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# Operational efficiency of cargo vehicles in terms of energy and environmental criteria

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**Abstract.** Rising fuel costs, stricter decarbonisation requirements for freight transport, and the increasing use of telematics monitoring call for a shift from assessing freight vehicles solely based on average fuel consumption to a mode-specific assessment of their performance on specific routes. The purpose of the study was to substantiate and formalise the model of operational efficiency of vehicles of category N3, which combines fuel, environmental, route, regime, and information indicators. The source base was formed from peer-reviewed publications from 2020-2025, selected based on direct relevance to heavy trucks, real route conditions, telematics or on-board data, eco-management, and emissions. System, comparative, and structural and functional analysis, formalisation of indicators, and scenario modelling were applied. The information of the smart tachograph, Global Positioning System-telematics, Controller Area Network/Fleet Management System/On-Board Diagnostics and fuel sensors was differentiated; equations for fuel consumption per 100 km and tonne-kilometre, weight $CO_2$, idle and Eco-Roll fractions, average acceleration, speed stability, and integral index were proposed. An analysis of the factors showed that the route and the weight of the road train determine the base load, whilst the most readily controllable factors are the duration of idling, the frequency of acceleration, speed stability, the use of coasting, and the carrier's organisational decisions. Practical operation of the model was demonstrated on a conditional 100-kilometre route of a road train with a gross weight of 36 tonnes with a load of 20 tonnes. Reducing idle speed from 24 to 12 minutes, forming an Eco-Roll share of 6.9% of driving time, and speed stabilisation reduced estimated fuel consumption from 32.4 to 31.1 litres, and direct $CO_2$ emissions from 85.54 to 82.10 kg; the integral index increased from 0.804 to 0.933. The above scenario is a demonstration scenario and requires further verification based on actual route data. The practical value lies in the ability to use the model to compare trips, identify the causes of cost overruns, and provide recommendations to the driver and dispatcher under specific route and operational conditions

**Keywords:** fuel efficiency; route profile; Eco-Roll; smart tachograph; telematics; Controller Area Network; Fleet Management System

## Introduction

Freight road transport provides a significant part of domestic and international commodity flows, but its operational effectiveness is increasingly linked to energy consumption and environmental impact. For vehicles of category N3, this issue is aggravated due to the large gross weight of the road train, long routes, variable longitudinal road profile, and a high share of engine performance under load. The average fuel consumption per route characterises the final result, but does not explain how much of the overspending occurred as a result of idling, heavy acceleration, unstable speed, unfavourable slope, underloading, or technical deviations. Therefore, it is advisable to interpret operational efficiency as the result of interaction between the vehicle, route, cargo, driver, and

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information control system. The transition to real-world evaluation requires reliable measurements. J. Pavlovic *et al.* (2021) showed that the accuracy of determining actual fuel consumption depends not only on on-board fuel metering, but also on the correctness of measuring the distance travelled and matching On-Board Diagnostics (OBD) and Global Positioning System (GPS) data. J.I. Huertas *et al.* (2022) and F. Jelti & R. Saadani (2024) confirmed on the material of the logistics corridor with variable topography that the route profile significantly changes the actual fuel consumption compared to standard estimates. These results suggest that the energy indicator should be formed after synchronisation of spatial, temporal, and fuel data, and not by a single final value.

A separate area is related to the use of on-board and telematics parameters. H. Abediasl *et al.* (2024) proved the possibility of estimating instantaneous flow from OBD parameters coming from an electronic control unit. J.J. Posada-Henao *et al.* (2023) found a statistically significant effect of total weight and road slope on truck fuel consumption. L. Fang *et al.* (2025) proposed segmentation of time series of speed, acceleration, and other sensory parameters to recognise driver behaviour and generate targeted recommendations for eco-driving. The combination of these approaches creates grounds to consider individual driving modes as independent objects of assessment. The environmental result of exploitation should be considered together with the energy result, but not reduced to it. A. Magnino *et al.* (2024) showed that the choice of a power unit for heavy fleets should consider both efficiency and sustainability of operation. Systematic review by G. Gentilucci *et al.* (2025) showed significant variability in the life cycle estimates of diesel and non-emission trucks depending on the boundaries of the system and energy source. P.D. Larson *et al.* (2024) identified the infrastructure and logistics barriers of emission-free mainline transport, whereas M. Penchev *et al.* (2025) emphasised the need to use real-world data in a full life assessment. Therefore, for the existing diesel fleet, reducing unproductive fuel consumption remains a practically significant means of reducing direct $CO_2$ emissions.

