

MULTIMODAL METHODOLOGY FOR INTEGRATED DRIVING STYLE ASSESSMENT OF CONSTRUCTION MACHINERY OPERATORS BASED ON COORDINATED USE OF CAN DATA AND TELEMATICS

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The operation of construction machinery is associated with high fuel costs and intensive wear of components, which are largely determined by the operator's driving style. This paper proposes a multimodal methodology for integrated driving style assessment based on the coordinated use of low level CAN data (signal plane) and aggregated fuel consumption indicators (user plane) using an end to end trip identifier. Unlike existing approaches focused on classifying driving style by individual parameters, the proposed methodology allows the formation of an integrated Driving Aggressiveness Index (DAI) correlated with fuel efficiency. Validation was performed on the open Vehicle Energy Dataset (VED) containing second by second CAN records of 299 vehicles (26,286 trips). It is shown that DAI has a significant positive correlation with mean mass air flow (MAF) used as a proxy for fuel consumption: at the trip level $\rho = 0.280$ ($p < 0.0001$), at the driver level $\rho = 0.292$ ($p < 0.0001$). The scientific novelty consists in transferring the methodology of coordinated analysis of two planes (similar to TEID in LTE networks) to the driver scoring task, as well as in adapting the approach for construction machinery. The practical significance lies in creating a basis for fleet monitoring systems that can reduce fuel consumption and operating costs through objective driving style assessment.

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1 Introduction

Modern road construction companies incur significant operating costs associated with fuel consumption, transmission and chassis wear, and unscheduled repairs. According to industry research, up to 30% of excess fuel consumption in fleets is due not to the technical condition of the vehicles, but to the individual driving style of operators [1]. Aggressive acceleration, harsh braking, suboptimal gear selection, and prolonged operation at elevated engine speeds not only increase fuel consumption but also reduce the lifespan of components, especially in off-road conditions and under the heavy-duty operating conditions typical of construction and quarry equipment.

At the same time, fleet monitoring systems based on standard telematics devices provide, as a rule, generalized information about mileage, engine operating time and fuel consumption, but do not allow detailed analysis of operator behavior in real time. To objectively assess driving style, it is necessary to integrate data from the CAN bus (Controller Area Network), reflecting instantaneous parameters of the engine and controls, and telematics fuel efficiency indicators. However, existing approaches to driver behavior analysis typically either use only CAN/OBD data for style classification or are limited to fuel consumption statistics without deep correlation with driving events.

In the field of telecommunications, a method for the coordinated use of signaling and user data via an end-to-end identifier (TEID) [2] was proposed to address the problem of identifying mass streaming video in LTE networks. This methodology, based on the correlation of the control plane (session parameters, QoS) and the user plane (IP addresses, SNI, packet sizes), allows for increased accuracy of traffic analysis without decoding the content. Transferring this approach to the transportation problem of assessing driving style opens up new possibilities: CAN events (sharp accelerations, gas pedal positions, engine speed) act as the "signaling plane," while data on instantaneous and average fuel consumption act as the "user plane." A unique trip identifier serves as the end-to-end identifier linking both planes.

The aim of this work is to develop a multimodal methodology for the integrated assessment of the driving style of road construction equipment operators, based on the coordinated use of CAN data and telematic fuel consumption indicators using an end-to-end trip identifier.

To achieve this goal, the following tasks have been set:

1. To analyze the current state of research in the field of driving style classification and scoring systems based on CAN/OBD data.
2. Propose a formalization of two data planes (signal and user) similar to the TEID telecommunications methodology.
3. Develop an integrated Driver Aggressiveness Index (DAI) that combines CAN parameters and fuel consumption data.
4. Test the methodology on the open Vehicle Energy Dataset (VED).
5. Assess the correlation of DAI with fuel efficiency (MAF as a proxy) at the trip and driver levels.

The scientific novelty of the work lies in:

1. Transferring the methodology for the coordinated analysis of two planes (control and user) from the field of telecommunications to the task of scoring vehicle drivers.
2. Developing a formalized approach to the integrated assessment of driving style based on an end-to-end trip identifier combining CAN events and fuel consumption telematics.

