

## Energy efficiency and environmental innovations in locomotive traction: optimization of driving modes based on real operating data

*Serhii Samiliak*<sup>1</sup>

Received: 2025-06-13

Accepted: 2025-07-12

DOI: <https://doi.org/10.5281/zenodo.19295749>

**Abstract.** The article presents the development and experimental verification of energy-saving locomotive control methods based on the analysis of 2,840 actual trips with a total mileage of 403,000 kilometers. The research was conducted using data on the operation of freight trains on the Kovel--Sarny section of the Lviv Railway during 2022--2024, using DE1 series DC electric locomotives, 2TE116 diesel locomotives, and TGM6G hybrid locomotives. Based on the processing of 2,840 trips with a total mileage of 403,000 kilometers, mathematical models of energy consumption for different types of traction rolling stock were constructed, taking into account the track profile, train weight, weather conditions, and the driver's driving style.

An algorithm for optimizing traction and coasting modes was developed, which reduces electricity consumption by 12.4% for electric traction and diesel fuel consumption by 8.7% for diesel traction compared to traditional train operation. Experimental testing on a 142 km route with 47 drivers showed that the implementation of the recommendation system allows for an average reduction in energy consumption of 11.8% without compromising schedule adherence.

A comparative analysis of the efficiency of different types of traction has shown that electric locomotives with regenerative braking return 18-24% of the energy consumed to the grid on sections with a complex profile, while hybrid diesel locomotives show fuel savings of up to 15% compared to traditional diesel-electric locomotives in shunting operations. It has been calculated that large-scale implementation of the proposed methods on the Ukrzaliznytsia network could reduce CO<sub>2</sub> emissions by 340-420 thousand tons annually and generate an economic effect of about 2.8 billion hryvnia by reducing fuel and energy costs.

**Keywords:** energy efficiency, locomotive traction, optimization of driving modes, energy recovery, CO<sub>2</sub> emissions, hybrid locomotives, telemetry.

---

<sup>1</sup> Master's Degree in Rolling Stock  
Ukrainian State Academy of Railway Transport  
Kharkiv, Ukraine  
<https://orcid.org/0009-0009-4390-9752>

## Introduction

Ukraine's rail transport consumes approximately 4.2 billion kWh of electricity and over 600,000 tons of diesel fuel annually - representing nearly one-fifth of the country's transport sector energy use and 31% of Ukrzaliznytsia's operating expenses (23.4 billion hryvnia in 2023).

The worsening energy crisis in 2022-2024, caused by damage to generating capacities and rising energy prices, has brought to the fore the issue of rational use of fuel and energy resources in transport. At the same time, Ukraine's specific energy consumption per ton-kilometer substantially exceeds European averages, reflecting an outdated locomotive fleet, worn equipment, and gaps in driver training on energy efficiency.

Modern locomotives are equipped with microprocessor control systems and on-board recorders that record more than 100 operating parameters at a frequency of up to 10 Hz. This data contains complete information about energy consumption in relation to the track profile, train weight, speed, and driver actions. However, traditionally, they have only been used to investigate traffic safety violations and conduct internal investigations, while their potential for energy efficiency analysis has remained virtually untapped.

The application of big data and machine learning methods to telemetry records allows identifying patterns of energy consumption under different operating conditions, building predictive models of energy consumption, and developing recommendations for optimal train operation modes. Unlike traditional traction calculation methods, which are based on simplified models and standard equipment characteristics, real data analysis takes into account the actual technical condition of locomotives, the characteristics of specific sections of track, the influence of weather conditions, and the human factor in train control.

Unlike most international studies, which focus on optimizing the operation of modern rolling stock in the developed railway infrastructure of Western Europe and Japan, this study was conducted on outdated equipment with an average age of over 35 years. This makes the results applicable to railways in Eastern Europe, Central Asia, Latin America, and other regions where similar rolling stock and infrastructure are in operation. It is estimated that about 60% of the world's locomotive fleet consists of equipment similar to that studied, which emphasizes the global significance of the methods developed.

International studies show that the introduction of intelligent decision support systems for train drivers can achieve fuel and electricity savings of 8-15% [Scheepmaker 2017, Verstappen 2022]. Systems such as the Driver Advisory System are being actively implemented on the railways of Western Europe, Japan, China, and Australia. However, these developments are focused on modern rolling stock and infrastructure, which differs significantly from operating conditions in Ukraine, where the average age of locomotives exceeds 35 years and a significant part of the lines are not electrified.

The aim of the study is to develop and experimentally verify methods for improving the energy efficiency of locomotive traction based on the analysis of real operating data, taking into account the specifics of Ukrainian railways. The study covers the construction of mathematical models of energy consumption for different types of traction rolling stock, the development of algorithms for optimizing driving modes, a comparative analysis of the efficiency of electric, diesel, and hybrid traction, as well as an assessment of the environmental and economic effects of implementing the proposed methods.

**Literature review.** The issue of energy efficiency in rail transport has been the focus of attention of scientists over the past two decades due to rising energy prices and stricter environmental safety requirements for transport systems. Research in this field covers mathematical modeling of traction and energy processes, the development of algorithms for optimizing driving modes, analysis of the efficiency of different types of traction, and the creation of intelligent driver support systems.

