traffic optimizes energy recovery. The study offers practical insights for designing more efficient regenerative systems and promoting driving techniques that enhance EV range.

Key words: *electric vehicle, regenerative braking, energy recovery, K-Means clustering, braking parameters*

1. Introduction

Vehicles with electric powertrains, encompassing both fully electric vehicles (EVs) and hybrid electric vehicles (HEVs), play a pivotal role in transforming the transportation sector towards sustainable and environmentally friendly solutions. The increasing availability of public charging stations, enhanced amenities for electric vehicle owners, and financial incentives such as purchase subsidies serve as powerful motivators for choosing an electric vehicle and offer additional encouragement to undecided potential buyers [2, 4, 13]. EVs contribute to the reduction of greenhouse gas emissions and the improvement of energy efficiency. All vehicles equipped with an electric powertrain possess the capability to recover kinetic energy during braking. The Regenerative Braking System (RBS) converts kinetic energy into electrical energy via an electric motor operating in generator mode. This energy is then transferred to the battery and can be subsequently reused to propel the vehicle or power onboard systems. For purely electric vehicles, regeneration directly extends range and enhances energy efficiency, forming an integral part of their propulsion system. Conversely, in hybrid vehicles, where the electric drive interacts with an internal combustion engine, the energy regeneration system improves overall energy efficiency by reducing fuel consumption and exhaust emissions. With growing interest in electromobility, research into optimizing regeneration processes is becoming increasingly vital, particularly in the context of urban driving, where frequent stops and speed changes create unique opportunities for energy recovery.

Research on energy recuperation in electric vehicles encompasses a wide range of theoretical and experimental approaches, from integrating regenerative braking systems with friction brakes to designing advanced strategies for managing and controlling recovered energy. Control strategies for kinetic energy recovery are developed to maximize the efficiency of regenerative braking in vehicles with electric powertrains [3]. Previously published studies primarily focus on developing and presenting optimization or predictive algorithms, all based on specific braking process parameters. Optimization algorithms are used to maximize energy recovery through mathematical models. For example, in [25], a fuzzy logic-based control strategy with genetic algorithms was presented. The developed algorithm was projected to increase braking energy recovery efficiency by 10% and extend EV range by 8% in the urban cycle. Similarly, torque optimization, as described in [7], improved the recovery coefficient by 3.35% in WLTC tests by minimizing energy losses. Neural networks, applied in [14], enhanced the adaptability of RBS to varying road conditions, increasing recovered energy by 7% compared to classic PID controllers. However, studies [12, 21] indicate that the computational complexity of these methods limits their practical application in vehicles.

Predictive algorithms are used to forecast braking demand and optimize regenerative force. These algorithms draw on both real-time driving data (such as route topography from GPS, speed, acceleration, and brake pedal position) and historical data. This enables the recuperation system to adapt its operation to current road conditions, thereby optimizing energy recovery across various scenarios. For instance, as demonstrated in [23], an energy management strategy based on Model Predictive Control (MPC) boosted energy recovery by 5% in urban environments by precisely adapting to speed profiles. Study [16] utilized Artificial Neural Networks (ANNs) and fuzzy controllers to calculate recovered braking energy based on battery state of charge and braking demand. Linear programming was then applied to optimize the regenerative force, leading to a 25.7% increase in vehicle range. Due to their ability to better account for variable conditions and uncertainties (such as driver behaviour and route topography), predictive algorithms in EV regenerative braking systems surpass classical optimization algorithms in effectiveness. This advantage enables continuous, real-time recalibration of recuperation control, resulting in more accurate estimations of energy recovery efficiency and, consequently, improved range and reduced energy consumption.

The efficiency of recuperation systems in electric vehicles is highly dependent on operating conditions. In urban environments, characterized by dynamic driving with frequent acceleration and braking cycles, the effectiveness of the kinetic energy recovery system can be substantial. It is estimated that under such conditions, energy recovered during braking can account for 20% to 40% of the energy consumed for vehicle propulsion [19]. Similar conclusions were presented in [9]. Furthermore, [11] demonstrated that in urban settings, recuperation can be responsible for 15–25% of the vehicle's total energy demand, depending on driving dynamics and road infrastructure.

In studies [5, 18, 24], the authors emphasize the significance of frequent braking in urban traffic, which results from the high number of intersections and traffic lights, thus favouring greater energy recovery. Within the context of HEVs, studies such as those presented in [15, 22] indicate that recuperation in urban driving can significantly reduce fuel consumption by increasing the electric powertrain's contribution to the overall driving cycle. However, the majority of existing research relies on standard driving cycles, such as WLTP or NEDC, which do not fully reflect the variability of real-world urban conditions. This limitation restricts their practical application in powertrain system design. This applies to both electric vehicles and those equipped with internal combustion engines [26, 27, 28].

Despite extensive research on energy recuperation in electric vehicles, a notable gap persists in the literature concerning a detailed analysis of how specific braking parameters – such as the number of braking events, average braking speed, deceleration, or maximum braking force – influence energy recovery under real-world urban driving conditions. Most prior studies focus on standardized driving cycles, which fail to account for the complexities of urban traffic, including varying congestion levels, the number of intersections, or changes in terrain elevation. Furthermore, attempts to integrate data from real-world drives with advanced simulations are infrequent, yet such an approach could yield more realistic and applicable conclusions for designing recuperation systems in both EVs and HEVs. This study addresses this gap by analysing the impact of braking parameters on energy recovery across 60 real-world urban driving events, utilizing simulations in AVL Cruise software.