3. Adapting the methodology for road construction equipment and verifying it on the large open VED dataset.

The practical significance lies in creating the basis for intelligent fleet monitoring systems that enable real-time classification of operator driving styles and the reduction of fuel consumption and operating costs through objective feedback.

2 Literature review

An analysis of the current state of research in driver behavior analysis, driving style classification, and scoring systems reveals the emergence of several established research trends. This review examines studies on general methodologies, classification and scoring methods based on CAN/OBD data, the use of telematics for fuel efficiency assessment, and safety and behavior prediction systems.

2.1 Review papers on driver behavior and machine learning methods

A systematic analysis of approaches to studying driver behavior is presented in the works of Kiyamov and Moseva [3], which examine machine learning methods for driver classification, data sources (including MEMS sensors), and the types of problems to be solved. The authors emphasize that the choice of classification method directly depends on the available data and interpretability requirements.

Of considerable interest is the review by Michailidis et al. [4], which focuses on machine learning-based OBD-II applications for improving the resilience, efficiency, safety, and security of automotive systems. The paper systematizes the tasks of fuel optimization, emissions control, driver behavior analysis, anomaly detection, and cybersecurity.

A specialized review of driver behavior scoring was conducted by Shirole et al. [5]. The authors analyze a two-stage approach: first, aggressive events are classified using ML/DL models, then an overall driver score is formed. The review emphasizes the relevance of developing interpretable and computationally efficient scoring systems for commercial vehicles.

In the work of Mobini Seraji et al. [6] presents a review of clustering and classification methods for driver behavior analysis. Algorithms ranging from k-means and SVM to hybrid deep learning models are discussed in detail, and the role of data preprocessing and feature extraction is demonstrated.

2.2 Methods of driving style classification and behavior scoring

A significant portion of research is devoted to the development of models for recognizing driving style (aggressive, normal, cautious) using various algorithms.

Wang et al. [7] proposed a fuzzy logic-based driving style classification method for a lane departure warning system, identifying four categories: aggressive, relatively aggressive, relatively cautious, and cautious. The classification parameters included the distance to the vehicle in front, the frequency of speeding, and the steering wheel angle.

Szumaska and Stańczyk [8] conducted a preliminary classification of the driving style of 69 city bus drivers based on the average maximum values of longitudinal and lateral accelerations obtained from inertial sensors. Age and experience were shown to correlate weakly with accelerations, confirming the universality of the approach.

Zhao et al. [9] developed a method for recognizing the starting

style of electric buses based on deep learning and CAN data, achieving 98.3% accuracy for three classes (cautious, normal, and aggressive). They used a convolutional neural network that automatically extracts spatiotemporal features from multichannel time series.

Nie et al. [10] proposed the MSCA-Net network for commercial vehicles, which combines multi-scale convolution and a channel attention mechanism to account for both short-term maneuvers and long-term behavioral trends. Experiments on real CAN data confirmed the effectiveness of the approach.

Sun et al. [11] presented a comprehensive driving safety assessment method that includes clustering to identify three driving styles (conservative, aggressive, impatient), a BP neural network for prediction, and a weighted scoring function based on a combination of subjective and objective weights.

Kumar and Jain [12] used SVM, AdaBoost, and Random Forest to classify driver behavior into ten categories based on OBD data (speed, RPM, throttle position, engine load). Random Forest performed best with 100% accuracy on the test set.

Singh and Sharma [13] applied Random Forest, AdaBoost and K-nearest neighbors (K-NN) to classify ten types of maneuvers (including yaw, roll, and skid) using g-forces obtained from OBD data.

Bergasa et al. [14] presented the DriveSafe smartphone app, which uses computer vision (drowsiness and distraction detection) and inertial sensors. The system evaluates driving quality in real time, achieving 82% detection accuracy and 92% completeness. Sai [15] developed this approach in DriveSafe-AI, a browser-based system based on MediaPipe and TensorFlow.js with rule-based scoring and driver state categorization (safe, warning, critical).

