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A method for predictive maintenance of freight wagons taking into account reliability indicators and the risk of loss of serviceability

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Abstract

This article presents a method for predictive maintenance of freight wagons that integrates operational failure data with a probabilistic description of the failure-occurrence process, while retaining the logic of classical FMECA (Failure Modes, Effects, and Criticality Analysis). The method involves replacing selected coefficients with a continuous function of the cumulative distribution function, F(t), and introduces dynamic risk-mitigation priority indices, AP(t), and dynamic criticality classes, CP(t). These findings can serve as a basis for modifying the scope and frequency of maintenance activities, supporting the transition from a maintenance strategy based solely on cycles to a predictive maintenance strategy aligned with the principles of RBM (Risk-Based Maintenance) and RCM (Reliability-Centered Maintenance). The application of the method was demonstrated using operational data collected from a very large sample of 3,500 freight wagons over 96 months. The results obtained indicate that the method makes it possible to determine the point in time at which additional maintenance actions should be taken, and also serves as a basis for identifying and defining additional corrective actions, taking into account their implementation within the framework of the various functions of the MMS (Maintenance Management System).

Keywords: *freight wagons, predictive maintenance, FMECA, risk of loss of serviceability*

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Highlights

- A dynamic FMECA method combines operational failure data with Weibull reliability models.
- Dynamic AP(t) and CP(t) indices capture changes in risk priority and criticality over time.
- The method was applied to 3,500 freight wagons and 68 failure modes over 96 months.
- The results support risk-based inspections and hybrid RBM/RCM maintenance planning.

1. Introduction and literature review

The maintenance of freight wagons must ensure the required level of safety and reliability at an acceptable cost. In practice, freight wagon maintenance strategies are often based on fixed time or mileage intervals. The relationship between the adopted intervals and the level of risk or criticality from a reliability standpoint – which varies as a function of operating exposure (e.g., time) – is often described only in limited terms. Operational data collected by entities responsible for maintenance (ECM) represent a significant source of information for quantitative risk assessment.

The literature on this subject includes studies on risk assessment modeling in railway vehicle operation systems. One example is the study by Dinmohammadi et al., in which a risk assessment of rolling stock component failures was conducted using the FMECA method, based on the example of a railway vehicle door system [1]. This line of research was further developed in a subsequent paper by Dinmohammadi, who proposed a risk-based approach to optimizing the frequency of maintenance tasks for rolling stock components [2]. Appoh et al., in turn, presented a hybrid model that integrates reliability, risk, and maintenance decisions for a rail vehicle subsystem, highlighting the need to simultaneously consider the criteria of safety, reliability, and maintenance efficiency [3]. Wang et al. proposed a dynamic FMEA analysis for railway systems, in

which risk prioritization takes into account the variability of assessments over time [4]. Catelani et al., however, pointed out the limitations of the traditional thresholds used in FMECA analysis for railway safety systems and proposed a new approach to determining risk acceptance thresholds [5]. From a reliability assessment perspective, the work by Seyedan Oskouei et al. on identifying critical components from the standpoint of rolling stock reliability is also significant; it confirms the validity of a hierarchical approach to assessing the importance of individual system elements [6].

The literature therefore addresses risk assessment for railway systems using the FMEA and FMECA methods in accordance with the PN-EN IEC 60812 standard [7], as described in detail in a publication by the authors of this paper [8]. However, the results of this work, while valuable, do not always lead to a direct link between the assessment of risk and criticality from a reliability standpoint and the point at which additional maintenance actions should be taken.

2. Factors influencing the development of a maintenance strategy

The railway rolling stock maintenance system, which is a key element of the railway traffic safety system, is governed by a set of formal and legal requirements set forth, in particular, in the Railway Transport Act [9] and in the regulations and interoperability specifications relating to the maintenance of railway vehicles [10–14]. The implementation of ECM (Entity in Charge of Maintenance) certification and the use of a maintenance management system means that vehicle maintenance should be carried out in a traceable manner, in accordance with the maintenance documentation and safety requirements [11].

From a methodological standpoint, FMEA analysis according to standard [7] is one of many methods for explicit risk assessment. The purpose of the FMEA analysis is to assess the risks associated with the occurrence of hazards and to take measures to mitigate or eliminate those risks, particularly concerning hazards that are significant to the railway system. This method is a recommended tool in the RAMS procedure according to the PN-EN 50126 standard [15] and provides a systematic approach to identifying the causes and effects of potential failures. It can be applied at various levels of an object's decomposition. This is particularly true for highly complex systems, which railway systems undoubtedly are.

A review of regulatory acts and the literature [7,16–18] points to numerous limitations in the application of rigid RPN thresholds. Among these, it should be noted that:

- identical RPN values may result from completely different combinations of S, O, and D ratings, which means that the same values do not always represent a similar level of risk,
- types of failure modes with a low RPN may in fact pose a significant risk if their consequences are critical but occur rarely (high S value, low O value),
- different projects, systems, or stages of a system's lifecycle may require a tailored approach to risk that rigid thresholds do not account for,
- there is a risk that ratings could be manipulated to artificially lower the RPN below the acceptance threshold, rather than through actual improvements to the product or process.

The absence of a single dominant standard thus opens up opportunities to implement solutions better suited to the specific nature of the freight wagon maintenance system. Based on a literature review, it was determined that there is a need to define a method that allows for the integration of operational failure data with a probabilistic description of the process by which failures occur, while adhering to the logic of FMECA analysis.

3. Predictive maintenance method for freight wagons

3.1. Purpose and scope of the analysis

The limitations of classical FMECA analysis served as the starting point for developing a predictive maintenance method for freight wagons. The authors of the publication presented the principles and practical application of this analysis in [8]. The FMECA method includes the RPN and FMC indices, which, in their classical form, are static in nature, are based on semi-quantitative, non-empirical rating scales, and do not reflect changes in risk over time, taking into account its distribution within the asset's hierarchical functional structure. In practice, this means that it is not possible to track changes in risk levels over time or in relation to another variable. As a result, it is difficult to link the results of the analysis to the actual

operational process and to decisions regarding modifications (or the development) of maintenance strategies.

The goal of the developed method is therefore to establish a coherent approach that allows for the integration of operational failure data with a probabilistic description of the process by which failures occur, while maintaining the logic of classical FMECA analysis. The method is geared toward practical applications for freight wagons, for which the maintenance cycle is still largely determined by time- and mileage-based cycles that have developed over time.

The developed method consists of six steps, which are shown schematically in Figure 1. The concept behind this method is specifically designed for freight wagons and can be extended to other modes of rail transport. The purpose of the analysis may be to modify the current maintenance strategy, identify corrective actions, systemic changes, or recommendations to minimize risk, improve reliability, and reduce operating costs. The scope of the analysis may include, for example, the service life of a wagon from the completion of a periodic repair to a selected end point of the study, the identification of risks (failure modes) and an assessment of the probability of their occurrence as the service life progresses, an assessment of freight wagons' ability to maintain serviceability and operate safely under specified conditions, and the identification of components most susceptible to damage. It is important to identify the practices and principles that underpin the current maintenance strategy for the wagons under study. Consideration should be given not only to the documentation that entities involved in the maintenance of railway vehicles should possess and the scope that documentation related to the railway vehicle maintenance process should cover, but also to the overall approach to maintenance in the context of the MMS system in use and the procedures operating within that system – including the implementation of MMS functions.

3.2. Decomposition of the system's functional structure

The breakdown of a freight wagon's functional structure is essential for classifying operational data and subsequently aggregating the results of criticality assessments. Functional decomposition involves breaking down a freight wagon into assemblies, subassemblies, and components in a way that allows for the unambiguous assignment of the location of each type of defect and its functional significance within the system's structure.

To decompose a system, it is necessary to examine its structure at successive levels of detail, creating appropriate subsystems that are indivisible elements within the system as a whole. Subsequent higher levels of detail are again treated as independent systems divided into subsystems, which are considered indivisible elements. This approach allows for a multi-level representation of the system, with each successive level of detail reflecting the system as a whole. The universal structure of a rail vehicle is defined in the PN-EN 60300-3-3 standard [19]. It is specified in greater detail in the PN-EN 15380-5 standard, "Railway Applications – Classification System for Rail Vehicles – Part 5: System Classification Structure" [20].

The rail vehicle classification structures presented in the cited standards may be insufficient for reliability testing and risk assessment. In this case, taking into account the proposed standards, a hierarchical structure of the system should be developed by breaking the system down into subsystems, drawing on expert knowledge and experience. The universal structure defined in standard [20], which is used to decompose various rail transport systems into subsystems, served as the basis for conducting our own decomposition of the system under study – a freight wagon – into three levels of detail, where the first level should be interpreted as an assembly, the second as a subassembly, and the third as a component. Based on a three-level functional decomposition of the object of analysis, for each element interpreted as an independent system (an indivisible element), the failure modes that could occur in the system under study were identified. Taking into account the assumptions adopted for the new coding system, a multilevel code was assigned using the coding matrix at the lowest level of decomposition. Table 1 presents the results of the functional decomposition of the system and the identified failure types for one of the selected wagon subassemblies (the braking system). Overall, for a complete freight wagon at Level I, the following were included: running gear, braking system, draw gear and coupler system, body, underframe, and other components.