Based on the literature review and the identified research gap, the following hypotheses have been formulated:

- Hypothesis 1: The number of braking events (n_{ham}) is positively correlated with the amount of recovered energy (E_{reg}) in urban driving conditions for both EVs and HEVs.
- Hypothesis 2: Braking parameters, such as average braking velocity (v_{h_sr}), average deceleration (d_{sr}), and maximum braking force (F_{h_max}), have a varied impact on energy recovery, with their significance depending on the specific driving pattern.
- Hypothesis 3: Driving patterns characterized by frequent, moderate braking (e.g., in heavy urban traffic) exhibit higher energy recovery efficiency compared to patterns with less frequent but more intense braking. This is particularly relevant for HEVs in the context of fuel consumption reduction.

The study's methodology employs a two-stage approach: (1) data acquisition from real-world urban driving and (2) simulations conducted in AVL Cruise software. This dual approach allows for capturing authentic driving patterns that are challenging to replicate in standardized laboratory cycles, while simultaneously enabling a precise analysis of braking parameter impact on energy recovery under controlled simulation conditions. A single driver was used to eliminate driving style variability, thereby isolating the influence of the studied parameters. The application of correlation analysis and K-Means clustering then aids in identifying key relationships and patterns, which are vital for developing more effective recuperation systems for both EVs and HEVs.

2. Methods

2.1. Real-world data acquisition

Research into energy recovered during braking was conducted in two stages. First, the kinematic parameters of an electric vehicle were recorded under real-world urban traffic conditions. The resulting speed profiles then served as input data for the simulation software. In the second stage, simulation studies were performed using AVL Cruise software, where a vehicle model corresponding to the real one was developed. The data from these simulations were then subjected to statistical analysis.

Real-world tests were conducted on five selected urban road sections, each approximately 5 km long, characterized by varying traffic densities and road conditions. A total of 60 drives were completed, encompassing both city outbound roads and urban routes with different levels of congestion. Some routes were outbound roads, where traffic was relatively light, and the vehicle moved smoothly with few stops. The remaining routes involved driving through the city center, where traffic density was higher, necessitating more frequent stops and speed changes. Drives were carried out at two times of day: around midday, between the morning and afternoon rush hours, and during the afternoon rush hour itself.

The routes varied in the number of signalized intersections, pedestrian crossings, and permissible speeds. The investigated routes included:

- city outbound road (70 km/h speed limit) featured 3 signalized intersections, 4 marked pedestrian crossings, and one roundabout
- city outbound road (50 km/h speed limit) characterized by a varied elevation profile with an altitude change exceeding 60 m between its highest and lowest points.

This route included 8 intersections (5 signalized) and 4 marked pedestrian crossings
- city center routes:
  1) the first city center route, known for heavy traffic and a varied elevation profile, comprised 9 signalized intersections, 5 marked pedestrian crossings, and 3 roundabouts
  2) the second city center route included 15 intersections (12 signalized) and 3 marked pedestrian crossings;
- residential area route encompassed 29 intersections (4 signalized) and 9 marked pedestrian crossings. It featured significant speed restrictions (in places down to 20 km/h) typical of residential roads, along with speed reductions enforced by speed bumps.

The selection of five routes ensures that the study reflects typical urban driving scenarios. This prevents the results from being limited to specific, atypical situations, allowing them to be generalized to the real-world usage of electric vehicles in urban environments.

The test vehicle used was a Hyundai Kona electric. A Kistler™ type GPS Data Logger was employed to measure vehicle motion parameters, recording data such as travel time, instantaneous velocity, instantaneous longitudinal acceleration, distance traveled, and instantaneous position (10 Hz sampling frequency, GPS position accuracy < 2.5 m). The collected data were used to create velocity profiles characteristic of each route. All drives were performed by a single driver. Examples of the recorded velocity profiles as a function of time are presented in Fig. 1.

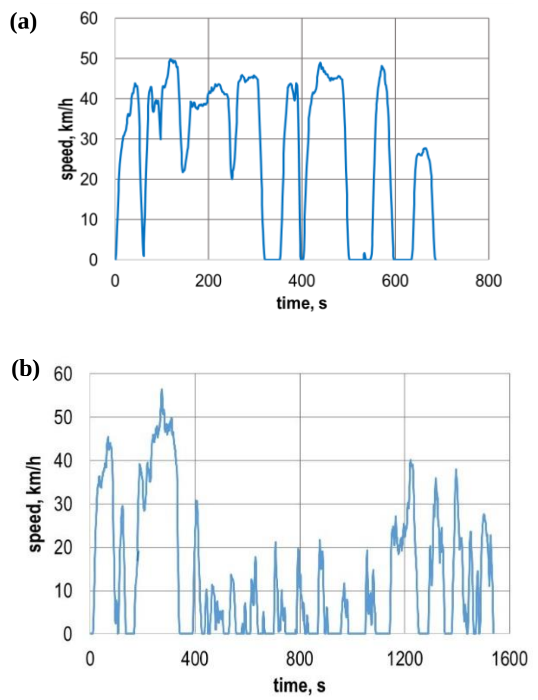

Fig. 1. Representative speed profiles from the investigated routes (a) midday, (b) peak hours

2.2. AVL Cruise modeling and simulation

AVL CRUISE is an advanced analytical tool designed for detailed modeling of both mechanical and regenerative systems. This capability allows for the optimization of braking strategies concerning energy efficiency, safety, and driving comfort. The software serves as a sophisticated instrument for analyzing vehicle dynamics and optimizing its powertrain and braking systems, with particular emphasis on the energy recuperation system. The developed vehicle model facilitates advanced analyses of the kinetic energy recovery process via the recuperation system, while simultaneously accounting for the mechanical and thermal aspects of the braking system's operation. A schematic representation of the electric vehicle model is provided in Fig. 2.