Lerch et al. [16] investigated the potential of vision-language models for driver monitoring by creating a labeled dataset based on Drive&Act. They demonstrated that additional training on specialized data increased the accuracy of driver action interpretation from 66 to 76%.

2.3 Using OBD-II/CAN data and telematics to analyze behavior

Most modern studies rely on data from on-board diagnostic systems and CAN-bus as the main source of objective information about driving parameters and engine operation.

Molina-Campoverde et al. [17] classified gears and analyzed the fuel efficiency of passenger cars using OBD-II PID signals (MAP, RPM, VSS) and GPS. The KNN algorithm achieved 99.7% accuracy in gear classification, and multiple linear regression allowed estimating instantaneous fuel consumption with $R^2 = 0.897$.

Ahmad et al. [18] proposed a hybrid DDD-GC-ViT transformer model for driver drowsiness detection based on OBD-II parameters (speed, throttle position, steering torque) converted into MFCC features. The classification accuracy was 97.9%, which outperformed baseline CNN models.

Nicolosi et al. [19] trained a feedforward neural network on OBD and geographic data from the DDD20 dataset (51 h, 4000 km), achieving accuracy above 98% for three driver behavior classes.

Nawarathna et al. [20] developed a transparent, rules-based scoring system based on OBD-II parameters (speed, RPM, throttle position, brake application, steering speed) with categorization of trips as "excellent," "safe," "cautious," and "risky." The system

demonstrated the ability to differentiate driving styles without the use of labeled big data.

2.4 The impact of driving style on fuel efficiency

The direct relationship between driving style and fuel consumption and energy consumption is confirmed by a number of experimental studies.

Pilnik et al. [21] developed a fuel efficiency model for corporate fleets based on telematics data, demonstrating that taking longitudinal acceleration into account improves the model's performance. Key factors influencing excess fuel consumption were identified.

Cechulin et al. [22] conducted a comparative study of urban fuel consumption for calm and aggressive driving styles on the same route. A mathematical model of driving with an acceleration limit of $\pm 1.5 \text{ m/s}^2$ was proposed, allowing for a quantitative assessment of fuel savings potential.

Algin [23] analyzed the operational factors of urban electric bus energy consumption, identifying driving style as one of the key factors (along with passenger load, rolling resistance, and obstacles). A probabilistic approach for calculating energy consumption for calm and aggressive driving styles is proposed.

Lu et al. [24] presented FedDriveScore, a federated learning framework for unsupervised privacy-preserving driver behavior scoring using homomorphic encryption. The proposed method is shown to achieve high correlation with centralized learning ($\text{MSE} < 0.0001$).

2.5 Safety and behavior prediction

A number of studies focus on the relationship between driving style and accident risks and the development of warning systems.

Lobanova [25] proposed a resource-style approach to designing the human-machine system, considering individual performance style as a compensatory mechanism for the lack of professionally important driver qualities. It has been shown that the technical characteristics of a vehicle can compensate for an insufficient level of professionally important qualities, forming a safe driving style.

Safiullin and Sorvanov [26] analyzed the application of fuzzy logic methods to assessing the risk of road accidents, taking into account weather conditions, driving style, and traffic congestion. An adaptive system based on fuzzy sets allows for the processing of high-quality data and decision-making in real time.

Jiao et al. [27] developed a risk assessment model for bus drivers that takes into account demographic characteristics, driving style, and physical and mental health. A hybrid weighting method (AHP (Analytic Hierarchy Process) + entropy) enabled drivers to be ranked according to risk level.

Tong et al. [28] assessed driver alertness on mountain roads using XGBoost and TabPFN (AUC 0.98) by integrating physiological (heart rate, eye movement) and behavioral data. The TabPFN model performed better than logistic regression and XGBoost.

Madras et al. [29] developed a personal bistability index (PBI) method – a six-component vector for multidimensional assessment of driver-operator performance based on fuzzy logic with hysteresis membership functions. The method was verified on 150 drivers in Moscow and St. Petersburg.

Gornostaev and Shevchenko [30] examined the influence of

operating modes on the safety and reliability of automotive equipment, proposing a generalized criterion for assessing driving quality.

