MODELLING OF ENERGY RECOVERY FROM BRAKING IN VEHICLE DRIVE SYSTEMS

Edward Kozlowski[1], Magdalena Zimakowska-Laskowska[2], Boris Snauko[3], Piotr Wisniowski[2]
[1]Lublin University of Technology, Poland; [2]Environment Protection Centre, Motor Transport. Institute, Poland; [3]Center of European Projects, Poland
e.kozlovski@pollub.pl, magdalena.zimakowska-laskowska@its.waw.pl, bsnauko@plsk.eu, piotr.wisniowski@its.waw.pl

Abstract. Technology development requires searching for new solutions that improve the energy efficiency of commercial vehicles used in rural areas. The article presents a comprehensive approach to analysing and modelling energy recovery in drive systems that can be used in agricultural vehicles such as tractors and combines and other agricultural machines. The research included developing mathematical models that consider vehicle dynamics, such as speed, acceleration and energy recovery during braking (recuperation). Based on linear regression, KNN algorithms and neural networks, these models allow for estimating the amount of recovered energy in various operating states, such as acceleration, braking or driving at a constant speed. Statistical analysis confirmed the significance of the impact of key parameters, such as speed and acceleration intensity, on recuperation efficiency. The research results indicate that implementing advanced energy management strategies in vehicles can contribute to reducing fuel consumption and greenhouse gas emissions. Energy recovery during braking is significant in machines performing cyclical tasks, such as transporting crops or field work on uneven terrain. Examples indicate that energy recovery can be optimised by better matching vehicle operating parameters, which is crucial in reducing farm operating costs. The proposed technological solutions and predictive models support energy efficiency and sustainable development in the agricultural sector. The possibility of integrating these solutions with autonomous vehicles and agricultural fleet management systems opens prospects for further technological progress. This research contributes to developing ecological and energy-saving technologies that support modern agriculture and its transformation towards a low-emission economy.

Keywords: energy recovery, vehicles, recuperation, mathematical modelling, efficiency.

Introduction

Developing energy-efficient technologies is a key priority in modern agriculture, where optimising energy use in machinery can lead to significant reductions in fuel consumption and environmental impact. One of the promising approaches in this area is the implementation of energy recovery systems in agricultural vehicles, particularly in the braking and acceleration phases. Energy recuperation has been extensively studied in the context of electric and hybrid vehicles. However, its potential application in off-road agricultural machinery remains an emerging field of research [1-3].

Energy recovery in agricultural machinery primarily focuses on regenerative braking systems, which convert kinetic energy into electrical energy that can be stored and reused. Studies on braking energy recovery devices have demonstrated their effectiveness in reducing overall energy consumption in agricultural robots and machinery designed for field operations [4; 5]. Moreover, advancements in high-voltage electrification for tractors and other agricultural machines present new opportunities for integrating regenerative technologies into farming operations [6; 7].

Integrating alternative energy sources with recuperation systems is a key research direction, and one promising solution is hybrid hydrogen systems in vehicles, which improve energy efficiency and sustainability by increasing range and reducing dependence on conventional fuels [8]. Optimisation of energy management in hydrogen buses has confirmed that advanced recuperation strategies significantly increase the efficiency of transport fleets [9], and similar solutions can improve energy flow and regenerative braking in agricultural machines.

Electrification and hybridisation of agricultural vehicles are crucial in achieving sustainability goals. Researchers highlight that hybrid tractor powertrains can significantly improve fuel efficiency while reducing greenhouse gas emissions [10; 11]. Additionally, the transition toward fully electric or hybrid agricultural machines aligns with broader sustainability trends in the energy sector, emphasising the role of agriculture in a low-emission economy [12; 13].

The potential benefits of energy recovery systems extend beyond efficiency improvements. Studies on optimising regenerative braking systems suggest that fine-tuning key parameters, such as vehicle speed and acceleration, can enhance recuperation rates [14; 15]. Furthermore, integrating energy management strategies into agricultural fleet operations can reduce operating costs while ensuring long-term sustainability in farm machinery usage [16; 17].

