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Assessment of the diagnostic significance of freight wagon subsystems using the Shannon entropy method

Franciszek Restel[1*], Mateusz Oziębłowski[1], Martin Starčević[2]

[1] Department of Technical Systems Operation and Maintenance, Faculty of Mechanical Engineering, Wroclaw University of Science and Technology, 27 Wyspianskiego Str., 50-370 Wroclaw, Poland
[2] Department of Railway Transport, Faculty of Transport and Traffic Sciences, University of Zagreb, ZUK Borongaj, Borongajska cesta 83a, 10000 Zagreb, Croatia
* Corresponding author's e-mail: franciszek.restel@pwr.edu.pl

ABSTRACT

This study presents a data-driven approach to determining the diagnostic significance of freight wagon components using Shannon entropy method combined with multi-criteria decision analysis. The research is based on operational data from 24888 incidents recorded on five railway lines in south-western Poland during 2009–2013. Six principal wagon systems were evaluated: wheel sets, axle bearings, suspension, brakes, wagon coupler and wagon body. A decision matrix was developed taking into account five criteria: participation in incidents, percentage of incidents without confirmation of emergency status, diagnostic error probability, potential need for re-homologation, and the number of components that can be diagnosed using a single system. Following normalization and application of Shannon entropy method, weights were assigned to each criterion. The results show that wheel sets represent the most diagnostically significant component (score: 0.98 on a scale of 0–1), followed by axle bearings (0.61) and suspension (0.43). The use of Shannon entropy minimizes the subjectivity inherent in expert assessments. The presented method allows the determination of the diagnostic significance of individual freight wagon components, which allows for effective prioritization during the implementation of diagnostic systems.

Keywords: freight wagon diagnostics, Shannon entropy method, diagnostic significance

INTRODUCTION

The safety and reliability of rail transport systems depend to a large extent on the correct identification and assessment of component criticality and risk levels. Modern railway operations require a systematic approach to understanding which elements pose the greatest threat to continuity of service, passenger safety, and economic efficiency. In [1], the authors proposed an extended FMECA (failure mode, effects and criticality analysis) method for assessing the criticality of components in railway wagons, introducing additional criticality indices. This method is based on real operating data and reliability models. It allows the identification of components with the highest failure rate. In paper [2], it was also noted that sources of failures of trains can originate already at the production stage of individual parts. The paper presents a systematic quality component risk assessment for railway components, integrating two methods: FMEA (failure mode and effect analysis) and FTA (fault tree analysis). The most significant defects were identified and subject to detailed cause analysis. In [3], risk assessment methods, including FMEA analysis and statistical analysis of failures, were used to identify and assess critical elements of railway rolling stock, the failure of which can lead to serious consequences for safety and reliability. These methods were used to analyze operating data and determine prevention action priorities and the selection of remedial measures in rolling stock maintenance. The authors of [4] introduce a new objective method for determining the RPN (risk priority number) criticality threshold in an FMEA method based on finite difference. Eliminates the subjectivity of traditional approaches through algorithmic detection of the first significant local maximum in the RPN value distribution. Analyzed using the example of train HVAC systems. The article [5] presents the practical application of FMECA analysis to assess the risk of failure in the passenger door system of rolling stock. The case study is based on an analysis of data on door failures on Class 380 trains in Scotland, indicating which failure modes and components are most critical to reliability and safety. This publication demonstrates the real-world use of FMECA for component risk prioritization and supports effective rolling stock maintenance planning. A modern approach to determining the criticality and prioritization of risks for railway train components has been presented in article [6]. The authors propose extending the classic FMEA method by combining Cumulative Prospect Theory with Type-2 intuitionistic fuzzy logic (TFNIFN) and the VIKOR multi-criteria compromise algorithm. The publication [7] presents an advanced risk analysis model using type 2 fuzzy logic with intervals (IT2-FLS) for railway infrastructure projects. Tested on projects in Serbia. It takes uncertainty into account through higher-order fuzzy membership functions. The authors of the article [8] describe the application of the FMEA method in railway signaling system designs. They discuss the effectiveness of the method at the design stage as part of the safety management process. They present a Safety Case for two separate railway signaling systems. The article [9] presents the diagnostics of urban rail vehicles using FMEA and fuzzy set theory. It develops a computer-aided decision support system for the maintenance strategy of subway vehicles in Shanghai. It uses fuzzy FMEA assessment. The article [10] presents a systematic analysis of the quality risk of railway components by integrating classic FMEA with FTA. Using the example of railway wagon production, it analyzes the defects that occur, determines their RPN, performs a Pareto analysis and related FTA to identify the root causes. In [11] the authors compare two methods of modeling the safety of critical elements in railways: FTA and BN (Bayesian Networks), and their applications in analyzing the causes of derailments after SPAD (signal passed at danger) incidents. The paper [12] analyzes the reliability and availability of the 6Dg diesel locomotive using fault tree analysis (FTA) and Monte Carlo simulation. It models the impact of component failures on rolling stock reliability, identifies the weakest links, and estimates availability indicators. The authors of paper [13] describe a method for prioritizing the risks of failure modes in mining wagons. It uses a combination of FMEA and AHP (Analytical Hierarchy Process) in a fuzzy environment. It analyzes main components of wagons transporting iron ore in a mine in Sweden. The authors of [14], used an analytical method based on an AHP, using fuzzy consistent matrix, to assess risk in an urban rail transport system. This method allowed for the identification and ranking of the most important risk factors, based on experts' opinions and operating data. The article [15] presents an advanced RCM (reliability-centered maintenance) methodology for rolling stock, based on RBD (reliability block diagrams). The authors implement a detailed assessment of component criticality based on reliability parameters – indicators such as MTTR (mean time to repair), MTTF (mean time to failure), analysis of the impact of repairs on reliability, criticality indices, and sensitivity analysis. The case study concerns the metro in Tabriz (Iran).

