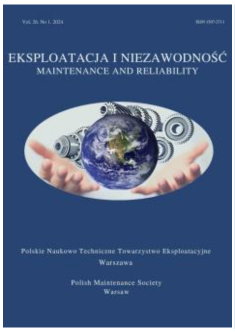


# Eksploatacja i Niezawodnosc – Maintenance and Reliability

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# Failure and reliability analysis of heavy firefighting and rescue vehicles: a case study

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## Highlights

- The presented research results represent unique knowledge on life cycle performance analysis, reliability, maintainability, and mainly availability estimation, as well as modelling and prediction of the reliability of firefighting and rescue vehicles.
- The presented research results represent unique knowledge that is rarely reported in the scientific literature.



## Abstract

The purpose of the article was to analyse the reliability, maintainability, and availability estimates of firefighting and rescue engines. Analysing the reliability parameters of heavy firefighting and rescue vehicles over time requires knowledge of their failures. In this article, failure data from the six years of maintenance of ten heavy firefighting and rescue vehicles from ten were analysed in relation to two main subsystems. Reliability analysis was performed and the best-fit distribution was found, with the parameters calculated. For both subsystems, the chassis combined with the cabin and the superstructure, the 2P-Weibull distribution was identified as the most suitable fit. The availability and maintenance indicators for each vehicle and the individual subsystems were calculated. It was clearly defined that there exists a significant difference between the two subsystems analysed in terms of failure characteristics, as well as maintainability and availability parameters.

## Keywords

firefighting and rescue vehicle, reliability, maintainability, availability

## 1. Introduction

Over the past few years, significant scientific and technological progress has been observed within the State Fire Service (SFS), as highlighted by recent research [36]. This progress can be attributed to several factors, including optimising firefighters' tasks, providing access to high-quality equipment, and improving their ability to utilise personal protective equipment (PPE). Several challenges in the operation of equipment and gear within the State Fire Service were identified several years ago. Since then, efforts have intensified to discover innovative methods that aim to eliminate or, to some extent, address these challenges.

The reliability of safety systems is fundamental for human society and all civilisations [32]. Random events, the outcome of which humans cannot unequivocally predict (adverse effects) [45], are the determinants of rescue services' actions. Emergency services are designed to prevent the consequences

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of adverse natural phenomena such as earthquakes, hurricanes, avalanches, floods, and fires, as well as deliberate actions, including destructive human activities, acts of terrorism, and sabotage [31]. For these reasons, the ability (a concept taken from the qualitative definition of reliability [34]) to carry out operational activities of rescue services, including but not limited to the largest State Fire Service (SFS) and volunteer firefighting units in National Firefighting and Rescue System (NFRS), is of fundamental importance.

It became evident that relying solely on practical knowledge in this context is insufficient. To find modern and, more importantly, adaptable solutions suitable for a wide range of often unpredictable situations, it became necessary to use the latest engineering and computational methods while keeping up-to-date with current scientific findings. Consequently, a consortium was established consisting of the Józef Tuliszkowski Scientific and Research Centre for Fire Protection - National Research Institute, CMGI Sp. z o.o., The Main School of Fire Service (currently Fire University), MLabs Sp. z o.o., and TELDAT Sp. z o.o. Sp. k. This consortium conducted project No. DOBR-BIO4/051/13087/2013, which received funding from the National Centre for Research and Development. The project aimed to develop a methodology for continuous monitoring of the operation of specific components of firefighting equipment, focussing on reliability and performance.

Among the tangible outcomes of this collaborative effort is the publication titled "Problems of monitoring the exploitation of equipment and appliances in the fire department" [37]. This publication identifies challenges related to monitoring the operation of specific components of firefighting equipment in terms of reliability and performance. It also suggests methods to address these challenges, including the potential development of system-based solutions. Furthermore, the research presented modern solutions for personal protection for the emergency services of the National Firefighting and Rescue System, aligned with the needs of the end users, namely firefighters involved in rescue operations. This illustrates the benefits derived from the synergy of practical experience and the continuous development of knowledge in this field.