Research on the durability and performance of vehicle components emphasises the importance of structural integrity in energy recovery systems. It has been shown that small changes in mechanical design can significantly affect the efficiency of energy transfer and mechanical strength, which is particularly important in agricultural machinery exposed to high loads [18]. Improving design standards and material selection can increase the durability and performance of energy recovery systems.

The research results on electric buses indicate their usefulness as a model for energy recovery systems in agriculture. Brake energy recovery in these vehicles can be adapted to agricultural machinery, but it requires optimisation for uneven terrain, variable loads, and specific duty cycles. Integrating energy recovery systems in agriculture supports global efforts towards sustainable mechanisation and energy efficiency in agricultural transport.

The acquired knowledge constitutes a valuable basis for optimising the recuperation strategy in agricultural machines. The relationship between battery configuration and energy recovery in buses can be analysed in agriculture, and further research should focus on adapting these technologies to specific agricultural applications, ensuring their effective integration with economic operations [18; 19].

Despite these promising developments, challenges remain in adapting energy recovery technologies to off-road environments. Unlike urban electric vehicles, agricultural machinery operates under highly variable conditions, including uneven terrain, heavy loads, and frequent stopping and starting cycles. These factors necessitate advanced control algorithms and predictive models to optimise energy recovery without compromising vehicle performance [20; 21]. Additionally, hybrid hydraulic powertrains have emerged as an alternative solution for energy efficiency, offering potential advantages in agricultural applications where hydraulic systems are already widely used [17; 20].

Integrating renewable energy sources with vehicle charging and energy management systems, including photovoltaic carports, improves energy autonomy [19]. Adapting this solution to agriculture could increase energy efficiency and sustainable use, reducing dependence on the electricity grid. Moreover, research on energy system reliability emphasises the importance of predictive maintenance, and Semi-Markov models are an effective method to assess the availability and performance of energy recovery mechanisms [22]. These technologies can be adapted to optimise the maintenance and performance of agricultural energy recovery systems.

This study builds upon existing research by developing mathematical models and predictive algorithms to estimate energy recovery in agricultural vehicles. By leveraging techniques such as linear regression, k-nearest neighbours (KNN), and neural networks, the research aims to enhance the accuracy of energy recuperation predictions under various operating conditions. The findings contribute to the ongoing efforts to modernise agricultural machinery, supporting the transition toward more energy-efficient and environmentally sustainable farming practices [16; 21].

Studies on instantaneous energy recovery in electric buses have provided valuable insights into optimising energy recovery strategies [23]. The SORT test analysis of energy consumption and recovery patterns revealed key factors influencing efficiency, such as battery configuration and driving dynamics. SORT cycles were developed by the International Association of Public Transport (UITP) to assess the energy efficiency of vehicles under controlled conditions [23; 24]. These standardized cycles enable precise assessment of a vehicle's energy efficiency by eliminating environmental variables, allowing for reliable comparisons between different vehicle models and verification of manufacturers' claims [23; 24].

These conclusions can be applied to agricultural vehicles, considering variable terrain and operating conditions. Furthermore, machine learning technologies, such as LSTM networks, effectively predict the performance of energy systems in industry [25], and their implementation in agricultural recuperation systems could improve energy monitoring and optimisation. Despite many advantages, implementing energy recovery systems in agricultural vehicles requires further research, especially in their adaptation to demanding terrain conditions and variable workloads. The key challenge remains the development of control algorithms and predictive systems that will effectively manage recovered energy.

In this article, an analysis of instantaneous energy recuperation (IER) was conducted during the operation of an electric bus in the SORT test. The study examined different configurations of electric buses: one with a single battery and pantograph, another with four batteries, and the last with eight batteries. Each bus performed ten test runs to evaluate the impact of different battery setups on energy recuperation efficiency. This work provides important guidelines for using energy recovery systems in agriculture. The research results on electric buses constitute a valuable basis for designing modern agricultural machinery with higher energy efficiency. Future research should focus on adapting these technologies to the specific working conditions in agriculture and on developing intelligent energy management strategies that support the sustainable development of the agricultural sector.