The article [16] discusses risk assessment methods in the context of rolling stock maintenance. The authors point out that maintenance has a key impact on safety and operational reliability. The paper presents various risk assessment methods (including FMEA, FTA, Pareto analysis) and their application in the design, operation, and maintenance of rail vehicles. The article [17] describes the application of the STPA (System-Theoretic Process Analysis) method for the systematic identification of hazards and critical safety situations during the remote operation of automated trains (GoA4). The paper identifies key critical situations, analyzes the control and interaction structure, and proposes preventive measures in vehicle architecture and operation, comparing STPA to traditional FMEA/FTA. Publication [18], analyzes the legal requirements and practices concerning SCC identification on the Polish railway market, presenting examples of the most frequently identified critical elements. The author also compiled his own list of critical elements based on an analysis of available publications and data from Polish entities involved in the maintenance of rail vehicles. The article [19] presents an advanced approach to risk analysis in transport systems, combining traditional FTA, DFT (dynamic fault trees), and fuzzy logic. This model allows for the consideration of not only typical technical failures, but also subjective factors such as human error and the impact of fatigue and untrained personnel. In the railway segment, it was indicated that both engineering and human factors have the greatest impact on global risk. The article [20] presents an innovative Picture Fuzzy MARCOS (Multi-Attributive Ideal-Real Comparative Approach) approach for railway infrastructure risk assessment, combining fuzzy logic with the MARCOS method. The authors utilize a hybrid approach combining subjective (Fuzzy PIPRECIA) and objective Tsallis-Havrda-Charvát entropy) methods for criteria weight determination. The authors of paper [21] developed an integrated Entropy-Fuzzy PIPRECIA-DEA (PIvot Pairwise RElative Criteria Importance Assessment – Data Envelopment Analysis) model for safety evaluation of railway sections in Bosnia and Herzegovina. The model combines the entropy method (for input criteria) with the fuzzy PIPRECIA method (for outputs) and DEA analysis. This work [22] uses Shannon entropy to objectively determine the weights of criteria in the multi-criteria analysis of intermodal transport. The entropy method permits mathematical determination of the significance of individual criteria without involving subjective expert evaluation, leading to more objective results in selecting transport technologies.

The review clearly shows progress in railway risk assessment methods, evolving from basic approaches to advanced hybrid models. Important developments include using fuzzy logic to manage uncertainty, applying multi-criteria decision-making for better prioritization, and employing objective weighting methods like Shannon entropy to limit subjectivity. These improvements allow for more accurate detection of critical components, data-driven maintenance planning, and stronger safety and reliability in rail operations.

RESEARCH METHODOLOGY

Operational data analysis

Taking advantage of in-service experience in the years 2009–2013 on 5 railway lines in south-western Poland, 24888 unfavorable incidents were analyzed. A database has been constructed basing on diverse public available sources (for example Infopasażer, Portal Pasażera) and own observations conducted independently as well as in cooperation with railway companies. Rail traffic on the railway lines was mixed – passenger and freight. About one-fourth of the incidents had their cause in passenger trains, and one-eighth in freight trains. The aim of further analysis was to determine the impact of vehicle failure on the operation of the railway system. The incidents were initially divided into four groups:

- related to infrastructure,
- related to the impact of the environment,
- related to the activities of passenger carriers,
- related to the activities of freight carriers.