Available studies reveal individual elements of the problem in detail, but less often combine the origin of operational data, mode segmentation, energy formulas, environmental indicators, and control output in one transparent procedure. For Ukrainian carriers, this is of additional importance due to the heterogeneity of the fleet: vehicles of different brands and generations may have a smart tachograph, GPS terminal, access to the Controller Area Network (CAN)/Fleet Management System (FMS) or only a limited set of parameters. Uncertainty of the indicator source creates a risk of misinterpretation: the tachographic speed does not characterise the engine load, the GPS coordinate does not determine fuel consumption, and the value with CAN/FMS needs to be checked by an independent measuring channel. The purpose of the study was to develop a formalised structure for evaluating the operational efficiency of cargo vehicles based on energy and environmental criteria, considering driving modes, route conditions, Eco-Roll, and digital monitoring. To achieve this objective, the following measures were established:

1. To differentiate the information capabilities of the smart tachograph, telematics platforms and on-board vehicle systems and formalise key indicators necessary for assessing traffic, load, fuel consumption, and operational efficiency;
2. To identify and rank the main factors affecting the fuel efficiency of heavy cargo transport, considering their influence, handling, and connection with the Eco-Roll mode and the logic of the structural model;
3. To demonstrate the practical application of the proposed approach to the calculated route scenario and compare the results obtained with the provisions of contemporary research on modelling the fuel efficiency of cargo vehicles.

## Materials and Methods

The object of the study was the operational efficiency of cargo vehicles of category N3 in domestic and international transportation, and the subject was the relationship between driving modes, fuel efficiency, direct $CO_2$ emissions, and information completeness of monitoring. The source database was formed in May-June 2025 among peer-reviewed publications of 2020-2025. The final sample included papers that simultaneously met at least two criteria: examined heavy cargo vehicles or road trains; used real route, telematics, OBD/CAN/FMS, or fuel data; analysed idle speed, acceleration, steady motion, coasting, or predictive control; contained energy or environmental indicators and DOI. Duplicates, materials without a description of the methodology, studies only of passenger cars, and papers in which the route context was not separated from the design characteristics were excluded. As a result, 22 sources were selected. The theoretical basis for formalisation consisted of studies by A. Hamednia *et al.* (2022) and G.R. Gonçalves Da Silva & M. Lazar (2022) on eco-management, H.I. Ashqar *et al.* (2024) on behavioural parameters. The study had a theoretically-analytical and computationally applied design. System analysis was used to build the "vehicle – route – driver – data – energy result – environmental result" contour. Comparative analysis was used to establish common and distinctive positions in models of real fuel consumption, telematics control, and eco-control. Structural and functional analysis provided a distribution of factors by origin, influence, manageability, and information needs. Scenario modelling was used to demonstrate a practical sequence of calculations without presenting a conditional example as a field experiment.

The operational profile of the route was divided into idle, acceleration, steady motion, inertia/Eco-Roll, and braking. Idling was identified by zero speed and engine running; acceleration – by positive acceleration; steady motion – by deviation of speed and acceleration within the specified limits; Eco-Roll – by movement of a vehicle without traction load with a confirmed transmission condition or the corresponding on-board flag; braking – by negative acceleration in combination with the state of the service braking system, retarder, or engine braking. This segmentation provided a separate calculation of duration, distance, and fuel consumption for each mode.

Operational data sources were differentiated by their actual function. The smart tachograph provided timestamps, speed and distance travelled, driver identification, work and rest modes, events, malfunctions, and GNSS positions; it did not measure engine load or actual fuel consumption. GPS telematics provided continuous data on coordinates, route, speed, stops, geofences, and estimated acceleration. CAN/FMS/OBD was the source of engine speed and load, accelerator pedal position, selected gear, cruise control status, retarder, operating hours, and available fuel consumption values. Independent fuel probes or flow meters were used to detect changes in fuel reserve, refueling/draining events, and cross-check on-board accounting. The choice of approach was based on synchronising these channels on a single timeline, rather than attributing all metrics to a single device. The evaluation criteria were grouped into energy, environmental, regime, and information blocks. The energy block contained route and specific fuel consumption; environmental – direct $CO_2$ emissions and the context of NOx and PM generation; mode – idle and Eco-Roll fractions, average acceleration and speed stability; information – the presence and consistency of tachographic, GPS, and on-board parameters. To compare routes, the indicators were normalised to the interval 0-1 and combined into a weighted integral index:

$$q_{100} = 100 \cdot Q^f / L, \quad (1)$$

where $q_{100}$ – fuel consumption per 100 km, L/100 km; $Q^f$ – fuel volume per route, l; $L$ – route length, km.

$$q_{tkm} = Q^f / (m^c \cdot L), \quad (2)$$

where $q_{tkm}$ – specific fuel consumption, L/(t·km); mc – cargo weight, t.

$$MCO_2 = k_{CO_2} \cdot Q^f, \quad (3)$$

where $MCO_2$ – direct $CO_2$ emissions, kg; $k_{CO_2}$ – accepted conversion factor for a specific type of fuel, kg/L.