Methodology/Research tools

Kruskal-Wallis test

The Kruskal-Wallis test [26; 27] was used to analyse differences in the process of electric energy recuperation during braking. SORT has been performed at each bus pass. Let $\{y_i^k\}_{1 \le i \le n_k}$ denote a sequence representing the amount of energy recovered during braking. Where $k \in \{1b, 4b, 8b\}$ (means "1 battery with pantograph", "4 batteries", "8 batteries"). The Kruskal-Wallis test is used to detect differences between groups when the assumption of normality of distribution in groups is not met. In the considered case, the number of batteries installed in the bus was selected as the differentiating variable. To verify the differences, at the significance level $\alpha \in (0,1)$ we create the null hypothesis:

H_0: $F_{1b}(x) = F_{4b}(x) = F_{8b}(x)$ for $x > 0$ (the distributions of the recovered energy are equal and do not depend on the number of batteries installed in the bus) and the alternative hypothesis

H_1: $\exists i, j \in \{1b, 4b, 8b\}$ $F_i(x) \neq F_j(x)$ (the number of batteries installed in the bus significantly impacts the amount of energy recovered during braking).

For the entire sample $\{y_i^k\}_{1 \le i \le n_k}, k \in \{1b, 4b, 8b\}$ the ranking was performed, the value R_{ki} denotes the rank of the i-th element from the k-th group in the sample. The formula gives the test statistic

$$T = \frac{12}{n(n+1)} \sum_{k \in \{1b, 4b, 8b\}} \left(\overline{R}_k - \frac{n+1}{2}\right)^2 n_k \tag{1}$$

where $n = n_{1\mathrm{b}} + n_{4\mathrm{b}} + n_{8\mathrm{b}}$

$\overline{R}_k = \frac{1}{n_k} \sum_{i=1}^{n_k} R_{ki}$.

The test statistic (1) measures the deviation of the sample rank means from the mean value of all ranks, equal to $(n + 1)/2$. The T statistic has a χ^2 distribution with 2 degrees of freedom.

Linear model

Let $\{(IRE_t, b_t, v_t, a_t)\}_{1leqt \le n}$ denote a data set, where IRE_t denotes the amount of recovered energy within 1 s during measurements (Wh), v_t – average vehicle speed (km·h^{-1}), a_t acceleration m·s^{-2}, $b_t \in \{1b, 4b, 8b\}$ - number of batteries. Since the variable describing the number of batteries is qualitative, we chose the bus with one battery and pantograph as the reference level. To identify the effect of the number of installed batteries, speed, and acceleration on the value of instantaneous recovered energy IRE_t, we consider a linear model [6, 25] as follows

$$IRE_t = \theta_0 + \theta_1 I_t(4\mathrm{b}) + \theta_2 I_t(8\mathrm{b}) + \theta_3 v_t + \theta_4 a_t + \theta_5 a_t^2 + \theta_6 v_t a_t + \varepsilon_t, \tag{2}$$

where $I_t(s) = \begin{cases} 1, & b_t = s, \\ 0, & b_t \neq s \end{cases}$ for sin $\in \{4b, 8b\}$, and the influence of external factors is described by random variable with a normal distribution $N(0, \sigma^2)$.

The least squares method was used to estimate the structural parameters $\theta_0, \theta_1, \ldots, \theta_5$ based on the observation of the dependent variable $\{IRE_t\}_{1 \le t \le n}$ and the predictors $\{\{(b_t, v_t, a_t)\}_{1 \le t \le n}$ in the model (2). The predicted value of the instantaneous energy recuperation is assumed to be

$$\hat{IRE}_t = \hat{\theta}_0 + \hat{\theta}_1 I_t(4\mathrm{b}) + \hat{\theta}_2 I_t(8\mathrm{b}) + \hat{\theta}_3 v_t + \hat{\theta}_4 a_t + \hat{\theta}_5 a_t^2 + \hat{\theta}_6 v_t a_t$$

where $\hat{\theta}_0, \dots, \hat{\theta}_5$ – estimators of structural parameters in the model (2).