For each group of incidents, the total amount of primary and secondary delays resulting from these incidents were calculated. Then, the share of each group in the total delay was determined. Due to the significant participation of freight trains in delays, the incidents associated with the activities of freight carriers were divided into two further groups, i.e.:

- commercial, organizational or related to traction vehicles incidents,
- incidents related to wagons.

The results are shown in Figure 1. The conducted tests were dominated by the effects of incidents involving freight trains, despite the higher number of incidents involving passenger trains. Therefore, diagnostic tests for freight wagons were selected, also due to their specific design and operational characteristics:

- they are characterized by a simple construction,
- they allow for relatively easy installation of diagnostic equipment without complex adaptation,
- they do not undergo continuous diagnosis, but only periodic checks while passing checkpoints or stations,
- damage may not be noticed by the train driver for hundred meters, which could cause a fire or damage to infrastructure.

Selection of wagon systems for diagnostic tests

Analyzing the operating data, four current sources of knowledge about potential failure states of freight wagons were observed:

- track-based diagnostic devices,
- infrastructure employees,
- train drivers,
- third parties.

The share of individual sources for the considered operating data is shown in Figure 2.

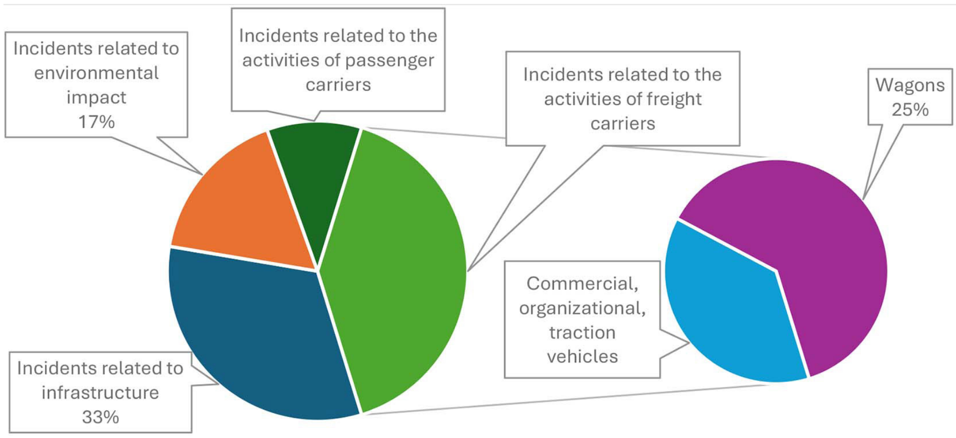

Figure 1. Share of each group in the total amount of delays

Incidents detected by drivers mainly concerned damage to the brake system, which usually caused the entire train to stop. It should be noted that when individual wagons are braking, the driver's ability to detect the incident is limited. Only in some cases can an experienced train driver notice changes in power and associate them with the wagon stopping. Infrastructure employees are train dispatchers, signallers or watchmen. They visually or acoustically identify damage of the brake or the wheel set and load-related anomalies. It should be noted that in older traffic control systems, infrastructure workers are represented on average every 3.5 kilometers, which allows for frequent observations of the same trains. It should be noted that these individuals have varying degrees of sensitivity to visual or acoustic diagnostic signals. On the other hand, at busy stations and remote signal boxes, it is almost impossible to identify faults in passing trains. In addition, traffic control is now centralized in local control centers, which also limits the use of this type of diagnostics.

Track-based diagnostic devices account for the largest share of detected faults. They are used to detect faults in the running gear of rail vehicles, including:

- flat spots of wheels,
- dynamic overloads,
- overheated wheelset,
- overheated axle bearings,
- overheated brakes,
- exceeded load.

These devices are gaining importance, but their implementation is slow. Currently, these devices occur on Polish tracks on average every just about 90 km.

Identification of key freight wagon systems

Taking into account the characteristics of sources of information about failure states of freight wagons, it can be concluded that the diagnosis of these vehicles is discrete, error-prone and incomplete. Therefore, the role of on-board diagnostic systems increases, which with advance can indicate the occurrence of a failure state.