Consequently, modern engineering and computational methods are actively used and advanced by firefighters today to implement innovations in products, processes, and organisational aspects. The concept presented in this article for managing firefighting and rescue vehicle operations is in alignment with this trend. A scientific approach enables optimisation of fire vehicle activities and potential system enhancements, such as improving the functionality of the Decision Support System – ST (DSS-ST). These efforts aim to benefit SFS's material and financial management, including cost rationalisation for vehicle operations, inspections, maintenance, repairs, and increasing awareness among users, especially rescue drivers, fire-fighting equipment plays a crucial role in the public fire protection infrastructure [10]. It consists mainly of fire trucks, fire and rescue units, fire suppression, and personal protective equipment. Fire trucks are particularly important. All firefighting actions are based on fire trucks [49]. According to the PN-EN 18461 technical standard [32], a fire truck is a vehicle used in firefighting and rescue operations. Fire trucks are divided into vehicles used in direct firefighting operations and vehicles used to carry personnel and equipment. A fire truck is a specially designed vehicle in terms of its firefighting capabilities built on the chassis of a high mobility heavy-duty vehicle. The vehicle is equipped with machinery such as a water pump, water reservoir, specialised equipment, additional portable equipment, and fire suppression agents necessary to carry out the firefighting operation. Fire trucks can transport equipment, fire suppression agents, and personnel to the scene [11]. Therefore, it is important to maintain the reliability determined qualitatively and quantitatively based on descriptive statistics and probability models [18].

The literature provides a variety of indicators that allow the measurement and evaluation of the reliability and availability of transport means [4,7,15,16,50]. Each characteristic is defined by the PN-EN 50126-1 standard and can be described using different indicators [34]. The choice of particular metrics is based on various factors, including the nature of the object and its operational context [22,28,41,52]. Regarding fire trucks, significant indicators are mean time between failures (*MTBF*), mean time to repair (*MTTR*), mean residual life (MRL), and operational availability ($A_o$) [8,12,43]. One of the fundamental tasks in reliability analysis involves creating a model for the distribution of lifetimes using actual run-to-failure data [1,20,39,48].

Therefore, the objective of the article is to analyse life cycle performance, quantified reliability, maintainability, and mainly availability estimation, as well as modelling and prediction of the reliability of firefighting and rescue vehicles with respect to two subsystems, the chassis with a cabin and the superstructure [11,12]. The uniqueness of the presented research lies in the fact that, so far, the topic has been reported to be very rarely addressed in scientific publications. Thus, it provides an ascent to the initiation of more extensive research in the area of firefighter system reliability.

## 2. Research object

The object of the research was a group of 10 identical heavy firefighting and rescue vehicles. One of such vehicles is shown in Figure 1. In terms of gross vehicle weight (GVW) three categories of firefighting trucks can be distinguished: light (3000 kg > GVW ⩾7500 kg), medium (7500 kg > GVW ⩾16 000 kg) and heavy (GVW >16 000 kg) according to PN-EN 18461 Standard can be distinguished. GVW is defined as the weight of an unloaded vehicle plus the weight of personnel, equipment, and the fire suppression agent.


Fig. 1. Heavy firefighting and rescue vehicle.

The vehicles analysed are made up of two main subsystems, the chassis with the cabin and the specialised firefighting superstructure [42]. Fire trucks should have the ability to obtain high speeds and accelerations, as well as high stability and manoeuvrability. Fire truck chasses are standard serial production units or special designs with specifically selected subcomponents. Some of the fire trucks are built on the platforms of off-road vehicles. In terms of types of fire truck chassis and powertrain, the following vehicle categories can be distinguished: urban, terrain-ready, and off-road. Medium-sized fire trucks are built on standard or special chasses. Two axle chasses are applied most frequently with the 4x2 or 4x4 axle configuration (6x6 is less popular) [14]. The investigated group of vehicles (chassis and cabin) was based on the all-wheel-drive MAN TGM 18.340 vehicle. The vehicle engine (MAN Truck & Bus AG) is a straight 6-cylinder diesel with direct injection. The rated power output is 250 kW and 2300 rpm. The vehicle is fitted with a manual 9 speed forward and 1 speed reverse dual range transmission. The vehicle has an automatically lifted single piece steel four-door, six-seat cabin with a seat configuration of 1+1+4.