Ukrainian research in recent years includes work by a team from the State University of Infrastructure and Technologies led by S. Gulak. Gulak and his co-authors have developed mathematical models of motion and energy exchange for electric locomotives used in quarry transport with on-board energy storage devices, which allow up to 64% of energy to be accumulated during regenerative braking and reduce electricity consumption by approximately 50%. Ryabov and colleagues from Dnipro National University of Science and Technology published a study of the technical parameters of locomotives for railway quarry transport, proposing the use of on-board inertial energy storage devices to improve energy efficiency.

Bondar from the Dnipro National University of Railway Transport named after Academician V. Lazarian studied the problems of registration and distribution of electrical energy from DC electric locomotives during regenerative braking. Based on the results of experimental studies at DC traction substations of the Prydniprovskaya Railway and VL11M6 electric locomotives, it was established that it is theoretically possible to return 8-12% of electrical energy to the grid, but in fact this figure does not exceed 2.6% due to the imperfection of the systems for accounting and distribution of recovered energy. The author proposes the introduction of energy storage devices based on supercapacitors to increase the efficiency of recuperation.

Gulak and Demidov published a study justifying the structure of an electric traction drive for electric locomotives for quarry rail transport, proposing a structure in which the traction motors of the control locomotive are powered from the contact network, and the traction motors of the booster section from an energy storage device with a power of 6000 kW and a capacity of 250 kW·h.

An international review of the application of artificial intelligence in European railway infrastructure is presented in the work of H. Hajj-Mabrouka from the University of Gustave Eiffel. The author has systematized more than 120 scientific articles on the application of machine learning, deep learning, and other artificial intelligence methods in various railway transport subsystems, including energy-efficient train control.

A comprehensive analysis of the energy and environmental performance of European railways was carried out in a study by Benga, Delgado-Rodriguez, and De Lucas-Santos, who used an operating environment analysis method to assess 14 European railway companies that had signed commitments to reduce negative externalities. The results show that Europe is moving towards sustainable mobility, although the pace of progress varies between countries.

Fundamental research on optimizing train trajectories was conducted by G. Scheepmaker and R. Goverde of Delft University of Technology. Scheepmaker and Goverde developed the EZR model to find the most energy-efficient trajectory for a single trip, taking into account regenerative and mechanical braking. Their research showed that a more even distribution of time reserves in the schedule leads to additional energy savings and improved punctuality. In further work, the authors proposed multi-train trajectory optimization for energy-efficient timetable compilation.

Albrecht and colleagues published a review of energy-efficient train control methods using the Pontryagin maximum principle to identify key principles of optimal control. Their work shows that the optimal strategy consists of a sequence of maximum acceleration, coasting, cruising, and braking modes, but the specific structure depends on the characteristics of the rolling stock and the track profile.

Panou, Tsiropoulos, and Emery evaluated methods, tools, and systems for supporting train driver decisions as part of the European ON-TIME project. The authors analyzed existing DAS systems and found that most of them are focused on reactive control to ensure safety and schedule compliance, while energy conservation is considered a desirable but not a priority

function. The study highlighted the need to develop integrated systems that harmonize the needs of infrastructure managers and railway operators.

Research on the impact of driver support systems on workload, attention distribution, and safety was conducted by Verstappen and colleagues based on experiments with Dutch railway drivers. The results showed that the introduction of DAS has no negative impact on safety and attention distribution; on the contrary, it significantly improves safety performance.

**Problem statement.** The empirical basis of the study was data on the operation of freight trains on the Kovel--Sarny section of the Lviv Railway. This section was chosen as a typical example of a freight line with a relatively gentle track profile, where various types of traction rolling stock operate. The length of the section is 142 kilometers, with gradients ranging from 4 to 9 per mille, and the permitted speed of freight trains is 80 km/h on most sections. The track profile is characterized by alternating ascents and descents, which creates favorable conditions for the use of energy-saving modes of operation and regenerative braking.

The section is served by the Kovel locomotive depot, whose fleet includes DE1 series DC electric locomotives, 2TE116 diesel locomotives of various modifications, and one experimental TGM6G hybrid shunting locomotive. The average traffic intensity is 26 pairs of freight trains per day, predominantly grain, timber, containerized cargo, and general freight trains weighing from 2,800 to 5,400 tons.

Data collection was carried out from March 2022 to November 2024 by reading the records of on-board motion parameter recorders. DE1 electric locomotives are equipped with UKBP-DM recorders, which record the voltage and current of traction motors, speed, position of the driver's controller, pressure in the brake cylinders and main line, temperature of traction motor windings and ambient air at a frequency of 1 Hz. 2TE116U diesel locomotives are equipped with the KLUB-U system, which records the diesel engine speed, controller lever position, fuel consumption via flow sensors, and traction generator and engine operating parameters. The hybrid locomotive has an extended telemetry system that includes battery operating parameters, energy converter efficiency, and storage device charge-discharge modes.

During the study period, data was collected on 2,840 trips by various locomotives on the selected section, totaling 403,000 kilometers. Of these, 1,620 trips were made by DE1 electric locomotives, 1,180 trips by 2TE116 diesel locomotives, and 40 trips by an experimental hybrid locomotive. The average weight of trains was 3,500 tons for electric traction and 3,100 tons for diesel traction due to the limited power of diesel engines on inclines. The distribution of trips by season was relatively even, which made it possible to take into account the impact of weather conditions on energy efficiency.