$$k_{id} = t_{id} / _{teng} \cdot 100\%, \quad (4)$$

where $k_{id}$ – idle speed share; $t_{id}$ – its duration; $t_{eng}$ – total engine operating time.

$$k_{ER} = t_{ER} / t_{mov} \cdot 100\%, \quad (5)$$

where $k_{ER}$ – share of Eco-Roll; $t_{ER}$ – duration of the mode; $t_{mov}$ – vehicle travel time.

$$\bar{a} = (1/n) \cdot \Sigma[(v_{2,i} - v_{1,i}) / \Delta t_i], \quad (6)$$

where $\bar{a}$ – average acceleration in the selected overclocking events; n – number of events.

$$I_v = \max[0; 1 - \sigma_v / \bar{v}], \quad (7)$$

where $I_v$ – speed stability index; $\sigma_v$ – standard deviation; $v$ – average speed on a homogeneous area.

$$I_{eff} = w_Q \cdot I_Q + w_{CO_2} \cdot I_{CO_2} + w_{id} \cdot I_{id} + w_{ER} \cdot I_{ER} + w_v \cdot I_v; \ \Sigma w_j = 1, \quad (8)$$

where $I_{eff}$ – integral index; $I_j$ – normalised partial indicators; $w_j$ – weighting coefficients set in accordance with the evaluation purpose.

## Results and Discussion

The formalisation results showed that the operational efficiency of the vehicle has a hierarchical structure. The first level consists of parameters that are only loosely controlled within the context of a single route – the vehicle's design, gross vehicle weight, body type, and road profile. The second level comprises the driving modes that can be controlled in real time – idle, acceleration intensity, speed stability, coasting, and the use of braking systems. The third level covers the carrier's organisational decisions: loading, route planning, maintenance, and driver control. Digital monitoring performs an end-to-end function, as it converts the listed factors into measurable parameters and provides their comparison between routes.

**Table 1.** Factors of operational efficiency of cargo vehicles by energy and environmental criteria

| Group of factors | Content | Impact on energy efficiency | Impact on environmental efficiency |
|---|---|---|---|
| Vehicle-related factors | Engine type, transmission, environmental standard, vehicle weight, technical condition | Determine the basic fuel requirement and power loss | Affect the level of emissions under real operating conditions |
| Route factors | Road profile, slope, traffic density, speed limit, route length | Change the proportion of acceleration, steady-state movement, and inertia movement | Affect $CO_2$ emissions and pollutant generation |
| Operating modes | Idling, acceleration, steady motion, inertia motion, engine braking | Determine instantaneous and average fuel consumption | Form the intensity of emissions under different engine loads |
| Driver behaviour | Choice of speed, acceleration intensity, braking style, use of cruise control | Can increase or decrease fuel consumption under comparable route conditions | Affects excessive fuel combustion and associated emissions |
| Digital monitoring | Smart tachograph, telematics, event recording, mileage and speed data | Provides data for detecting inefficient use | Supports monitoring of violations and deviations in environmental indicators |
| Organisational factors | Maintenance, route planning, loading planning, compliance monitoring | Reduce avoided fuel losses and unproductive mileage | Provide a systematic reduction of harmful effects on the environment |

**Source:** developed by the author

The data in Table 1 allowed ranking factors based on two characteristics – the strength of impact and the possibility of operational adjustment. The gross weight, slope, and speed of the road train have the greatest basic impact, as they determine the need for traction. J.J. Posada-Henao *et al.* (2023) attributed weight and slope to factors whose influence exceeded that of velocity under the studied conditions. However, these parameters may not always be changed by the driver during the route. Idle time, acceleration amplitude, speed selection, and the moment of transition to coasting have the highest operational handling. Their adjustment does not require vehicle replacement but does require reliable time series of speed, acceleration, and powertrain operating status. Technical factors are divided into constructive and state-dependent ones. The type of engine and transmission determines potential efficiency, while tyre pressure, condition of injectors, transmission supports, and operation of neutralisation systems can be improved by maintenance. Monitoring study by M.A. Costagliola *et al.* (2025) showed that the effect of technical measures depends on the initial condition of the vehicle: older or polluted power systems have the greatest reserve. Thus, technical modernisation is a capital-intensive area, and maintenance is a managed medium-term factor. Route and organisational factors require different data. Slope, curvature, speed limit, and traffic density are determined by GPS tracking and a digital map; loading is determined by documents or weight estimation; idling and acceleration are determined by telematics; speed, transmission, cruise control, and braking modes are determined by CAN/FMS. Backload planning, reducing empty mileage, and agreeing on arrival times mostly depend on dispatching decisions. Therefore, digital monitoring itself does not reduce fuel consumption, but provides an evidence-based basis for choosing technical, security or organisational intervention. Figure 1 shows a generalised logic of the relationship between route conditions, operating modes, energy and environmental indicators of a cargo vehicle of N3 category.