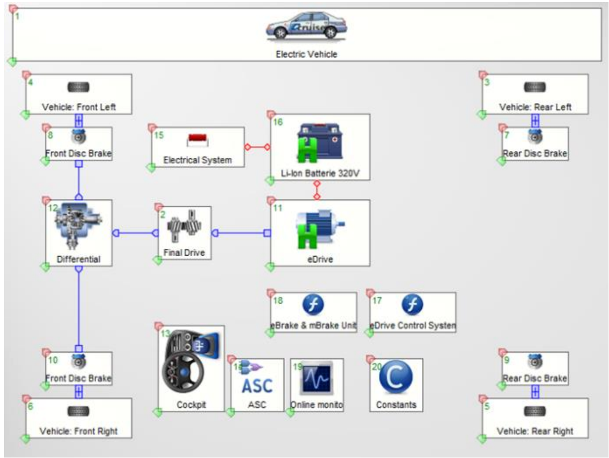

Fig. 2. Electric vehicle model in AVL Cruise

Table 1. Selected technical parameters of the electric vehicle

Electric motor	Motor type	Permanent Magnet Synchronous Motor (PMSM)
	Maximum motor power	100 kW
	Maximum torque	395 Nm
Battery	Type	Lithium-ion
	Energy capacity	39.2 kWh
Vehicle dimensions and mass	Length	4180 mm
	Width	1800 mm
	Height	1570 mm
	Wheelbase	2600 mm
	Curb weight	1535 kg
	Payload capacity	150 kg

The electric vehicle braking system in AVL Cruise comprises two primary components:
- mechanical braking system, which consists of disc brakes actuated by a hydraulic system, which includes a pump, pressure lines, and wheel cylinders located at each wheel;
- kinetic energy recuperation system, that incorporates an electric machine operating in generator mode, converting the vehicle's kinetic energy into electrical energy, which is then directed via an inverter to the battery.

These two systems operate concurrently, with their interaction dictated by braking torque control algorithms.

The electric vehicle model used in the simulation studies replicated the parameters of the actual Hyundai Kona electric. Table 1 presents selected technical parameters of this electric vehicle. For each simulation performed, the initial battery state of charge was set to 75%.

2.3. Data analysis

The data collected were analysed using Statistica software. Pearson correlation analysis was applied to assess the relationships between braking parameters – such as the number of braking events (n_{ham}), average braking speed (v_{hsr}), average braking deceleration (d_{sr}), and maximum braking force (F_{h_max}), and the amount of recovered energy (E_{reg}). Additionally, the K-Means clustering method was used to group drives into four distinct clusters. This allowed for the identification of driving patterns that influence recuperation efficiency. The results were validated using ANOVA and 10-fold cross-validation, ensuring the robustness and reliability of the obtained data.

3. Results

3.1. Analysis of energy recovered in selected test routes

The analysis is based on data obtained from 60 real-world trips and their corresponding AVL Cruise simulations. The influence of key braking parameters – such as the number of braking events, average braking speed, deceleration, and maximum braking force – on the amount of energy recovered (E_{reg}) is examined. The results are organized into two subsections: Subsection 3.1 details the energy recovery characteristics across the test routes, including statistical correlations between braking parameters and recovered energy. Subsection 3.2 applies K-Means clustering to identify distinct driving patterns and their impact on recuperation efficiency, highlighting optimal conditions for maximizing energy recovery. These findings provide insights into the effectiveness of regenerative braking systems in diverse urban traffic scenarios.

Energy recuperation in electric vehicles is most effective in urban traffic conditions, where the number of braking events is highest. Optimizing recuperation in such environments can significantly boost vehicle energy efficiency. Increasing the initial braking velocity and braking force within moderate limits can favorably impact the amount of energy recovered. Therefore, the goal should be to design recuperation systems that enable maximum energy recovery across a wide range of traffic conditions. Urban driving, while leading to higher energy consumption due to frequent speed changes, also offers the greatest potential for energy recovery during braking.

Simulation studies utilized velocity profiles from 60 urban driving trips, each approximately 5 km in length. The routes were diverse, and data collection took place on weekdays. Figure 3 and Fig. 4 present the number of braking events recorded on the test routes.

An average of 77 braking events was logged per trip. The highest recorded instance was 158 braking events in a single trip, translating to 31 braking events per kilometre. Figure 5 presents the distribution of total energy consumption (E_c) across the analysed trips.

The analysed trips showed an average energy consumption of 2772.6 kJ (0.77 kWh), with values ranging from 1292.28 kJ (0.36 kWh). On a per-kilometre basis, the vehicle consumed an average of 554.52 kJ (0.15 kWh). The peak energy consumption, approximately 3597.24 kJ (1 kWh), occurred during a rush-hour trip through the city centre. This particular instance was characterized by heavy traffic and an average driving speed of 16.36 km/h. Figure 6 presents the distribution of recovered energy values (E_{reg}) for all trips.