$\varepsilon_t = IRE_t - \hat{IRE}_t$ – denotes the differences between empirical and predicted values of instantaneous recovered energy for $1 \le i \le n$

$\varepsilon = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n)$ – denotes the vector of residuals,

$\sigma^2 = \frac{\varepsilon^T \varepsilon}{n-6}$ – denotes the variance of residuals.

To assess the impact of individual features on explaining the variability of the dependent variable, we estimate the standard deviation for each structural parameter θ_i, $i \in \{0,1,\dots,5\}$.

To assess the impact of predictors [26; 27] at the significance level of $\alpha = 0.05$ for each structural parameter, we create a null hypothesis

H_0: $\theta_i = 0$ (the influence of the $i-th$ factor is irrelevant on the instantaneous recovered energy)

against the alternative hypothesis

H_1: $\theta_i \neq 0$ (i −ty factor significantly affects the instantaneous recovered energy).

A statistic describing the ratio of estimator of parameter θ_i to the standard deviation of this parameter S_{θ_i}

$$t_i = \frac{\hat{\theta}_i}{S_{\theta_i}} \tag{3}$$

has a Student’s *t*-distribution with $(n-k-1)$ degrees of freedom (in equation (2) we have $k = 6$ predictors). For each parameter, we determine the test probability

$$p_i = 2 * P(T > |t_i|),$$

where T – a random variable with a Student’s *t*-distribution with $(n-k-1)$ degrees of freedom.

If $p_i < \alpha$, then at the significance level α, the null hypothesis H_0 is rejected in favour of H_1. Therefore, the structural parameter is significantly different from zero, and the predictor significantly impacts explaining the dependent variable.

To analyse the fit of the model [3,6,25] the coefficient of determination R^2 was estimated

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(IRE_i - \hat{IRE}_i\right)^2}{\sum_{i=1}^{n}\left(IRE_t - \bar{IRE}\right)^2}$$

where IRE_i – denotes the observed value of the recovered energy;

$\hat{IRE}_i$ – the predicted value based on the model, $i = 1,2,\dots,n$,

$\bar{IRE}$ – the mean value of the recovered energy.

The coefficient of determination shows what part of the variability of the recovered energy is explained by the model. The correlation coefficient between the actual and predicted values on the test set was estimated as Mean Squared Error, Root Mean Squared Error, and Mean Absolute Error [3; 6; 25].

Results and discussion

During the electric bus ride according to the SORT test [23], the collected and recovered energy was analysed, recording its values using the Yokogawa WT-1806 power analyser, where the readings were presented in the form of time series

$$\left\{ICE^+_{t_j}\right\}_{0 \le j \le n} \text{ i } \left\{IRE^-_{t_j}\right\}_{0 \le j \le n}.$$

The impact of the bus ride on recovered energy was analysed, as well as the vehicle’s speed, acceleration, and number of batteries. The vehicle ride is described by staying in the states $A-$

acceleration, B – braking, D – driving, S – stop. Energy is recovered during braking, which is why this state was analysed. All calculations were performed in the R programming language [28]. An example ride in the SORT test and the recuperation of electric energy for a bus with one battery and a pantograph are shown in Fig. 1.