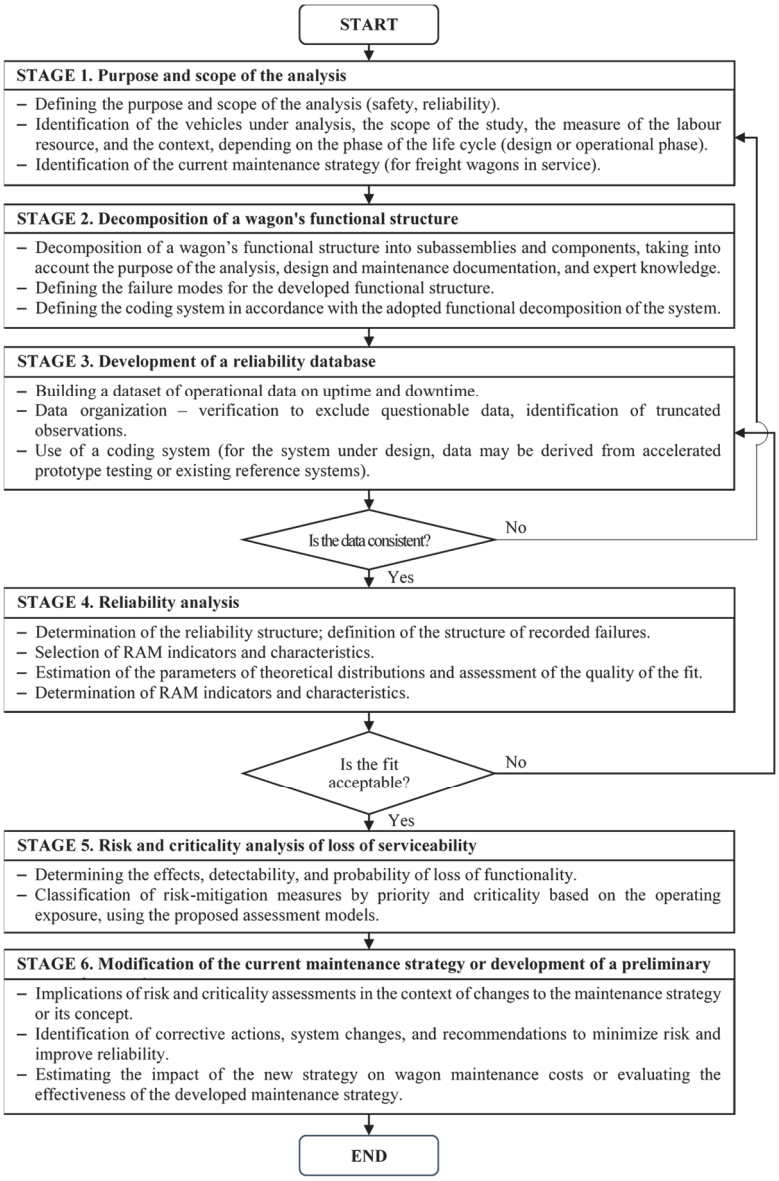


Figure 1. Block diagram of the developed method for predictive maintenance of freight wagons.

Table 1. Functional decomposition of a freight wagon, supplemented with failure modes – braking system.

Assembly Level I	Subassembly Level II	Component Level III	Failure mode (defective component)	Code
Braking system	Mechanical brake system	Lever mechanism	Parts of the lever mechanism are broken or hanging loose	2.1.1.1
			The brake triangle is deformed or sagging, and the protective bar is broken or missing	2.1.1.2
			The empty/loaded, G/P (goods/passenger) change-over device, on/off function and release rod operates incorrectly	2.1.1.3
			Stroke adjuster (SAB) operates incorrectly	2.1.1.4
			The manual hand brake is not working properly	2.1.1.5
			Improperly adjusted	2.1.1.6
		Actuating elements (brake blocks)	Brake block insert damaged or missing	2.1.2.1
			Brake block holder damaged or missing	2.1.2.2
			The wedge securing the insert is damaged or missing	2.1.2.3
	Pneumatic brake system	Brake control system	Distributor valve operates incorrectly	2.2.1.1
			Leaky or damaged air tank	2.2.1.2
		Brake force devices	The brake cylinder is leaking or not working properly	2.2.2.1
			Air brake inoperable	2.2.3.1
		Compressed air distribution system	Main pipe unserviceable	2.2.3.2
			Air coupling is leaking or missing	2.2.3.3
			Shut-off valve is clogged or leaking	2.2.3.4

3.3. Development of a reliability database

The next step in the developed method is the preparation and organization of operational data. At this stage, the manner in which the data was recorded in the ECM information system or the freight wagon operator's system is of particular importance. Although this data is often collected over many years, in practice it is not always immediately useful for reliability analyses. It requires verification and transformation into a form that enables estimation of the parameters of theoretical distribution models.

Currently, data on maintenance work performed is, in most cases, stored in structured databases and managed by dedicated IT systems. The operational data collected and stored in the database is subject to uncertainty. This stems from imperfections in the processes of acquiring, archiving, and processing the data and is related to assumptions and model limitations regarding object perception and behavior over time [21]. During the modeling and management phases of the data collection process, it is not possible to anticipate all scenarios, particularly those that may occur with a probability close to 0. Failure to properly prepare the data would lead to estimation errors and incorrect conclusions. A well-organized dataset serves as the foundation for building reliability models for subsequent stages of the assessment and as the primary source of information on the actual progression of the failure process.

In the proposed approach, it is essential to clearly define the boundary events – that is, the start of observation, the onset of unserviceability, the end of recovery, and the end of observation. This is particularly important in the case of incomplete or right-censored data, when not all objects were damaged during the observation period.

Inspections are often conducted according to the [n, R, t] schedule, in which n wagons were inspected; damaged wagons underwent routine maintenance, and the inspection was completed after time t. During the experiment, only some of the wagons may be damaged because the observation period is strictly defined and the number of damaged wagons is a random variable. A reliability analysis of wagons, taking the above scenario into account, requires the use of right-censored data.

3.4. Reliability analysis

In the proposed method, reliability analysis is not an end in itself but serves as the basis for assessing the level of risk and criticality from a reliability perspective. Its purpose is to fit distribution models – which describe the occurrence of failures as a function of time or another operating parameter – to operational data. In practice, this means estimating the statistical parameters of unknown distributions for specific failure modes.

This approach enables a shift away from the static perspective characteristic of traditional FMEA and FMECA analyses. Instead of a one-time assessment of the frequency of a given failure type, a continuous function is obtained that describes changes in the probability of its occurrence over the analyzed time horizon. This makes it possible to monitor how the risk of failure changes over the course of the asset's service life.

The statistical estimation of the time to failure and the recovery time involves fitting a probabilistic model to a random variable. This is made possible by several computer programs; for example, the ReliaSoft software suite offers many mathematical models of continuous random variables that account for probability distributions such as the Weibull distribution, the normal distribution, the exponential distribution, and the log-normal distribution. The probabilistic models listed above can be successfully applied in reliability studies of railway systems [22].

In the case of rail vehicles, the most common types of damage are those characterized by gradual propagation, as well as strength-related problems. Therefore, the Weibull distribution – in either its two-parameter or three-parameter form – is a common choice for modeling the reliability of these systems. For the three-parameter Weibull distribution, the cumulative distribution function is given by the following equation:

$$F(t) = 1 - e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}} \quad (1)$$

where:

β – shape parameter,

η – scale parameter,

γ – shift parameter.

From the perspective of classical FMEA analysis, the distribution function F(t) serves as a coefficient describing the probability of a hazard occurring. However, while the classic O

factor – occurrence – is discrete in nature and is usually set arbitrarily on a scale from 1 to 10 (similar to the S factor – severity – and the D factor – detectability), the cumulative distribution function is a continuous quantity derived directly from operational data. This is what makes it possible to move from a qualitative assessment to a quantitative one. The cumulative distribution function is also a key factor in assessing criticality from a reliability perspective.

3.5. Risk and criticality analysis of serviceability

3.5.1. Risk assessment

The assessment of the risk of failure in the classical FMECA method is based on the use of the RPN (Risk Priority Number), which for any failure mode i can be written as the following relationship [23]:

$$\mathrm{RPN}(z_j) = \prod_{k=1}^{3} r_k(z_j) \Rightarrow \mathrm{RPN}_j = S_j \cdot O_j \cdot D_j \qquad (2)$$

where:

$r_1(z_j)$ – a risk component corresponding to the severity impact assessment criterion S of the failure mode j,

$r_2(z_j)$ – a risk component corresponding to the criterion for assessing the probability of occurrence of O a failure mode j,

$r_3(z_j)$ – a risk component corresponding to the criterion for assessing the probability of detecting a threat D of a specific failure mode j.

An important part of risk assessment is determining which failure modes require the implementation of additional corrective and preventive actions to minimize risk. In the FMECA method, based on the classical approach, the RPN threshold values are arbitrarily determined for this purpose.

One of the objectives of the developed method is to replace the O coefficient – which is scaled discretely, typically in the range from 0 to 10 – with the value of the cumulative distribution function F(t) determined based on a fitted theoretical distribution model. The distribution function defines the probability of failure occurring over time (or as another operating resource is consumed). This definition therefore corresponds to that of the probability of occurrence factor, except that F(t) allows this probability to be determined as a function of time t. From the perspective of FMEA semantics, the cumulative distribution function F(t) thus serves as the dynamic equivalent of the O-factor. Still, unlike the O-factor, it allows for an unambiguous link between the risk assessment and the analysis time horizon. To prevent the S and D coefficients from having a dominant influence on the result – given that the cumulative distribution function determines the probability, and thus $F(t) \in [0;1]$ – a normalization process was applied by multiplying the value of the cumulative distribution function by 10. For the three-parameter Weibull distribution, this is described by the following relationship:

$$O_j = \max\{1, \lceil 10F_{ij}(t) \rceil\} = \max\left\{1, \left\lceil 10\left(1 - e^{-\left(\frac{t-\gamma_j}{\eta_j}\right)^{\beta_j}}\right)\right\rceil\right\}, \qquad O_j \in \{1,2,\ldots,10\} \qquad (3)$$

where:

η_j – the scale parameter of the fitted 3-P Weibull distribution of failure mode j,

β_j – the shape parameter of a fitted 3-P Weibull distribution for failure mode j,

γ_j – the location parameter of the fitted 3-P Weibull distribution of failure mode j.