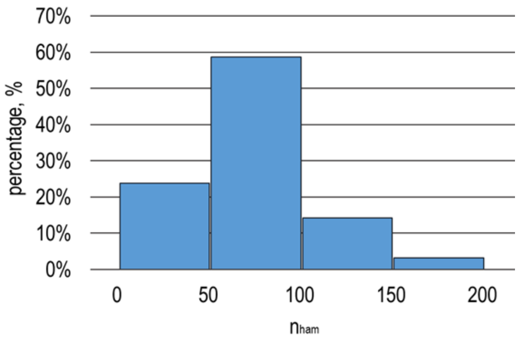

Fig. 3. Distribution of braking events (n_{ham}) in test routes

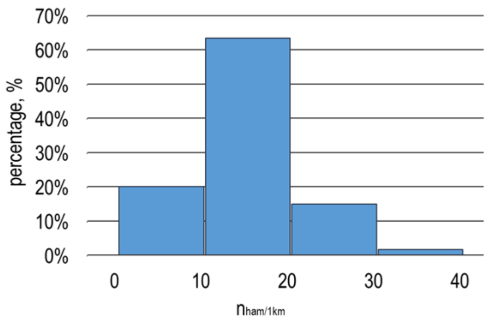

Fig. 4. Distribution of braking events per km ($n_{ham/km}$) in test routes

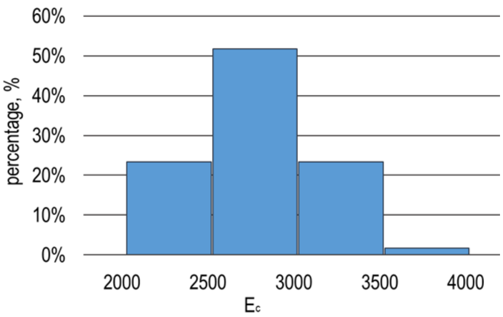

Fig. 5. Distribution of energy consumption (E_c) in test routes

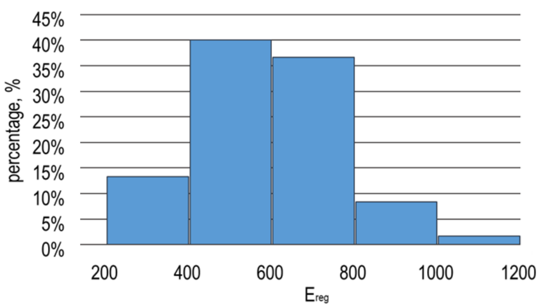

Fig. 6. Distribution of recovered energy values (E_{reg}) in test routes

On average, 595.42 kJ (0.17 kWh) of energy was recovered per trip. The range of recovered energy values was 710.71 kJ. The highest recorded value of recuperated energy during braking in the analysed trips was 1026.64 kJ (0.29 kWh). This particular trip also showed the highest energy consumption.

The number of braking events in urban driving reflects traffic dynamics; intense traffic and frequent stops lead to greater energy recovery. In areas with numerous stops (e.g., city centres), higher recuperation efficiency can be expected. It is evident that the amount of recovered energy increases with the number of braking events. In the analysed trips, these parameters exhibit a linear relationship. A correlation coefficient (r) equal to 0.9 indicates a very strong positive correlation between the number of braking events and the energy recovered (Fig. 7).

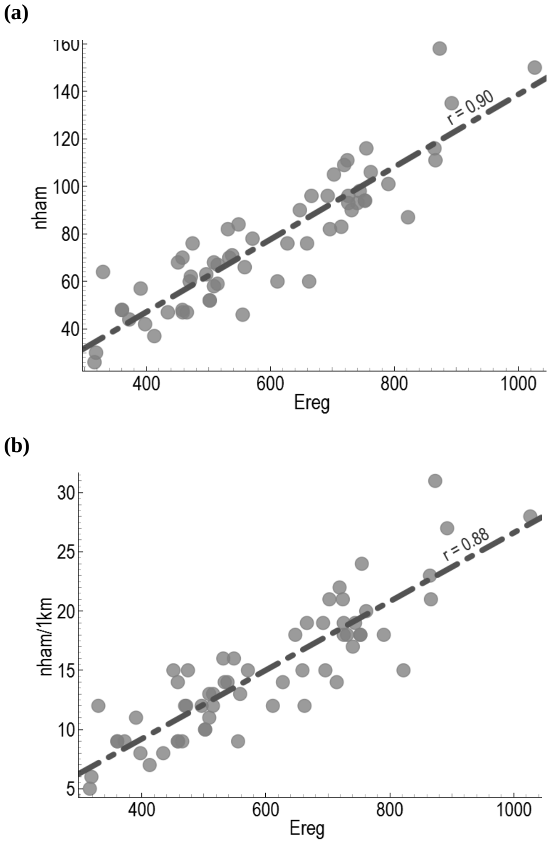

Fig. 7. Scatter plots of total energy recovered during braking and number of braking events (a), and number of braking events per 1 km (b) in a trip

The kinetic energy a vehicle possesses – and can potentially recover – is directly tied to its mass and initial braking velocity. Consequently, even minor increases in velocity lead to a significant rise in the energy available for recuperation. Deceleration reflects the dynamics of the braking process – that is, the rate at which vehicle velocity changes. Intense braking with high deceleration leads to a faster conversion of kinetic energy, requiring an appropriate response from the recuperation system to effectively recover the energy.

For each recorded braking manoeuvre, the initial braking velocity and deceleration were estimated. An average of these values was then calculated for each individual trip. Figure 8 presents the distribution of the average initial braking velocity (v_{hsr}), and Fig. 9 presents the average deceleration (d_{sr}) across the analysed trips. Figure 10 shows scatter plots of the total energy recovered during braking, along with the average braking velocity and average deceleration values.

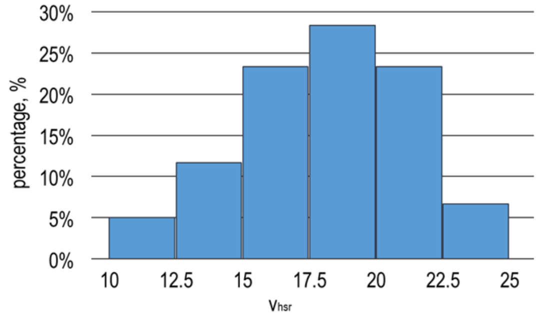

Fig. 8. Distribution of average initial braking velocity (v_{hsr}) in test routes