The superstructure (second subsystem) is made by a Polish manufacturer that specialises in such types of products. The specialised superstructure of the investigated vehicles is composed of an aluminium casing, dual range Ruberg Euroline pump (0.0667 $m^3/s$), water reservoir (5 $m^3$), foaming agent reservoir (0,5 $m^3$), a water/foam cannon, high-pressure fire hose (0.00417 $m^3/s$), power generator, lighting mast (two reflectors, 1000 W each) and a winch pull force up to 68 646,55 N.

The data on vehicle operation time span from the beginning of 2013 to the end of 2018, which is a total of 52,584 hours of uptime. During that time, each vehicle operated in one of the following regions: Jawor, Wroclaw, Kamienna Gora, Luban, Lubin, Polkowice, Strzelin, Swidnica, Wołow and Zabkowice Slaskie (tab. 1). In the tab. 2 the basic data collected for each of the fire departments operating the vehicles is presented. They include the following information:

- identification of the fire department where the vehicle was investigated,
- vehicle mileage at the end of the investigations,
- number of responses for each of the vehicles in the investigated period,
- an indicator determining the mean mileage per single firefighting response,
- recorded number of malfunctions of each vehicle divided into chassis/cabin and specialised superstructure.

The indicator determining the mean mileage per single firefighting event has been determined based on the total mileage divided by the number of events.

Tab. 1. Characteristics of the operational regions where vehicles were used.

| Fire department | Area of coverage [km²] | Population | Population density [inhabitants/km²] | Type of region | Prevailing economic activity |
|---|---|---|---|---|---|
| Jawor | 581,25 | 50 116 | 86,2 | agricultural, industrial | crop production, livestock production, food processing |
| Kamienna Góra | 396 | 43 239 | 109,2 | agricultural, industrial | industry |
| Luban | 428,3 | 54 254 | 126,7 | forest, agricultural | commerce, processing |
| Lubin | 711,99 | 106 150 | 149,1 | urban, industrial | industry |
| Polkowice | 779,93 | 63 065 | 80,9 | forest, agricultural | industry, tourism |
| Strzelin | 622,37 | 43 570 | 70 | agricultural, industrial | agriculture, industry |
| Swidnica | 742,89 | 156 921 | 211,2 | urban, agricultural | agriculture, services, industry |
| Wołow | 675 | 46 828 | 69,4 | rural, forest | commerce, tourism |
| Wrocław | 118,9 | 643782 | 2199 | urban, industrial | industry, services |
| Zabkowice Slaskie | 801,75 | 64 802 | 80,8 | rural, industrial | excavation industry, production |

Tab. 2. Number of responses, course and number of failures in the analysed period.

| Fire department | Mileage [km] | Number of responses [N] | Mileage/ number of responses [km/N] | Number of failures [NF] | | |
|---|---|---|---|---|---|---|
| | | | | Chassis + cabin | Superstructure | Total |
| Jawor | 36 828 | 903 | 37,35 | 25 | 16 | 41 |
| Kamienna Gora | 22 014 | 1255 | 19,79 | 4 | 6 | 10 |
| Luban | 55 500 | 2540 | 17,08 | 20 | 17 | 37 |
| Lubin | 20 514 | 121 | 19,08 | 4 | 0 | 4 |
| Polkowice | 36 467 | 1393 | 142,46 | 16 | 4 | 20 |
| Strzelin | 33 760 | 960 | 24,82 | 3 | 4 | 7 |
| Swidnica | 38 143 | 1594 | 33,79 | 7 | 12 | 19 |
| Wołow | 35 481 | 1502 | 21,18 | 20 | 8 | 28 |
| Wroclaw | 43 792 | 1947 | 22,94 | 10 | 14 | 24 |
| Zabkowice Slaskie | 64 467 | 2672 | 22,15 | 17 | 11 | 28 |