The contemporary approach to risk management – including that promoted by current editions of standards and guidelines, e.g., [7,16–18] – highlights many limitations of using rigid thresholds. None of the documents listed that address FMEA or FMECA analyses specify universal threshold values for the RPN index. These documents leave the determination of thresholds to experts, suggesting that threshold values should be based on empirical data, the organization's experience, customer requirements, safety requirements, or other internal risk management criteria. An alternative approach to defining RPN threshold values is described in the AIAG & VDA FMEA Handbook standard [17]. It presents a new method for prioritizing actions resulting from an FMEA analysis. The RPN threshold value was no longer used as a decision-making tool. Instead, an action priority (AP) indicator was introduced, whose value is derived from a combination of the S, O, and D factors. The RPN value, therefore, no longer serves as the basis for decisions regarding risk mitigation measures; the highest priority is assigned not so much to the risk itself as to the decision about the order and necessity of taking action.

The three-level classification of the AP index assigns each

combination of S, O, and D factors (each rated on a scale of 1 to 10) to one of three priority categories for risk mitigation measures. On this basis, a temporary priority class is introduced for risk mitigation actions for failure mode j of component i at time t, denoted as $AP_{ij}(t)$:

$$AP_{ij}(t) = \begin{cases} H - high \\ M - medium \\ L - low \end{cases} \quad (4)$$

Unlike in the case of RPN, no algebraic function is used for this purpose. Instead, a matrix classifying the priority of risk-mitigation measures is used.

The AIAG & VDA standard [17] clearly states that, from the perspective of the expected safety level, the severity (S) is the overriding factor. Only after taking this into account are the probability of occurrence (O) and detectability (D) analyzed in turn. In practice, this means that a high S-factor value almost always results in an AP = H classification, even though the probability of a given failure mode may be low and its detectability high. This approach eliminates one of the fundamental drawbacks of the classic RPN, in which scenarios with high severity and low probability of occurrence could be assigned the same RPN value as scenarios with low severity but high probability of occurrence, thereby losing significance in the risk assessment.

3.5.2. Assessment of the criticality of a failure

An FMECA analysis allows for the inclusion of the criticality factor in the analysis [1]. In practice, this means that for each identified risk, a measure of its criticality is also assigned. FMC criticality index (Failure Mode Criticality) takes into account the assessment of failure, failure rate, and the probability of loss of functionality. For the failure mode j of component i , the value is determined using the following formula:

$$\mathrm{FMC}(c_j) = \prod_{k=1}^{3} c_k(z_j) \Rightarrow \mathrm{FMC}_j = \mathrm{CU}_{ij} \cdot \mathrm{RU}_{ij} \cdot \mathrm{PL}_{ij} \quad (5)$$

where:

$r_1(z_j)$ – the criticality component corresponding to the unreliability assessment criterion CU of the failure mode j of the component i,

$r_2(z_j)$ – the criticality component corresponding to the failure rate RU of the failure mode j of the component i,

$r_3(z_j)$ – a criticality factor corresponding to the criterion for assessing the probability of loss of functionality PL of a specific failure mode j of a component i.

Converting the FMC index to a continuous form requires that the value of the CU coefficient depend on the passage of time. It is therefore assumed that, for failure mode j of component i , the relationship between the CU coefficient and the cumulative distribution function of the time of reliable operation is:

$$\mathrm{CU}_{ij} = F_{ij}(t) \quad (6)$$

where:

$F_{ij}(t)$ – the cumulative distribution function of the time to occur of failure mode j of element i.

It is also necessary to change the method used to determine the failure rate $RU_{ij}(t)$ so that its value depends on time. This coefficient indicates what proportion of all failure modes of component i during time t is attributable to failure mode j. In the classical sense, it is defined as the ratio of the number of defects in element i attributable to failure mode j to the total number of defects in component i. In the developed method, this empirical failure rate is replaced by a value determined based on a fitted theoretical distribution, i.e., as the quotient of the value of the cumulative distribution function for failure mode j at time t and the sum of the values of the cumulative distribution functions for all failure modes j of component i at time t , which is described by the following relationship:

$$RU_{ij}(t) = \begin{cases} 0, & t = 0 \\ \dfrac{F_{ij}(t)}{\sum_{j=1}^{n_i} F_{ij}(t)}, & t > 0 \end{cases} \quad (7)$$

where:

n_i – the number of failure modes j of the component i.

The coefficient PL_{ij}, like the factors S_j and D_j in the risk assessment function, remains unchanged because the degree of loss of functionality is defined as a value that does not change over the object's lifecycle. Based on this, the CEF (Criticality Evaluation Function) is defined as follows:

$$CEF_{ij}(t) = \mathrm{CU}_{ij}(t) \cdot \mathrm{RU}_{ij}(t) \cdot \mathrm{PL}_{ij} \quad (8)$$

where:

$RU_{ij}(t)$ – failure rate for the failure mode j of component i at time t,

PL_{ij} – the probability (degree) of loss of functionality due to a failure mode j of component i at time t.

In accordance with the guidelines in standard [16], it is possible to aggregate risk assessment function values to the element, subassembly, and assembly levels – in accordance with

the adopted hierarchical decomposition of the system under study. To calculate the criticality of the assembly p at time t, consisting of s subassemblies, use the following formula:

$$\mathrm{CA}_p(t) = \sum_{c=1}^{s} \mathrm{CS}_s(t) \tag{9}$$

where:

$\mathrm{CS}_s(t)$ – the criticality of component s at time t, defined as:

$$\mathrm{CS}_s(t) = \sum_{i=1}^{c} \mathrm{CC}_i(t) \tag{10}$$

where:

$\mathrm{CC}_i(t)$ – the criticality of the element i at time t, defined as:

$$\mathrm{CC}_i(t) = \sum_{j=1}^{m} CEF_{ij}(t) \tag{11}$$

Changing the method for determining the factors CU and RU makes it possible to link the reliability criticality assessment directly to a probabilistic description of the time-dependent failure process. This leads to the transformation of the discrete FMC index, characteristic of the classical FMECA method, into a continuous criticality assessment function $\mathrm{CEF}_{ij}(t)$. A function defined in this way remains consistent with the criticality index in its interpretation, while also allowing for quantitative differentiation of the contributions of various types of unavailability over time at different levels of decomposition. This provides a consistent, hierarchical description of the criticality of the system's structure. The PN-EN IEC 60812 standard [7] permits the use of various forms of criticality indices and risk matrices, leaving the method of defining them to the discretion of the entity conducting the analysis, provided that the criteria remain transparent and consistent with the objectives of the study. It should be noted that, in the area of criticality assessment, there is no standard equivalent to the AIAG & VDA FMEA Handbook [17].

To use the risk assessment function $\mathrm{CEF}_{ij}(t)$ as a tool to help identify actions aimed at reducing criticality in terms of reliability, it is necessary to define a procedure for classifying failure modes into specific priority levels.

Let t be a continuous variable representing the passage of time in the interval:

$$t\epsilon[0, T_{max}] \tag{12}$$

where:

$\mathrm{T}_{\max}$ – the maximum value of the time horizon under analysis.

For each given time instant t, we consider the family of values of the criticality assessment function for all types of failure modes in the system under analysis:

$$\mathrm{C}(t) = \{CEF_{ij}(t) : i = 1, \dots, I; j = 1, \dots, n_i\} \tag{13}$$

where:

I – the number of components (subassemblies, assemblies, depending on the chosen level of decomposition),

n_i – the number of failure modes j of the element (subassembly, assembly) i.

The set $\mathrm{C}(t)$ defines the empirical distribution of criticality at time t. Let:

$$N = \sum_{i=1}^{I} n_i \tag{14}$$

denote the total number of failure modes in the system, and the values of the risk assessment function $\mathrm{CEF}_{ij}(t)$ will be sorted in non-decreasing order:

$$CEF_{(1)}(t) \le CEF_{(2)}(t) \le \cdots \le CEF_{(N)}(t) \tag{15}$$

then, the empirical quantile of order p at time t will be defined as follows:

$$q_P(t) = CEF_{(k)}(t) \tag{16}$$

where:

$\mathrm{k} = \lceil \mathrm{pN} \rceil$ and $\mathrm{p}\epsilon(0,1)$.

Of particular importance are the levels $\mathrm{q}_{0.95}(t)$ – the 0.95 quantile – and $\mathrm{q}_{0.90}(t)$ – the 0.90 quantile. On this basis, a temporary criticality class is assigned to the failure mode j of component i at the time t, designated as $\mathrm{CP}_{ij}(t)$. Similar to the prioritization categories for risk mitigation measures $\mathrm{AP}_j(t)$, it has three levels:

$$CP_{ij}(t) = CP_{ij}(t) = \begin{cases} H - high, & when CEF_{ij}(t) \ge q_{0.95}(t), \\ M - medium, & when\ q_{0.90}(t) \le CEF_{ij}(t) < q_{0.95}(t) \\ L - low, & when\ CEF_{ij}(t) < q_{0.90}(t). \end{cases} \tag{17}$$

Adopting a quantile threshold $\mathrm{q}_{0,95}(t)$ for class H means that only the upper, extreme portion of the distribution of $\mathrm{CEF}_{ij}(t)$ values – corresponding to the 5 percent of the most critical failure modes at a given moment t – is classified as the highest criticality priority level. Class M includes types falling within the range between the 90th and 95th percentiles of the $\mathrm{CEF}_{ij}(t)$ distribution. In contrast, Class L includes failure modes for which the $\mathrm{CEF}_{ij}(t)$ value has been classified below the 90th percentile. The defined thresholds are relative, which means that they are determined on a case-by-case basis based on the current distribution $\mathrm{CEF}_{ij}(t)$ of failure modes within the population, ensuring that the classification adapts to the structure of criticality as it changes over time.

Quantile orders of 0.90 and 0.95 were adopted to provide a selective classification in which approximately the top 10% of the criticality distribution receives greater attention, while class H is limited to approximately the top 5%. These values represent methodological assumptions, not normative ones. Criticality limits can be adjusted depending on the analysis objectives and the implementation capabilities of the maintenance organization. Changing the quantile orders does not affect the calculated $CEF_{ij}(t)$ values or the relative ranking of failure modes, but only their assignment to classes L, M, and H. Therefore, the classification is most sensitive to changes in the thresholds for failure modes located near the class boundaries. For finite populations with identical criticality values, the actual proportions assigned to individual classes may differ from the nominal quantile ranges.