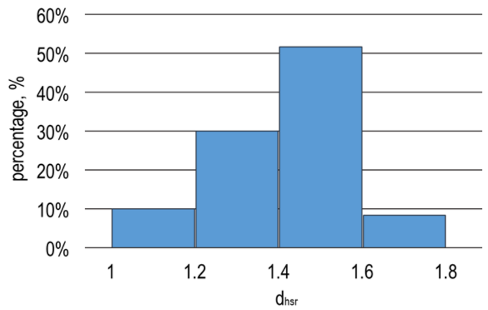

Fig. 9. Distribution of average deceleration (d_{sr}) in test routes

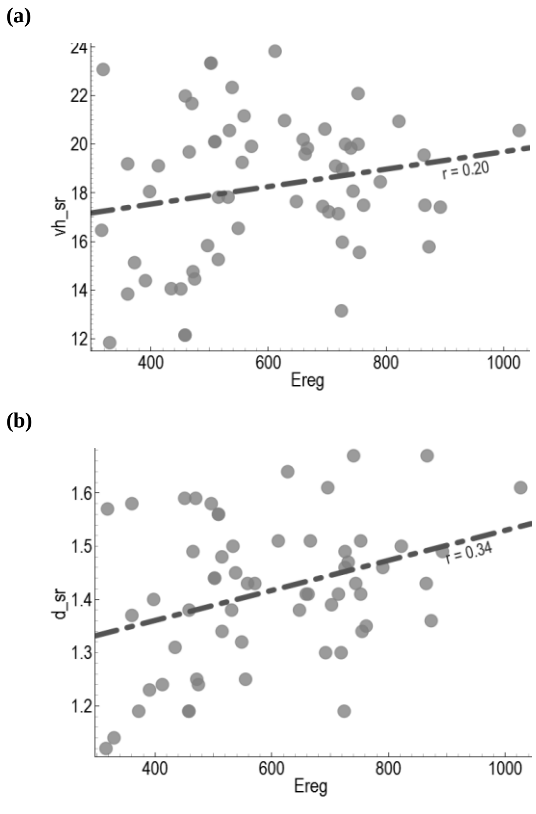

Fig. 10. Scatter plots of total energy recovered during braking and average initial braking velocity (a), and average deceleration (b) in a trip

For the analysed trips, the average initial braking velocity was 18.24 km/h, with an average deceleration of 1.42 m/s^2. Analysis of the averaged deceleration and initial velocity values for each trip indicated only a weak influence of these parameters on the total recovered energy. The trend line exhibits a slight positive slope, suggesting that increased average braking velocity could lead to a minor rise in recuperated energy. This is largely attributable to the fact that higher initial velocity inherently offers more kinetic energy for recovery. However, average braking deceleration shows a stronger correlation with the amount of recovered energy than the average initial braking velocity.

For each braking manoeuvre during the trips, the braking force was estimated. Figure 11 presents the distribution of averaged maximum braking force (F_{h_max}) values for each completed trip.

Braking force is a critical factor in the recuperation process as it dictates how effectively a vehicle's kinetic energy can be converted into electrical energy. The average braking force for the analysed trips was 1749.07 N. The averaged braking force values per trip show a moderate correlation with the energy recovered. An increase in braking force allows for a greater amount of energy to be recovered during electric vehicle braking (Fig. 12).

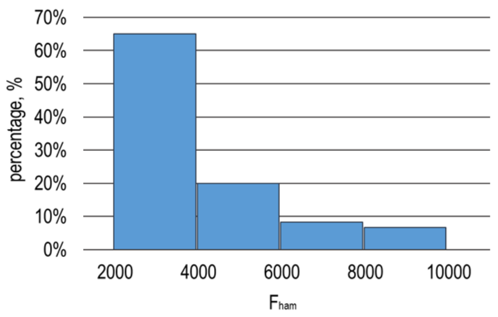

Fig. 11. Distribution of averaged maximum braking force (F_{h_max}) in test routes

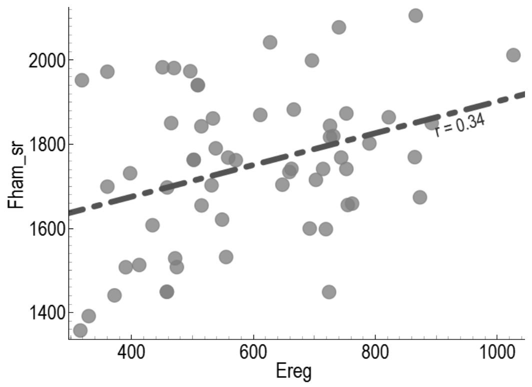

Fig. 12. Scatter plots of total energy recovered during braking averaged maximum braking force

Urban conditions offer substantial potential for effective recuperation, with braking force and dynamics being key factors influencing energy recovery. Based on averaged values for initial braking velocity, deceleration, and braking force, the foregoing analyses aim to elucidate the general influence of these parameters on the total energy recuperated during a trip.

The obtained results indicate that initial braking velocity influences the amount of kinetic energy available for recovery. A higher initial velocity during a braking manoeuvre presents an increased potential for energy recovery; however, the correlation observed at the trip level is weak, which may be attributed to the significant variability in prevailing road conditions and the diversity of braking scenarios encountered. The deceleration during braking is associated with the dynamic characteristics of the braking event. A moderate correlation indicates that more aggressive braking manoeuvres may result in enhanced recuperation efficiency. Simultaneously, braking force, being directly proportional to the kinetic energy conversion into electrical energy, exhibits a moderate reliance on the overall energy recovered throughout a given trip.

3.2. K-Means clustering of routes based on recuperation patterns

Another objective of this research was to identify energy recovery patterns during braking in electric vehicles and to segment routes based on key braking parameters using the K-Means algorithm. This algorithm partitions data into k clusters by minimizing the sum of squared distances between observations and centroids. The dependent variable was the total energy recovered during braking per trip (E_{reg}).

The following parameters were utilized in the study:

– number of braking events in trip (n_{ham})
– number of braking events per kilometer ($n_{ham/1km}$)
– average initial braking velocity (v_{h_sr}) in trip
– average deceleration (d_{sr}) in every trip
– averaged braking force (F_{h_max}) values for each completed trip.