2.6 Conclusions from the literature review

The conducted analysis shows that a robust methodological framework for driving style classification using ML/DL based on OBD-II/CAN data and telematics has now been established. However, existing studies focus primarily on passenger cars, city buses, and electric buses. Similar studies for road construction and mining equipment are virtually nonexistent. Furthermore, most approaches use either only CAN data for classification or only aggregated fuel consumption indicators, without implementing deep integration of the two data types through a common identifier. The methodology proposed in this paper fills these gaps by transferring the methodology of coordinated analysis of two dimensions from telecommunications to the transportation task of driver scoring.

In this study, the two-plane analysis methodology is conceptually adapted for the task of scoring road construction equipment operators. However, experimental validation was performed on the open VED dataset, which contains data on passenger cars and hybrids. Direct testing of the methodology on real construction equipment (excavators, graders, quarry trucks) with direct measurements of fuel consumption is planned for future studies.

3 Research methodology

3.1 General concept of two-plane analysis

The proposed methodology is based on an analogy with the method of identifying mass streaming video in LTE networks, where the signal plane (Control Plane) contains session parameters (QCI, MBR, ARP, IMSI), and the user plane (User Plane) contains the actual traffic characteristics (IP addresses, SNI, packet sizes). The connection between the planes is achieved through an end-to-end identifier (TEID).

In the transportation task (Fig. 1), the signal plane is formed by low-level CAN data received at a frequency of ≥ 1 Hz: speed, engine speed, throttle position, and the calculated acceleration and braking events. The user plane consists of aggregated energy consumption indicators: average mass air flow (MAF) or direct fuel consumption. The end-to-end identifier is the unique trip ID, formed as a combination of {vehicle_id, trip_id}.

The TEID methodology in LTE networks is based on the fact that an end-to-end identifier links the control plane (session parameters, QoS) and the user plane (IP addresses, packet sizes), allowing for increased traffic analysis accuracy without decoding the content.

In the transport problem, a similar structure is achieved as follows:

- The signal plane is formed by low-level CAN events (speed, RPM, throttle position, sudden acceleration/braking);
- The user plane is formed by aggregated energy consumption indicators (MAF or Fuel Rate);
- The end-to-end identifier is a unique trip identifier {vehicle_id, trip_id}. This formalization allows for the correlation of driver behavioral events with energy consumption without the need to model detailed physical and chemical processes of the engine.

Multimodal methodology for driving style assessment

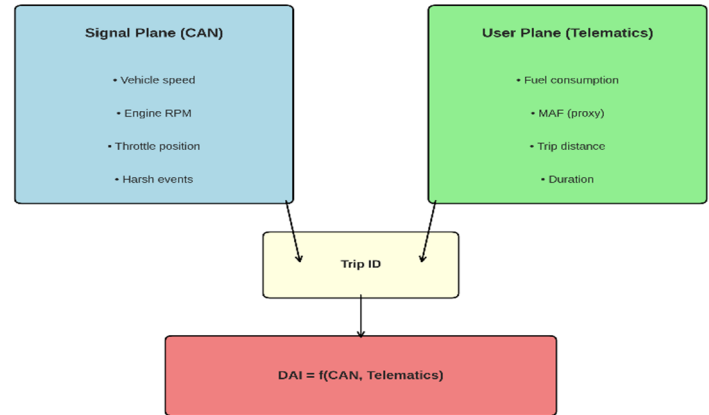


Fig. 1. Scheme of the methodology of the proposed approach (two-plane analysis)

3.2 Integral Driving Aggressiveness Index (DAI)

For each trip, the following features from the signal plane are calculated:

- std_speed – standard deviation of speed (characterizes the unevenness of movement);
- m_x_rpm – maximum engine speed;
- h_rsh_accel – number of sharp accelerations (velocity derivative > 3 m/s²);
- harsh_brake – number of sharp decelerations (velocity derivative < -3 m/s²).