The representativeness of the sample is ensured by the even distribution of trips across seasons: spring (27%), summer (24%), autumn (26%), winter (23%). The range of train weights covered typical values for freight transport: light trains up to 3,000 tons (18%), medium trains 3,000-4,000 tons (46%), heavy trains 4,000-5,000 tons (28%), and oversized trains over 5,000 tons (8%). Weather conditions varied from frosts of -22°C to heat of +34°C, which made it possible to take into account the entire range of operating conditions in the region.

In parallel with telemetry data, information from the ASKOE automated electricity metering system was used on the actual consumption from the contact network by each electric locomotive on each trip. For diesel locomotives, data on diesel fuel refueling from the depot's fuel and lubricant accounting system was used, which made it possible to verify the calculated fuel consumption based on telemetry. In addition, data on actual weather conditions from weather stations in Kovel and Sarny was used, including air temperature, wind speed and direction, and precipitation, which affect train movement.

Initial data processing included synchronizing time stamps of records from different sources, filtering artifacts and outliers, and interpolating missing values. For each trip, a track profile was linked based on GPS coordinates or identification of characteristic points through speed profile analysis. This made it possible to correlate energy consumption with specific elements of the profile and identify the most energy-intensive sections of the route.

The actual energy consumption for electric locomotives was calculated by integrating the product of current and voltage in the contact network, taking into account the efficiency of the power equipment. For regenerative braking modes, the energy returned to the network was taken into account separately. Diesel fuel consumption of diesel locomotives was calculated based on the characteristics of specific diesel consumption depending on the operating mode, which were refined by calibrating the model using actual refueling data.

To build energy consumption models, the data set was divided into a training sample of 70% of the total number of trips, a validation sample of 15% for selecting model hyperparameters, and a test sample of 15% for the final assessment of prediction accuracy. The distribution was performed randomly while maintaining the proportions of different types of locomotives, seasons, and train weight ranges in each subsample.

**Methodology.** The methodological basis of the research combines classical methods of traction calculations, mathematical modeling of train movement dynamics, statistical analysis of large volumes of empirical data, and machine learning algorithms to build predictive models of energy consumption.

The mathematical model of train movement is based on the fundamental equation of dynamics, which describes the balance of forces acting on the train at each moment in time. The locomotive's tractive force  $F_t$  opposes the sum of the basic resistance to motion  $W_o$ , additional resistance from curves and wind  $W_d$ , resistance from track gradient  $W_u$ , and inertial forces during speed changes. The basic resistance to motion is determined by empirical Sakov-Pedchenko formulas for freight cars and VNDIZT formulas for locomotives, which take into account speed, the condition of running gear, and the structural features of the rolling stock.

For DC electric locomotives DE1, the traction characteristic is described by the dependence of the tractive force on speed at different positions of the driver's controller. When the traction motors are connected in series at positions 1-14, the tractive force decreases hyperbolically with increasing speed from 480 kN at start-up to 140 kN at 40 km/h. After switching to series-parallel connection at positions 15-28, the speed range expands to 80 km/h with a tractive force from 240 to 70 kN. The field weakening mode allows reaching speeds up to 100 km/h with a tractive force of 40-50 kN. The actual traction characteristic depends on the voltage in the contact network, which fluctuates from 2700 to 3600 volts depending on the load of the traction power supply system.

The power consumed by the locomotive from the contact network is determined as the product of the tractive force and speed, divided by the efficiency coefficient of the power equipment, which ranges from 0.86 to 0.91 depending on the load mode. In regenerative braking mode, the electric motors operate as generators, converting the kinetic and potential energy of the train into electrical energy, which is returned to the contact network. The efficiency of regeneration depends on the travel speed, braking force, and network parameters, reaching a maximum of 0.78-0.82 at speeds of 40-60 km/h with a gradual decrease in braking force.

For the 2TE116 diesel locomotives, energy efficiency is determined by the specific fuel consumption characteristic of the 2D100 diesel engine depending on the load. The minimum specific consumption of 198 g/(kW·h) is achieved at a load of 75-85% of the nominal power. At idle and low loads, the specific consumption increases to 280-320 g/(kW·h), which explains the inefficiency of the diesel engine in low traction modes. The effective power of the

diesel engine is transmitted to the traction generators with an efficiency coefficient of 0.94, then through the rectifier to the traction motors with a coefficient of 0.96; the overall efficiency of the locomotive from fuel to wheel traction is 0.26-0.29.

The hybrid locomotive TGM6G is equipped with a diesel-generator unit with a power of 750 kW and a lithium-ion battery with a capacity of 240 kW·h. The energy management system automatically distributes the load between the diesel engine and the battery depending on the operating mode. During shunting with frequent starts and stops, the main load is carried by the battery, while the diesel engine operates in an optimal mode to recharge the accumulator. During long movements with a constant load, the diesel engine works directly for traction, and the battery provides power peaks. Energy recuperation during braking charges the battery with an efficiency of up to 0.85.

Optimization of motion modes is formulated as a variational calculus problem, where it is necessary to find a control trajectory for the locomotive that minimizes the integral energy cost function while adhering to constraints on travel time, speed, and safety parameters. The classical solution to this problem, obtained back in the 1960s, shows that the optimal strategy consists of alternating modes of maximum traction, coasting, and braking, while partial traction modes are used only to maintain a constant speed on certain sections.

