

Article

Concept of Early Prediction and Identification of Truck Vehicle Failures Supported by In-Vehicle Telematics Platform Based on Abnormality Detection Algorithm

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Abstract: As automotive technology advances in the realm of digitization, vehicles are becoming smarter and, at the same time, more vulnerable to various threats. This paper focuses on techniques for detecting faults to mitigate the risk of freight transportation. Our observations show that vehicle uptime varies significantly even under similar operating conditions. This variation stems from differences in the wear and tear of moving and stationary parts, the characteristics of transported loads, driving styles, the quality of maintenance, etc. These factors are particularly crucial for abnormal vehicles designed to carry AILs (Abnormal Indivisible Loads). Such vehicles are especially prone to surprising threats, requiring efficient techniques for monitoring separate vehicle components and providing drivers with vital information about their operational status. The presented article proposes an original concept of an integrated three-level monitoring system based on the AOP (All-in-One Platform) principle, using the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm, which is a tool oriented to distinguish points from three categories: basic, boundary, and external. This is a solution not yet found in the literature. It is based on assessments of LOFs (Local Outlier Factors) and to detect anomalies in the measured values of operational parameters. The purpose of our study was to determine whether providing truck drivers with current information from an active threat warning system could help reduce unplanned downtimes.

Keywords: in-vehicle telematics; sensors networks; anomaly detection; fault identification and mapping



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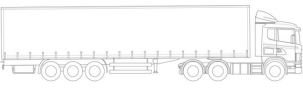
1. Introduction

Transporting oversized loads is a unique type of operation that uses various abnormal vehicles, as shown in Table 1. These operations encompass both heavy or super-heavy items and oversized loads known as AILs (Abnormal Indivisible Loads). To successfully complete these complex deliveries, transport companies require the following [1–3]:

1. During the preparation phase:
 - A fleet suitable for transporting AILs;
 - Proper transport means equipped with axle load monitoring systems, speed control systems for the route, and systems for checking their condition [4].
2. During the organizational phase:

- Taking into account the terrain shape (road geometry) for the transport route, as increased complexity can cause driver fatigue, increase the likelihood of the load's center of gravity shifting, etc.;
 - Choosing the appropriate route and timing for transport, considering specific road infrastructure elements, including potential emergency parking spots, refueling stops, possible detour routes, etc.;
 - Preparing the load for transport, considering how it reacts to adverse weather conditions during the transport;
 - Securing AILs to minimize the risk of it falling or the Semi-Tractor-Trailer (STT) tipping;
 - Developing an incident management plan (policies, procedures, recommendations), including contingency plans for incidents such as breakdowns, fuel/oil spills, accidents, etc.
3. During transport operations:
- Ensuring adherence to the transport schedule;
 - Identifying emerging threats to ensure the safety of all road users;
 - Using necessary devices (e.g., securing, communication) during the transport of AILs.

Table 1. Types of vehicles used for transporting AILs.

LGV/HGV	Tractor Truck with One Low-Bed Trailer	Tractor Truck with Two Low-Bed Trailers
		
Requires equipping with markings and warning lights.	Requires a Transport Execution Plan for any transport route.	Requires a Transport Execution Plan. The selected route must cover the minimum distance.
Vehicle characteristics: Axle load—normative Width up to 3.2 m Length up to 15 m Height up to 4.3 m	Vehicle characteristics: Speed: $v \leq 65$ km/h—highways $v \leq 56$ km/h—4-lane roads $v \leq 48$ km/h—2-lane roads Load characteristics: Width ≤ 3.2 m Length ≤ 18.75 m Height ≤ 4.5 m Mass ≤ 60 t axle load: ≤ 15 t	Vehicle characteristics: Speed: $v \leq 5$ km/h (remote control), $v \leq 25$ km/h (manual control) Load characteristics: Width 3.2–6.5 m Length ≥ 18.75 m Height ≥ 4.5 m AIL mass ≤ 5000 t axle load: ≤ 15 t data ¹

¹ Own elaboration based on [5]. Source: <https://stock.adobe.com/> (accessed on 7 August 2024).

The U.S. Federal Motor Carrier Safety Administration (FMCSA) along with the National Highway Traffic Safety Administration (NHTSA) prepared the LTCCS (Large Truck Crash Causation Study) report based on a sample of nearly 1000 road accidents involving trucks that occurred from 2018 to 2020 [6]. The report indicates that over the entire study period (2010–2020), the overall number of fatal truck accidents increased by 31%, with a 3% decrease from 2019 to 2020. However, the rate increased from 0.162% to 0.177% per 100,000,000 km from 2019 to 2020. In fatal accidents, STTs with one trailer accounted for 53%, with two trailers for 3%, and with three trailers for less than 0.1% (Table 2). The analysis presented in the report shows that accidents occurred in two ways: either when the STT was the main cause (First Harmful Event, Table 3) or when it was just a factor increasing the risk of the event (Second Harmful Event, Table 4).

Table 2. Large trucks in fatal crashes by vehicle configuration, 2018–2020 [6].

Vehicle Configuration	2018		2019		2020	
	Number	Percent	Number	Percent	Number	Percent
Single-Unit, 2 Axles	1.179	24.0%	1.172	23.3%	1.219	25.2%
Single-Unit, 3+ Axles	499	10.2%	517	10.3%	458	9.5%
Truck/Trailer(s)	237	4.8%	276	5.5%	247	5.1%
Tractor/Semi-trailer	2.700	55.0%	2.767	55.0%	2.566	53.0%
Tractor/Double	131	2.7%	124	2.5%	123	2.5%
Tractor/Triple	7	0.1%	5	0.1%	2	0.05%

Table 3. Large trucks in fatal crashes by vehicle-related factors, 2018–2020 [6].

First Harmful Event /Vehicle-Related Factors/	2018		2019		2020	
	Number	Percent	Number	Percent	Number	Percent
Collision with Vehicle	3.257	73.0%	3.290	73.1%	3.183	71.6%
Overturn (Rollover)	187	4.2%	165	3.7%	160	3.6%
Jackknife	9	0.2%	12	0.3%	12	0.3%
Cargo Equipment Loss or Shift	2	0.03%	10	0.2%	6	0.1%

Table 4. Large trucks in fatal crashes by vehicle age, 2018–2020 [6].

Second Harmful Event /Vehicle-Related Factors/	2018		2019		2020	
	Number	Percent	Number	Percent	Number	Percent
Tire blowouts or damage	68	1.4%	60	1.2%	43	0.9%
Brake System	46	0.9%	55	1.1%	37	0.8%
Turn indicators as well as marker, parking, and warning lights	6	0.1%	4	0.1%	8	0.2%
Power Train	10	0.2%	8	0.2%	4	0.1%
Headlights	5	0.1%	6	0.1%	3	0.1%
No Details	3	0.1%	7	0.1%	7	0.1%

A significant risk was the reduced performance of the STT, which was attributed to faults in both the trucks and their trailers, as highlighted in the 2021 report [7]. This report reveals that 74% of fatal accidents involved STTs, whereas only 27% involved HGVs. The authors of this and later reports [8] suggest that transport companies frequently disregard regulations in an attempt to lower operational costs and maintain delivery schedules.