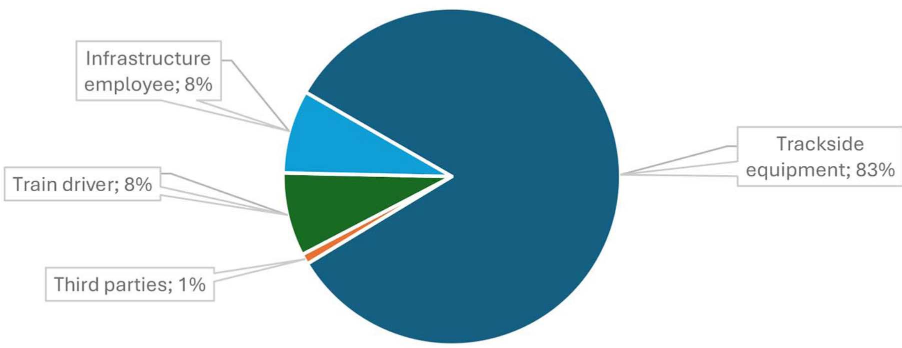

Figure 2. Share of each source of knowledge about potential failure states

The structure and capabilities of the diagnostic system depend significantly on the constructive-functional structure of the technical object. The wagon is supported on the running gear, i.e. on a turnover truck. The truck transfers forces in all directions between the wagon frame and the track. The wagon frame serves as a support for the superstructure and independently from the construction must also transfer at least longitudinal tensile and compressive forces originating from the coupling devices of the wagon coupler. If the body is not self-supporting, the frame also serves as a supporting structure for it. The wagon body frame contains in itself the setting elements of the brake (cylinder, ties, load setting lever, hand brake and brake release and deactivation devices). The wagon coupling, in the case of a freight wagon, contains in addition to the mechanical connection also the pneumatic main brake line coupling, and in exceptional cases also the coupling of the main tank line. The general structure of a freight wagon is shown in Figure 3.

The most complex system in freight wagon is the running gear. Its detailed construction is presented in Figure 4.

The following systems have therefore been specified to characterize the origin of the damage or incident:

- wheel sets
- axle bearing
- suspension
- brakes
- coupler
- body

The share of individual systems as the cause of incidents is shown in Figure 5.

Categorization of incidents

In order to determine the significance of introducing diagnostics for a given system, incidents caused by the wagon system were divided into three categories showing the decision taken in connection with a given report of a potential failure:

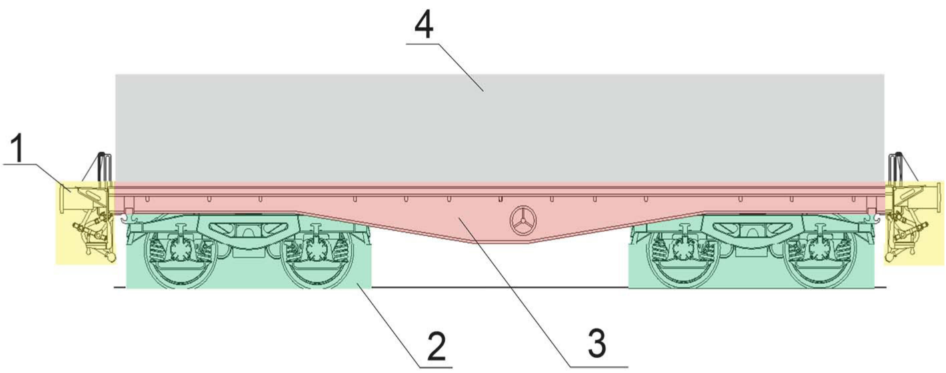

Figure 3. The general structure of a freight wagon: 1 – wagon coupler, 2 – running gear, 3 – wagon frame, 4 – wagon body