## 3. Methods

### 3.1. Failure data

The data were obtained from the Decision Support System - ST. That is an integrated multi-module system aiming at utilising database-contained information to assist the operation of the State Fire Service. The system is used by SFS organisational units. Information related to fire trucks is recorded at the fire departments level and automatically replicated to higher levels. The information in the DSS-ST includes the technical parameters of the vehicles (power output, type of powertrain, vehicle manufacturer, and superstructure). The system also records the times necessary to restore vehicle operational availability after failures and preventive downtime (inspections).

In the period under analysis, for all units 7615 responses were recorded (7272 local and 1381 prank calls). In the research carried out, objects, that is, 10 identical fire trucks, were treated as a fleet of vehicles performing similar tasks, varying with their operational time, mileage, and response rates. Data were collected from the beginning of their operation (new roadworthy vehicles, zero mileage).

Each vehicle was divided into two subsystems, the chassis/cabin and the superstructure, both treated as separate components, which is why the reliability characteristics were also determined for each of them separately. It was assumed that the chassis and cabin are components whose wear and failures depend mainly on mileage. Depending on the operational area of a given fire department, the vehicles generated different mileage responding to calls; therefore, it was assumed that their failures were not a derivative of time expressed in hours, but distance in kilometres. On the other hand, the characteristics of wear and failures in the case of the firefighting superstructure depended mainly on the number of responses and the operating time of the rescue equipment expressed in hours. Therefore, in this case, the authors analysed the time elapsed until failure was expressed in hours.

The outlined approach for determining the lifespan of the two repairable subsystems considers all accessible data related to the vehicle's operational durations, measured in kilometres (km) for the first system, chassis and cabin, and in hours (h) for the second system, superstructure. This encompasses instances where a studied subsystem is operational at the point when the research is concluded, with the lifespan of such a subsystem being termed right-censored. The technique for compiling statistical data based on operational data was formulated in studies [39,46]. The 10 vehicles operated in ten different fire departments, implying that the usage conditions were likely similar. Data for both subsystems were tested separately and independently. During the study, estimated availability was assessed, and in some cases the two subsystems were studied together. Reliability analysis and parameter estimation were performed on subsystems that were treated as repairable.

In the first stage of the analysis, the authors presented as an example the moment of occurrence of the first 30 chassis/cabin and superstructure failures expressed in the covered distance (chassis/cabin) and time (superstructure). Then, in a graphical form, the authors presented the moment of occurrence of all failures divided into subsystems. Then, the types of vehicle and their cumulative downtimes were shown.

### 3.2. Fitting of the probability distribution fitting and basic characteristics of failures of two subsystems

In the given case, the research objects were also treated as a fleet of identical vehicles composed of two subsystems: chassis/cabin and superstructure. In the work, the authors used an aggregated method to select a hypothetical empirical distribution function [39]. The software used in the calculations helps to select the most suitable distribution for the data through independent statistical tests conducted for each subsystem [35]. Fundamental probability distributions, including 1P-Exponential, 2P-Exponential, 2P-Weibull, 3P-Weibull, Gamma, G-Gamma, Logistic, Loglogistic, Lognormal, Normal, and Gumbel, were considered in the analysis. Three criteria were used to rank the distributions: the Kolmogorov-Smirnov (*K-S*) test, the normalised correlation coefficient (rho), and the likelihood value (*LKV*). These selected distributions are then ranked on the basis of their fit to the input data. The ranking involves considering the three tests with weights assigned to each. In this study, the maximum likelihood estimation (MLE) method was used and the weights assigned for each test were as follows. *K-S* – 40%, *rho* – 10%, and *LKV* – 50% [46]. The assignment of weights for each test is derived from engineering practice, with more details on weight calculation and selection available in [46]. It is important to note that the sum of the three weights for each parameter estimation method must be equal to 100%. For a more complete understanding of the procedural algorithm and calculation methods used [37].