There are four types of accidents recorded in AIL transport, including:

1. STT rollover. Oversized loads must be properly balanced and secured, as loading them leads to a sudden increase in the weight of the STT and a shift in the center of gravity. This can result in the instability of the STT, increasing the risk of crushing, cracking, or other damage to the transported load due to the tipping or rollover of the STT [9,10].
2. Tire blowouts. Loading an STT with a super-heavy load can cause excessive strain, stretching, and blowouts of tires during AIL transport [11].
3. Failure to break in time. Large trucks require more time to stop. When loaded, the mass of the STT increases further, extending this time even more. When a driver relies solely on their intuition, an STT with an emergency braking system can lead to collisions.
4. Jackknife accidents occur when the trailer moves at a different speed than the tractor. It results in the STT folding in a manner similar to a jackknife, with the trailer skewed at a 90-degree angle to the tractor. This can lead to rollovers or collisions with vehicles moving next to the STT (Figure 1).

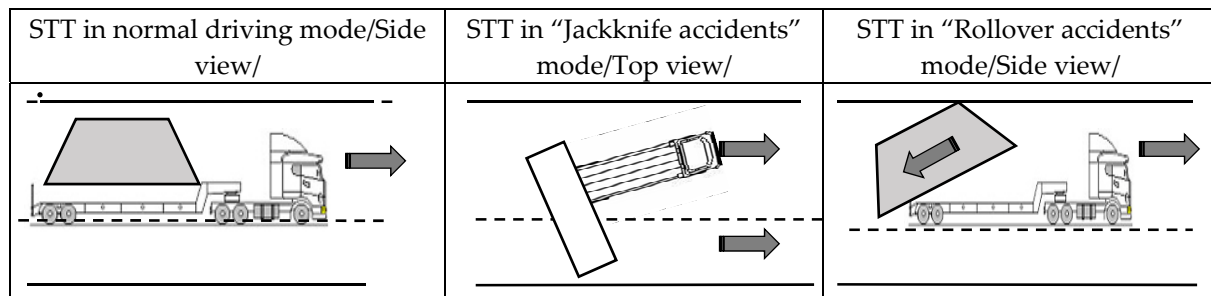


Figure 1. Types of accidents recorded during AIL transport.

Another cause is the limited space on the route of STTs. A heavy STT requires a longer braking distance, while an STT transporting long loads needs additional space for maneuvering turns. For example, a truck and trailer have a minimum inner turning radius of 7.76 m, while a turnpike double semi-trailer has a minimum turning radius of about 18.29 m [12,13].

Each accident involving an STT due to component failure results in losses from unplanned downtime, reducing the Overall Equipment Effectiveness (OEE) index, which can be used in analyses of the effectiveness of transport operations. The comprehensive metric OEE is calculated as the fleet availability index, the actual performance of the fleet, and the quality of work performed by this fleet [14]. With this index in mind, the aims of the present article are shown in Figure 2.

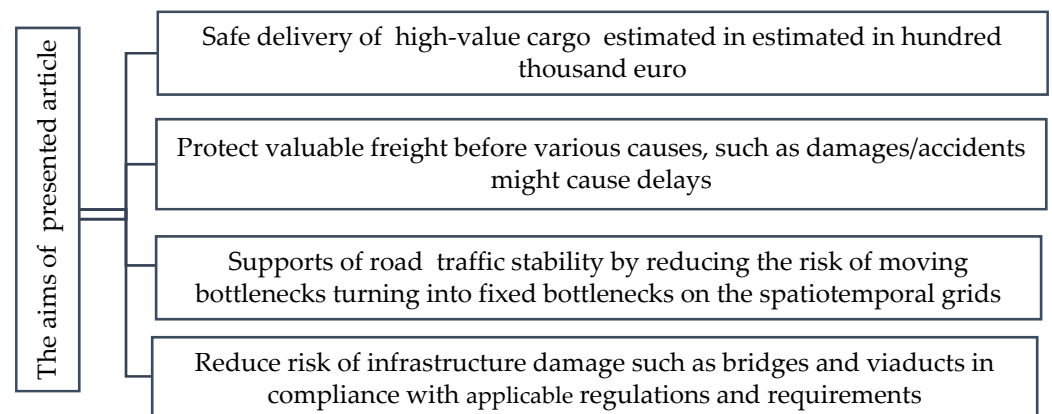


Figure 2. Research focus.

The aims listed in Figure 2 indicate what is to be achieved.

2. Basic Propositions and Research Objectives

One way to increase the OEE value is to reduce the risk of component failures by using fault detection technology to unconditionally adhere to the planned transport schedule. The problem is complicated by the fact that each STT is a unique transport means, consisting of specialized motor vehicles and oversized semi-trailers capable of carrying unique AIL items that vary in both size and weight [15]. Transporting such loads involves a heightened risk of accidents. Therefore, the authors suggest that each STT should be equipped with a three-level threat prediction and STT capability monitoring system that operates in real-time and employs non-invasive technologies for monitoring vibrations and noise, with the following objectives (Figure 2):

1. Identifying defects, manufacturing faults, and procedural breaches (e.g., load securing);
2. Detecting anomalies (both isolated and continuous) to prevent vehicle component failures;
3. Recognizing signs of cyberattacks on the diagnostic system within the CPS (Cyber Physical System) block;
4. Predicting catastrophic events in each STT component;

5. Detecting critical steering errors impacting the work schedule.

For AIL transport, it is essential to continuously monitor the correct placement and securing of loads. Traditional methods that rely on identification codes to detect potential issues are not effective for AIL transport, as STTs face not only occasional but also surprising threats occurring due to the unique nature of super-heavy loads, asymmetric center of gravity positions as a result of shape asymmetry, and bending/tipping moments with cascading effects. Figure 3 shows the three blocks of the Monitoring and Diagnosis System concept. The components of each are illustrated.