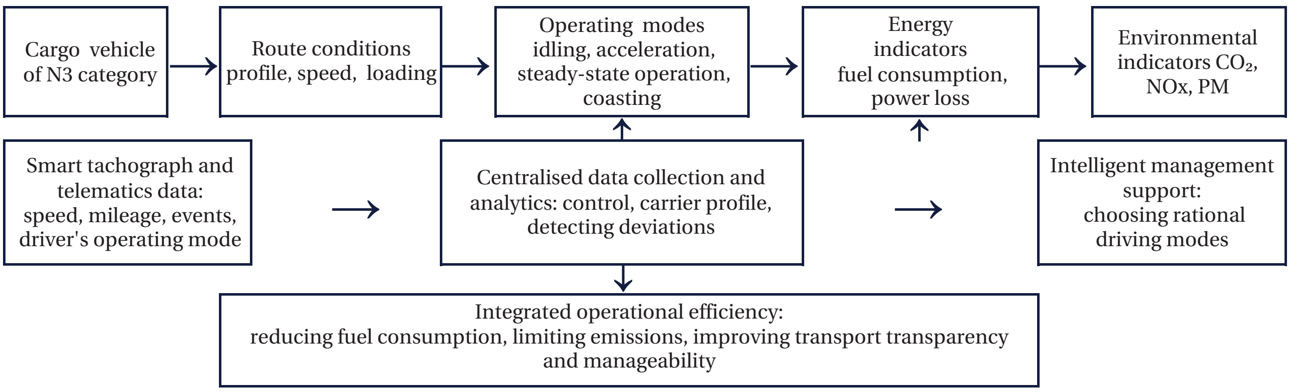


**Figure 1.** Structural model for evaluating the operational efficiency of cargo vehicles

**Source:** compiled by the author

The logic of Figure 1 starts with four groups of input data. Static parameters include category, mass, engine type, transmission and emissions standard; route-related parameters include coordinates, gradient, length, speed limits and load; dynamic parameters include speed, acceleration, revs, engine load, gear selection and the condition of the braking systems; organisational parameters include driver identification, working hours, stops and deviations from the schedule. The smart tachograph provides normatively significant time and mode recordings, telematics provides a detailed route profile, and CAN/FMS/OBD provides the state of the power unit. After synchronisation, the data is segmented into driving modes. The energy block of the model calculates $q_{100}$, $q_{tkm}$, the proportion of unproductive idle speed, mode flow rate, and speed stability. The environmental unit determines direct $CO_2$ emissions by the amount of fuel burned, and interprets NOx and PM only if appropriate on-board or measurement data is available, as they depend on the temperature, load, and operation of neutralisation systems. This separation prevents methodological errors when tachographic or GPS data is attributed to indicators that are actually generated by an electronic control unit or an external meter. At the output, partial indexes are normalised and combined into $I_{eff}$. The integral value does not replace individual indicators, but is used to rank comparable trips under the same cargo and route conditions. Low $I_{eff}$ must be decomposed into the following components: excess $k_{id}$ indicates an organisational or behavioural problem; low $I_v$ – on unstable management; and insufficient $k_{ER}$ with a favourable profile – on the unused reserve of kinetic energy. It is this schedule that forms the management recommendation, and not just states the final fuel consumption. The sequence of making control decisions on the choice of rational driving modes on a section of a route with a complex profile, in particular using Eco-Roll, is summarised in Figure 2.