3.6. Modification or development of a new maintenance strategy concept

The proposed method takes into account the existence of two complementary evaluation perspectives:

1. A safety perspective that refers to a dynamic priority indicator for actions aimed at minimizing risk $AP(t)$,
2. The perspective of criticality in terms of reliability, described by dynamic criticality classes $CP(t)$ determined by taking into account the criticality assessment function $CEF(t)$ and quantile thresholds.

Developing a maintenance strategy using the first of these perspectives takes into account the principles of risk-based maintenance (RBM). In contrast, the second aligns with the reliability-centered maintenance (RCM) approach. Therefore, a maintenance strategy modified or developed using the proposed method can be described as a hybrid strategy – a special case that combines the principles of both RBM and RCM – and thus serves as an example of a complementary approach.

3.6.1. AP indicator values in the context of changes to or the development of a maintenance strategy

From a risk assessment perspective, the $AP_j(t)$ indicator can be treated as a decision variable that identifies the point in time t at which the risk associated with the occurrence of a given failure mode is no longer acceptable and requires an appropriate response. In this context, the moment t – when one of the indicators first took on the value $AP_j(t) = H$ – is particularly significant. This means that the combination of the effects of failure, occurrence frequency, and detectability corresponds to a scenario for which, according to the normative FMECA approach, high-priority actions are recommended – that is, when the risk level ceases to be acceptable or tolerable and becomes unacceptable. The developed method calls for performing a preventive maintenance task – based on a risk-based conditional inspection (RBCI) assessment – before the end of this period, with a particular focus on diagnosing the potential occurrence of a specific failure mode j. It is desirable to link this to the maintenance procedures used in operational practice and, in assessing the technical condition, to take into account the possibility of other types of unserviceability occurring, for which $AP_j(t)$ may reach values of H or M at a later time.

It should be noted that, especially for large freight wagon fleets, dynamically scheduling maintenance interventions can create organizational constraints. Maintenance activities identified using the proposed method cannot always be performed immediately at the designated time due to workshop capacity, personnel availability, spare parts availability, and the need to coordinate wagon outages. Therefore, the designated time points should be treated as information supporting decision-making and taken into account in the planning process.

3.6.2. CP indicator values in the context of changes to or the development of a maintenance strategy

The second level of reasoning concerns the freight wagon's criticality. The $CP_{ij}(t)$ indicators differ in nature from the $AP_j(t)$ indicators. While $AP_j(t)$ remains a tool directly related to risk assessment and serves as a decision-making criterion in the context of taking specific risk-mitigation actions, $CP_{ij}(t)$ is used to identify the failure modes that are most significant for reliability. Unlike $AP_j(t)$, for at least one failure mode j, the indicator $CP_{ij}(t) = H$ is already active at any given moment $t > 0$. Factors that determine the likelihood of certain failure modes occurring – which, for a significant portion of the time horizon, fall into the $CP = H$ class – should not only be given special attention when assessing the technical condition of freight wagon as part of standard in-service technical inspections (such as the types for which $AP = M$ applies). It is also appropriate

to define additional corrective actions and incorporate them into the implementation of specific MMS functions, such as maintenance management, maintenance execution, and maintenance development. This should be understood to mean, in particular, modifying or changing the frequency or scope of preventive maintenance activities, introducing new design solutions, changing component suppliers, using materials with greater durability, as well as evaluating the quality of periodic repairs performed.

4. Application of the method to an open high-sided wagon

The application of the proposed risk and criticality assessment method involved an analysis of 68 identified types of defects in 3,500 open high-sided wagons examined over a 96-month period. The input data for the analysis was saved in a file created in Microsoft Excel. Table 2 shows a portion of the table containing the input data for three selected failure modes.

Table 2. Input data – the parameters β, η, and γ of the fitted 3-P Weibull distributions, and the coefficients S, D, and PL.

Values Type of unserviceability	Parameters of the fitted 3-P Weibull distribution			Components of the RPN index		Component of the FMC index
	β	η [days]	γ [days]	D	S	PL
1.1.1.1	1.05	2.22E+04	37.81	2	10	0.8
1.1.1.2	0.35	3.83E+11	256.43	3	10	1.0
1.1.1.3	0.88	3.54E+03	3.37	2	8	0.1

The relevant calculations were performed using a tool developed in the Python environment. The program is an integral part of the proposed method for predictive maintenance of freight wagons, combining a probabilistic description of the failure process, classical FMECA analysis factors, and the concept of risk mitigation priority (AP) and criticality classes (CP), creating a practical tool to support the development or modification of maintenance strategies.

Implementing the method in a Python environment serves several important functions in the research process. First and foremost, it eliminates the need to perform numerous FMECA analyses manually for successive time steps t, replacing labor-intensive static calculations with a single, coherent dynamic computational model. Furthermore, it ensures reproducibility and transparency in the practical application of the proposed method, since all computational steps are clearly documented in the form of a computational algorithm. It also allows for changes to the parameters of the time horizon under analysis (or other performance metrics), quantile thresholds, or classification criteria, thereby enabling the testing of alternative maintenance strategies. The program is an integral part of the proposed method for predictive maintenance of freight wagons, combining a probabilistic description of the failure process, classic FMECA analysis factors, and the concept of risk mitigation priority (AP) and criticality classes (CP) to create a practical tool that supports the development of maintenance strategies.

4.1. Results of the risk assessment

Based on the values of the AP(t) indicators, risk mitigation measures were prioritized for each type of unserviceability. For example, for failure mode 1.1.1.1 (Running gear – Wheel set – Road wheel – Tire loosened or offset to the wheel), taking into account a fitted Weibull distribution, the probability of failure will be described by the following formula:

$$O_{1.1.1.1}(t) = max\left\{1, \left\lceil 10\left(1 - e^{-\left(\frac{t-37.81}{22163.80}\right)^{1.05}}\right)\right\rceil\right\} \qquad O_j \in \{1,2,\dots,10\} \quad (18)$$

For failure mode 1.1.1.1, according to the table containing the input data, the values of the remaining coefficients are $D_{1.1.1.1} = 2$ and $S_{1.1.1.1} = 10$. The next stage of risk assessment is the prioritization of risk-mitigation measures AP(t) using the matrix specified in the AIAG & VDA FMEA Handbook [17]. For the entire study period, the risk associated with the possibility of mode 1.1.1.1 occurring is equal to $AP(t) = L$, where $t \in [0\ \text{months.}, 96\ \text{months}]$.

For easier interpretation and visualization of the results, days were converted into months using the relation $1\ \text{month} \cong 30.42\ \text{days}$. It is assumed that for each time t expressed in months, the program calculates the value of the cumulative distribution function F(t) for all failure modes. Based on the value of F(t) and the coefficients S and D, the value of the AP action priority index is calculated in accordance with the AIAG & VDA matrix [17]. The probability value O(t) is determined indirectly as a function F(t) mapped to a ten-point scale and then, in combination with the fixed values of S and D, used to determine the priority AP(t) in classes L, M, and H, in accordance with the risk assessment matrix. The results of the AP(t) calculations for each failure mode are recorded in the AP worksheet as a matrix, with the rows representing the failure modes and the columns representing the consecutive months of

the analysis horizon (from 1 to 96). The matrix is as shown in Table 3.

Table 3. A portion of the matrix of priority values for risk mitigation measures for each month of the analysis – AP Worksheet.

Type of unserviceability	Months 1	2	3	…	36	37	38	…	76	77	78	…	94	95	96
1.1.1.1	L	L	L	…	L	L	L	…	L	L	L	…	L	L	L
1.1.1.2	L	L	L	…	L	L	L	…	L	L	L	…	L	L	L
1.1.1.3	L	L	L	…	L	M	M	…	M	H	H	…	H	H	H

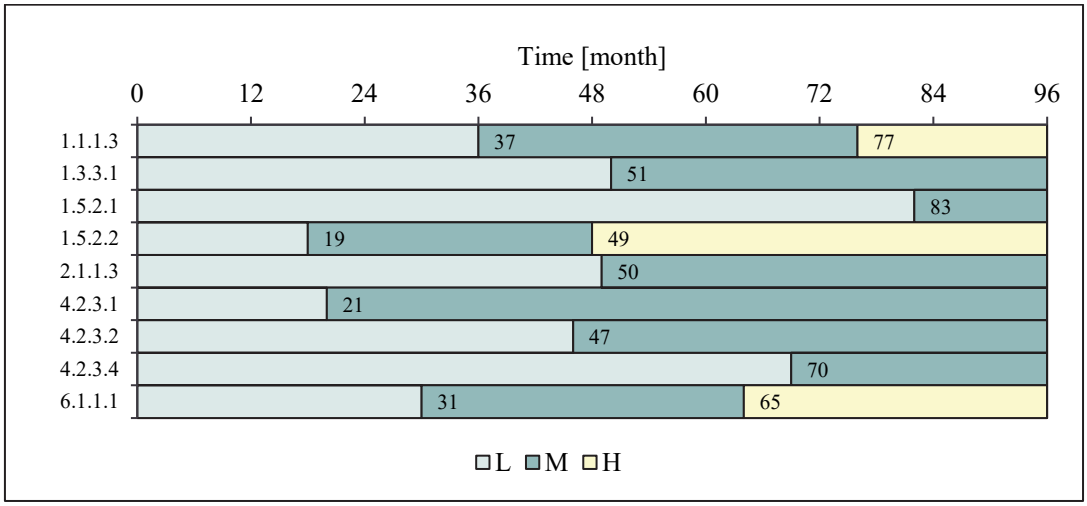


Figure 2. Priority classes for risk mitigation measures AP(t) for failure modes.

Of the 68 failure modes, 59 remained in the lowest acceptable risk class, AP = L, throughout the entire analysis period. Nine modes reached at least class AP = M, and three of them also reached class AP = H during part of the analysis period. Figure 2 shows the matched priority classes for risk-mitigation actions AP(t) for failure modes other than L.