To ensure data comparability and mitigate issues arising from differing units and value ranges, all data underwent standardization, scaling them to a mean of 0 and a standard deviation of 1. This standardization was crucial because the K-Means algorithm utilizes a Euclidean metric, where variables with larger values could otherwise dominate the analysis and skew the results.

The initial centroids were established using a method of maximizing the distance between them, which promotes a better separation of natural clusters. The optimal number of clusters (k = 4) was determined by analysing the "elbow method" and the silhouette coefficient. Each trip, represented as a feature vector, was assigned to its nearest centroid using Euclidean distance. Subsequently, the centroids were updated as the mean of the vectors assigned to their respective clusters. This iterative process continued until convergence was achieved (i.e., minimal changes in centroid positions). All computations were performed using Statistica software.

The data from 60 trips were divided into four distinct groups (Fig. 13), suggesting the presence of four clear behavioural patterns related to braking parameters and the energy recovery system. Trips within each cluster (C) exhibit comparable characteristics, specifically regarding the number of braking events, braking events per kilometre, average initial velocity, average deceleration, and average maximum braking force recorded for each trip.

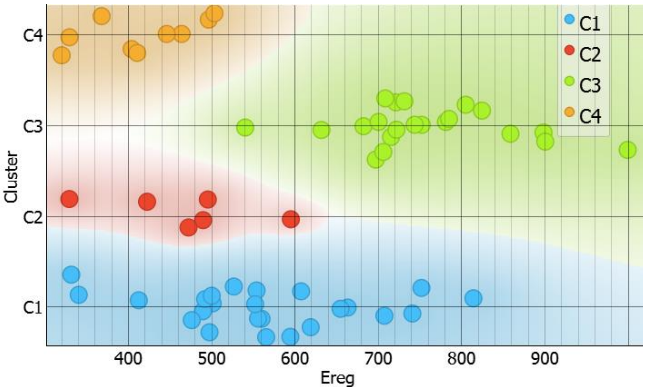

Fig. 13. K-Means clustering results for E_{reg}

Verification of the four-cluster division's capacity to accurately represent significant differences in the analyzed variables' behavior was achieved through an Analysis of Variance (ANOVA), performed on all quantitative variables (Table 2). A significance level of 0.05 was adopted. The effect size was calculated based on the F-statistic and the sums of squares (*SS*).

The ANOVA results demonstrated that the differences between clusters are statistically significant ($p < 0.001$ for most variables). The K-Means segmentation is thereby confirmed to effectively differentiate trips based on braking and energy recovery parameters. The exceptionally high F-statistic values observed for the chosen parameters underscore their critical role in distinguishing trips by their energy recuperation characteristics.

Table 2. ANOVA test results

Parameter	Between-Group SS	Within-Group SS	F-statistic	p-value
E_{reg}	37.86	21.14	33.42	0.0000
n_{ham}	40.11	18.89	39.64	0.0000
n_{ham}/1 km	39.58	19.42	38.05	0.0000
v_{h_sr}	26.85	32.15	15.59	0.0000
d_{sr}	31.28	27.72	21.06	0.0000
F_{h_max}	42.14	16.86	46.67	0.0000

To verify the stability of the results, 10-fold cross-validation was applied, and outliers that could distort the clustering outcomes were removed. The final error in the training sample was 0.371, indicating a relatively good quality of dependent variable assignment to the clusters.

The subsequent stage of analysis involved evaluating the energy recovered within the four clusters generated by the K-Means algorithm. This analysis specifically considered key braking process parameters: average braking velocity, average braking deceleration, and maximum braking force. The study aimed to identify the correlations between these variables and the total recovered energy. Figure 14 visually represents the E_{reg} values in relation to these parameters across the 4 clusters.

Cluster 1 (C1) comprises trips with the lowest energy recovery, ranging from 315.93 to 514.54 kJ. These trips are characterized by a low average braking velocity (11.84–16.46 km/h), slight deceleration (1.12–1.48 m/s²), and moderate braking force (2227.78–4192.34 N). The low number of braking events (26–76 per trip) suggests a smooth driving style. This cluster likely represents trips conducted under lower traffic density, which consequently limits the effectiveness of energy recuperation.

In Cluster 2 (C2), the recovered energy ranges from 318.50 to 822.03 kJ, indicating greater recovery efficiency than in Cluster 1. The average braking velocity falls between 15.83 and 23.82 km/h, with average deceleration ranging from 1.24 to 1.64 m/s^2. Braking force values (2624.99–6391.37 N) suggest more dynamic braking maneuvers. These trips are characterized by more frequent stops (30–87 braking events). This cluster likely includes both midday trips and those conducted under higher traffic density.