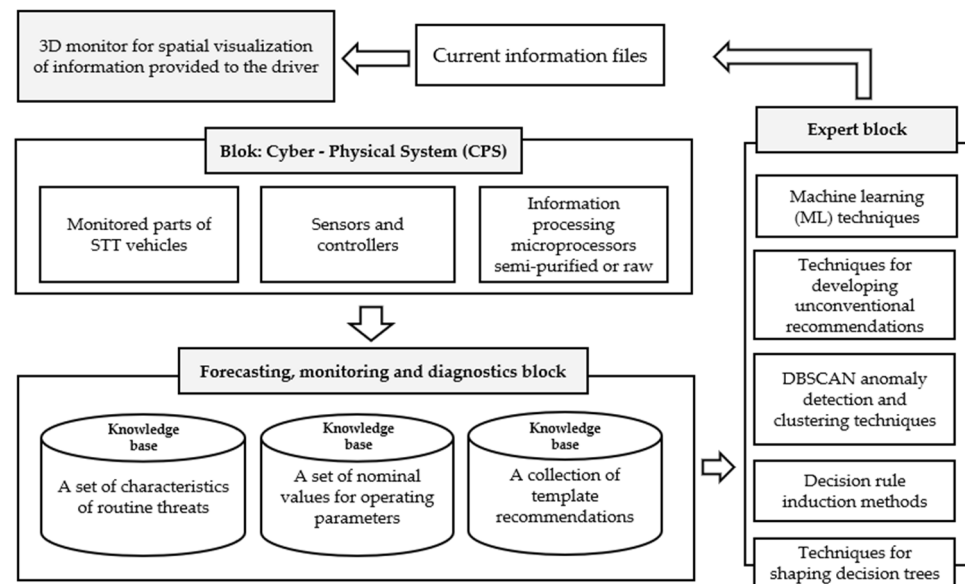


Figure 3. Concept of distributed monitoring and diagnosis system architecture for STT using IoT (Internet of Things) techniques and related services.

The Cyber-Physical System block contains STT components, sensors and controllers, and microprocessors. The Forecasting, Monitoring, and Diagnosis block contains three knowledge bases, which, in turn, are responsible for the following: reading the values of working process parameters (set of characteristics of routine threats), detection and analysis of anomalous values (set of nominal values for operating parameters), and discovering new knowledge (collection of template recommendations). The expert block includes the techniques and methods needed to be used in the whole process described. The information coming from these three blocks is being provided in a visualized form to the driver (Figure 3).

The above analysis underscores the critical need for ongoing diagnosis, detection, and mapping of both potential and existing faults, along with research to mitigate their risk. This need is driven by the rapid advancement of IT technologies, which facilitate real-time monitoring of key parameters and the transmission of crucial information. This paper introduces a proposed three-level model encompassing application, control, and communication layers, along with a system for monitoring, diagnosing, and predicting threats. Both occasional and surprising threats were analyzed, considering the risk of losing the STT's transport capability.

The purpose of the study was to determine whether providing truck drivers with information from an active threat warning system could help reduce unplanned downtimes. It also sought to develop an integrated platform for monitoring, diagnosing, and mapping faults to inform the driver about the STT's operational status, with threat probability assessments and preventive measures displayed visually on a 3D monitor.

3. Related Work/Literature Studies

The literature studies were conducted using information sourced from online databases like Scopus and Web of Science. The analysis indicates that the stability of road freight transport is crucial for economic growth, market accessibility, and the support of local businesses and regions [16]. In 2021, the sector's share of the EU freight services market (tkm) increased by 1.7% compared to 2011 [17].

Among the 19 product categories transported between 2018 and 2022, the “Unidentified Goods” category, which includes AILs, saw the highest growth, with a 9.3% increase (Table 5) [18]. As a result, vehicle manufacturers are incorporating various fault monitoring and detection systems during the design phase [19–21].

Table 5. EU road freight transport, 2018–2022 [18].

EU Road Freight Transport between 2018 and 2022 (Million Tons)					
Transport of unidentified goods, including AILs	2018	2019	2020	2021	2022
	155.0	165.9	158.7	164.4	188

The development of these systems can be categorized into four phases:

1. Early days. Initially, road freight transport utilized basic monitoring systems to measure engine parameters such as RPM, fuel consumption, and exhaust gas temperature.
2. Second half of the 20th century. Advances in technology led to the introduction of more sophisticated monitoring systems with sensors for braking, tire pressure, and exhaust emissions.
3. Early 21st century. The integration of electronic control units (ECUs) in trucks enabled more extensive monitoring through On-Board Diagnostic (OBD) systems. These systems utilize internal Fault Detection and Diagnosis (FDD) networks to monitor operational parameters and On-Board Computers (OBCs) to collect, record, process, and transmit data to drivers while controlling the operation of all components and detecting possible anomalies.
4. Current developments. The rapid increase in monitored components has led to longer wiring and more connectors, which has impacted the reliability of monitoring systems. To address this issue, Controller Area Network (CAN) buses have been introduced. These include the serial Local Interconnect Network (LIN) and the ring-based Media Oriented System Transport (MOST), both facilitating bidirectional communication.

Literature studies reveal four interconnected applications of such systems:

1. Supporting the daily activities of drivers through periodic monitoring of vehicle technical conditions, including:
 - Monitoring transport operations and informing the driver about internal (e.g., faults in critical systems) and external (e.g., ice on the road) threats [22].
 - Choosing alternate routes in emergencies (traffic congestion, infrastructure failures in the travel lane, etc.) [23,24].
2. Supporting managers in decision-making regarding planning and adjusting transport and maintenance operations in response to client requirements or incidents on transport routes that cause unplanned stops. Managers who have current information are better equipped to avoid planning mistakes, accelerate report preparation, and provide detailed geographical insights [25,26].
3. Enabling departments within the Transport & Logistics (T&L) sector to continuously monitor transport operations, streamline technical inspection scheduling, and assess maintenance downtime. Early identification of vehicle reliability issues facilitates timely preventive maintenance and repairs, preventing vehicles from becoming inoperative [20,27,28].

4. Supporting T&L companies in enhancing last-mile logistics, optimizing supply chains, tracking transport activities, ensuring schedule adherence, and managing operational expenses [29,30].

In the literature, the authors place particular emphasis on the effectiveness of the OBD I system used in US vehicles since 1988 and the subsequent version, OBD II, which became mandatory in 1996. They highlight the benefits of these systems and note that they are now standard [31,32], contributing to improved vehicle reliability [33–36].

In the past decade, there has been a notable increase in publications focused on telematics tools in road freight transport [37], including their integration with IoT networks and telecommunication systems [38,39].