All features are normalized to the range [0,1] using MinMaxScaler. The integral index DAI is calculated as a weighted sum (1):

$$DAI = \omega_1 \cdot \tilde{\sigma}_v + \omega_2 \cdot \tilde{RPM}_{max} + \omega_3 \cdot \tilde{N}_{accel} + \omega_4 \cdot \tilde{N}_{brake} \quad (1)$$

where $((\cdot))^\sim$ are normalized values, the weights satisfy the condition $\sum \omega_i = 1$. In this paper, we used weights that reflect the increased contribution of abrupt maneuvers: $\omega=0.15;0.25;0.30;0.30$. The choice of weights is justified by the results of correlation analysis (Table 4): max_rpm, harsh_accel and harsh_brake have the highest correlation with mean_maf, which is reflected in the increased weights.

3.3 Target variable

Since direct measurements of instantaneous fuel consumption are often unavailable in open datasets, trip-average mass air flow (MAF, g/s) is used as a proxy. MAF is widely used in automotive equipment as an engine load indicator and closely correlates with fuel consumption (at a constant air-fuel ratio). Validating the methodology on VED data, including MAF, allows for an objective assessment of the relationship between DAI and energy consumption. An additional advantage is that this method can also be applied to equipment equipped with diesel engines, as found in most road construction equipment.

The VED dataset includes a direct fuel consumption parameter, Fuel Rate [L/hr]. The initial version of the methodology used MAF as a proxy for fuel consumption, but to improve accuracy, it is recommended to use mean Fuel Rate as the target variable in future studies. In this paper, the results are presented for MAF; the correlation of DAI with mean Fuel Rate will be added in subsequent studies.

4 Experimental Results

4.1 Characteristics of the Data Used

To verify the methodology, we used the publicly available Vehicle Energy Dataset (VED) [31], which contains one-second CAN/OBD-II data records from 383 vehicles (both internal combustion and hybrid). The data was collected over several months in Ann Arbor, Michigan, USA. The total data size is 22 million rows (54 CSV files). After removing records with missing speed, RPM, and MAF values, and breaking down trips by Trip ID, we obtained 26,286 trips from 299 unique vehicles (each vehicle was treated as a single driver, which is acceptable due to the constant assignment).

From the entire set of features, the following were selected for this study (Table 1).

Table 1

VED dataset fields used

Field	Units	Description
VehId	–	Unique vehicle identifier
Trip	–	Unique trip identifier
Timestamp(ms)	ms	Absolute recording time
Vehicle Speed[km/h]	km/h	Instantaneous speed
Engine RPM[RPM]	RPM	Engine speed
MAF[g/sec]	g/sec	Mass air flow (fuel consumption proxy)

After removing records with missing or zero values in key fields and grouping by VehId and Trip identifiers, 26,286 trips from 299 unique vehicles were generated. Each vehicle was treated as an independent "driver," which is acceptable, as in real-world use, a vehicle is typically assigned to a single operator.

4.2 Preprocessing and feature extraction stages

All calculations were performed in Python 3.12 using the pandas, numpy, scikit-learn, and scipy libraries.

The 3 m/s² threshold was chosen based on industry guidelines for assessing aggressive maneuvers in fleet monitoring telematics systems and corresponds to short-term accelerations that significantly increase fuel consumption and transmission wear.

Main preprocessing steps:

1. timestamp conversion – Timestamp (ms) values were converted to seconds to calculate derivatives.
2. Outlier filtering – records with speeds >200 km/h or RPMs >8000 rpm (less than 0.01% of the data) were removed.
3. Speed derivative calculation – acceleration (m/s²) was calculated for each individual trip as the speed difference divided by the time difference. The resulting values were used to identify sudden accelerations and decelerations.
4. Trip feature calculation – the following were aggregated for each trip:
 - mean_speed, std_speed – average speed and its standard deviation;
 - max_rpm – maximum rpm;
 - harsh_accel – number of accelerations > 3 m/s²;
 - harsh_brake – number of decelerations < –3 m/s²;
 - mean_maf – average air mass flow (target variable).
5. Normalization – the features included in the DAI were scaled to the range [0, 1] using MinMaxScaler.
6. DAI calculation – using formula (1) with weights [0.15; 0.25; 0.30; 0.30].
7. Driver aggregation – for each VehId, the DAI and mean_maf were averaged across all of its trips, yielding 299 points for driver-level analysis.