This means that approximately 4% of nonconformity types were classified as those whose occurrence is associated with an unacceptable risk. This is a significant advantage of the proposed method, which does not classify too many types of failure as potentially dangerous. In general, the values of the AP(t) indicators for individual failure modes demonstrate that risk mitigation efforts should prioritize those types that are intuitively – and based on expert knowledge – perceived as potentially critical to safety. Specifically, these include the following types:

- 1.1.1.3 – illegible control markings – the risk ceases to be acceptable and becomes tolerable (class AP = M) starting in the 37th month, while it ceases to be tolerable and becomes unacceptable (class AP = H) starting in the 77th month,
- 1.5.2.2 – pivot pin and turning socket (including lubrication system) – the risk ceases to be acceptable and becomes tolerable starting in the 19th month, while it ceases to be tolerable and becomes unacceptable starting in the 49th month,
- 6.1.1.1 – steps, handrails, and ladders in poor condition, cracked, or unusable – the risk ceases to be acceptable and becomes tolerable starting in the 31st month. In contrast, it ceases to be tolerable and becomes unacceptable starting in the 65th month.

4.2. Results of the criticality assessment

For the value of the coefficient CU to be a function of time, equation (6) must hold. When using the three-parameter Weibull distribution, the value of the coefficient $\mathrm{CU_{ij}(t)}$ is described by the following relationship:

$$\mathrm{CU}_{ij}(t) = \mathrm{F}_{ij}(t) = 1 - e^{-\left(\frac{t-\gamma_j}{\eta_j}\right)^{\beta_j}} \tag{19}$$

In accordance with the adopted methodology, to modify the method for determining the failure mode reliability coefficient RU so that its value depends on time, equation (7) should be used. When using the three-parameter Weibull distribution, this equation should be transformed into the following form:

$$RU_{ij}(t) = \begin{cases} 0, & t = 0 \\ \dfrac{1 - e^{-\left(\frac{t-\gamma_j}{\eta_j}\right)^{\beta_j}}}{\sum_{j=1}^{n}\left(1 - e^{-\left(\frac{t-\gamma_j}{\eta_j}\right)^{\beta_j}}\right)}, & t > 0 \end{cases} \quad (20)$$

where:

n – the number of failure modes j of the component i.

The coefficient PL_{ij} , like the normalized coefficients S and D in the risk assessment function, remains unchanged because the degree of loss of functionality is a characteristic assigned to a given mode of unserviceability and does not depend directly on the passage of time. Therefore, the CEF criticality evaluation function takes the following form:

$$CEF_{ij}(t) = \mathrm{CU}_{ij}(t) \cdot \mathrm{RU}_{ij}(t) \cdot \mathrm{PL}_{ij} \quad (21)$$

where:

$RU_{ij}(t)$ – failure rate for the failure mode j of component i at time t,

PL_{ij} – the probability (degree) of loss of functionality due to failure mode j of component i at time t.

For the Weibull three-parameter distribution, the Criticality Evaluation Function (CEF) defines the following relationship:

$$CEF_{ij}(t) = \begin{cases} 0, & t = 0 \\ \dfrac{\left[1 - e^{-\left(\frac{t-\gamma_j}{\eta_j}\right)^{\beta_j}}\right]^2 \cdot \mathrm{PL}_{ij}}{\sum_{j=1}^{n}\left[1 - e^{-\left(\frac{t-\gamma_j}{\eta_j}\right)^{\beta_j}}\right]}, & t > 0 \end{cases} \quad (22)$$

where:

n – the number of failure modes j of the component i.

The following equation is an example formula for the criticality evaluation function CEF for failure mode 2.2.1.1 Brake System – Pneumatic Brake System – Brake Control System – distribution valve malfunctions:

$$CEF_{2.2.1.1}(t) = \begin{cases} 0, & t = 0 \\ \dfrac{\left[1 - e^{-\left(\frac{t-8.83}{61132.97}\right)^{1.06}}\right]^2 \cdot 0.8}{\left(1 - e^{-\left(\frac{t-8.83}{61132.97}\right)^{1.06}}\right) + \left(1 - e^{-\left(\frac{t}{31130.86}\right)^{2.16}}\right)}, & t > 0 \end{cases} \quad (23)$$

The aggregation of criticality evaluation function values to the level of element 2.2.1 – Brake Control System – is defined by the following equation:

$$CC_{2.2.1}(t) = \begin{cases} 0, & t = 0 \\ \dfrac{0.8\left[1 - e^{-\left(\frac{t-8.83}{61132.97}\right)^{1.06}}\right]^2 + 0.5\left[1 - e^{-\left(\frac{t}{31130.86}\right)^{2.16}}\right]^2}{\left[1 - e^{-\left(\frac{t-8.83}{61132.97}\right)^{1.06}}\right] + \left[1 - e^{-\left(\frac{t}{31130.86}\right)^{2.16}}\right]}, & t > 0 \end{cases} \quad (24)$$

According to the method's definition, it is possible to further aggregate functions down to the level of subcomponents and assemblies. In practice, the quantiles of the criticality assessment function depend on the distribution of its values, including its aggregate form. For example, when classifying freight wagon assemblies by criticality level, one should use the quantiles of the distribution of criticality function values at the assembly level. For a given time t , the vector of criticality function values for the assemblies is considered:

$$\{CA_p(t)\}_{p=1,\ldots,P} \quad (25)$$

where:

$\mathrm{CA_p}(t)$ – the criticality of the assembly p at time t,

P – number of assemblies.

For a given time t, calculate the values of $\mathrm{CA_p}(t)$ for all assemblies. The resulting set is sorted in ascending order, yielding the sequence:

$$CA_{(1)}(t) \leq CA_{(2)}(t) \ldots \leq CA_{(P)}(t) \quad (26)$$

For example, for $t = 12$ months, it will look like this:

$$0.014 \leq 0.023 \leq 0.074 \leq 0.185 \leq 0.376 \leq 0.377 \quad (27)$$

The quantile of order α at time t , denoted as $\mathrm{Q_\alpha^{CA}}(t)$, is determined by interpolation between the elements of an ordered sequence according to the adopted convention, for example, based on the position of $(P + 1)\alpha$. When there are only a few assemblies, a quantile with a high level (for example, 0.90 or 0.95) will usually be close to the value of one of the largest elements in the set. For example, for the time point $t = 12$ months , the criticality quantiles of the groups were obtained – see Table 4.

For P = 6, the position corresponding to the quantile of order α is $(P + 1)\alpha = 7\alpha$. For $\alpha = 0.90$, the position is $k_{0.90} = 6.3$, and for $\alpha = 0.95$, the position is $k_{0.95} = 6.65$. Both of these values lie between six and larger values, which do not occur in this case. This means that both the quantile $\mathrm{Q_{0.90}^{CA}}(12\ \mathrm{months})$ and $\mathrm{Q_{0.95}^{CA}}(12\ \mathrm{months})$ are equal to the value at the upper end of the distribution, that is:

$$Q_{0.90}^{CA}(12\ months) \approx Q_{0.95}^{CA}(12\ \mathrm{months}) \approx 1.000 \quad (28)$$

Table 4. Criticality quantiles of assemblies.

Assembly	$\mathrm{CA_P}$ (12 months)	Assembly	$\mathrm{CA_P}$ (12 months)
1	1.000	4	0.833
2	0.667	5	0.167
3	0.333	6	0.500

Consequently, only the assembly with a value of $\mathrm{CA_p}(12\ \mathrm{months}) = 1.000$ (i.e., assembly 1 – the running gear) is classified in the highest criticality class $\mathrm{CP}(12\ \mathrm{months}) = \mathrm{H}$,

while the remaining assemblies, whose values $CA_p(12\ \text{months})$ are lower than $Q_{0.90}^{CA}(12\ \text{months})$, belong to criticality class $CP(12\ \text{months}) = L$. In subsequent levels of decomposition, as the number of elements in the ordered sequence increases, the $CP(t) = M$ criticality class will, of course, occur. The quantiles of the criticality function defined in this way constitute a criticality assessment.

As mentioned above, due to the high computational complexity, a Python implementation of the proposed method was used to assess failure risk and reliability criticality systematically. For each failure mode j of component i, the value of the distributive function $F(t)$ – the equivalent of $CU_{ij}(t)$ – is determined. Next, the coefficient $RU_{ij}(t)$ is calculated. The value of the function $CEF(t)$, according to the given definition, is the product of $F(t)$, $RU(t)$, and PL_{ij}. The program performs calculations for months 1 through 96, saving the results in the CEF_modes worksheet – Table 5.

Table 5. A portion of the matrix of criticality assessment function values for CEF(t) failure modes in each month of the analysis – CEF_modes worksheet.

Type of unserviceability \ Months	1	2	3	…	94	95	96
1.1.1.1	0.00E+00	1.01E-05	4.13E-05	…	8.07E-03	8.18E-03	8.28E-03
1.1.1.2	0.00E+00	0.00E+00	0.00E+00	…	1.94E-06	1.94E-06	1.94E-06
1.1.1.3	8.69E-04	1.70E-03	2.45E-03	…	2.77E-02	2.78E-02	2.78E-02

On this basis, and taking into account the system's hierarchical decomposition, criticality aggregation is performed within the object's structure. For each month t, the program:

- sums the values of $CEF_{ij}(t)$ across all failure modes assigned to the given component i, calculating $CC_i(t)$,
- sums $CC_i(t)$ over the components that make up the subassembly s, calculating $CS_s(t)$,
- sums $CS_s(t)$ across the subassemblies that make up assembly p, yielding $CA_p(t)$.

The received series $CC_i(t)$, $CS_s(t)$, and $CA_p(t)$ are stored in the CEF_comp (Table 6), CEF_subassemb (Table 7), and CEF_assemb (Table 8) sheets, respectively. This data organization reflects how the FMC index is aggregated in classical FMECA analysis; it can also be calculated dynamically, essentially at any given moment.

Figures 3 and 4 show example graphs of criticality functions for selected failure modes, aggregated according to the adopted hierarchical decomposition structure.

Table 6. A portion of the matrix of values for the criticality assessment function aggregated to the level of element CC(t) for each month of the analysis – CEF_comp worksheet.