An interesting conclusion presented in publication [40] suggests that a truck is considered unmonitored if its diagnostics rely solely on information about the condition of its systems. The analysis suggests that most research focuses on optimizing the number of sensors used and rationalizing their placement [41,42]. Various research approaches have been proposed, including empirical studies [31,43], graph theory [44], and decision-making algorithms in conditions of informational uncertainty [45]. Interesting results are reported in publications [46,47], where fault diagnosis based on Bayesian Networks (BNs) is proposed. Procedures for modeling, identifying, and diagnosing faults, validating and verifying the results obtained, and modeling BN structure and parameters have also been examined. The literature analysis indicates the following:

1. The diagnostic systems discussed in the publications studied align with the classification presented in Figure 4.
2. Recent publications primarily address the modeling of fault dynamics, evaluating their characteristics, and the decision-making processes of drivers [25,48,49]. Key areas of focus include:
 - A. Machine Learning, which is the leading approach utilized in contemporary in-vehicle telematics devices for trucks;
 - B. The fault identification techniques used can be grouped as follows:
 - Techniques for identifying operating parameters based on modeling changes in their values and verifying the results. They help in identifying faults based on established patterns and anticipated responses, focusing on detecting faults by recognizing multiplicative effects.
 - Techniques for clustering individual subsystems and components of the transport vehicle include adapting a network of monitoring sensors to identify faults. By analyzing sensor data, deviations from normal behavior can be flagged as potential faults. These techniques are particularly suited for identifying individual faults [50].
 - Adaptive fault detection techniques are based on a combination of the above two techniques.
 - Techniques based on predictive algorithms that analyze statistical data include learning to identify relationships between different operational parameters. They aid in predicting fault progression and are oriented toward detecting faults by identifying additive effects [51].

The key distinction among the discussed approaches is the necessity for prior knowledge of the faults that need to be detected [34,52]. The first three methods rely on certain assumptions for effective and reliable fault identification, such as the faults being quasi-stable or changing slowly over time. In contrast, the authors propose that effective fault detection systems should be designed to diagnose both occasional and surprising threats, map existing faults, and evaluate the probability of both new faults and multiplicative effects. Furthermore, such a system should provide multi-scenario preventive measures and include a feature for real-time updates on the STT's operational status through a visual representation on a 3D monitor.

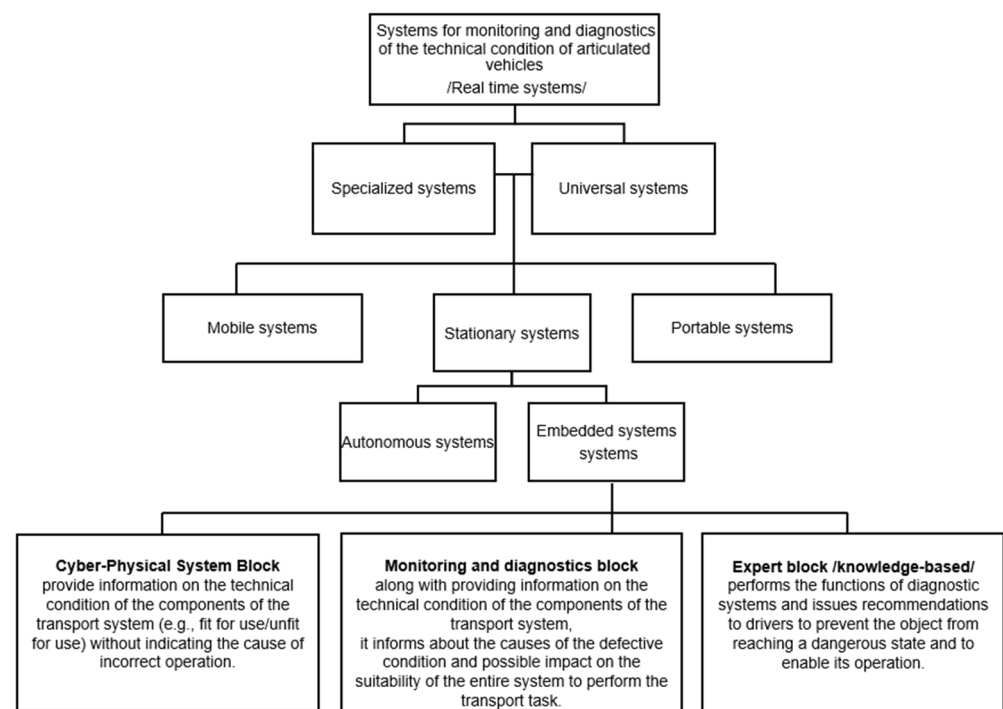


Figure 4. Classification of technical diagnostic systems in road transport.

Given the rapid developments in this field, the authors have decided to use for comparative analysis only specialized publications dated before 2014 (Table 6).

Table 6. Comparative analysis of more modern diagnostic methods with the method proposed (own elaboration on based literature studies).

Results of the Benchmarking Study		
Diagnostic Methods Used		Proposals for Solving the Problems Identified
Process Issues	Technical Issues	
1 The methods used relate to the task of monitoring a narrow group of operating parameters for only one type of vehicle, specifically trucks	Diagnostic systems have limited areas to monitor and focus generally on the engine, emissions, or fuel consumption	Proposal 1: Refers to the use of diagnostic systems that are oriented towards both the monitoring of tractor-trailer systems and of the AIL being transported
2 The methods used increasingly have problems with data transmission between the ECUs (Electronic Control Unit) sensors and the vehicle drivers, which reduces the effectiveness of these methods	Low reliability of the system, where a fault in even one of the ECU sensors can lead to an incorrect diagnosis of the state of fitness of the truck as a whole	Proposal 2: Assumed high reliability by means of a function for the timely performance testing of ECUs with the application of a self-learning function for the storage of information on previous faults of ECU sensors
3 On-board communication networks are easily overwhelmed by incoming messages, making it difficult to transfer them in real time.	On-board communication networks are sensitive to electromagnetic interference, which poses a risk to the functioning of the navigation system or other safety services	Proposal 3: Concern messages to drivers, communicated in graphic form (an example is shown in Figure 5)
4 Lack of comprehensive diagnostics makes it difficult to identify unconventional faults, especially in the complex CTT structure	They only display error codes, which can be identified with the help of reader instructions or the specialized literature	Proposal 4: Assumed feasibility of extending the system with further segments and subsystems
5 No possibility of even short-term forecasting of possible faults	Different modes of identifiers of the measurable parameters are used by accessing data from the ECU via CAN (Controller Area Networks), which does not provide protection against tampering	Proposal 5: The system includes functions not only for the short-term prediction of faults with the accuracy of the failed component but also for the prediction of medium-term possible problems in the course of the transport operation

Table 6. Cont.