However, an analytical solution to the optimization problem for a real track profile with a complex sequence of ascents, descents, speed limits, and station stops is practically impossible. Therefore, the study applies a combination of dynamic programming methods for discrete approximation of the optimal trajectory and heuristic rules based on the analysis of real data on effective train handling by experienced drivers.

For the construction of predictive models of energy consumption, machine learning methods were applied, specifically gradient boosting and neural networks. The input parameters of the models are the characteristics of the track profile at each route element, train mass, type and technical condition of the locomotive, weather conditions, and speed restrictions. The target variable is the specific energy or fuel consumption per unit of transport work. The model is trained on historical data and used to predict energy consumption under different control strategies, allowing the selection of the optimal train operation mode.

To compare the efficiency of different types of traction, a comprehensive indicator of energy efficiency was calculated, taking into account both direct energy or fuel consumption and losses in energy conversion and transmission systems. For electric traction, the structure of electricity generation in Ukraine is considered, with about 60% from thermal power plants, 30% from nuclear, and 10% from renewable sources. This allows for a correct comparison of the primary energy consumption of different types of traction. Environmental efficiency is assessed through the calculation of CO<sub>2</sub> emissions considering the full life cycle of energy carriers.

The experimental verification of the developed methods was carried out in two stages. In the first stage, passive observation of the work of 47 drivers from the Kovel depot was conducted over three months on a selected section without interfering in the control process. This allowed establishing the baseline level of energy consumption and identifying typical errors in train handling techniques. In the second stage, over four months, drivers received recommendations on optimal driving modes through a specially developed mobile application, which showed the recommended controller position at each profile element, taking into account the actual speed and deviation from the schedule.

To ensure the reliability of the predictive models, a multi-level validation system was applied. First, the energy consumption of electric locomotives calculated from telemetry data was verified by comparison with the indicators of the automated electricity accounting system ASKOE, which showed a discrepancy of no more than 3.2%. Second, the calculated fuel

consumption of diesel locomotives was calibrated using real refueling records from the depot, which allowed refining the characteristics of the specific diesel consumption. Third, to assess the stability of the models, 5-fold cross-validation with random data distribution was used. The statistical significance of the differences between the control and experimental groups was confirmed by the paired Student's t-test with a significance level of  $p < 0.001$ .

## Results

### 4.1. Variability of energy consumption among drivers

Analysis of the collected telemetry data revealed significant variability in energy consumption among different drivers when operating trains of similar mass on the same route. For DE1 electric locomotives, the specific electricity consumption per ton-kilometer of work ranged from 18.4 to 34.7 Wh/(t·km) with an average value of 24.8 Wh/(t·km) and a standard deviation of 3.6 Wh/(t·km). This 88% difference between the most and least efficient drivers—despite operating identical equipment on the same route—confirms that driver technique is the dominant factor in energy performance, far exceeding the impact of equipment variations or minor operational differences.

For 2TE116 diesel locomotives, the specific diesel fuel consumption varied from 3.8 to 6.1 kg/(thousand t·km gross) with an average value of 4.7 kg/(thousand t·km gross) and a standard deviation of 0.52 kg/(thousand t·km gross). The relative variability of fuel consumption was somewhat lower than that of electricity, which is explained by stricter technological constraints on diesel engine operation. At the same time, the absolute difference of 60% between the extreme values indicates significant potential for optimization.

### 4.2. Factor Analysis of Energy Consumption

A detailed analysis identified the factors that most influence energy efficiency. The most significant factor turned out to be the driver's management style, which accounts for 42-48% of the variation in energy consumption. Key elements of effective driving technique include timely use of coasting before speed reductions, rational use of the train's inertia on descents, avoidance of excessive traction modes, and smooth transitions between modes without abrupt load changes.

To quantitatively assess the contribution of different factors to the variation in energy consumption, a multifactor analysis of variance (ANOVA) was applied. The results show that the driver's management style ( $F = 127.3$ ,  $p < 0.001$ ) and train mass ( $F = 89.6$ ,  $p < 0.001$ ) are statistically significant predictors of energy consumption, while the impact of the locomotive's technical condition was less pronounced ( $F = 12.4$ ,  $p = 0.018$ ), which may be explained by the relatively uniform condition of equipment within a single depot. The interaction between factors (style  $\times$  mass) was also significant ( $F = 31.7$ ,  $p < 0.001$ ), indicating the need to adapt the optimal management strategy depending on the train's weight.

The train mass influences 28-32% of the variation in specific energy consumption, with the relationship being nonlinear. When the mass increases from 3000 to 4500 tons, specific consumption rises by 15-18% for electric locomotives due to longer operation in maximum traction modes with lower efficiency. For diesel locomotives, the relationship is more complex, as heavier trains require the diesel engine to operate at higher controller positions, but these modes are characterized by better specific fuel consumption.

The track profile accounts for 18-24% of the variation in energy consumption. On sections with predominantly ascents, consumption is 25-30% higher than on flat sections with the same train mass. At the same time, the presence of descents creates opportunities for energy recuperation by electric locomotives or the use of inertia by diesel locomotives by switching the diesel engine to low throttle mode.