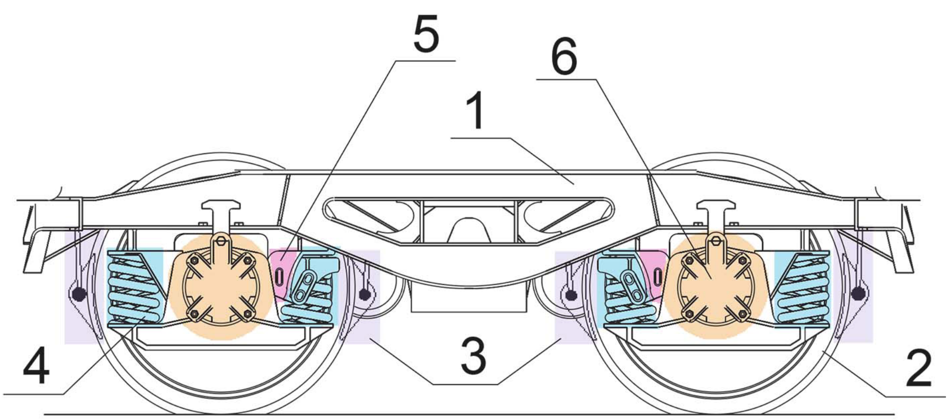

Figure 4. Construction of the running gear: 1 – bogie frame, 2 – wheel set, 3 – friction elements of the brake, 4 – suspension springs, 5 – suspension damping elements, 6 – axle bearing

- no irregularities were found,
- the condition of the wagon was assessed as non-hazardous,
- wagon withdrawal, repair, dispatch to repair at reduced speed.

Figure 6 presents the results of incident categorization and decisions made for analyzed systems. When a wagon was taken out of service, repaired, sent in for repair at reduced speed, the damage was recognized and classified as critical for traffic safety. As a result, the wagon was repaired on site after diagnostics or transported to a workshop.

Recognition of the wagon condition as non-threatening was preceded by prior confirmation of anomalies, and then classified by the driver or inspector as not critical. It should be noted that the decision-maker may have knowledge only of some of the symptoms indicating a failure state, while full knowledge would have resulted in a different decision. No finding of anomalies was preceded by verification. Similarly to the above case, the diagnosing person could have incomplete knowledge about the symptoms.

Expert opinion survey

In connection with measurement uncertainty, 6 inspectors with at least 5 years of experience were surveyed to estimate the probability of diagnostic error due to limited access to a component

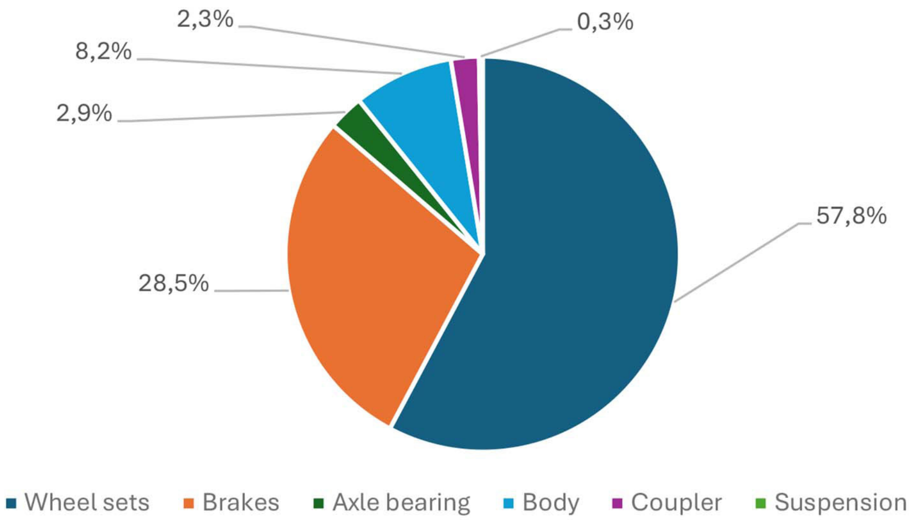

Figure 5. Share in the number of incidents resulting from failures of a given system