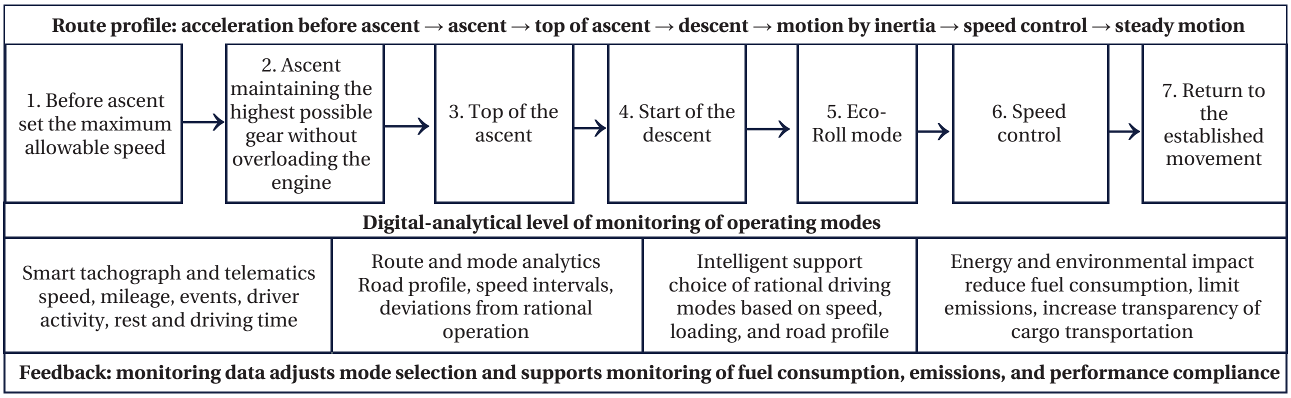


**Figure 2.** Road train driving modes on a route section with a complex profile
**Source:** compiled by the author

Figure 2 shows a sequence in which the decision on Eco-Roll is made not after the appearance of a descent, but after predicting the speed at its end. The mode is suitable when the longitudinal slope and accumulated kinetic energy allow maintaining traction without traction, the predicted speed remains below the limit with a safe reserve, and the transmission structurally supports automatic disconnection. For the conditional scenario, descents of 2-4% are accepted, the initial speed is 5-10 km/h lower than the permissible and the total weight of 36 tonnes; these limits are the parameters of the example, and in the real system should be calculated by drag forces, weight, curvature, pavement, and road situation. The effect of driving by inertia is reduced if the driver accumulates excessive speed in advance and is forced to actively apply a retarder, engine braking, or service brakes. In this case, some of the kinetic energy that was supposed to be used to overcome the next section is converted into heat in the braking mechanisms. The transition to braking should occur after reaching the calculated speed threshold, and not immediately after the start of descent. The proposed logic is consistent with approach of G.R. Gonçalves Da Silva & M. Lazar (2022), where mode control is related to previous slope information and the result by J. Hong *et al.* (2025), which received savings of 5.73% for their coordinated predictive cruise control and coasting strategy. This value characterises specific research conditions and is not automatically transferred to other routes. At least the GPS/tachograph speed and time, longitudinal profile, transmission status or on-board designation, engine speed, instantaneous/accumulated fuel consumption, and retarder and brake signals are required to record the Eco-Roll duration and performance. Temperature, wind, tyre pressure, and traffic density are auxiliary factors. Without confirming the condition of the transmission, normal downhill driving should not be automatically classified as Eco-Roll. The regime structure determines not only the average consumption, but also the reason for it. Idling has the worst fuel-transport ratio, since the denominator of useful work is zero. Acceleration generates the highest short-term costs due to the need for inertial force, especially with a large weight. Steady-state driving is the basic economy mode when the engine is running in an efficient zone, and Eco-Roll has the greatest conditional savings potential on suitable descents. Braking provides safety, but its excessive frequency indicates a loss of previously stored energy. Table 2 shows the dependence of energy and environmental indicators of cargo vehicles on operating modes.

**Table 2.** Impact of operating regimes on the energy and environmental performance of cargo vehicles

| Operating mode | Technical characteristics | Energy effect | Environmental impact | Monitoring parameter |
|---|---|---|---|---|
| Idle speed | Engine runs without performing useful transport work | Unproductive fuel consumption | Emissions without moving cargo | Idle time, engine operating time |
| Overclocking | Increased speed with a high tractive effort requirement | Increased instantaneous fuel consumption | Increased intensity of emissions under load | Speed gradient, acceleration, engine load |
| Steady motion | Driving at a relatively stable speed and gear ratio | Potentially efficient mode at rational speed | Stable emissions when the engine is running in the efficient zone | Speed stability, route section, fuel consumption |
| Motion by inertia/ Eco-Roll | Vehicle is moved by kinetic energy; the power unit can be disconnected from the transmission | Reduction of engine load and fuel requirements | Reduction of $CO_2$ in proportion to fuel economy | Duration of movement by inertia, road slope, speed limit |
| Engine/retarder braking | Controlled speed reduction on descents | Prevents speeding, but reduces the effect of driving by inertia | Supports traffic safety; has an indirect impact on emissions | Braking events, descent sections, speed limit compliance |

**Source:** compiled by the author

According to Table 2, the most problematic in the specific dimension is idling, and in the instantaneous – intensive acceleration. Cuts have the greatest potential without constructive modernisation of $k_{id}$, decrease in average acceleration, speed stabilisation, and increase of $k_{ER}$ in safe areas. Mandatory analysis parameters are time, speed, distance travelled, engine condition, fuel volume, and identified mode. Acceleration requires additional acceleration and load, while Eco-Roll requires slope, transmission/transmission condition, and brake signals. Temperature, wind, and coating conditions increase accuracy, but are auxiliary in the absence of appropriate sensors. Quantitative interpretation involves calculating the idle speed fraction as a percentage of engine running time, Eco-Roll duration and distance, the average and 95th acceleration percentile, the number of decelerations per 100 km, the speed range and fuel consumption for each mode. Approach of A. Liu *et al.* (2025) confirmed the significance of engine parameters, driver behaviour, and weight, and A. Schoen *et al.* (2019) showed the suitability of telematics data for modelling the flow rate of heavy trucks. The proposed model differs in that it preserves the transparent origin of each indicator and allows it to be used even for a fleet with different digital equipment. The resulting system of priorities showed that the average route consumption should be analysed after rationing for cargo and separating the regime components. For two routes with the same $q_{100}$ the reasons can be different: in one case – prolonged idling, in the second – high weight and lifting. Therefore, the comparison was performed first in homogeneous groups by vehicle, weight, route, and weather conditions, and then by $k_{id}$, $k_{ER}$, $\bar{a}$ and $I_v$.