4.3 Statistical analysis of features

Table 2 presents the main feature statistics for the trip sample. It is clear that the values have a wide range, ensuring the data is representative.

Table 2

Descriptive statistics of features (26,286 trips)

Feature	Average	Median	Std. var.	Minimum	Maximum
std_speed, км/ч	12,84	10,92	9,31	0,00	63,70
max_rpm, об/мин	2954	2778	835	587	7821
harsh_accel	2,43	1	4,18	0	57
harsh_brake	1,89	1	3,56	0	49
mean_maf, г/с	13,47	10,28	11,96	0,18	73,44

The distribution of DAI among drivers (Figure 2a) is close to normal, indicating the absence of systematic bias. The distribution of the mean MAF is right-skewed (Figure 2b), confirming the appropriateness of using the Spearman rank correlation instead of the Pearson one. The Scheer-Wilk test for mean_maf showed a violation of normality ($p < 0.001$), while the distribution of DAI is close to normal.

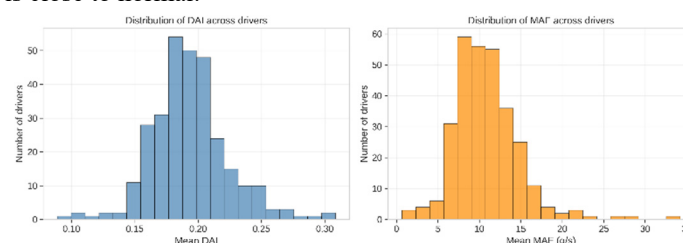


Fig. 2. Distribution of average DAI and average MAF by drivers

4.4. Correlation analysis

To assess the relationship between DAI and average MAF, we used the Spearman rank correlation coefficient (ρ), which is robust to outliers and does not require a normal distribution. The results are presented in Table 3.

Table 3

Correlation of DAI with average MAF

Aggregation level	Number of observations	Spearman's coefficient (ρ)	95% confidence interval	p-value
Trips	26 286	0,280	[0,270; 0,290]	< 0,0001
Drivers (average)	299	0,292	[0,180; 0,398]	< 0,0001

According to the generally accepted scale for interpreting the Spearman rank correlation coefficient, values of $\rho \approx 0.1$ –0.3 correspond to a weak relationship, while 0.3–0.5 correspond to a moderate relationship. The obtained values of $\rho \approx 0.28$ –0.29 correspond to a weak positive correlation, which, with a sample size of $N > 26,000$, is statistically highly significant ($p < 0.0001$).

The confidence interval for the driver level ([0.18; 0.40]) is wider than for the trip level ([0.27; 0.29]), which is due to the smaller number of observations ($N=299$) and the increasing uncertainty when averaging across trips. This emphasizes the importance of interpreting the result as a weak but systematic relationship.

The scatter plots (Figures 3 and 4) clearly demonstrate a positive slope for the regression line, confirming that an increase in DAI is accompanied by an increase in the average MAF. The points in the driver plot (Figure 4) are more densely clustered than those for individual trips, as expected due to noise averaging.

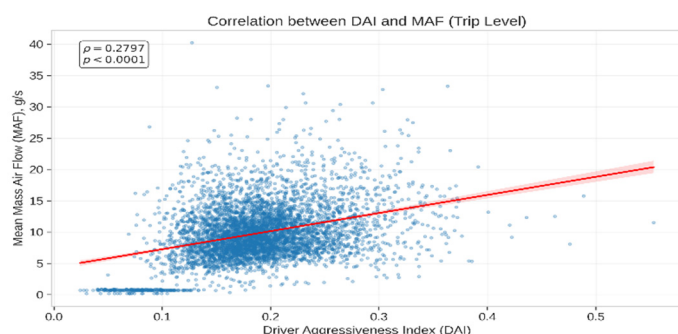


Fig. 3. Correlation between DAI and average MAF (trip level)