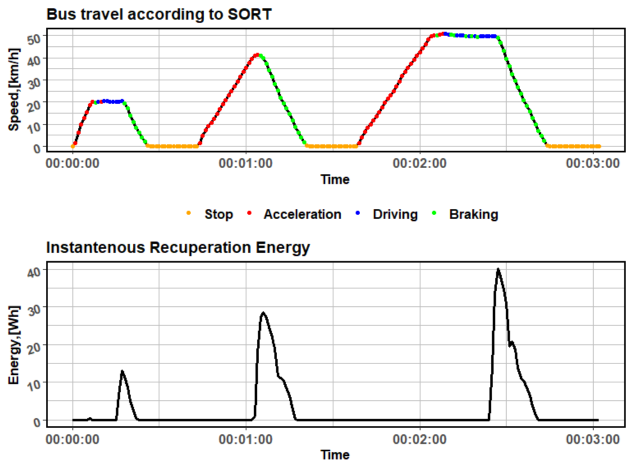

Fig. 1. **Test driving and Instantaneous Consumption/Recuperation Energy for a bus with 1 battery and pantograph**

The normality of the distribution of instantaneous energy recuperation for a bus with different numbers of batteries was also analysed using the following tests (Table 1): Shapiro–Wilk normality test, Lilliefors (Kolmogorov-Smirnov) test, D`Agostino Omnibus Test. Table 1 contains the statistic values and test probabilities.

Table 1

Result of normality test

Test	1 battery		4 batteries		8 batteries	
	Statistics	***P*-value**	**Statistics**	***P*-value**	**Statistics**	***P*-value**
Shapiro-Wilk normality	0.4801	$< 2.2 \cdot 10^{-16}$	0.4744	$< 2.2 \cdot 10^{-16}$	0.4620	$< 2.2 \cdot 10^{-16}$
Lilliefors (Kolmogorov-Smirnov)	0.4459	$< 2.2 \cdot 10^{-16}$	0.4493	$< 2.2 \cdot 10^{-16}$	0.4453	$< 2.2 \cdot 10^{-16}$
D`Agostino Omnibus	1030.656	$< 2.2 \cdot 10^{-16}$	1033.788	$< 2.2 \cdot 10^{-16}$	1604.755	$< 2.2 \cdot 10^{-16}$

Since the assumption of normality of the IRE distribution is not met for each group (the test probability is below the required level of 0.05), next Kruskal-Wallis test was used to test the significance of differences in the distributions. The test statistic value for the Kruskal-Wallis test is 12.699, while the test probability is 0.0017; therefore, at the significance level, we reject the null hypothesis in favour of the alternative hypothesis; the energy recuperation distributions differ significantly due to the number of installed batteries.

To analyse the effect of the number of batteries, acceleration and speed, the entire set was divided into a training set (80%) and a test set (20%). We analyse the linear relationship (2) and explain the effect of the number of batteries, acceleration and speed on the instantaneous electricity recuperation on the training set. The values of the estimators, standard deviations of these parameters, the value of the test statistic T (1) and the test probability for each of the parameters are presented in Table 2.

Table 2 shows that at the significance level of $\alpha = 0.05$ for each parameter, we reject the null hypothesis in favour of the alternative hypothesis. Therefore, the intercept and the predictors: number of batteries (4 or 8), speed, acceleration, acceleration squared, and the product of acceleration and speed significantly affect the explanation of instantaneous energy recovery.

On the training set, the value of the coefficient of determination is 0.8324, so the variability of instantaneous energy recovery is explained by 83.24%. The correlation coefficient between the actual and predicted values was estimated on the test set. The value of this coefficient is 0.9453, which means that the obtained forecasts are strongly correlated with the actual values, and the correlation is quite strong. The forecast accuracy measures were also determined on the test set: RMSE = 3.3925, MSE = 11.5091, MAE = 2.5396.