Results of the Benchmarking Study		
Diagnostic Methods Used		Proposals for Solving the Problems Identified
Process Issues	Technical Issues	
6 The production of increasingly complex vehicles increases the likelihood of early unknown faults not on the fault code list of the SAE J2012 standard [53]	Existing measurement and diagnostic systems use the 5-character error codes specified in the “Diagnostic Trouble Code Definitions SAE J2012” [53] standard, which can make them difficult to read	Proposal 6: Messages on the suitability status of each monitored CTT component must be communicated in a graphical format structured on a time scale
Complex diagnostics is time-consuming, especially in the case of atypical or hidden faults, which increases the likelihood of unscheduled downtime for the HGV		Integrated proposal: The system should ensure that information on the state of serviceability of each STT component is collected and communicated to the driver, as well as information on actual and predicted failures in graphic form

The research was continued based on two assumptions:

Assumption 1. *The efficient operation of vehicles designed for transporting heavy and oversized loads requires continuous monitoring of the entire vehicle, including the area occupied by the load.*

Assumption 2. *Realizing Assumption 1 necessitates creating a concept for an integrated platform for diagnosing, predicting, and mapping faults on a 3D monitor. This platform should actively alert truck drivers to existing or potential faults and provide visual interpretations of the information displayed.*

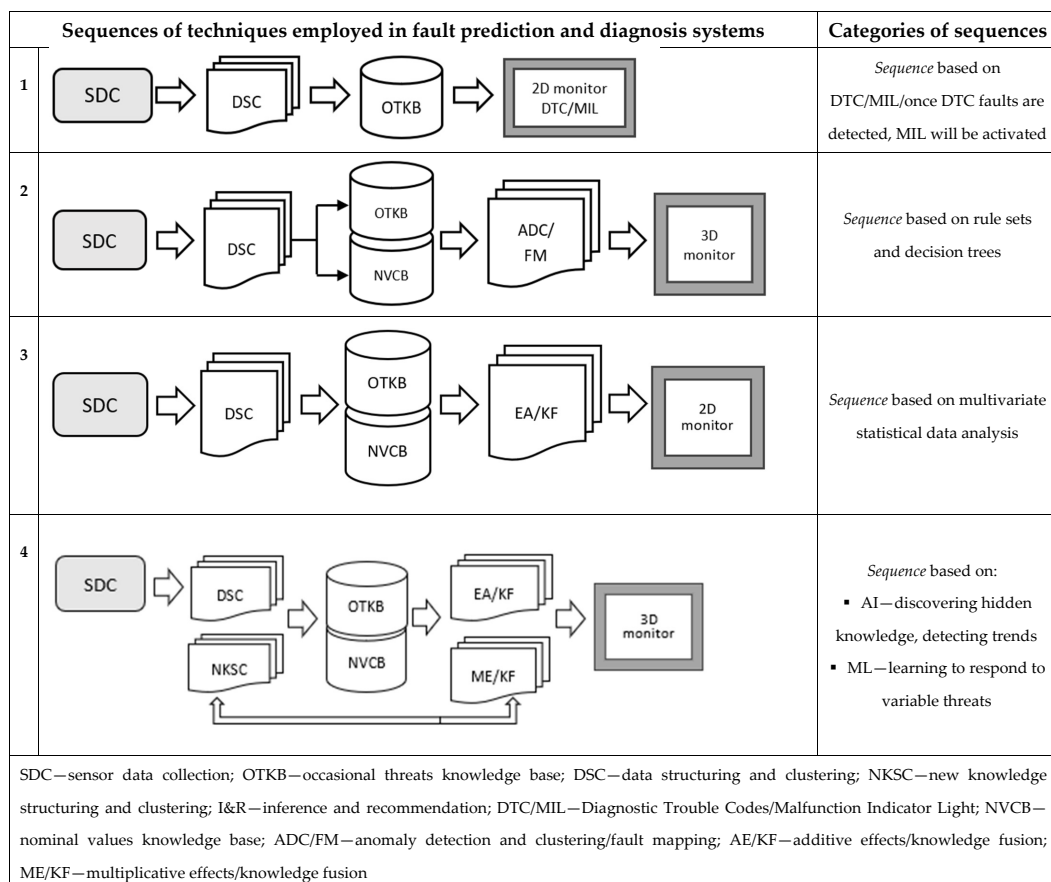


Figure 5. Concept of the sequence of techniques used in diagnostic and monitoring systems.

4. Fundamentals of the Developed Concept

4.1. Concept of Distributed Condition Monitoring System Architecture

One approach to improving this metric involves mitigating the risk of failure in STTs by utilizing technologies to detect condition-related threats and ensuring adherence to the planned transport schedule. The problem is complicated by the fact that each STT is unique, consisting of specialized motor vehicles and oversized semi-trailers capable of carrying unique AILs [15].

There is a pressing need to develop a comprehensive concept for monitoring the technical condition of the STT as a whole, including the ability to predict both occasional and surprising local threats during the transport of AILs. Experience indicates that even minor faults can potentially lead to significant multiplicative effects. Addressing these issues requires the development of an integrated, self-learning system capable of predicting, detecting, and mapping faults, which should include the following functions:

1. Gathering and displaying on a 3D monitor real-time information about the condition of each component of the STT. This function should adhere to the APOP (All-Parts-in-One Platform) principle.
2. Visualizing existing and potential faults based on risk levels. This includes identifying dangerous symptoms and comparing them to nominal values. This function is grounded in the ABFDA (Anomaly-Based Fault Detection Approach).
3. Informing the driver about the likelihood of imminent failures. This should be carried out using the KMA (Knowledge Mining Approach), which aids drivers in decision-making processes.

The EF&AD (Early Fault and Anomaly Detection) system designed to achieve these objectives should:

- A. Provide a comprehensive overview of the STT condition on-line, with the capability to drill down from subsystems to separate components of the vehicle, trailer, or cargo, while considering the vehicle's operational regime. The EF&AD should carry out the following tasks:
 1. Mechanical fault detection. In the network of sensors, converters, and controllers. Detecting physical degradation or damage to parts or components.
 2. Total functional failure detection. Identifying unacceptable deviations in process parameters from normal values, like engine failure to start [54].
 3. Partial functional failure detection. Identifying acceptable deviations in process parameters, such as reduced engine performance, vibrations from components, sudden accelerations or braking, and oil leaks. Symptoms could include diminished braking efficiency or increased fuel consumption.
 4. Electrical failure detection—typically involving the battery, alternator, connectors, fuses, and relays. Possible causes include alternator bearing failure, blocked starter solenoid, damaged insulation, or corroded connections.
 5. Developing and providing visual prompts to assist drivers in managing the abnormal vehicle effectively.
- B. Exhibit the following characteristics:
 1. Openness to interoperability by exchanging information with the sensor network and responding to signals received regardless of the vehicle's configuration.
 2. Adaptability to various scenarios, including those influenced by initial conditions and random factors. Therefore, assessing the current state of the STT should be based on both the analysis of the distribution of operational parameter values for occasional threats and the analysis of anomalous value sets for surprising threats.
 3. Functional activity capable of self-organization (e.g., optimizing sensor network efficiency by promptly addressing faults), self-regulation (e.g., adjusting information provided to the driver in response to abrupt changes in the parameters

of operating processes), and self-improvement (e.g., continuously enhancing performance).