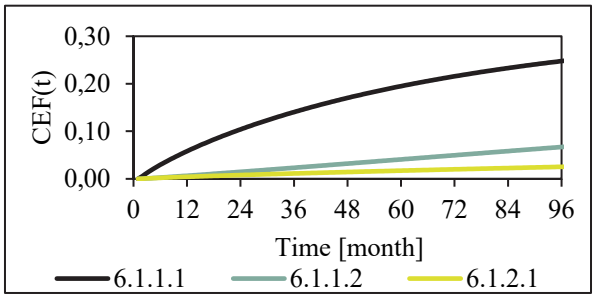
Component \ Months	1	2	3	…	94	95	96
1.1.1	1.48E-03	2.64E-03	3.70E-03	…	7.16E-02	7.23E-02	7.30E-02
1.1.2	0.00E+00	2.76E-04	5.94E-04	…	5.28E-03	5.31E-03	5.34E-03
1.2.1	4.05E-04	1.64E-03	2.79E-03	…	8.20E-02	8.28E-02	8.36E-02

Table 7. A portion of the matrix of values for the CS(t) criticality assessment function, aggregated to the subassembly level, for each month of the analysis – CEF_subassemb worksheet.

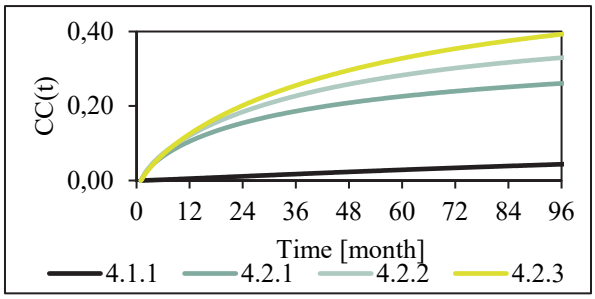
Subassembly \ Months	1	2	3	…	94	95	96
1.1	1.48E-03	2.92E-03	4.30E-03	…	7.69E-02	7.76E-02	7.84E-02
1.2	4.05E-04	1.64E-03	2.79E-03	…	9.34E-02	9.43E-02	9.52E-02
1.3	7.05E-02	1.04E-01	1.30E-01	…	6.38E-01	6.40E-01	6.42E-01

Table 8. A portion of the matrix of values for the aggregated criticality assessment function at the CA(t) assembly level for each month of the analysis – CEF_assemb worksheet.

Assembly \ Months	1	2	3	…	94	95	96
1	7.70E-02	1.20E-01	1.55E-01	…	1.51E+00	1.52E+00	1.53E+00
2	1.81E-02	3.67E-02	5.43E-02	…	8.51E-01	8.56E-01	8.61E-01
3	1.35E-03	3.11E-03	4.98E-03	…	2.28E-01	2.31E-01	2.33E-01

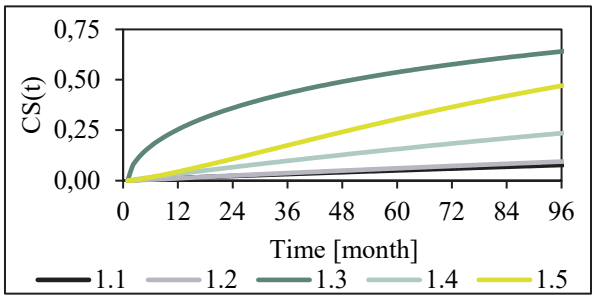


(a)

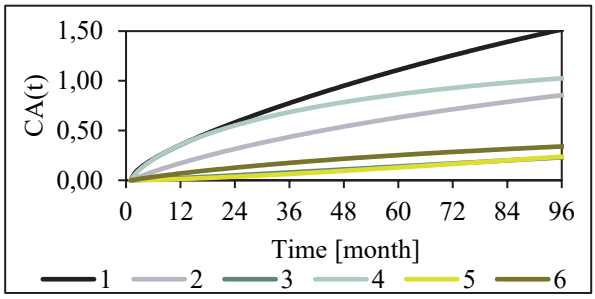


(b)

Figure 3. (a) The CEF(t) criticality assessment function for selected failure modes, (b) The CC(t) aggregated criticality assessment function for selected components.



(a)



(b)

Figure 4. (a) Aggregate criticality assessment function CS(t) for selected subassemblies, (b) Aggregate criticality assessment function CA(t) for assemblies.

The values of the CEF(t) function are not taken into account in the decision-making process. Instead, they are used to calculate the percentile rank of the value CEF(t) for a given failure mode, item, subassembly, or assembly relative to the entire population at a given level of decomposition. Thus, for each matrix CEF(t) (including those that take aggregated values into account), the program calculates a quantile on a scale from 0 to 1, where 0 represents the object with the lowest criticality, and 1 and values close to 1 represent the objects with the highest criticality at that moment. The resulting percentile matrices are saved in the PCT_modes, PCT_comp, PCT_subassemb, and PCT_assemb worksheets. Portions of these matrices are presented in Tables 9 through 12. Figures 5 and 6 show sample graphs illustrating changes in quantiles for selected failure modes, aggregated according to the adopted hierarchical decomposition structure into the levels of components, subassemblies, and assemblies.

Table 9. A portion the percentile matrix for failure modes in each month of the analysis – PCT_modes worksheet.

Failure mode	1	2	3	…	94	95	96
1.1.1.1	0.0000	0.2143	0.2787	…	0.4328	0.4328	0.4328
1.1.1.2	0.0000	0.0000	0.0000	…	0.0448	0.0448	0.0448
1.1.1.3	0.7500	0.7321	0.7377	…	0.6269	0.6269	0.6269

Table 10. A portion of the percentile matrix for selected components in each month of the analysis – PCT_comp worksheet.

Component	1	2	3	…	94	95	96
1.1.1	0.5238	0.5652	0.5833	…	0.4400	0.4400	0.4400
1.1.2	0.0000	0.1304	0.1667	…	0.1200	0.1200	0.1200
1.2.1	0.2857	0.4783	0.5000	…	0.4800	0.4800	0.4800

Table 11. A portion of the percentile matrix for selected subassemblies in each month of the analysis – PCT_subassemb worksheet.

Subassembly	1	2	3	…	94	95	96
1.1	0.4615	0.4615	0.4615	…	0.1538	0.1538	0.1538
1.2	0.0769	0.2308	0.2308	…	0.2308	0.2308	0.2308
1.3	1.0000	0.9231	0.9231	…	0.9231	0.9231	0.9231

Table 12. A portion of the percentile matrix for assemblies in each month of the analysis – PCT_assemb worksheet.

Assembly	1	2	3	…	94	95	96
1	1.0000	1.0000	1.0000	…	1.0000	1.0000	1.0000
2	0.6667	0.6667	0.6667	…	0.6667	0.6667	0.6667
3	0.3333	0.3333	0.3333	…	0.1667	0.1667	0.1667

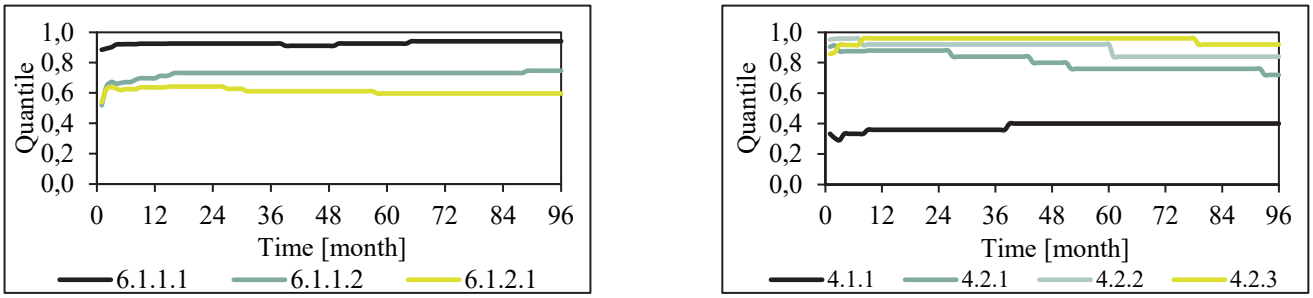


Figure 5. (a) Quantiles of the CEF criticality assessment function (t) for selected failure modes, (b) Quantiles of the aggregated criticality assessment function CC(t) for selected components.

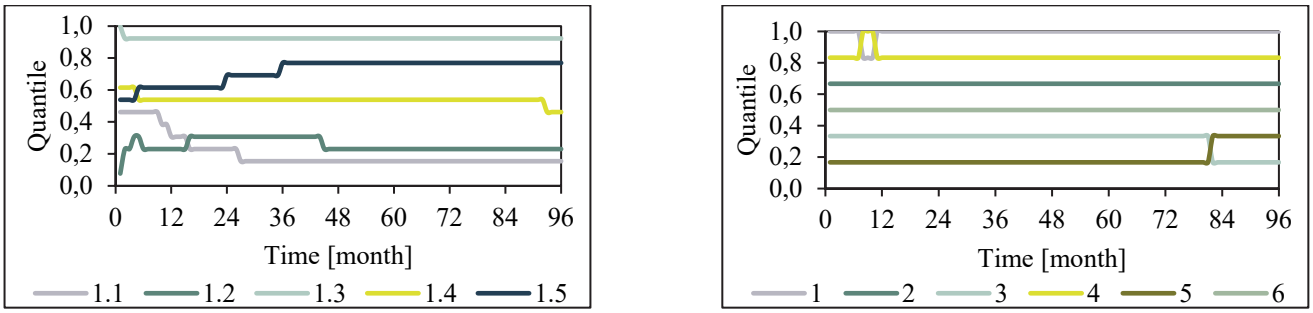


Figure 6. (a) Quantiles of the aggregated criticality assessment function CS(t) for selected subassemblies, (b) Quantiles of the aggregated criticality assessment function CA(t) for assemblies.

The final step is to classify criticality based on quantiles. For each time point t and each level of the adopted system decomposition hierarchy (failure modes, components, subassemblies, assemblies), the program calculates the 0.90 and 0.95 quantiles of the CEF(t) distribution. Based on this, at time t, it assigns a criticality class:

- H when CEF(t) is in the top 5 percentiles,
- M, when CEF(t) lies between the 90th and 95th percentiles,
- L in all other cases.