The initial factor involves a modified Kolmogorov-Smirnov (KS) test, specifically used to assess the suitability of a continuous distribution with known parameters [34]. This test quantifies the statistical disparity between the anticipated and observed results and can be executed with the null and alternative hypotheses as follows:

- $H_0$: distribution represents the data,
- $H_1$: distribution does not represent the data.

The *K-S* test statistic ( $D_{max}$ ) represents the maximum difference between the observed and predicted probabilities [21]:

$$D_{max} = \max_{1 \le i \le n} |S_i - Q_i| \tag{1}$$

where:

$D_{max}$ – value of the statistic,
$n$ – number of observations,
$Q_i$ – observed probability,
$S_i$ – predicted probability based on the distribution.

It is important to mention that the observed probability is calculated using median ranks, and the difference between these two values is computed to find the largest absolute difference, which is represented as $D_{max}$.

The modified *K-S* test assesses the probability that the critical value $D_{CRIT}$ – obtained from tables, is smaller than the maximum $D_{max}$ acquired through the computational process [21]:

$$\mathrm{P}(D_{CRIT} < D_{max}) \tag{2}$$

The high values of the K-S test, approaching 1, suggest a significant difference between the theoretical distribution and the data set. Therefore, a smaller *K-S* test value indicates a better fit to the hypothetical distribution.

The second factor is the correlation coefficient test, represented by "*rho*." This test evaluates the degree to which the plotted points align with a straight line [21]. Assesses the mean absolute deviation between the hypothetical and empirical distributions, and the test statistics for the assessment of conformity are calculated using the following formula [21]:

$$rho = 100 \frac{1}{n} \sum_{i=1}^{n} |S_i - Q_i| \tag{3}$$

where:

$n$ – number of observations,

$Q_i$ – observed probability,

$S_i$ – predicted probability based on the distribution.

The likelihood function, also known as the likelihood value test, was used as a measure to determine how well a probabilistic model fits the empirical data [38]. The basic idea behind this method is to obtain the most likely values of the parameters for a given distribution that best describe the data. The logarithmic value of the likelihood function (*LKV*) is calculated for empirical data [21, 23]. The likelihood function $L$ is dependent on the random sample $T_1, T_2, \ldots, T_n$ (representing observed failures) and $S_1, S_2 \ldots S_m$ (representing suspensions). It also depends on the unknown parameters that require estimation, denoted as $\theta_1, \theta_2, \ldots, \theta_k$, for which it seeks to attain maximum values. The general form of the likelihood function is given by formula [19,26]:

$$L(\theta_1, \theta_2, \ldots, \theta_k | T_1, T_2, \ldots, T_n, S_1, S_2 \ldots S_m) = \prod_{i=1}^{n} f(T_i; \theta_1, \theta_2, \ldots, \theta_k) \cdot \prod_{j=1}^{m} [1 - F(S_j; \theta_1, \theta_2, \ldots, \theta_k)] \tag{4}$$

where:

$L$ – likelihood function,

$n$ – number of observed failures at time point $T_1, T_2, \ldots, T_n$,

$m$ – number of suspended data points at $S_1, S_2, \ldots, S_m$,

$k$ – number of estimated parameters,

$T_i$ – failure time of the *i*-th component,

$S_j$ – suspension time of the *j*-th component,

$\theta_1, \theta_2, \ldots, \theta_k$ – $k$ unknown parameters that need to be estimated,

$f(T_i; \theta_1, \theta_2, \ldots, \theta_k)$ – probability density function *pdf*,

$F(S_j; \theta_1, \theta_2, \ldots, \theta_k)$ – cumulative density function *cdf*.