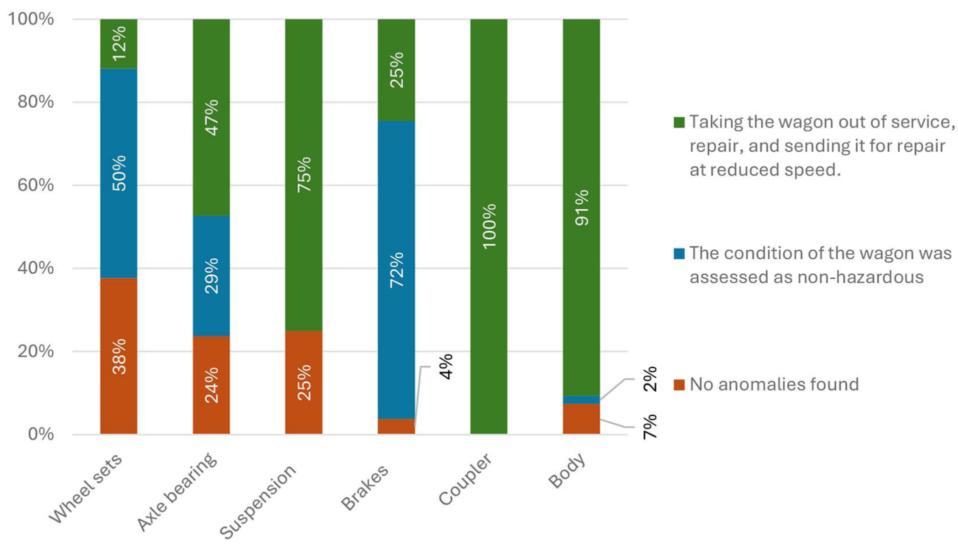

Figure 6. Share of decisions for each analyzed system related to the reported potential failure condition

or difficulty in identifying damage during vehicle stop. The experts linguistically chose the level of probability by selecting one of the possible ratings:

- probable – 5,
- rather probable – 4,
- possible – 3,
- rather impossible – 2,
- impossible – 1.

Then, using the same scale, they determined the probability that installing a diagnostic device (examples of possible solutions were provided) to a given system may cause interference in the construction and require the need for re-homologation of the wagon. The results, presented as mean expert assessments on a five-point Likert scale, are shown in Figure 7, where a score of 5 indicates the lowest probability and a score of 1 the highest.

Diagnostic capabilities

An analysis of the symptoms of damage to individual components was performed. Diagnostic methods that can be used during train stop were specified, as well as transducers that can be used for diagnostics. The collected data was placed in Table 1.

The analysis of the presented data shows that wheelsets, axle bearings, and the suspension can be diagnosed together using the same diagnostic system. In all three cases, the primary fault symptoms are related to vibration, so the use of a common vibration diagnostic system allows simultaneous monitoring of their technical condition. This is another criterion in determining the diagnostic significance of the considered freight wagon components.

DEVELOPMENT OF A METHOD

Shannon's entropy method

In the field of multicriteria decision analysis (MCDA), one of the key stages is the determination of criteria weights, which reflect their relative importance in the decision-making process. An objective and widely used approach for this purpose is the Shannon entropy method. Shannon entropy itself is a fundamental concept in information theory that determines the degree of uncertainty or disorder of a random variable [23, 24]. Mathematically, it represents the average amount of information contained in a probability distribution: the more uniform the distribution, the higher the entropy and the lower the predictability of the outcome. As a result, a low-entropy distribution implies high information content associated with significant variability in the data structure. In the context of decision support, the application of this concept allows for the determination of weights based on the dispersion of assessments in the decision matrix, reducing the subjectivity often associated with expert evaluations. The Shannon entropy method assumes that a criterion with more diverse assessment values (showing greater dispersion) brings more information to the decision-making process and should be assigned a greater weight. Criteria for which all alternatives have similar values are less important because they offer limited discriminatory power between options.

Compiling a decision matrix

We compiled the research results into a decision matrix presented in Table 2. The base for

Table 1. Failure symptoms and applied diagnostic methods and transducers in railway vehicles

Parameter	Diagnostic method during train stop	Diagnostic symptoms during movement	Diagnostic signal transducers
Wheel sets	Visual (prone to error) or in-workshop (time-consuming)	Vibration, noise (knocking), brake sticking	Vibration transducer
Axle bearings	Visual (prone to error) or in-workshop (time-consuming)	Vibration, noise, high temperature of bearing	Vibration transducer, Temperature transducer
Suspension	Visual (only mechanical damage)	Vibrations, noise	Vibration transducer
Wagon body	Visual	Suspension deflection	Vision system, limit sensors, strain gauges
Coupler	Visual, acoustic	Train parting, pressure drop in the main reservoir pipe (air leak sound)	Limit sensors, pressure sensors
Brakes	Brake check (visual, acoustic)	Pressure drop in the main reservoir pipe, noise, high temperature of the wheel assembly (brake disc) or brake pads	Encoders, limit switches, temperature sensors