Table 2

Values of structural parameters, standard deviation, statistic T values and probility values for null hypothesis

Predictor	i	α_i	S_{α_i}	t_i	$P(T > \lvert t_i \rvert)$
-------	0	-6.4815	1.59205	-4.0712	$5.0961 \cdot 10^{-5}$
4 batteries	1	1.2754	0.40285	3.1660	$1.5981 \cdot 10^{-3}$
8 batteries	2	3.6473	0.37913	9.6203	$6.6163 \cdot 10^{-21}$
a_t	3	-7.8981	3.5521	-2.2235	$2.6432 \cdot 10^{-2}$
v_t	4	0.5093	0.03779	13.4747	$8.8027 \cdot 10^{-38}$
a_t^2	5	-12.9419	2.3962	-5.4009	$8.5202 \cdot 10^{-8}$
$a_t v_t$	6	-0.5576	0.05382	-10.3602	$8.08139 \cdot 10^{-24}$

Studies have shown that the number of batteries in electric buses significantly impacts the efficiency of instantaneous energy recovery. The Kruskal-Wallis test confirmed statistically significant differences between battery configurations, consistent with previous studies on electric vehicles and their regenerative braking systems [10]. Similar analyses were also conducted in the context of agricultural machinery, where optimising energy storage systems increased energy recovery efficiency in working machines and other off-road vehicles [4].

The results of the regression analysis indicate that the key factors influencing the efficiency of energy recovery are the speed, acceleration of the vehicle, squared acceleration and product of acceleration and speed. This is consistent with previous studies on electric vehicles, where dynamic braking torque control improved the ability to recover energy [11]. In agricultural machinery, which often operates under variable load conditions and uneven terrain, energy recovery efficiency can be increased by integrating advanced control algorithms [3].

The research results confirm the great potential of using energy recovery systems in agricultural machinery. Their effectiveness will, however, depend on adapting control systems to changing terrain conditions, optimising the number of batteries and implementing intelligent energy management strategies. Future research should focus on implementing adaptive control algorithms and connecting recuperation systems with precision farming technologies, which will allow for even greater efficiency and reduction of operating costs in agriculture [7].

Conclusions

Energy recovery systems are an important tool for improving energy efficiency in agriculture. The results of the research on electric buses indicate that using similar solutions in agricultural machinery can bring tangible benefits, especially in terms of energy savings and increased operational autonomy of vehicles.

The analysis confirmed that the number of installed batteries significantly impacts energy recuperation efficiency. For example, the average instantaneous energy recovery increased from 12.64 Wh for one battery to 14.27 Wh for four batteries and up to 15.99 Wh for eight batteries. Moreover, the correlation coefficient between the predicted and actual recuperation values reached 0.9453, indicating a strong model performance. The model explained 83.24% of the variability in the training set.

Forecast accuracy was also satisfactory, with RMSE = 3.39 Wh, MSE = 11.51 Wh^2, and MAE = 2.54 Wh.

Modular battery systems can improve the flexibility of agricultural vehicles, enabling their adaptation to specific operating conditions. Additionally, the integration of predictive algorithms and intelligent energy management strategies will allow for the optimization of the use of energy resources.

Despite many advantages, implementing energy recovery systems in agricultural vehicles requires further research, especially in their adaptation to demanding terrain conditions and variable workloads. The key challenge remains the development of control algorithms and predictive systems that will effectively manage recovered energy. Like urban buses, many agricultural machines operate in stop-and-go conditions, especially during fieldwork (e.g. harvesting, ploughing, or baling), which creates frequent deceleration events. This makes regenerative braking highly applicable, as these scenarios provide multiple opportunities to recover kinetic energy. Just as energy recovery in buses contributes to lower emissions and fuel costs, the same benefits can be achieved in agriculture - a sector under pressure to decarbonize and improve efficiency due to global sustainability targets.

This work provides important guidelines for using energy recovery systems in agriculture. The research results on electric buses constitute a valuable basis for designing modern agricultural machinery with higher energy efficiency. Future research should focus on adapting these technologies to the specific working conditions in agriculture and on developing intelligent energy management strategies that support the sustainable development of the agricultural sector.

Author contributions

Conceptualization, E.K., M.Z.-L., P.W., B.S., methodology, E.K., software, E.K., validation, E.K. and M.Z.-L., formal analysis, E.K., investigation, E.K., M.Z.-L., P.W., B.S., data curation, M.Z.-L., P.W., writing – original draft preparation, E.K., M.Z.-L., B.S., writing – review and editing, E.K., M.Z.-L., P.W., B.S. All authors have read and agreed to the published version of the manuscript.