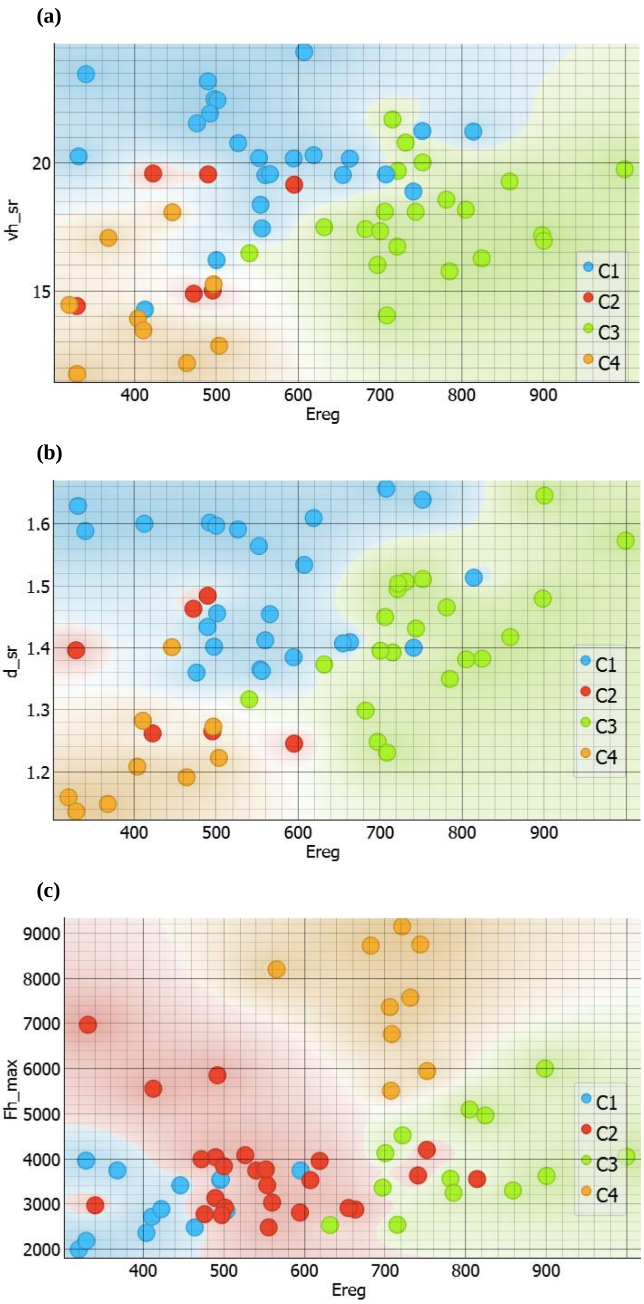

Fig. 14. Clustering of E_{reg} in 4 clusters based on average braking velocity (a), average braking deceleration (b), and maximum braking force (c) in analyzed trips

Cluster 3 (C3) exhibits significantly higher energy recovery, ranging from 450.80 to 752.47 kJ, compared to the first two clusters. Braking events in this cluster are more intense, with an average velocity of 14.05–20.56 km/h and greater deceleration (1.3–1.67 m/s^2). The maximum braking force values are the highest among all clusters, recorded between 5432.10 and 8737.75 N. The high frequency of braking events (68–98 per trip) suggests driving conditions typical of heightened urban traffic during the afternoon rush hour.

Cluster 4 (C4) exhibits the highest energy recovery, ranging from 548.51 to 1026.64 kJ. Despite braking velocity (13.15–22.08 km/h) similar to those in C2 and C3, the critical factor is the very high number of braking events (84–158 per trip). Braking in this cluster is frequent but not excessively intense, as indicated by maximum braking force values between 2612.34 and 6280.18 N. These trips likely occurred under conditions of the highest traffic density, necessitating frequent stops and accelerations.

In summary, the highest energy recovery was observed under conditions of intensive urban traffic, characterized by frequent, though not necessarily abrupt, braking (C4). Conversely, the lowest recovered energy values were recorded during trips defined by smooth driving with infrequent braking (C1), which corresponds to off-peak driving conditions.

To further analyse the efficiency of the recuperation system in electric vehicles under varying urban driving conditions, the percentage recuperation efficiency (η_{reg}) was evaluated for each of the four clusters identified by the K-Means method. This efficiency was defined as the ratio of energy recovered (E_{reg}) to the total energy consumed per trip (E_c), expressed as a percentage, according to the following formula:

$$\eta_{reg}\ [\%] = \left(\frac{E_{reg}}{E_c}\right) \cdot 100 \quad (1)$$

The recuperation system's effectiveness in transforming the vehicle's kinetic energy into electrical energy across varying urban driving conditions can be assessed using this metric. The percentage energy recovery efficiency (η_{reg}) for the four identified clusters is presented in Fig. 15.

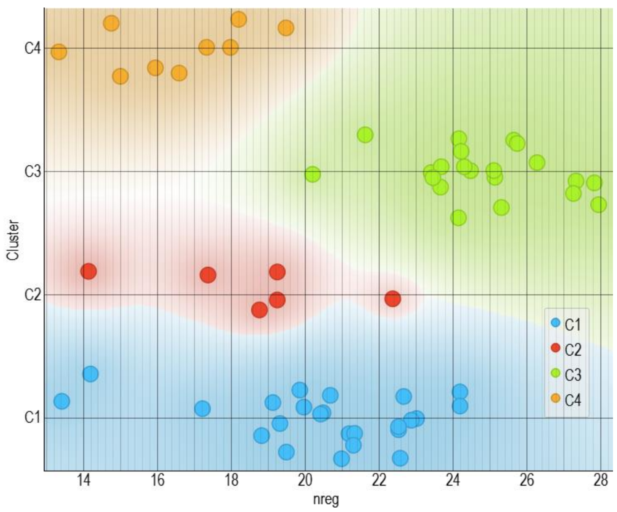

Fig. 15. Percentage of energy recovery efficiency (η_{reg}) by cluster

A direct relationship between energy recovery efficiency and the number of braking events is evident, notably within C4, where the combination of frequent, albeit moderate, braking in high-traffic scenarios optimizes recuperation. In contrast, C1 and C3, characterized by fewer braking events, demonstrate reduced efficiency. This diminished efficiency in C3, despite more intense braking, may suggest the occurrence of energy dissipation during abrupt manoeuvres.

The impact of initial braking velocity and maximum braking force on overall energy recovery efficiency is notably constrained. This observation implies that traffic dynamics, rather than the intensity of isolated braking events, constitute the predominant factor. Such findings are instrumental in guiding the further optimization of recuperation systems, especially in the development of control algorithms designed for the specificities of urban driving.