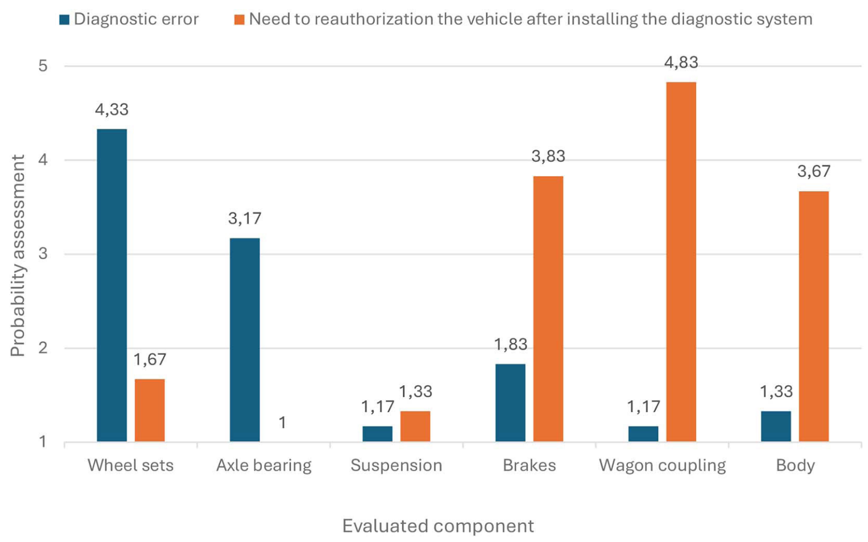

Figure 7. Mean expert assessments of system failure probability and diagnostic error probability (5 = lowest probability, 1 = highest)

Table 2. Decision matrix

Criterion Evaluated component	(1) Participation in incidents	(2) Incidents without confirmation of emergency status	(3) Diagnostic error assessment (5 – likely, 1 – unlikely)	(4) Assessment of the potential need for re-homologation (5 – likely, 1 – unlikely)	(5) Possibility of common diagnostics with one system
Wheel sets	57.8%	38.0%	4.33	1.67	3
Axle bearings	2.9%	24.0%	3.17	1	3
Suspension	0.3%	25.0%	1.17	1.33	3
Brakes	28.5%	4.0%	1.83	3.83	1
Coupler	2.3%	0%	1.17	3.67	1
Wagon body	8.2%	7.0%	1.33	4.83	1

calculation values presented in columns (1) and (2) was the constructed database consisting of knowledge from several mentioned data sources. Column (1) represents the participation percentage in all undesirable events caused by the given subsystem. In fact, it represents the conditional probability of failure occurrence in a given subsystem if a failure occurs. The probability of failure occurrence was not relevant for the presented approach, thus it was not estimated. Column (2) represents the percentage of events without confirmation of emergency status. It can be understood as the conditional probability that the event will be with no emergency confirmation if a failure occurred. The columns (3)-(5) represent experts' rating of diagnostic failure frequency, the possibility of re-homologation need as well as the possibility to use one diagnostic signal to get knowledge about several subsystems.

Normalization

In order to apply Shannon's entropy method to determine the weights of criteria by measuring the uncertainty of the information contained in the data, the obtained results were normalized using the min-max method, which made it possible to compare criteria with different scales and units. Almost all of the considered criteria are stimulants, the normalization of which describes Equation 1. The only exception is the assessment of the potential need for reapproval, which is a destimulant criterion. Its normalization describes Equation 2.

$$p_{ij} = \frac{x_{ij} - \min(x_j)}{max(x_j) - min(x_j)} \tag{1}$$

$$p_{ij} = \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)} \tag{2}$$

where: p_{ij} – normalized value of the i-th evaluated element and the j-th criterion, x_{ij} – original value of the i-th evaluated element and the j-th criterion, x_j – set of values of the j-th criterion.

Next, proportional scaling was performed to create a matrix of relative shares according to equation to Equation 3. The results of the calculations are presented in Table 3.

$$p'_{ij} = \frac{p_{ij}}{\sum_{i=1}^{m} p_{ij}} \tag{3}$$

where: m – number of evaluated components

Shannon entropy

Shannon entropy E_j for criterion j is expressed by the Equation 4.

$$E_j = -\frac{1}{\ln(m)} \cdot \sum_{i=1}^{m} (p'_{ij} \cdot \ln(p'_{ij})) \tag{4}$$

where: m – number of evaluated components.

Degree of diversification

For each criterion, the diversification d_j is calculated according to Equation 5.

$$d_j = 1 - E_j \tag{5}$$

The higher the diversification value, the greater the diversity of assessments and the greater the importance of the criterion.

Criteria weights

The weight w_j for criterion j is defined as the share of diversification of a given criterion in the total diversification of all criteria, which is described by Equation 6. The results of the criteria weights calculations are presented in Table 4.

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{6}$$

where: n – number of criteria

The results show that the most important criterion is the share of a given type of incident in the total, with a weight of 0.47, which accounts for almost half of the overall assessment. The next most important criteria is the share of incidents without confirmation of an emergency condition, with a weight of 0.28. The remaining criteria have significantly lower weights.