The results of this classification are stored in the CP_modes, CP_comp, CP_subassemb, and CP_assemb worksheets, along with summary worksheets similar to those used for the AP indicator (e.g., CP_comp_agr).

The assessment of criticality in the context of reliability takes into account three criticality classes CP(t) (analogous to risk classes AP(t)), which are determined based on the quantiles of the criticality assessment function CEF(t). Of the 68 failure modes, 59 remained in the CP = L class throughout the entire study period. Nine types reached at least the CP = M class, and six of these also reached the CP = H class during part of the analyzed time horizon. Figure 7 shows the fitted criticality classes CP(t) for failure modes other than L.

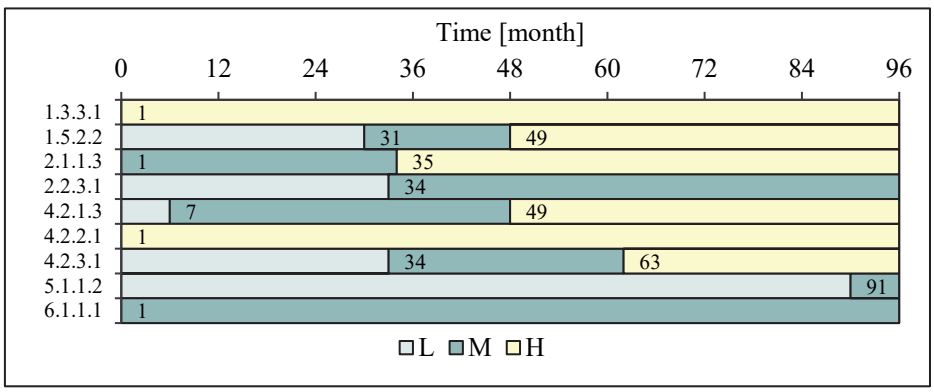


Figure 7. CP(t) criticality classes for failure modes.

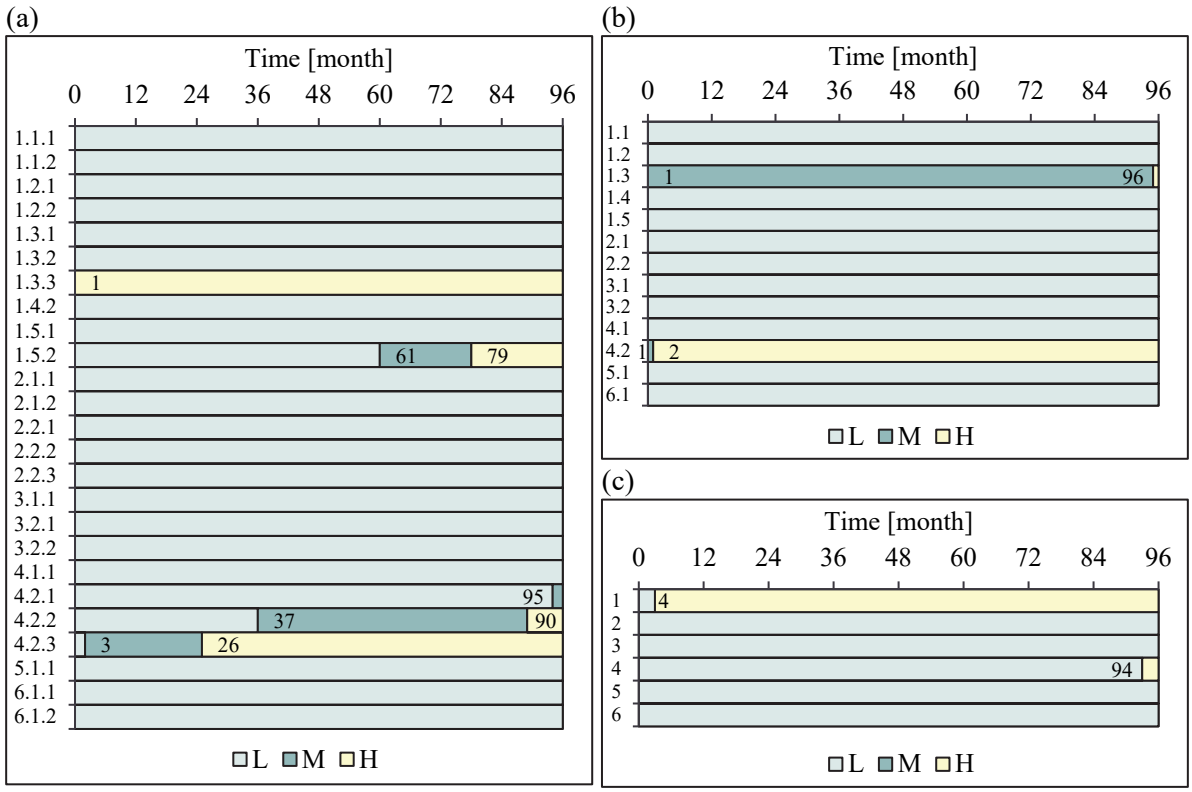


Figure 8. (a) Criticality classes CC(t) of components, (b) Criticality classes CS(t) of subassemblies, (c) Criticality classes CA(t) of assemblies.

Two failure modes are particularly significant, for which the criticality class CP = H occurs throughout the entire 96-month period under analysis:

- 1.3.3.1 – grease nipple sleeves – cracked welds, sagging, or missing,
- 4.2.2.1 – doors that are not airtight, have holes in them, or are bent.

In both cases, the fact that the highest criticality class persisted throughout the entire study period means that these types dominate the criticality balance from a reliability standpoint.

Aggregating the values of the criticality assessment function CEF(t) to higher levels of hierarchical decomposition allows for the identification of components, subassemblies, and assemblies that are dominant in terms of criticality – Figure 8.

At the component level, the following are particularly critical:

- 1.3.3 Slippage of the wheel set guidance system, classified as the highest criticality class throughout the entire test period CP = H,
- 4.2.3 Body structural components whose criticality class reaches a level of CP = Mstarting in the 3rd month, and from month 26 level H, CP = H
- 4.2.2 doors and 1.5.2 the connection between the bogie and the underframe, which were classified as having a criticality class of CP = M for a significant portion of the time, and as CP = H during the final phase of the tests.

At the subassembly level, two of them stand out clearly:

- 4.2 body, which is classified in class CP = H for 95 out of 96 months,
- 1.3 the wheel set guidance system, which has been classified as class CP = M for almost the entire duration of the study, with a brief period in the last 96 months during which its criticality class was determined to be CP = H.

At the highest level of decomposition – corresponding to the wagon assemblies – the running gear plays the dominant role in the context of criticality assessment. This assembly has been in class CP = H for 93 out of 96 months, while the body assembly has been in class CP = H only during the last two months, and the remaining assemblies have remained in class CP = L throughout the entire analysis period. This means that from the perspective of criticality – understood as a combination of the

probability of failure and loss of functionality – the overall picture is determined primarily by the running gear and, to a lesser extent, by selected body components.

4.3. Development of a new maintenance plan

From a risk assessment perspective, the fundamental premise of the proposed method is to use the $AP_j(t)$ indicator as a decision variable that identifies the point in time t at which the risk associated with the occurrence of a given failure mode is no longer at an acceptable level and requires appropriate maintenance actions to be taken. In this context, the moment $t = 49$ months – when one of the indicators first took on the value $AP_j(t) = H$ – is particularly significant. Therefore, within 49 months of the completion of the periodic repair, preventive maintenance is carried out in accordance with the plan, based on the results of the RBCI (Risk-Based Conditional Inspection) risk assessment. It should focus in particular on identifying types of failure for which the risk of occurrence is unacceptable, namely:

- 1.1.1.3 – illegible control markings,
- 1.5.2.2 – pivot pin and turning socket (including the lubrication system),
- 6.1.1.1 – steps, handrails, and ladders that are in poor condition, cracked, or unusable.

In doing so, these visual inspections should be linked to the maintenance procedures followed in actual operation, and the assessment of the technical condition should take into account the possibility of other failure modes j, for which the estimated priority of risk-mitigation measures may reach values of $AP_j(t) = H$ or $AP_j(t) = M$ at a later time.

The natural reference in this context is the G4.3 inspection as defined by the VPI EMG [24]. A positive result of a conditional-based inspection defined in this manner serves as the basis for postponing the next review by 1 year (according to VPI EMG reviews G4.2 or G4.8, the inspection may be deferred twice), taking into account the results of the risk analysis conducted, compliance with formal requirements, and approval by the entity acting as the ECM. Otherwise, the maintenance activities specified in the current maintenance strategy must be carried out.

The moments t when the priority index for risk-mitigation measures for a given failure mode j reached the value $AP_j(t) = M$, meaning that the risk ceased to be acceptable and began to be tolerated, should serve as a decision-making criterion for determining the need to prioritize the diagnosis of a wagon's technical condition with regard to the possibility of a specific failure mode j occurring during standard visual inspections performed during service. Visual inspections of the wagon during operation, conducted in accordance with the provisions of the GCU agreement [25], constitute such an activity.

Taking the above conclusions into account, the proposed new maintenance plan for standard-design open high-sided wagon, in a practical format, is presented in Figure 9.