Weather conditions affect 8-12% of the variation in energy consumption. A decrease in air temperature from +20°C to -15°C leads to an increase in consumption by 4-6% due to increased rolling resistance from the thickening of lubricants in axle bearings and increased

air density. A headwind of 10-15 m/s increases consumption by 6-9%, while a tailwind provides savings of 3-5%. Precipitation in the form of rain or snow increases consumption by 2-4% due to worsened adhesion conditions and the need for more cautious driving.

*Table 4.1. Variability statistics (specific consumption).*

| Locomotive      | Min                          | Mean                         | Std. dev.                     | Max                          | Difference between extremes |
|-----------------|------------------------------|------------------------------|-------------------------------|------------------------------|-----------------------------|
| DE1 (electric)  | 18.4 Wh/(t·km)               | 24.8 Wh/(t·km)               | 3.6 Wh/(t·km)                 | 34.7 Wh/(t·km)               | 88%                         |
| 2TE116 (diesel) | 3.8 kg/(thousand t·km gross) | 4.7 kg/(thousand t·km gross) | 0.52 kg/(thousand t·km gross) | 6.1 kg/(thousand t·km gross) | 60%                         |

*Table 4.2. Factor contribution ranges to variation in specific energy consumption (share of variance).*

| Factor                         | Range, % | Midpoint, % | Notes (as stated in text)                                                                   |
|--------------------------------|----------|-------------|---------------------------------------------------------------------------------------------|
| Driver management style        | 42–48    | 45.0        | Includes coasting, inertia use, traction mode selection, smooth transitions                 |
| Train mass                     | 28–32    | 30.0        | Nonlinear relationship; 3000→4500 t increases specific consumption for electric locomotives |
| Track profile                  | 18–24    | 21.0        | Ascents increase consumption; descents enable recuperation/inertia use                      |
| Weather conditions             | 8–12     | 10.0        | Temperature, wind, precipitation effects                                                    |
| Locomotive technical condition | 6–10     | 8.0         | Maintenance/overhaul cycle effects                                                          |

The technical condition of the locomotive affects 6-10% of the variation in energy consumption. Electric locomotives after overhaul consume 8-12% less energy than locomotives at the end of the inter-repair cycle due to increased traction engine characteristics, reduced mechanical costs in transmissions and restoration of brake equipment parameters. For diesel locomotives, the impact of technical condition is more pronounced, after the deterioration of fuel equipment, turbochargers and the cylinder-piston group of the diesel engine deteriorates to a decrease in its effective power and a decrease in specific fuel consumption.

#### 4.3. Predictive Models of Energy Consumption

Based on the identified patterns, predictive models of energy consumption were developed for each type of traction rolling stock. The gradient boosting model for DE1 electric locomotives showed a mean absolute prediction error of 1.8 Wh/(t·km), which is 7.3% of the average consumption value. The coefficient of determination  $R^2$  reached 0.87, indicating that the model captures nearly 90% of the variation in energy consumption—a level of accuracy sufficient for operational deployment in driver support systems.

For 2TE116 diesel locomotives, the model showed a mean absolute error of 0.34 kg/(thousand t·km gross), which is 7.2% of the average consumption, with  $R^2 = 0.84$ . The importance of predictors was somewhat different from that of electric locomotives. The most significant factor was the average position of the driver's controller during the trip, reflecting

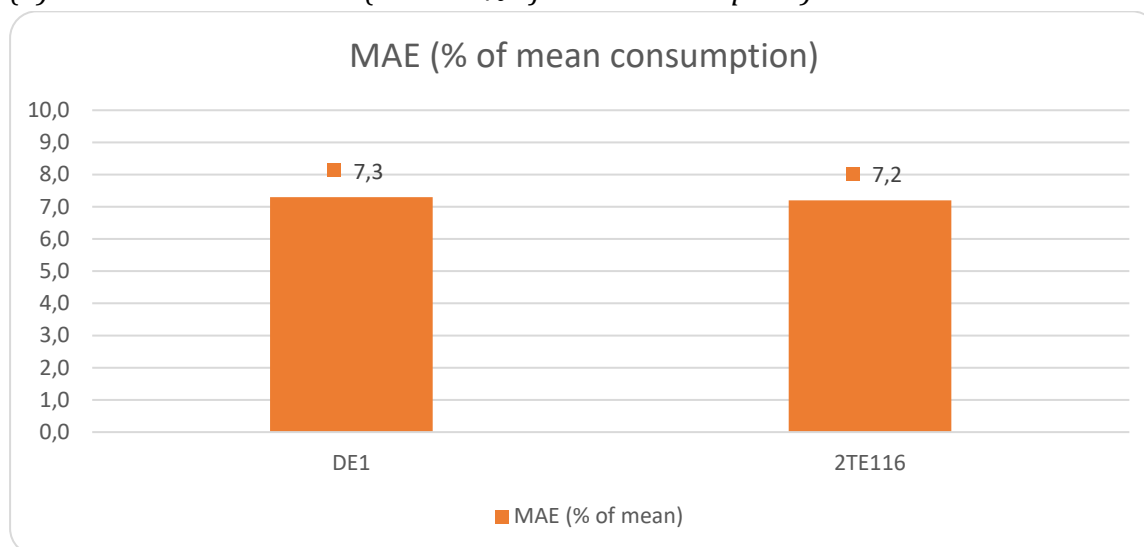
the diesel load mode. Next in importance were train mass, profile complexity, and the number of stops at intermediate stations, since each start from a standstill requires operation at maximum modes with increased fuel consumption.