The results also confirmed the need for cross-testing of fuel. The CAN/FMS value is suitable for high-frequency mode analysis, but it is advisable to compare the trip result with a calibrated fuel probe, flow meter, or refuelling documents. Channel divergence should be considered as an indicator of data quality, and not hidden by averaging. In the absence of a reliable fuel channel, the model can evaluate the operating profile, but should not claim accurate savings. The smart tachograph in the proposed structure performs a regulatory and temporal function. It confirms the driver's identity, speed, mileage, activity, and events, but does not replace CAN/FMS for RPM, load, gear, accelerator pedal, or fuel consumption. The telematics platform combines these channels, performs time synchronisation, and binds them to coordinates. This distribution ensures reproducibility of the calculation and allows specifying which indicator is measured and which is derived. Energy and environmental criteria remain interrelated, but functionally different. Reducing Qf directly reduces $MCO_2$, while NOx and PM can change non-linearly due to temperature, transient loads, and the operation of cleaning systems. Therefore, in the absence of PEMS or validated on-board data, the environmental section of the paper is limited to direct $CO_2$ measurements and a qualitative analysis of the conditions under which other components are formed. The practical application of the structure involves the sequence "conditions – segmentation – calculation – diagnosis – recommendation". First, the route profile is generated, then the synchronised data is distributed by mode, after which partial and integral indicators are calculated. The deviation is decomposed into factors, and only then the action is selected: reducing downtime, changing the acceleration profile, adjusting the speed, using Eco-Roll, technical verification, or changing the route organisation. The sequence of practical use of the model is presented in Table 3.

**Table 3.** Stages of evaluating the operational efficiency of cargo vehicles

| Stage | Analytical content | Expected result |
|---|---|---|
| Route characteristics | determining route length, slope, speed limits, traffic conditions, and stops | description of external operating conditions |
| Characteristics of the vehicle and cargo | identification of category, weight, engine, transmission, and environmental standard | technical basis for evaluation |
| Segmentation of driving modes | selection of idle, acceleration, steady state, inertia, and braking modes | operational profile of the route |
| Assessment of energy indicators | analysis of fuel consumption, idle speed, driving duration by inertia, and speed stability | energy efficiency profile |
| Assessment of environmental indicators | interpretation of $CO_2$ emissions and harmful substances according to fuel consumption and engine operating modes | environmental efficiency profile |
| Digital feedback | use of tachograph and telematics data to detect deviations and select rational modes | basis for intelligent control algorithms |

**Source:** compiled by the author

A fundamental feature of Table 3 is the prohibition of switching to integral evaluation until quality control and data segmentation are completed: an error in time binding or incorrect classification of the descent as Eco-Roll directly distorts the result. At the first stage, the dispatcher or researcher sets a homogeneous comparison group for the car, cargo, and route. On the second stage, passes, refuelling events, GPS, and on-board time consistency are checked. On the third stage, the route is segmented by mode, and then calculated $q_{100}$, $q_{tkm}$, $MCO_2$, $k_{id}$, $k_{ER}$, $\bar{a}$, and $I_v$. The fifth stage is compared to the reference trip or target limits. The final step turns the detected deviation into a specific recommendation and involves repeated measurement after its implementation. For the demonstration, a conditional route with a length of 100 km with 6 km of ascents with a slope of 3-5%, 8 km of descents with a slope of 2-4%, and 86 km of flat and mixed sections was used. The gross weight of the road train was 36 tonnes, the cargo weight was 20 tonnes, and the driving time was 105 minutes. The baseline scenario provided for 24 minutes of idle time, no confirmed Eco-Roll, a standard speed deviation of 9.0 km/h and a flow rate of 32.4 litres. The rational scenario provided for 12 minutes of idle time, 7.2 minutes of Eco-Roll, a standard deviation of 6.2 km/h and a flow rate of 31.1 litres. For the demonstration recalculation of $CO_2$, it is accepted that $k_{CO_2} = 2.64$ kg/L.