4. Synergy is achieved through supporting the interoperability of sensor networks that provide condition information, controllers that regulate component functions, and CPU microprocessors. This interoperability improves the system's overall effectiveness.
5. Resilience to degradation processes caused by changes in the external or internal environment [55,56]. Ensuring reliability, sustainability, and transportation safety.

4.2. Structure of the Early Fault and Anomaly Detection System as a Cyber-Physical System

To fulfill the outlined requirements, the in-vehicle monitoring system should comprise the following components:

CDIF Classifier Module (Classifier to Defect and Identify Faults). This component monitors, detects, and identifies faults using statistical data (History-Based Fault Diagnosis), measurements (Hardware-Based Fault Diagnosis), and modeling outcomes (Model-Based Fault Diagnosis) [57].

DIPCA Module (Dynamic Inner Principal Component Analysis). Task: monitors the condition of vehicle components and analyzes changes in conditions over time [58].

Experience has indicated that the EF&AD system should include the following additional modules:

1. Module for Mapping Faults and Abnormal Surfaces. During transport operations, identifying vehicle faults is part of the driver's responsibilities, typically supported by fault codes or indicator lights on the control panel, according to Tables 7 and 8.
2. Knowledge Fusion for the Deep Multi-Learning Module. This module extracts valuable explicit information recorded by sensors. In AIL transport, it is also crucial to detect hidden information by evaluating the likelihood of operational disturbances from rare faults (e.g., issues in the exhaust system) and the consequent multiplicative effects (e.g., decreased engine performance). It analyzes areas of anomalous parameter values and integrates data from various sensors to predict potential faults.
3. Preventive recommendation module. It is useful in cases with a high likelihood of faults, providing recommendations to the driver:
 - Routine—for occasional situations, it suggests actions such as changing driving modes or reducing speed to prevent fault propagation in vehicles—PFPV.
 - Non-routine—for surprising scenarios, like a steering system failure, it might suggest actions such as attempting to restart the engine, unlocking the steering by turning the ignition key, and engaging the brakes simultaneously.

Table 7. Characteristics of anomalies in selected operating parameters for monitored STT components for isolated anomalies.

Types of Anomalies	Characteristics of Anomalies in Selected Operating Parameters of Monitored Vehicle Components	Features of Operating Parameter Anomalies
Bias	Constant deviation of measured values. Measurements indicate a shift by a constant value from nominal values.	They occur sporadically in ROF (Randomly Occurring Fault) mode. They do not follow any rules and are typically caused by wear, corrosion, or aging.
Drift	Gradual deviations in measured values. Measurements indicate a shift over time.	
Freezing	Lack of response of measurement results to changes in the dynamics of monitored parameters.	
Noise	Random fluctuations in measurement results unrelated to changes in the dynamics of monitored parameters.	

Source: Own elaboration based on [54].

Table 8. Characteristics of anomalies in selected operating parameters for monitored STT components for continuous change anomalies.

Types of Anomalies	Characteristics of Anomalies in Selected Operating Parameters of Monitored Vehicle Components	Features of Operating Parameter Anomalies
Steady uptrend/downtrend	Gradual changes in anomalous values of operating parameters without abrupt changes.	These occur as RONS (Randomly Occurring Nonlinearities) due to disturbances in the operating processes.
Unsteady uptrend/downtrend	Regular (sinusoidal) or abrupt changes in anomalous values of operating parameters.	

Source: Own elaboration based on [54].

Continuous anomalies are detected based on the process capability index C_p , calculated as follows:

$$C_p = \frac{USL - LSL}{6\sigma} \quad (1)$$

where σ is the standard deviation calculated from the data obtained from the process.

Isolated anomalies are detected using the DBSCAN (method based on the evaluation of values of selected operating parameters and their classification).

The recommended procedures in this regard include the following [59,60]:

- Collecting data on the values of the operating parameters of individual vehicle systems;
- Performing a detailed analysis of the collected data and its clustering;
- Detecting anomalies and predicting potential short-term changes.

As recommended in [61], the idea of determining AN anomalies is to detect such values of the operating parameter $P(A)$, which significantly deviate in the time series (t_i) from the nominal values $P(\theta)$. Such an assumption can be written as follows:

$$\exists AN \ni \forall \{P[A(t_i) < P(\theta_p) \wedge P[A(t_i)] > P(\theta_p)\} \quad (2)$$

where

t_i is the i -th time point;

$P[A(t_i)]$ is the abnormal value of the monitored parameter at time t_i ;

$P(\theta)$ is the threshold value of the monitored parameter.

4.3. An Anomaly Detection Based on the DBSCAN Algorithm

The DBSCAN (Density-Based Spatial Clustering of Applications with Noise) method is orchestrated to extract points from three categories:

1. Baseline corresponds to normative values of measurable parameters. Located at a threshold distance from the main reference point.
2. Borderline. Located at threshold distances between neighboring baseline points and assessed by the Local Outlier Factors (LOFs) indicator.
3. Outliers correspond to above-normal values of measurable parameters. Located at an off-threshold distance from the main benchmark point.

The execution process of the DBSCAN algorithm is depicted in Figure 6.

The algorithm DBSCAN. Clarification.

The developed algorithm provides an opportunity to discover new knowledge about the reliability of processes occurring in the trajectory of AIL transports by repeatedly testing the relevance of the developed concept with a description of the possible consequences of its application. It is based on the assumption that changes in the cluster density of the measured parameter values are random and that multiple measurements of these values contribute to a clear difference in these densities. Two supporting parameters were required to perform the ba-d study:

- i. EPS—defines the neighborhood radius around the x-point under study. It is called its ϵ —neighborhood.
- ii. MinPts—defines the minimum number of neighbors within the “EPS” radius.

Consequently, the probability of detecting clusters of supernormal values of measurable parameters/generating an input set of anomalous points for the developed algorithm increases with time. The detected anomalous points are then sorted in ascending order and mapped to create a message to the driver (Figure 7).