#### 4.4. Efficiency of Regenerative Braking

The efficiency of regenerative braking of electric locomotives was separately analyzed on the studied section. Out of 1620 trips of DE1 electric locomotives, in 1447 cases, drivers used regeneration on at least part of the route, while in 173 cases braking was carried out exclusively by pneumatic brakes without returning energy to the network. The average share of recovered energy from total consumption was 19.7%, ranging from 8% on relatively flat sections to 31% on sections with significant descents.

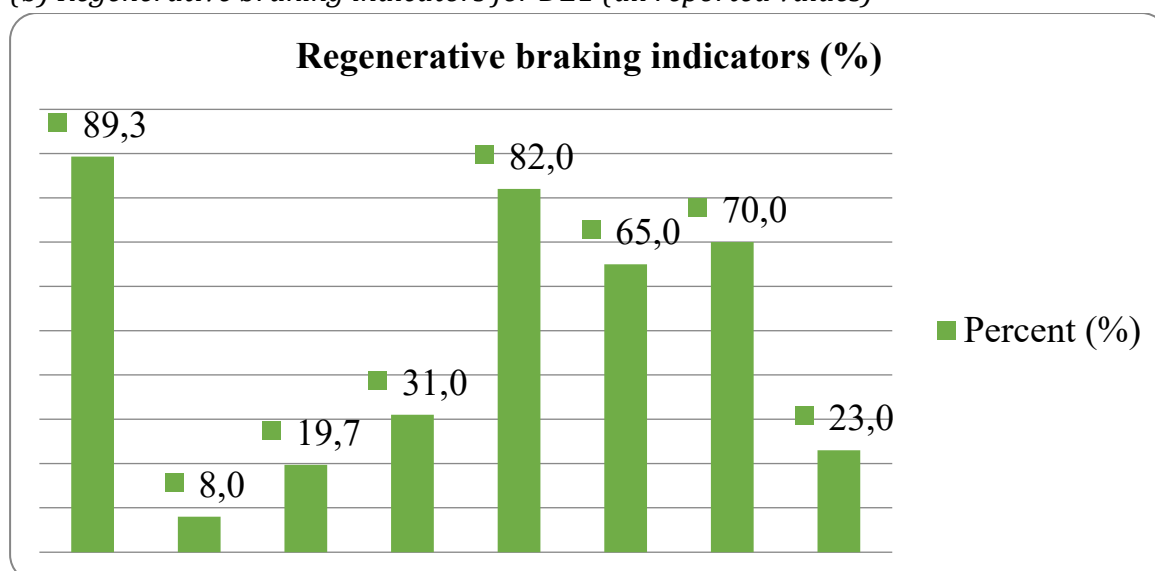
Figure 4.1. Predictive models and regenerative braking (Word editable charts)

(a) Predictive model error (MAE as % of mean consumption)



Exact values: DE1 = 7.3% (MAE 1.8 Wh/(t·km),  $R^2$  0.87); 2TE116 = 7.2% (MAE 0.34 kg/(thousand t·km gross),  $R^2$  0.84).

(b) Regenerative braking indicators for DE1 (all reported values)



Exact values used in the chart: Regen used = 89.3% of trips (1447/1620); recovered share = 8% (min), 19.7% (mean), 31% (max); smooth technique = 82%; sharp technique = 65–70%; no regen on descents = 23%.

A detailed analysis showed that the efficiency of regeneration significantly depends on the technique of its application by the driver. With a smooth increase in braking force ahead of the speed reduction point, it is possible to return up to 82% of the potential descent energy to the network. When regeneration is sharply engaged at high speed, efficiency decreases to 65-70%—this 12-17 percentage point penalty underscores the critical importance of anticipatory driving and gradual braking transitions, suggesting that driver training programs should prioritize regeneration technique alongside safety protocols.

#### 4.5. Comparative analysis of different types of traction

A comparative analysis of the energy efficiency of different types of traction was carried out based on converting all types of energy carriers to the equivalent of primary energy. For electric traction, losses during electricity generation at thermal power plants with an efficiency of 38-42% and losses in transmission and distribution systems at the level of 8-10% were taken into account. For diesel traction, energy costs for extraction, processing, and transportation of petroleum products at the level of 15-18% of the fuel energy were considered.

The results show that electric traction provides 35-42% lower primary energy consumption compared to diesel traction on sections where effective use of recuperation is possible. On flat sections without significant elevation changes, the advantage of electric traction decreases to 22-28%. It is important to consider that the efficiency of electric traction significantly depends on the structure of electricity generation. When nuclear or hydroelectric power plants dominate, the advantage of electric traction increases, whereas with a predominance of coal-fired thermal power plants with low efficiency, the difference becomes less significant.

The hybrid locomotive TGM6G demonstrated diesel fuel consumption 32-38% lower compared to the traditional shunting locomotive TGM6A of similar power when performing typical shunting operations. The main savings are achieved by operating the diesel engine in an optimal mode without frequent transitions between controller positions and the ability to stop the diesel engine during short breaks in operation by powering auxiliary systems from the battery. Energy recuperation during train braking allows charging the battery, reducing the load on the diesel generator unit.

The economic efficiency of using hybrid locomotives depends on the intensity of their use and the cost of electricity for charging the batteries. When operating 20 hours a day, the payback period for the additional capital costs of the battery system is 4.5-6 years. For locomotives with lower usage intensity, the economic feasibility of hybridization is less obvious.