**Table 4.** Calculated example of estimating a 100-kilometre trip

| Indicator | Basic scenario | Rational scenario | Change / interpretation |
|---|---|---|---|
| Route length; cargo; gross weight | 100 km; 20 t; 36 t | 100 km; 20 t; 36 t | Comparison conditions are the same |
| Idle speed | 24 min; $k_{id} = 18.60\%$ | 12 min; $k_{id} = 10.26\%$ | -8.34 pp |
| Eco-Roll | 0 min; $k_{ER} = 0\%$ | 7.2 min; $k_{ER} = 6.86\%$ | 8 km of suitable descents were used |
| Fuel consumption Qf | 32.4 L | 31.1 L | -1.3 l; -4.01% |
| $q_{100}$ | 32.4 L/100 km | 31.1 L/100 km | –4.01% |
| $q_{tkm}$ | 0.01620 L/(t·km) | 0.01555 L/(t·km) | -0.00065 L/(t·km) |
| Direct $CO_2$ emissions | 85.54 kg | 82.10 kg | -3.44 kg; -4.01% |
| Speed stability $I_v$ | 0.842 | 0.891 | +0.049 |
| Integral index $I_{eff}$ | 0.804 | 0.933 | +0.129; +16.0% |

**Note:** these figures are for illustrative purposes only
**Source:** compiled by the author

The calculation showed that reducing idle speed and rational use of coasting reduced Qf and $MCO_2$ by 4.01%. Since the load and length remained unchanged, the same relative improvement was obtained for $q_{tkm}$. The integral index is calculated with weights wQ = 0.35; $wCO_2 = 0.25$; wid = 0.15; wER = 0.10; wv = 0.15, a reference flow rate of 30 L/100 km and a target share of Eco-Roll of 8%. The 16.0% increase in the $I_{eff}$ exceeds the relative reduction in fuel consumption, as the index considers idling discipline, speed stability, and the use of suitable downhill gradients. The example demonstrates how the model works, but is not proof of universal savings of 4%. Its purpose is to show how scenarios that are identical in route and cargo are compared by regime structure. Field validation requires repeated trips, uncertainty assessment, weather monitoring, traffic, tyres, technical condition, and CAN/FMS verification via an independent fuel channel.

The proposed model is consistent with conclusions of A. Hamednia *et al.* (2022) that the economy mode should be determined not by an isolated driver response, but by a forecast over a longer horizon. Their algorithm optimises the velocity trajectory, while this study focuses on a transparent structure of metrics and data sources suitable for a heterogeneous park. Therefore, the result obtained does not replace the optimisation controller, but forms the measurement and criterion level necessary for its further application. The findings of G.R. Gonçalves Da Silva & M. Lazar (2022) confirmed the key role of preliminary slope information in driving trunk modes. The logic proposed in Figure 2 corresponds to the following approach: Eco-Roll is chosen after predicting the final speed, and not just based on descent. The difference is that data origin, weight control, transmission status, and brake signals have been added to the road profile, without which the actual mode can be classified incorrectly. The conclusion about high manageability of behavioural factors corresponds to H.I. Ashqar *et al.* (2024), who showed the feasibility of including driving style in fuel forecasting. A.S. Mane *et al.* (2021) also used telematics data to identify behavioural parameters associated with overspending. In this paper, the behavioural block was specified through $k_{id}$, $\bar{a}$, $I_v$, and the number of brakes, but its impact is separated from the weight and route. This is important because without rationing, the driver of a heavier road train on a more complex profile may get an unreasonably lower rating. Z. Zhang *et al.* (2023) found a significant association between truck driver behaviour, fuel consumption, and $CO_2$ emissions. The proposed model confirms this relationship for direct $CO_2$ emissions, since they are proportional to the volume of fuel burned. Simultaneously, it restricts the interpretation of NOx and PM in the absence of PEMS or a validated on-board channel. This precaution narrows down the environmental conclusion, but increases its validity and prevents fuel reduction from being identified with the same change in all pollutants. A. Schoen *et al.* (2019) and A. Liu *et al.* (2025) demonstrated the capabilities of telematics and explicable machine models for predicting the flow rate of heavy trucks. The advantage of such methods is their high predictive power, but they require a representative training sample. Proposed index $I_{eff}$ has another function: it provides an interpreted trip comparison to the accumulation of a large data set. In the future, formalised metrics can be used as attributes for machine learning, and model results can be used as controls for logical consistency of the forecast. The estimated cost reduction of 4.01% does not contradict the result of J. Hong *et al.* (2025), who received 5.73% for coordinated predictive cruise control and coasting under their own simulation conditions. The lower value in the above scenario is explained by the fact that Eco-Roll covered only 6.86% of the driving time, and part of the effect was formed by reducing idle speed. Thus, the model demonstrates a valid directional response: an increase in the proportion of rational coasting and a decrease in unproductive modes improve the energy and $CO_2$ result. The limitations of this study include the hypothetical nature of the scenario, the lack of field replicates, and the need to calibrate the $I_{eff}$ weights for a specific carrier. The practical significance of the model lies in the transition from rating cars by one average consumption to diagnosing the causes of the result. For the carrier, the source document can be a route profile with the share of modes, data quality, comparison with the standard, and a list of recommended actions. Recommendations should be checked by a repeat trip, which turns the model into a closed cycle of improvement. For the existing diesel fleet, this cycle complements long-term decarbonisation with short-term measures: reducing idle speed, stabilising speed, monitoring technical condition and rational use of kinetic energy. It does not replace the upgrade of power units, but it allows quantifying reserves until the fleet is updated.