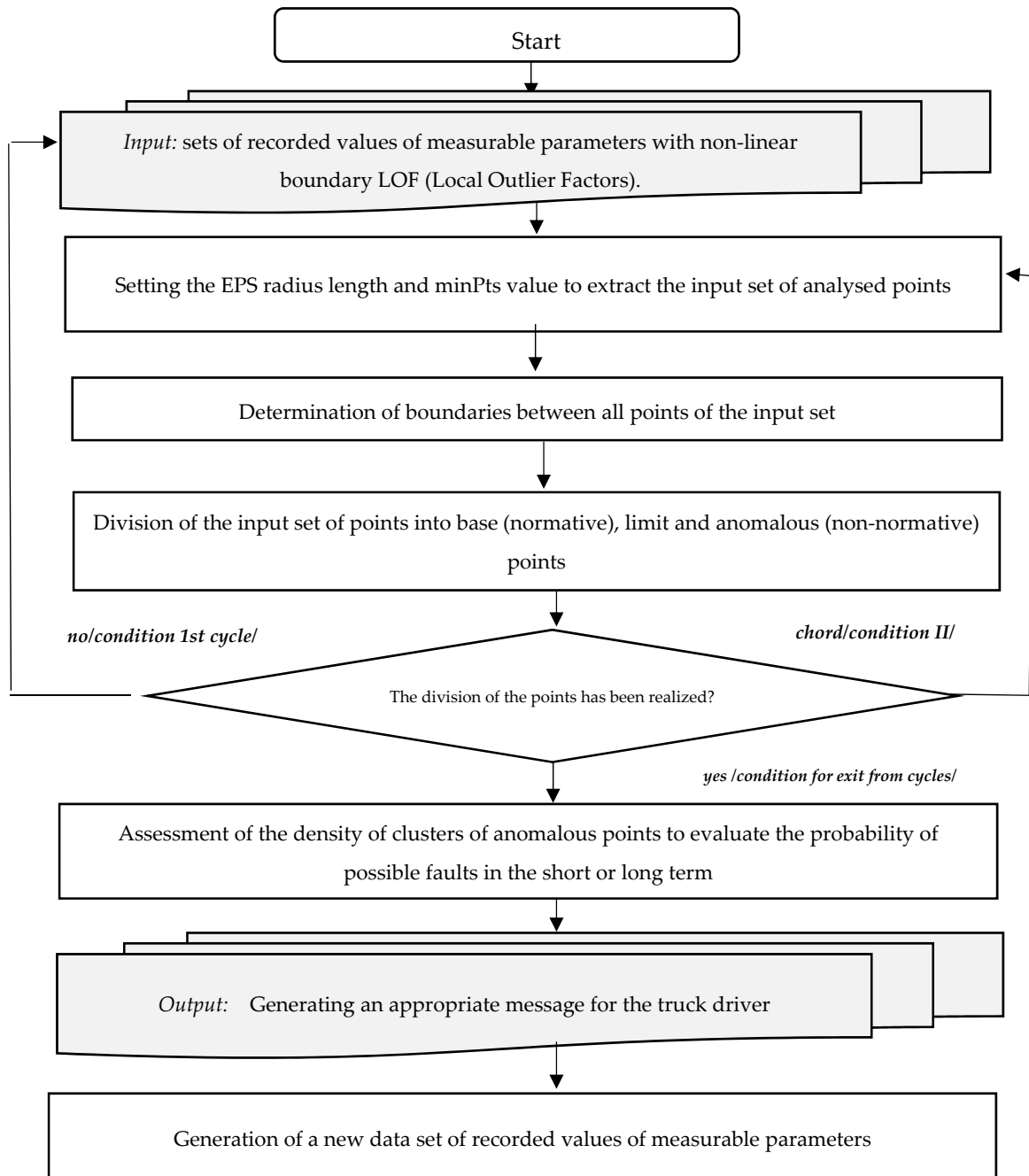


Figure 6. Flowchart of the steps involved in solving a anomaly mining task.

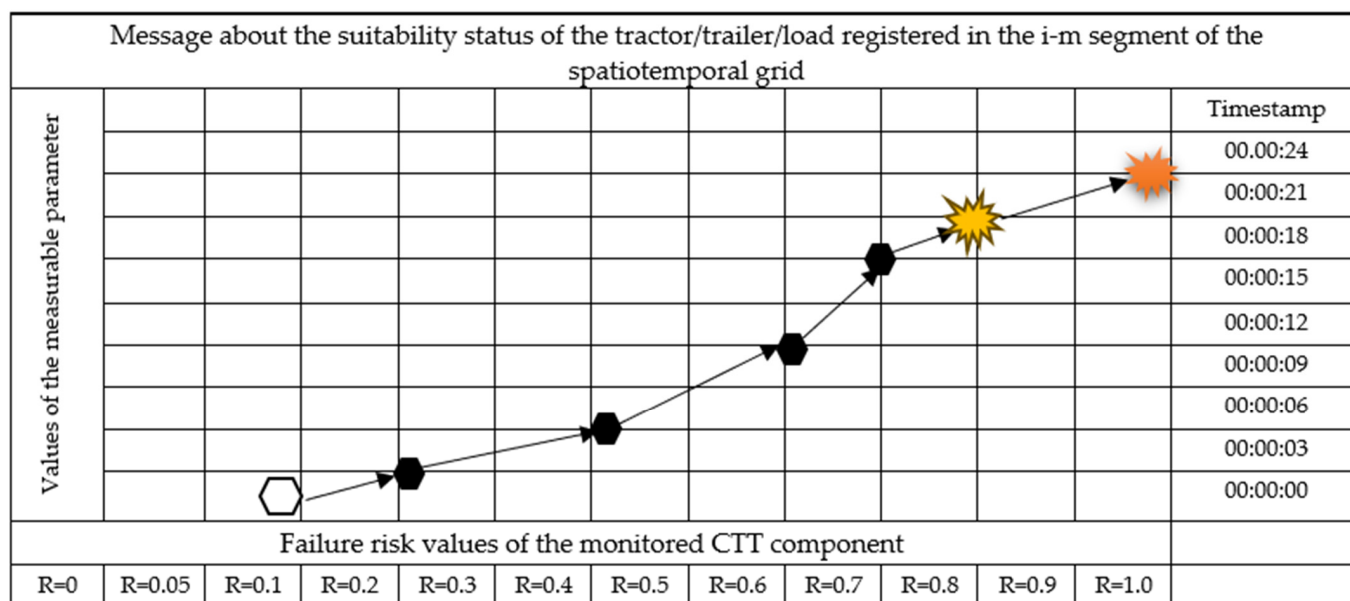


Figure 7. Przykład komunikatu graficznego wysyłanego kierowcy ciągniku siodłowego.

Advantages of the DBSCAN algorithm used in the study:

1. It is oriented to detect three-dimensional clusters of measurable parameter values of any shape;
2. It is adapted to detect both baseline and anomalous points;
3. It does not require the assumption of patterned shapes of the sought clusters into the algorithm;
4. It has an above-average speed for detecting points with anomalous values;
5. During the analysis of clustering results, the shapes of the examined clusters are not distorted;
6. If necessary, there is a possibility to take into account exceeding the measurable values of parameters, i.e., to extract, i.e., “anomalous points”, which, in our case, are the points of interest because they indicate non-normative values of measurable parameters of both individual CTT systems and their structural elements.