Final rates and ranking

The final assessment S_i is calculated as the sum of the products of the value p'_{ij} and the weights of the criteria w_j. This relation describes Equation 7.

$$S_i = \sum_{j=1}^{n} p'_{ij} \cdot w_j \tag{7}$$

The calculation results range from 0 to 1, with higher values showing a greater level of diagnostic significance of the evaluated components. The results of the assessment are presented in the chart in Figure 8.

The evaluation of diagnostic significance of the analyzed components clearly shows that wheelsets are the most important components, obtaining the highest overall score (0.98) and accounting for nearly 58% of all recorded incidents. Axle bearings place second in the ranking (0.61), followed by suspension (0.43). The next places in the ranking are taken by brakes (0.22), wagon body (0.11), and wagon coupling (0.01).

Table 3. Values after normalization and proportional rescaling

Evaluated component	Participation in incidents	Incidents without confirmation of emergency status	Diagnostic error assessment	Assessment of the potential need for re-homologation	Possibility of common diagnostics with one system
Wheel sets	0.59	0.39	0.53	0.25	0.33
Axle bearings	0.03	0.24	0.33	0.30	0.33
Suspension	0.00	0.26	0.00	0.28	0.33
Brakes	0.29	0.04	0.11	0.08	0.00
Wagon body	0.08	0.07	0.03	0.09	0.00
Coupler	0.02	0.00	0.00	0.00	0.00

Table 4. Calculated weights of criteria

Parameter	Participation in incidents	Incidents without confirmation of emergency status	Error Probability assessment	Assessment of the potential need for reauthorization	Number of systems that can be diagnosed together
Criterion weight	0.47	0.28	0.09	0.07	0.1

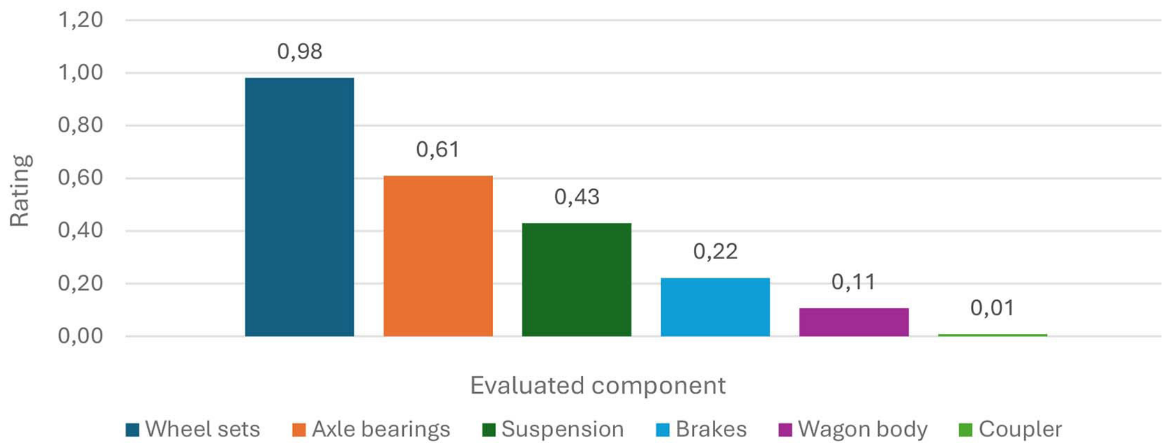

Figure 8. Results of the assessment of the diagnostic significance of railway wagon components

CONCLUSIONS

The research clearly shows the hierarchy of diagnostic significance of individual components. Wheels are undoubtedly the most important component, accounting for the majority of all recorded incidents and receiving the highest rating. The next highest ratings were obtained by axle bearings, followed by the suspension. The identical type of damage symptoms for these three components allows for the use of a single common diagnostic system, which further contributes to the economic aspect of installing a diagnostic system. The use of Shannon's entropy method to determine the weights of the criteria eliminates subjective expert opinions and replaces them with mathematically justified values. The weights determined showed that the most important criterion is participation in incidents (weight: 0.47), followed by the percentage of incidents without confirmation of an emergency situation (weight: 0.28). The other criteria were of much less importance, which allows for a more accurate reflection of the actual impact of individual factors. The presented method allows for determining the diagnostic significance of individual elements of freight wagons, enabling the setting of priorities during the implementation of diagnostic systems.

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