References

[1] Barbashov N.N., Barkova A.A. Development of a Braking Energy Recovery Device for an Agricultural Robot. IOP Conf. Ser.: Earth Environ. Sci. 2021, 677, 032095, DOI: 10.1088/1755-1315/677/3/032095.
[2] Moreda G.P., Muñoz-García M.A., Barreiro P. High Voltage Electrification of Tractor and Agricultural Machinery - A Review. Energy Conversion and Management 2016, 115, pp. 117-131, DOI: 10.1016/j.enconman.2016.02.018.
[3] Un-Noor F., Wu G., Perugu H., Collier S., Yoon S., Barth M., Boriboonsomsin K. Off-Road Construction and Agricultural Equipment Electrification: Review, Challenges, and Opportunities. Vehicles 2022, 4, pp. 780-807, DOI: 10.3390/vehicles4030044.
[4] Barbashov N.N., Shanygin S.V., Polyantseva A.A. Control of Energy Recovery of Braking of Agricultural Machinery. IOP Conf. Ser.: Earth Environ. Sci. 2023, 1231, 012018, DOI: 10.1088/1755-1315/1231/1/012018.
[5] Pascuzzi S., Łyp-Wrońska K., Gdowska K., Paciolla F. Sustainability Evaluation of Hybrid Agriculture-Tractor Powertrains. Sustainability 2024, 16, 1184, DOI: 10.3390/su16031184.
[6] Antila M., Galimova T., Breyer C., Norouzi S., Repo S., Pihlatie M., Pettinen R., Shah S. Future Energy Technology for Nonroad Mobile Machines. Adv Energy and Sustain Res 2025, 2400257, DOI: 10.1002/aesr.202400257.
[7] Hahn C., Lindkvist E., Magnusson D., Johansson M. The Role of Agriculture in a Sustainable Energy System - The Farmers' Perspective. Renewable and Sustainable Energy Reviews 2025, 213, 115437, DOI: 10.1016/j.rser.2025.115437.
[8] Gilewski M., Czarnigowski J., Hunicz J., Dubeński K., Szafran M., Fronc M. Model of a Prototype Vehicle Powered by a Hybrid Hydrogen System. J. Phys.: Conf. Ser. 2021, 2130, 012002, DOI: 10.1088/1742-6596/2130/1/012002.
[9] Małek A., Taccani R., Kasperek D., Hunicz J. Optimization of Energy Management in a City Bus Powered by the Hydrogen Fuel Cells. Komunikácie 2021, 23, E56-E67, DOI: 10.26552/com.C.2021.4.E56-E67.
[10] Xu L., He X., Shen X. Improving Energy Recovery Rate of the Regenerative Braking System by Optimization of Influencing Factors. Applied Sciences 2019, 9, 3807, DOI: 10.3390/app9183807.
[11] Guo J., Zhou J. Comprehensive Analysis of Braking Energy Recovery System for New Energy Vehicle. HSET 2023, 43, 504-511, DOI: 10.54097/hset.v43i.7470.
[12] Anh N.T., Chen C.-K., Liu X. An Efficient Regenerative Braking System for Electric Vehicles Based on a Fuzzy Control Strategy. Vehicles 2024, 6, 1496-1512, DOI: 10.3390/vehicles6030071.