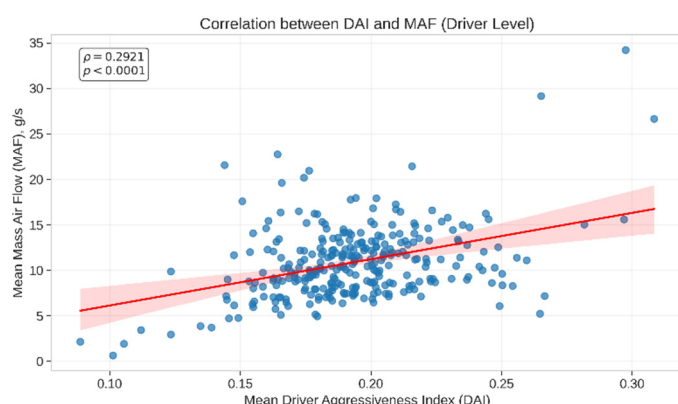


Fig. 4. Correlation between DAI and average MAF (driver level)

4.5 Analysis of the contribution of individual features

To understand which DAI components contribute most to MAF prediction, pairwise correlations of each feature with the target variable were calculated (Table 4).

Table 4

Correlation of individual features with mean_maf (trip level)

Sign	Spearman's coefficient (ρ)	p-value
std_speed	0,324	< 0,0001
max_rpm	0,560	< 0,0001
harsh_accel	0,476	< 0,0001
harsh_brake	0,412	< 0,0001

The highest correlation is observed for max_rpm ($\rho = 0.56$), which is physically understandable: higher engine speeds require increased air-fuel mixture delivery. Sharp accelerations ($\rho = 0.48$) and braking ($\rho = 0.41$) also significantly correlate with air flow. The standard deviation of speed has the smallest, but still significant, contribution ($\rho = 0.32$). These results justify the chosen weights in the DAI.

The maximum pairwise correlation (Figure 5) between harsh_accel and harsh_brake is 0.894, indicating a high correlation between these features. While this does not constitute critical multicollinearity for a simple linear combination in DAI, future work is recommended to consider combining these features into a single "harsh maneuvers" index or using regularization methods (Ridge, Lasso) to assess the stability of the weights.

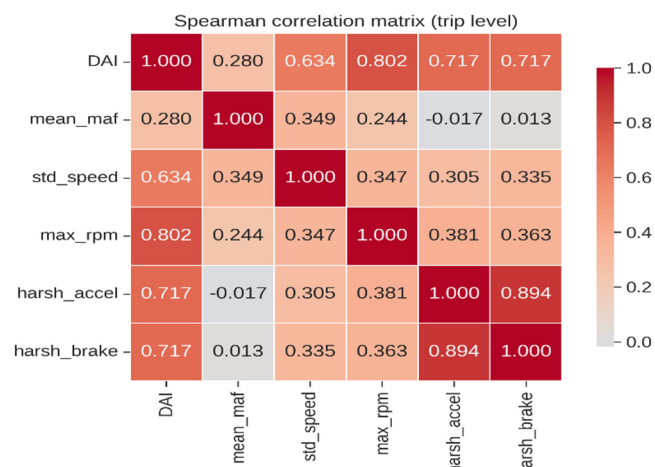


Fig. 5. Matrix of feature correlations (trip level)

4.6 Discussion of restrictions

Several limitations of the study should be noted:

1. Using the MAF as a proxy for fuel consumption – although the MAF correlates well with fuel consumption under steady-state conditions, during transients (sharp acceleration) deviations are possible due to mixture enrichment. The VED dataset lacks a direct fuel_rate (l/h), necessitating the use of an indirect indicator.

2. The VED dataset includes parameters such as Air Conditioning Power, Heater Power, HV Battery Current, and HV Battery SOC, which affect the MAF but are not directly related to driving style. In the current version of the methodology, these factors are not aggregated and may introduce noise into the correlation. Furthermore, the VED contains data for 27 PHEV/EV and 92 HEV vehicles, for which the MAF may be zero or incorrect; in future studies, it is recommended to conduct a separate analysis for ICE vehicles.

3. Lack of a labeled driving style – we do not have external benchmarks (expert assessments, questionnaires), so validation is based only on an objective criterion – energy consumption.