#### 4.6. Environmental Assessment of Greenhouse Gas Emissions

The environmental assessment of different types of traction was carried out by calculating greenhouse gas emissions converted to CO<sub>2</sub>-equivalent. For electric traction, emissions are determined by the structure of electricity generation in Ukraine. With an average carbon footprint of electricity at 0.38 kg CO<sub>2</sub>/kWh, DE1 electric locomotives generate 9.4 g CO<sub>2</sub>/(t·km) of transport work. The 2TE116 diesel locomotives, when burning diesel fuel with an emission factor of 2.68 kg CO<sub>2</sub>/kg of fuel, generate 12.6 g CO<sub>2</sub>/(t·km). The hybrid locomotive, due to reduced fuel consumption, generates 8.1 g CO<sub>2</sub>/(t·km) when charging batteries from the grid or 7.9 g when charging from its own diesel generator unit operating in optimal mode.

#### 4.7. Experimental Verification of the Recommendation System

The results of the experimental verification of the recommendation system for train drivers demonstrated its practical effectiveness. Over four months of pilot operation from November 2024 to February 2025, 47 drivers from the Kovel depot made 683 trips using the

system's prompts for optimal driving modes. For comparison, data from 671 trips by the same drivers during the previous period without the support system were used.

The average electricity consumption of DE1 electric locomotives decreased from 24.8 to 21.9 Wh/(t·km), representing a saving of 11.7%. For 2TE116 diesel locomotives, diesel fuel consumption decreased from 4.7 to 4.3 kg/(thousand t·km gross), resulting in an 8.5% saving. Statistical analysis using the Student's t-test confirmed the significance of the observed differences at  $p < 0.001$ . Energy savings were achieved without compromising adherence to the schedule. The average deviation from the schedule remained at 2.3 minutes, compared to 2.5 minutes before the system was implemented.

Analysis of drivers' acceptance of the recommendations showed a heterogeneous picture. Some drivers, mainly younger ones with up to 5 years of experience, actively used the system's prompts and followed 85-90% of the recommendations. Experienced drivers with over 20 years of service showed greater skepticism toward automated recommendations and followed them in only 45-60% of cases. At the same time, this group of drivers demonstrated relatively low energy consumption even without the system, thanks to their accumulated experience.

The greatest energy savings were observed among medium-skilled drivers with 5-15 years of experience. For this group, the reduction in energy consumption reached 14-18%, as they already possess basic skills for efficient train operation but do not yet have an intuitive understanding of the optimal modes for each profile element, which comes only after many years of working on the same section.

A survey of drivers after the experiment revealed a high overall evaluation of the system. 78% of respondents noted that the recommendations help reduce fatigue during work, as they lessen the need to constantly analyze the track profile ahead and make decisions about switching modes. 65% stated that they learned new energy-efficient train operation techniques, which they continue to apply even without system prompts. The main comments concerned the excessive frequency of recommendations on certain sections and the need for more flexible consideration of individual driving styles.

#### 4.8. Extrapolation to the Network Scale

Extrapolating the obtained results to the scale of the entire Ukrzaliznytsia network allows for estimating the potential effect of implementing energy consumption optimization systems. With an average reduction in electricity consumption of 11% for electric traction and diesel fuel by 8% for diesel traction, the annual savings will amount to about 460 million kWh of electricity and 48 thousand tons of diesel fuel. In monetary terms, at current rates, this amounts to approximately 2.8 billion hryvnias saved annually.

The environmental effect is expressed in the reduction of CO<sub>2</sub> emissions by 340-420 thousand tons annually, depending on the structure of the traction fleet and the intensity of traffic on different routes. Additionally, emissions of nitrogen oxides and particulate matter from diesel locomotives are reduced by 8-10% due to engines operating in more stable modes. The reduction in energy consumption also indirectly reduces the load on the traction power supply system, which may postpone the need for substation upgrades on certain sections.

### Conclusions

The study showed the possibility of significantly increasing the energy efficiency of freight rail transportation in Ukraine through the optimization of locomotive control modes based on the analysis of real telemetric data and mathematical modeling of traction and energy processes. The developed predictive models of energy consumption provide forecasting accuracy at the level of 7-8% of the average absolute error, which is sufficient for practical application in decision support systems.

The implementation of a recommendation system for train drivers on the experimental section Kovel - Sarny, 142 km long, showed an average reduction in electricity consumption by 11.8% for DE1 electric locomotives and a reduction in diesel fuel consumption by 8.5% for 2TE116 diesel locomotives compared to traditional train operation. The energy savings were achieved without compromising adherence to the schedule, confirming the practical applicability of the proposed approach.

A comparative analysis of the efficiency of different types of traction revealed that electric locomotives with regenerative braking return 18-24% of the consumed energy back to the network on sections with a complex profile, reducing primary energy consumption by 35-42% compared to diesel traction. Hybrid locomotives demonstrate fuel savings of up to 32-38% compared to traditional diesel locomotives in shunting operations, making them a promising solution for non-electrified access tracks and stations.