[13] Teasdale A., Ishaku L., Amaechi C.V., Adelusi I., Abdelazim A. A Study on an Energy-Regenerative Braking Model Using Supercapacitors and DC Motors. WEVJ 2024, 15, 326, DOI: 10.3390/wevj15070326.
[14] Kropiwnicki J., Gawłas T. Estimation of the Regenerative Braking Process Efficiency in Electric Vehicles. Acta Mechanica et Automatica 2023, 17, 303-310, DOI: 10.2478/ama-2023-0035.
[15] Ye M., Jiao S., Cao B. Energy Recovery for the Main and Auxiliary Sources of Electric Vehicles. Energies 2010, 3, 1673-1690, DOI: 10.3390/en3101673.
[16] Kozłowski E., Wiśniowski P., Gis M., Zimakowska-Laskowska M., Borucka A. Vehicle Acceleration and Speed as Factors Determining Energy Consumption in Electric Vehicles. Energies 2024, 17, 4051, DOI: 10.3390/en17164051.
[17] Zheng P., Gao J., College of Aerospace Science and Engineering, National University of Defense Technology, Changsha 410072, China Damping Force and Energy Recovery Analysis of Regenerative Hydraulic Electric Suspension System under Road Excitation: Modelling and Numerical Simulation. Mathematical Biosciences and Engineering 2019, 16, pp. 6298-6318, DOI: 10.3934/mbe.2019314.
[18] Pieniak D., Guzik M., Lonkwic P., Lesiak P., Selech J., Krzysiak Z., Matijosius J., Sejkorova M., Kilikevičius A. The Influence of Geometric Nonconformance of the SB4 Tension Clamps on Their Strength and Elasticity Characteristics. Sci Rep 2024, 14, 29540, DOI: 10.1038/s41598-024-80944-8.
[19] Sokolovskij E., Małek A., Caban J., Dudziak A., Matijošius J., Marciniak A. Selection of a Photovoltaic Carport Power for an Electric Vehicle. Energies 2023, 16, 3126, DOI: 10.3390/en16073126.
[20] Zhao P.-Y., Chen Y.-L., Zhou H. Simulation Analysis of Potential Energy Recovery System of Hydraulic Hybrid Excavator. Int. J. Precis. Eng. Manuf. 2017, 18, pp. 1575-1589, DOI: 10.1007/s12541-017-0187-0.
[21] Nguyen V.H., Do T.C., Ahn K.K. Investigation and Optimization of Energy Consumption for Hybrid Hydraulic Excavator with an Innovative Powertrain. Actuators 2023, 12, 382, DOI: 10.3390/act12100382.
[22] Kozłowski E., Borucka A., Oleszczuk P., Leszczyński N. Evaluation of Readiness of the Technical System Using the Semi-Markov Model with Selected Sojourn Time Distributions. Eksploatacja i Niezawodność - Maintenance and Reliability 2024, 26, DOI: 10.17531/ein/191545.
[23] Kozłowski E., Zimakowska-Laskowska M., Dudziak A., Wiśniowski P., Laskowski P., Stankiewicz M., Šnauko B., Lech N., Gis M., Matijošius J. Analysis of Instantaneous Energy Consumption and Recuperation Based on Measurements from SORT Runs. Applied Sciences 2025, 15, 1681, DOI: 10.3390/app15041681.
[24] Gis W., Kruczyński S., Taubert S., Wierzejski A. Studies of Energy Use by Electric Buses in SORT Tests. Combustion Engines 2017, 170, 135-138, DOI: 10.19206/CE-2017-323.
[25] Kłosowski G., Rymarczyk T., Niderla K., Kulisz M., Skowron Ł., Soleimani M. Using an LSTM Network to Monitor Industrial Reactors Using Electrical Capacitance and Impedance Tomography - a Hybrid Approach. Eksploatacja i Niezawodność - Maintenance and Reliability 2023, DOI: 10.17531/ein.2023.1.11.
[26] James G., Witten D., Hastie T., Tibshirani R. An Introduction to Statistical Learning: With Applications in R; Springer Texts in Statistics; Springer US: New York, NY, 2021; ISBN 978-1-0716-1417-4.
[27] Hastie T., Tibshirani R., Friedman J. The Elements of Statistical Learning; Springer Series in Statistics; Springer New York: New York, NY, 2009; ISBN 978-0-387-84857-0.
[28] R Core Team A Language and Environment for Statistical Computing. R Foundation for Statistical Computing; Vienna, Austria;