In the specific case being discussed, the likelihood function was extended to incorporate factors that consider the presence of right-censored data. The log-likelihood function is calculated by summing the natural logarithms of the probability density for each individual lifetime of the analysed component. [3]:

$$L\Lambda = ln\, L = \sum_{i=1}^{n} ln\, f(T_i; \theta_1, \theta_2, \ldots, \theta_k) + \sum_{j=1}^{m} ln[1 - F(S_j; \theta_1, \theta_2, \ldots, \theta_k)] \tag{5}$$

where:

$L$ - likelihood function,

$n$ - number of failed components,

$m$ - number of suspended data points in $S_1, S_2, \ldots, S_m$,

$\theta_j,\ j = 1, 2, \ldots, k$ - *j*-th parameter of the distribution,

$T_i,\ i = 1, 2, \ldots, n$ - time to failure of the *i*-th component.

The values of the estimators of the unknown parameters $\theta_1, \theta_2, \ldots, \theta_k$ are determined by maximizing the log-likelihood function $\Lambda(\theta_1, \theta_2, \ldots, \theta_k)$. A necessary condition for the existence of an extremum of this function is that all its partial derivatives are equal to zero.

To determine the estimators of the unknown parameters, we calculate the partial derivatives $\frac{\partial \Lambda(\theta_1, \theta_2, \ldots, \theta_k)}{\partial \theta_j}$ of function $\Lambda$ are calculated with respect to the parameters $\theta_j, j = 1, 2, \ldots, k$. To estimate the parameters, each partial derivative should be equal to zero and $the\ k$ equations should be solved [38]:

$$\begin{gathered} \frac{\partial \Lambda(\theta_1, \theta_2, \ldots, \theta_k)}{\partial \theta_1} = 0 \\ \ldots\ldots\ldots \\ \frac{\partial \Lambda(\theta_1, \theta_2, \ldots, \theta_k)}{\partial \theta_k} = 0 \end{gathered} \tag{6}$$

In the final step, each of the three goodness-of-fit criteria is applied to all eleven distributions, and ranks are assigned from the best-fitting to the worst-fitting theoretical distribution. To determine this ranking, all three tests are considered, each with its assigned weight. The results of these tests are weighted and then combined into a single overall value known as the Weighted Decision Variable (*WDV*) value, which is provided in [35]:

$$WDV = K\text{-}S\, Rank \times 40\% + rho\, Rank \times 10\% + LKV\, Rank \times 50\% \tag{7}$$

The distribution with the lowest *WDV* value is considered the best fit for the data. The software provides flexibility for the user to assign different weights depending on whether the parameter estimation method is rank regression or MLE; in this study the MLE method was used [17]. In the analysis, the two-parameter Weibull distribution was shown to be the best fit to the data for both subsystems. Therefore, the next considerations and formulas of the article were based on this distribution. The two-parameter Weibull distribution is described by a density function [25]:

$$f(t;\beta,\eta) = \frac{\beta}{\eta}\cdot\left(\frac{t}{\eta}\right)^{\beta-1}\cdot e^{-\left(\frac{t}{\eta}\right)^{\beta}}, \quad t \geq 0, \beta > 0, \eta > 0 \tag{8}$$

where:

$\beta$ – shape parameter,

$\eta$ − scale parameter.

The next parameter calculated is *MRL* (Mean Residual Life), which is given for any $t$ such that $R(t) > 0$ and can be simply represented with the reliability function as [3]:

$$MRL(t) = \frac{1}{R(t)}\int_0^{\infty} R(t+l)\,dl = \frac{1}{R(t)}\int_t^{\infty} R(l)dl \quad t \geq 0 \tag{9}$$

where:

*MRL*(*t*) – the mean residual life of the object at time *t*,

*R*(*t*) – the reliability function, representing the probability that an object survives beyond time *t*,

$l$ – is the additional lifetime of the object beyond time *t*,

$\int_t^{\infty} R(l)dl$ – the integral from *t* to infinity of the reliability function *R*(*l*) with respect to *l*.