## Conclusions

The study formalised an evaluation model for the operational efficiency of category N3 vehicles, integrating data acquisition, operating mode segmentation, and the calculation of energy and environmental performance indicators. It was established that the smart tachograph provides time, speed, and mode recordings of the driver; GPS-telematics – route and stops; CAN/FMS/OBD – parameters of the engine, transmission, and available fuel consumption; independent fuel channel – control of the actual stock change. This distinction defines the validity limits of each conclusion. The analysis of factors showed that the weight and profile of the road have a high basic impact, but limited operational handling. The most accessible adjustments without replacing the vehicle are the idle speed ratio, acceleration intensity, speed stability, rational coasting, and organisational decisions of the carrier. Eco-Roll is recommended only if the predicted compliance with speed and safety limits, the presence of a suitable slope and a confirmed condition of the transmission; excessive braking reduces its effect due to kinetic energy dissipation. Eight basic dependencies were proposed for $q_{100}$, $q_{tkm}$, $MCO_2$, $k_{id}$, $k_{ER}$, average acceleration, speed stability, and $I_{eff}$. On the conditional route of 100 km, reducing idle speed from 24 to 12 minutes, using Eco-Roll for 6.86% of the driving time and stabilising the speed reduced the estimated flow rate from 32.4 to 31.1 litres and direct $CO_2$ emissions from 85.54 to 82.10 kg; $I_{eff}$ increased from 0.804 to 0.933. The result obtained confirmed the operability of the proposed model, but it cannot be considered a full-fledged field validation. Practical application of the model involves the formation of homogeneous trip groups, data quality control, regime segmentation, calculation of partial indicators, diagnosis of the causes of deviations, and re-verification after the implementation of recommendations. Further research should be aimed at analysing the series of repeated trips, calibrating fuel channels, assessing the uncertainty of results, and adapting the scales of the integral index to the operating conditions of a particular fleet.

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## Conflict of Interest

None.

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# Експлуатаційна ефективність вантажних транспортних засобів за енергетичними та екологічними критеріями

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**Анотація.** Зростання вартості палива, посилення вимог до декарбонізації вантажних перевезень і поширення телематичного контролю потребують переходу від оцінювання вантажного транспортного засобу лише за середньою витратою палива до режимно-орієнтованої оцінки його роботи на маршруті. Метою дослідження було обґрунтувати й формалізувати модель експлуатаційної ефективності транспортних засобів категорії N3, яка поєднує паливні, екологічні, маршрутні, режимні та інформаційні показники. Джерельну базу сформовано з рецензованих публікацій 2020-2025 років, відібраних за безпосередньою релевантністю важким вантажним автомобілям, реальним маршрутним умовам, телематичним або бортовим даним, еко-керуванню та викидам. Застосовано системний, порівняльний і структурно-функціональний аналіз, формалізацію показників та сценарне моделювання. Розмежовано інформацію смарт-тахографа, Global Positioning System-телематики, Controller Area Network/Fleet Management System/On-Board Diagnostics і паливних датчиків; запропоновано формули витрати палива на 100 км і тонно-кілометр, маси $CO_2$, часток холостого ходу та Eco-Roll, середнього прискорення, стабільності швидкості й інтегрального індексу. Аналіз чинників показав, що маршрут і маса автопоїзда визначають базове навантаження, тоді як найбільш оперативно керованими є тривалість холостого ходу, інтенсивність розгонів, стабільність швидкості, використання вибігу та організаційні рішення перевізника. Практичну роботу моделі продемонстровано на умовному 100-кілометровому маршруті автопоїзда повною масою 36 т із вантажем 20 т. Скорочення холостого ходу з 24 до 12 хв, формування частки Eco-Roll 6,9 % часу руху та стабілізація швидкості зменшили розрахункову витрату палива з 32,4 до 31,1 л, а прямі викиди $CO_2$ – з 85,54 до 82,10 кг; інтегральний індекс зріс з 0,804 до 0,933. Наведений сценарій є демонстраційним і потребує подальшої перевірки за фактичними маршрутними даними. Практична цінність полягає у можливості використовувати модель для порівняння рейсів, виявлення причин перевитрати та формування рекомендацій водієві й диспетчеру за конкретних маршрутних та експлуатаційних умов

**Ключові слова:** паливна економічність; маршрутний профіль; Eco-Roll; смарт-тахограф; телематика; Controller Area Network; Fleet Management System