An abnormal point in the time series corresponds to an abnormal parameter value indicating the occurrence or high probability of a fault event. The fragment of the experiment results is shown in Figure 8.

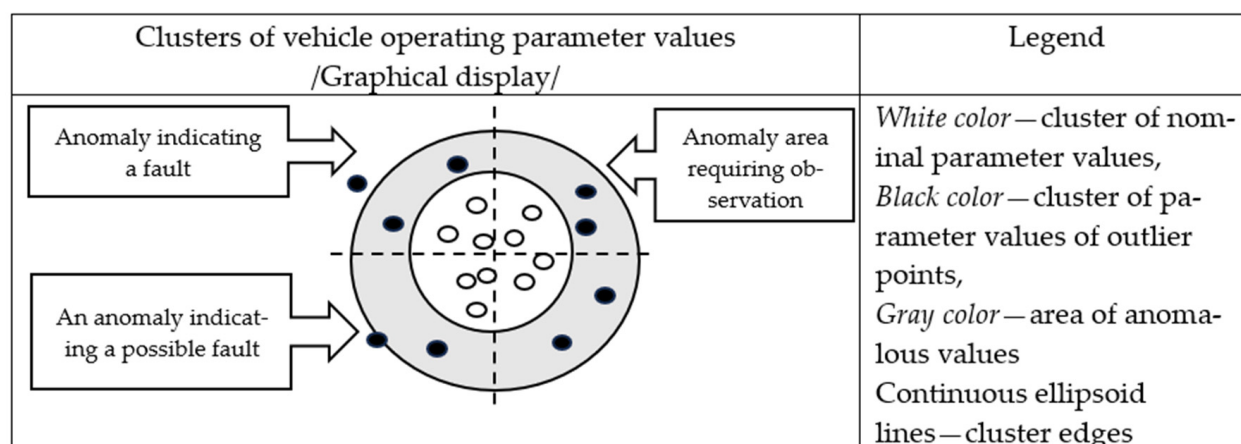


Figure 8. The vehicle operating parameter clustering based on DBSCAN Me.

The final component of the concept of monitoring the condition of STT as a whole proposed in this paper involves diagnosing both existing and potential faults and providing relevant information to the driver. This represents an original development that can be integrated into transportation systems. The research findings allowed for the assessment of a three-level model designed to monitor, diagnose, and predict both occasional and surprising threats while considering the risk of losing STT's transport capability.

4.4. Substantive Fundamentals for Future Research

Literature studies [62–64] have shown that engine, suspension, chassis, etc., components are constantly exposed to dynamic loads acting on the vehicle. These contribute to the development of microscopic manufacturing defects and their gradual transformation into faults. Thus, the monitoring system should not only identify abrupt changes in measured operating parameters but also detect anomalies and their variations, which are analyzed on a cluster-by-cluster basis. This approach enables the identification of unacceptable changes in operational process modes that could adversely affect other processes in the short term. There are two types of anomalies, which are detailed in Table 6.

- Isolated—describing short-term, atypical parameter values that appear sporadically during the operating process. They are evaluated using the LOF indicator, which computes the local density deviation of the tested point with respect to its neighbors. This may be a symptom of a fault that will develop in the short term.
- Continuous—describing constant changes in the values of operating process parameters due to their disturbance. For instance, a decrease in the injector opening pressure can influence the dynamics of temperature and pressure changes in both the working gas in the cylinder and the exhaust gases. Changes are evaluated within the LSL (Lower Specification Limit) and USL (Upper Specification Limit) using the process capability index C_p .

5. Conclusions

The accuracy and availability of information recorded with OBD systems and the efficiency of its transmission to drivers are essential to supporting the decision-making process undertaken by the truck driver in the traditional freight market. In the case of the AIL freight market segment, the availability and accuracy of information provided to drivers by the OBD system are prerequisites but not guarantees that the services provided will be delivered at the expected level of quality. The methodology proposed in the article takes into account best practices for ensuring the readiness of fleets of oversize vehicles and defines conditions for increasing the quality of these services.

The manuscript proposes the concept of an integrated three-level ASO (Active Warning System) based on the AOP (All-in-One Platform) principle, using the DBSCAN algorithm to detect anomalies in the measured values of operational parameters. The work on this concept was based on extensive literature studies. The results of the analysis of the available publications highlighted the need to upgrade the OBD systems currently in use, particularly in relation to non-normative vehicles. According to the author's concept, the primary task of the proposed ASO is to collect and transmit information to drivers about the current performance of STT systems as well as predictions about possible minor and major faults and malfunctions that threaten an unscheduled stop of this means of transport in the near future. An important distinguishing aspect of such an ASO is the assumption that the recorded information should be communicated to the driver in graphic form.

The overall objective of the study was to determine whether providing non-emergency information to drivers of non-emergency vehicles could help reduce unscheduled downtime. In contrast, the specific objective was to gain an understanding of the operational characteristics of ASO as a third-generation system that could replace the currently used OBD II. It was shown that such a system should be implemented as an integrated platform for monitoring, diagnosis, and mapping of faults capable of preliminary assessment of

risks and the proposal of preventive measures for these risks, displayed on a 3D monitor. According to the authors, such an ASO can be used for the following:

- Detecting sequences of changes and measuring operational parameters of the new states of efficiency of the monitored STT systems with an indication of the risk of their failure in the time dimension;
- Planning of drivers' actions to prevent unscheduled interruptions of transport services;
- Creation of a knowledge base that will be taken into account in the trajectory of the next planning of transport works, as well as in the improvement of used measuring-diagnostic equipment and software;
- Support T&L companies in managing their fleet of oversize vehicles (e.g., in evaluating the effectiveness of their transport work schedules, planning their maintenance, as well as the appropriate ordering of spare parts for their repair).

The proposed third-generation OBD focuses on three main application areas:

- I. Reducing the risk of tractor-trailer as well as semi-trailer adaptation to haulage, which is a key factor for the competitiveness of T&L companies. This area refers to supporting the physical reliability of these means of transportation. It does not cover more complex aspects, such as the risk of unfitness of the "tractor-trailer + like semi-trailer" combination as a whole.
- II. The overall readiness of the set "tractor-semi-trailer + like semi-trailer" to transport capacity on different transport routes and in different weather conditions, both within city limits and in suburban areas.
- III. Specific readiness of the set "tractor-semi-trailer + like semi-trailer" to transport AIL with the geometric parameters and weights established in the transport contracts, with appropriately limited speed.

Practical knowledge of the stability of the provision of transport services on the AIL transport segment gained by interpreting the results of each of their deliveries carried out is required for the purpose of preventing accidents in the future, as well as ongoing repair and maintenance tasks. The developed concept is a theoretical solution, as are the assumptions of the conducted analyses. Future research will focus on experimental studies to clarify it and make possible adjustments.

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