4. Route homogeneity – VED data are collected from one city (Ann Arbor), which may limit generalizability to other regions and road types.

5. Applicability to road construction equipment – despite the transfer of the methodology, direct extrapolation to excavators, graders, or quarry trucks requires additional experiments with real data from such machines, as their dynamic modes differ significantly from those of passenger cars.

All of the above limitations do not reduce the value of the proposed methodology, but should be taken into account when interpreting the results.

5 Conclusions

This paper proposes a multimodal method for integrated driving style assessment based on the coordinated use of CAN data (signal plane) and energy consumption indicators (user plane) with an end-to-end trip identifier. The methodology borrows a successful telecommunications approach (correlation via TEID) and adapts it to the transportation task of driver scoring.

Using the open VED dataset, containing one-second recordings of 299 vehicles (26,286 trips), we experimentally confirmed that the proposed driving aggressiveness index (DAI) significantly correlates with average mass air flow ($p = 0.292$, $p < 0.0001$ at the driver level). This confirms the presence of a statistically significant weak positive relationship between DAI and energy consumption, allowing us to consider DAI as an objective measure of driving style correlated with fuel efficiency.

Main scientific results:

- A formal two-dimensional model for driver scoring was developed.
- An integrated driver assessment index (DAI) was proposed and verified.
- A statistically significant relationship between DAI and energy consumption was demonstrated using real-world data.

The practical significance of this work lies in the possibility of creating fleet monitoring systems that, using CAN/OBD data, calculate DAI in real time and provide driver feedback. This is particularly relevant for road construction equipment due to high fuel consumption and operating costs.

Future research directions include:

- Collection of a specialized dataset on real road construction equipment (excavators, graders, dump trucks) with direct measurements of fuel consumption.
- Optimization of DAI weights using regression or reinforcement learning methods.
- Integration of DAI into on-board ADAS systems for personalized driver assistance.

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МУЛЬТИМОДАЛЬНАЯ МЕТОДИКА ИНТЕГРАЛЬНОЙ ОЦЕНКИ СТИЛЯ ВОЖДЕНИЯ ОПЕРАТОРОВ ДОРОЖНО-СТРОИТЕЛЬНОЙ ТЕХНИКИ НА ОСНОВЕ СОГЛАСОВАННОГО ПРИМЕНЕНИЯ CAN-ДАННЫХ И ТЕЛЕМАТИКИ

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Аннотация

Эксплуатация дорожно-строительной техники связана с высокими затратами топлива и интенсивным износом узлов, которые в значительной степени определяются стилем вождения оператора. В работе предлагается мультимодальная методика интегральной оценки стиля вождения, основанная на согласованном применении низкоуровневых CAN-данных (сигнальная плоскость) и агрегированных показателей расхода топлива (пользовательская плоскость) с использованием сквозного идентификатора поездки. В отличие от существующих подходов, ориентированных на классификацию стиля по отдельным параметрам, предложенная методика позволяет формировать интегральный индекс агрессивности вождения (Driver Aggressiveness Index, DAI), коррелирующий с топливной эффективностью. Валидация выполнена на открытом датасете Vehicle Energy Dataset (VED), содержащем секундные CAN-записи 299 автомобилей (26 286 поездок). Показано, что DAI имеет значимую положительную корреляцию со средним массовым расходом воздуха (MAF), используемым в качестве прокси расхода топлива: на уровне поездок $r = 0,280$ ($p < 0,0001$), на уровне водителей $r = 0,292$ ($p < 0,0001$). Научная новизна заключается в переносе методологии согласованного анализа двух плоскостей (аналогично TEID в сетях LTE) в задачу скоринга водителей, а также в адаптации подхода для дорожно-строительной техники. Практическая значимость состоит в создании основы для систем мониторинга автопарков, позволяющих снижать расход топлива и эксплуатационные расходы за счёт объективной оценки стиля вождения.

Ключевые слова: стиль вождения, CAN-шина, телематика, скоринг водителей, мультимодальный анализ, идентификатор поездки, дорожно-строительная техника, топливная эффективность

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