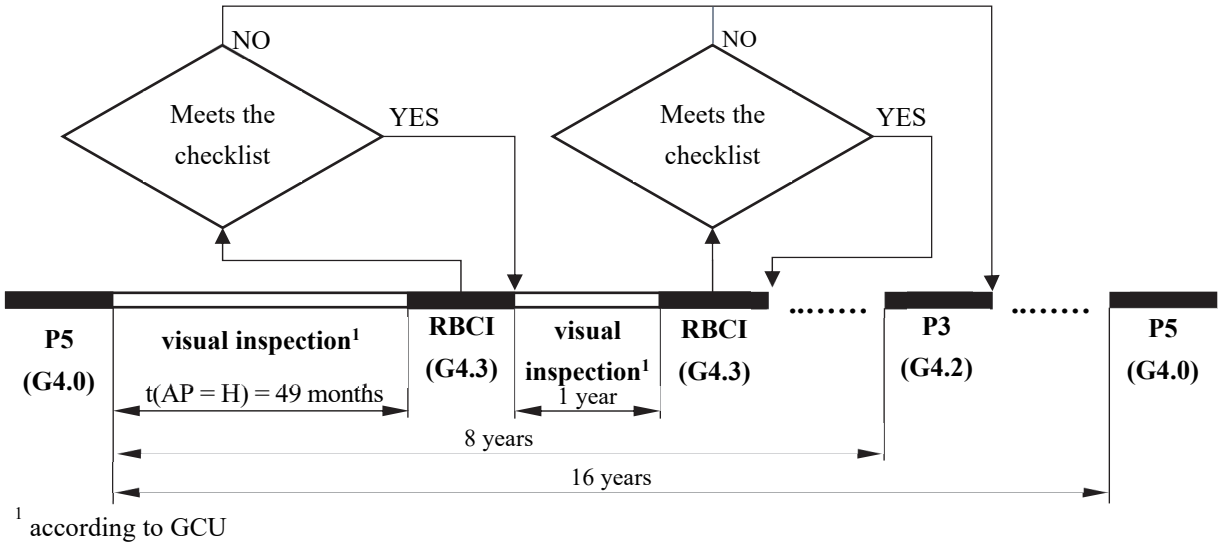


Figure 9. A maintenance plan for standard-design open high-sided wagons has been developed.

The new maintenance plan provides for three levels of preventive maintenance:

1. RBCI (equivalent to G4.3 according to VPI EMG), a test performed for the first time no later than 49 months of age, and then every year,
2. P3 (equivalent to G4.2 according to VPI EMG), a procedure performed no more than once every 8 years,
3. P5 (equivalent to G4.0 according to VPI EMG), a procedure performed no more than once every 16 years.

It should be emphasized that the 49-month intervention point and maintenance plan presented in Figure 9 are specific to the analyzed population of freight wagons and the operational data used in this study. Therefore, these values should not be interpreted as universal maintenance intervals applicable to all wagons of this type. Their practical usefulness should be confirmed through implementation in the maintenance process and further validation using independent operational data sets.

5. Conclusion

The developed method for predictive maintenance of freight wagons, which uses reliability and failure risk indicators, enables replacing standard maintenance schedules based on fixed intervals expressed in calendar time or mileage with dynamic schedules that account for the probability of failure as a function of the vehicle's operating history. This method enables moving away from a static interpretation of FMECA results and linking the assessment of risk and criticality levels from a reliability perspective to time or other operational resources of the asset. This makes it possible not only to determine the significance of a given failure mode, but also to track changes in that significance over the entire service life. The introduction of the AP(t) indicator eliminates the fundamental flaw of the classical RPN indicator, which consists in treating scenarios with completely different combinations of S, O, and D. In the application case, only a small group of failure modes achieved the highest priority class for risk mitigation measures, AP = H, which should be considered an advantage of the method, as it primarily identifies those failure modes that should indeed be subject to priority diagnostic and preventive measures.

The developed method enables the assessment of reliability criticality in a dynamic context, using criticality classes CP(t) determined from the quantiles of the criticality evaluation function CEF(t). Unlike AP(t), CP(t) classes are used to identify the failure modes, components, subassemblies, and assemblies that are most critical to reliability. This makes it possible to supplement the safety assessment perspective with a reliability assessment perspective.

An application example of the method enabled the identification of two failure modes that are particularly significant for reliability, for which the highest criticality class was observed throughout the entire period analyzed. This means they play a dominant role in the overall criticality assessment and should be considered key to the freight wagon's reliability. Aggregating the values of the criticality assessment function to higher levels of the hierarchical decomposition made it possible to further identify the elements, subassemblies, and assemblies that are most critical.

From a practical standpoint, the values of the AP(t) and CP(t) indicators can serve as a basis for modifying the scope and frequency of maintenance activities, supporting the transition from a strategy based solely on cycles to one aligned with RBM and RCM approaches. The AP(t) indicator shows when measures should be taken to reduce the level of risk, while the CP(t) classes identify areas of the freight wagon's design that require actions aimed at improving reliability, including preventive maintenance, corrective actions, organizational measures, and development activities carried out as part of the MMS system's functions.

However, in the case of large wagon fleets, the practical implementation of dynamically determined maintenance intervals should take into account organizational constraints and therefore requires appropriate advance planning.

References

1. Dinmohammadi F, Alkali B, Shafiee M, Bérenguer C, Labib A. Risk evaluation of railway rolling stock failures using FMECA technique: a case study of passenger door system. *Urban Rail Transit* 2016; 2(3-4): 128-145. doi:10.1007/s40864-016-0043-z.
2. Dinmohammadi F. A risk-based modelling approach to maintenance optimization of railway rolling stock: a case study of pantograph system. *Journal of Quality in Maintenance Engineering* 2019; 25(2):272-293. doi:10.1108/JQME-11-2016-0070.
3. Appoh F, Yunusa-Kaltungo A, Sinha JK, Kidd M. Practical demonstration of a hybrid model for optimising the reliability, risk, and

maintenance of rolling stock subsystem. *Urban Rail Transit* 2021; 7(2): 139-157. doi:10.1007/s40864-021-00148-5.

4. Wang W, Wang Y, Han X. A dynamic failure mode and effects analysis for train systems failures risk assessment using FCM and prospect theory. *Management System Engineering* 2022; 1(1): 8. doi:10.1007/s44176-022-00008-x.
5. Catelani M, Ciani L, Galar D, Guidi G, Matucci S, Patrizi G. FMECA assessment for railway safety-critical systems investigating a new risk threshold method. *IEEE Access* 2021; 9: 86243-86253. doi:10.1109/ACCESS.2021.3088948.
6. Seyedan Oskouei SF, Abapour M, Beiraghi M. Identifying critical components for railways rolling stock reliability: a case study for Iran. *Scientific Reports* 2024; 14(1): 12080. doi:10.1038/s41598-024-62841-2.
7. Polish Committee for Standardization. PN-EN IEC 60812: Failure modes and effects analysis (FMEA and FMECA). Warsaw: Polish Committee for Standardization; 2018.
8. Szkoda M, Kaczor G, Grzywna M. A method for assessing the criticality of failures of railway vehicle components using the FMECA method. *Transport Problems* 2024; 19(3): 93-106. doi:10.20858/tp.2023.19.3.08.
9. Act of 28 March 2003 on rail transport. Journal of Laws of 2024, item 697 [in Polish].
10. Regulation of the Minister of Infrastructure of 12 October 2005 on the general technical conditions for the operation of railway vehicles. Journal of Laws of 2016, item 226, as amended [in Polish].
11. European Commission. Commission Implementing Regulation (EU) 2019/779 of 16 May 2019 laying down detailed provisions on a system of certification of entities in charge of maintenance of vehicles pursuant to Directive (EU) 2016/798 of the European Parliament and of the Council and repealing Commission Regulation (EU) No 445/2011. Official Journal of the European Union 2019; L139I: 360-389.
12. European Parliament and Council of the European Union. Directive (EU) 2016/798 of 11 May 2016 on railway safety. Official Journal of the European Union 2016; L138: 102-149.
13. European Parliament and Council of the European Union. Directive (EU) 2016/797 of 11 May 2016 on the interoperability of the rail system within the European Union. Official Journal of the European Union 2016; L138: 44-101.
14. European Commission. Commission Regulation (EU) No 321/2013 of 13 March 2013 concerning the technical specification for interoperability relating to the subsystem rolling stock - freight wagons of the rail system in the European Union and repealing Decision 2006/861/EC. Official Journal of the European Union 2013; L104: 1-56.
15. Polish Committee for Standardization. PN-EN 50126-1:2018-02. Railway applications - Specification and demonstration of reliability, availability, maintainability and safety (RAMS) - Part 1: Generic RAMS process. Warsaw: Polish Committee for Standardization, 2018.
16. Department of Defense. MIL-STD-1629A Procedures for performing a failure mode, effects and criticality analysis. Washington (DC): Department of Defense; 1980.
17. Automotive Industry Action Group, Verband der Automobilindustrie. AIAG & VDA FMEA handbook: design FMEA, process FMEA, supplemental FMEA for monitoring and system response. 1st ed. Southfield, MI: Automotive Industry Action Group; 2019.
18. SAE International. Potential failure mode and effects analysis (FMEA), including design FMEA, supplemental FMEA-MSR, and process FMEA. SAE Standard J1739_202101. Warrendale, PA: SAE International; 2021. doi:10.4271/J1739_202101.
19. Polish Committee for Standardization. PN-EN 60300-3-3:2017-07. Dependability management - Part 3-3: Application guide - Life cycle costing. Warsaw: Polish Committee for Standardization; 2017.
20. Polish Committee for Standardization. PN-EN 15380-5:2014-11. Railway applications - Classification system for railway vehicles - Part 5: System breakdown structure. Warsaw: Polish Committee for Standardization; 2014.
21. Młyńczak M. Metodyka badań eksploatacyjnych obiektów mechanicznych [Methodology of field testing of mechanical objects]. Wrocław: Oficyna Wydawnicza Politechniki Wrocławskiej; 2012. [in Polish]. ISBN: 978-83-7493-683-5.
22. Oz MA, Kaymakcı OT, Koyun A. A safety related perspective for the power supply systems in railway industry. *Eksploatacja i Niezawodnosc – Maintenance and Reliability* 2017; 19(1): 114-120. 10.17531/ein.2017.1.16.
23. Manzini R, Regattieri A, Pham H, Ferrari E. Maintenance for industrial systems. London: Springer; 2010. doi:10.1007/978-1-84882-575-8.
24. VPI European Rail Service GmbH. VPI European Maintenance Guide (VPI-EMG). Edition 5.0. Hamburg: VPI European Rail Service GmbH; 2024.

25. GCU Bureau. General contract of use for wagons (GCU). Version of 1 January 2025.