Extrapolation of the results to the scale of the Ukrzaliznytsia network allows estimating a potential annual saving of 460 million kWh of electricity and 48 thousand tons of diesel fuel, equivalent to 2.8 billion hryvnias in annual savings. The environmental effect is expressed in a reduction of CO<sub>2</sub> emissions by 340-420 thousand tons annually, corresponding to Ukraine's commitments to decarbonize the transport sector.

A key factor in the successful implementation of energy-efficient methods is changing the approaches to training and motivating personnel. Locomotive drivers must not only possess technical skills in operating the locomotive but also understand the importance of energy conservation for the enterprise's economy and the environment. Including topics on rational energy consumption in training programs and creating a system of material incentives for saving energy resources can significantly enhance the effect of implementing technical solutions.

Prospects for further research are related to expanding the range of controlled parameters, adapting models to other types of traction rolling stock, accumulating a larger volume of data for applying more complex deep learning algorithms, and integrating driver support systems with centralized traffic management systems to optimize energy consumption at the entire network level. Of particular interest is the study of the possibilities for coordinating train operation modes to maximize the use of regenerated energy by one train by other trains on the same feeder of the traction substation.

### References

1. Albrecht T., Goverde R., Weeda V., et al. (2016). Principles of train control systems. In: Hansen I., Pachl J. (eds) Railway Timetabling & Operations. Eurailpress, Hamburg, pp. 95-120.
2. Aroso M., De Santos S., Araújo A. (2024). Energy Efficiency Improvement on Railway Lines: An Overview. *Energy Science & Engineering*, 12(11), 4823-4859. DOI: 10.1002/ese3.1971
3. Benga A., Delgado-Rodríguez M.J., De Lucas-Santos S. (2023). Energy-environmental efficiency analysis of railway transport: is Europe moving towards sustainable mobility? *Clean Technologies and Environmental Policy*, 25, 105-124. DOI: 10.1007/s10098-022-02390-2
4. Bondar O. (2019). Research on the efficiency of DC electric locomotives in regenerative braking mode on the Pridneprovskaya Railway. *MATEC Web of Conferences*, 294, 01005. DOI: 10.1051/mateconf/201929401005
5. Goolak S., Riabov I., Gorobchenko O., Yermolenko E. (2024). An Estimation of the Energy Savings of a Mainline Diesel Locomotive Equipped with an Energy Storage Device. *Vehicles*, 6(2), 611-631. DOI: 10.3390/vehicles6020028
6. Goolak S., Sapronova S., Tkachenko V., et al. (2023). Determination of the working energy capacity of the on-board energy storage system of an electric locomotive for quarry

railway transport during working with a limitation of consumed power. *Archives of Transport*, 65(1), 119-135. DOI: 10.5604/01.3001.0053.4067

7. Goolak S., Gubarevych O., Yermolenko E., et al. (2022). Justification of the Structure of the Electric Traction Drive of the Electric Locomotive for Railway Quarry Transport. *Science and Transport Progress*, 3(99), 57-70. DOI: 10.15802/stp2022/267984

8. Goverde R., Scheepmaker G., Wang P. (2016). Pseudospectral optimal train control. *European Journal of Operational Research*, 254(2), 619-631.

9. Hadj-Mabrouk H. (2024). A literature review on the applications of artificial intelligence to European rail transport safety. *IET Intelligent Transport Systems*, 18(11), 2088-2112. DOI: 10.1049/itr2.12587

10. Panou K., Tzieropoulos P., Emery D. (2013). Railway driver advice systems: evaluation of methods, tools and systems. *Journal of Rail Transport Planning & Management*, 3(4), 150-162. DOI: 10.1016/j.jrtpm.2013.11.001

11. Riabov I., Mosin S., Overianova L., et al. (2022). Evaluation of technical parameters locomotive for railway career transport. *Transport Systems and Technologies*, 40, 151-169. DOI: 10.32703/2617-9059-2022-40-14

12. Scheepmaker G.M., Goverde R.M.P. (2015). The interplay between energy-efficient train control and scheduled running time supplements. *Journal of Rail Transport Planning & Management*, 5(4), 225-239.

13. Scheepmaker G.M., Goverde R.M.P., Kroon L.G. (2017). Review of energy-efficient train control and timetabling. *European Journal of Operational Research*, 257(2), 355-376. DOI: 10.1016/j.ejor.2016.09.044

14. Scheepmaker G.M., Willeboordse H.Y., Hoogenraad J.H., Luipen J., Goverde R.M.P. (2024). Increasing realism in modeling energy losses in railway vehicles and their impact on energy-efficient train control. *Railway Engineering Science*, 32, 59-79. DOI: 10.1007/s40534-023-00322-4

15. Tian Z., Weston P., Zhao N., et al. (2023). Multi-train trajectory optimization for energy-efficient timetabling. *European Journal of Operational Research*, 272(2), 621-635.

16. Verstappen M., Theunissen E., Stroeve S. (2022). Assessing the impact of driver advisory systems on train driver workload, attention allocation and safety performance. *Applied Ergonomics*, 98, 103598. DOI: 10.1016/j.apergo.2021.103598

17. Yang L., Li K., Gao Z., Li X. (2012). Optimizing train movement on a railway network. *Omega*, 40(5), 619-633.

18. Zhao N., Roberts C., Hillmansen S., Nicholson G. (2015). A multiple train trajectory optimization to minimize energy consumption and delay. *IEEE Transactions on Intelligent Transportation Systems*, 16(5), 2363-2372.