4. Discussion

This study significantly contributes to understanding the dynamics of energy recovery in electric vehicles under urban driving conditions, focusing on the relationships between braking parameters and recuperation efficiency. A key finding is the strong correlation between the number of braking events and the energy recovered, underscoring that urban traffic with frequent stops is an optimal environment for recuperation. K-Means cluster analysis revealed four driving patterns, with Cluster C4 demonstrating the highest recuperation efficiency (23.16%). This cluster was characterized by the highest number of braking events (84–158) and moderate dynamics within intensive traffic. Conversely, Cluster C1, marked by smooth driving and a limited number of braking events (26–76), exhibited the lowest efficiency (18.45%). This highlights the crucial role of braking frequency in the recuperation process.

The presented results align with the fundamental physical principles governing recuperation systems. This alignment is further corroborated by existing literature [1, 6, 17], which concludes that a higher frequency of braking cycles translates to more efficient recovery of a vehicle's kinetic energy during deceleration.

Comparing our findings with existing literature, the average recuperation efficiency of 21.47% falls within the typical range for electric vehicles operating in urban environments, thereby confirming the robustness of our methodology [8, 10, 20]. However, this study's detailed segmentation of routes using K-Means clustering and the analysis of varied speed profiles differentiate it from standard research based on predefined cycles like WLTP. This approach offers deeper insights into the impact of real-world traffic conditions. Notably, Cluster C3 exhibited lower efficiency (18.52%) than Cluster C4, despite a substantial number of braking events (68–98) and significant braking forces (5432.10–8737.75 N). This discrepancy may suggest energy dissipation due to abrupt braking, wherein kinetic energy is converted into heat within the mechanical braking system.

The presented results have practical implications for both electric powertrain designers and electric vehicle users. For engineers designing recuperation systems, it is recommended to focus on maximizing the efficiency of regenerative braking under frequent, low-intensity braking conditions, such as those observed in Cluster C4. This may involve adjusting braking system control algorithms to prioritize recuperation in such scenarios. From the perspective of drivers, this study suggests that anticipating situations requiring stops and employing gentle braking can contribute to increased energy recovery efficiency, thereby extending vehicle range. Such driving strategies may be particularly beneficial in urban driving conditions, where numerous stops are necessitated by traffic infrastructure and density.

Several limitations warrant consideration within this study. Primarily, the exclusive use of a single driver for all trips constrained the diversity of driving styles, which, in turn, may limit the broader generalizability of the findings. It is acknowledged that variations in driving technique could potentially influence both braking dynamics and energy dissipation. Secondly, the AVL Cruise simulations were performed under consistent conditions of battery state of charge (SOC = 75%) and ambient temperature. This does not fully represent the complete range of real-world operating environments, given that a reduced SOC or colder temperatures can adversely affect battery performance. Finally, the analysis was confined to the Hyundai Kona Electric model, thus precluding a comprehensive assessment of design differences, such as vehicle mass or drivetrain type, across other electric vehicle models.

This study corroborates that frequent, moderate braking within high-density urban traffic optimizes energy recovery in electric vehicles. These findings have the potential to propel the development of more efficient recuperation systems and encourage driving techniques that extend vehicle range, thereby contributing to the advancement of electromobility. Continued research, encompassing a wider array of variables, will facilitate a more precise adaptation of this technology to authentic operational conditions.

5. Conclusions

This study, which investigated the influence of braking parameters on energy recovery in electric vehicles under urban driving conditions, confirmed our hypotheses and led to the following conclusions:

- Statistical analysis revealed a very high correlation (r = 0.9) between the number of braking events and the amount of energy recovered, confirming the crucial role of braking frequency in the recuperation process.
- The application of the K-Means clustering method identified four distinct regenerative braking patterns. The highest recuperation efficiency (23.16%) was achieved in the cluster characterized by the greatest number of braking events (84–158) and moderate braking force, whereas the lowest efficiency (18.45%) was observed in the cluster with fewer braking events (26–76) and a high average trip velocity.
- The average recuperation efficiency observed under the studied urban conditions was 21.47%, which aligns with the typical operational range observed for electric vehicles.

It can therefore be concluded that the key factor in maximizing recuperation is the frequency of braking events, along with their moderate intensity, which enables the efficient conversion of kinetic energy into electrical energy.

The findings of this study have broad applicability, extending beyond fully electric vehicles to include hybrid electric vehicles, which also utilize recuperation systems for energy recovery during braking. The study's key insights, such as the significance of braking frequency and characteristics for recuperation efficiency, are universal and can be directly applied to HEVs. Optimizing braking strategies based on the patterns identified in Cluster C4 could enhance energy recovery, thereby improving overall vehicle efficiency. In the context of hybrid vehicles, this could directly translate to reduced fuel consumption.

In conclusion, this study offers a significant contribution not only to the progression of electric drivetrain technology but also by providing universal insights directly applicable to hybrid vehicles, thereby fostering enhanced energy efficiency and promoting sustainable development within the automotive sector.

Nomenclature

d_{sr}	average braking deceleration
E_c	total energy consumption in test route
E_{reg}	total regenerated energy in test route
EV	electric vehicle
F_{h_max}	average maximum braking force
GPS	global positioning system
HEV	hybrid electric vehicle
NEDC	New European Driving Cycle
n_{ham}	number of braking events
n_{ham}/1 km	number of braking events per 1 kilometr
η_{reg}	percentage recuperation efficiency
r	Pearson correlation coefficient
RBS	regenerative braking systems
SOC	state of charge
v_{hsr}	average braking velocity
WLTC	Worldwide Harmonised Light Vehicles Test Procedure

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Emilia Szumska, DSc., DEng. – Faculty of Mechatronics and Mechanical Engineering, Kielce University of Technology, Poland.
e-mail: *eszumska@tu.kielce.pl*

Adriana Skuza, MEng. – Faculty of Mechatronics and Mechanical Engineering, Kielce University of Technology, Poland.
e-mail: *askuza@tu.kielce.pl*