When $R(0) = 1$ and $t = 0$, the *MRL* equals the mean lifetime, that is $MRL(0) = MTBF$ (Mean Time Between Failures). If a component has survived until time *t*, then the mean residual life at time *t*, denoted as *MRL*(*t*), represents the expected remaining time to failure for this component. For the two parameters of the Weibull distribution, the following is true [29]:

$$MRL(t) = \eta\cdot e^{\tau}\cdot\Gamma\left(1+\frac{1}{\beta}\right)\cdot\left(1-\frac{\Gamma_{\tau}\left(\frac{1}{\beta}\right)}{\Gamma\left(\frac{1}{\beta}\right)}\right), \tau = \left(\frac{t}{\eta}\right)^{\beta} \tag{10}$$

where:

$\eta$ – the scale parameter,

$\beta$ – the shape parameter,

*e* – the base of the natural logarithm,

*t* – the time or distance for which we compute *MRL*,

$\Gamma$ – the gamma function,

$\Gamma_{\tau}(r)$ – the incomplete gamma function defined as $\Gamma_{\tau}(r) = \int_0^{\tau} t^{r-1}e^{-t}dt$.

The Mean Time Between Failures, sometimes referred to as the Mean Distance Between Failures (*MDBF*), is a calculated parameter that represents the average amount of time or distance that units within a population are expected to operate before experiencing a failure [24]. In essence, it measures the average time or distance of reliable performance before a failure event occurs [17].

The *MTBF* for a 2P-Weibull distribution can be calculated as follows:

$$MTBF = \eta\cdot\Gamma\left(\frac{1}{\beta}\right)+1) \tag{11}$$

where:

Γ - gamma function,

$\eta, \beta$ - 2P Weibull shape and scale parameters.

A Reliable Life (warranty time) is the estimated time when the reliability will be equal to a specified goal and the reliable life ($T_R$) of a unit for a specified reliability ($R$) starting the mission at age zero, is given by

The reliable life of a unit denoted as ($T_R$) for a specified reliability starting the mission at age zero can be calculated using the following formula [51]:

$$T_R = \eta[-\ln(R)]^{\frac{1}{\beta}} \tag{12}$$

where:

- $T_R$ is the reliable life or warranty time,
- $\eta$ is a scale parameter,
- $\beta$ is a shape parameter,
- $R$ is the specified reliability goal,
- $-\ln(R)$ represents the natural logarithm of the specified reliability.

This formula is often used in reliability analysis to estimate the time in which the reliability of a unit will reach a specified level ($R$) starting from age zero.

### 3.3. Reliability indicators of individual vehicles

The objects were treated as a whole. The authors assumed that the vehicles are made up of two connected subsystems of series. Failure of any of the subsystems resulted in inaccessibility of the entire vehicle. Vehicles were divided in terms of fire protection functionality. First, corrective and preventive maintenance times, as well as availability, were determined. Other reliability indicators were determined as well: time to first failure (*TTFF*), mean time to repair, mean time between maintenance (*MTBM*), mean maintenance downtime (*MMD*), inherent availability (AI), and operational availability ($A_o$). The data have been presented in tables and the selected indicators have been shown in the form of graphs.

Inherent availability is a measure of how reliably a system operates when you only take into account the time it is unavailable due to corrective maintenance (*CM*). This calculation excludes any downtime caused by preventive maintenance, logistic problems, supply delays, or administrative delays. Essentially, it tells you how well the system performs when looking solely at the efficiency and speed of maintenance efforts, considering factors like the level of skill of maintenance personnel, their training, and the ease of performing repairs. For systems that can be repaired when they break down, it can be calculated as follows [23]:

$$A_I = \frac{MTBF}{MTBF + MTTR} \tag{13}$$

where:

$MTBF$ - uptime/number of system failures,

$MTTR$ - CM downtime/number of system failures.

Operational availability refers to a measure of the average availability of a system over a specific time period, taking into account all sources of downtime, including administrative and logistic delays. Operational availability is calculated as the ratio of system uptime to total time. Mathematically, it is expressed as follows [23]:

$$A_O = \frac{Uptime}{Operating\ cycle} \tag{14}$$

where uptime refers to the cumulative duration in which the system was actively operating throughout the operating cycle and is the overall time period of operation under investigation. In this research, the availability achieved is equal to the operational availability because logistic delays, supply delays, or administrative delays are included in maintenance downtime.

## 4. Results

### 4.1. Failure data analysis

Tab. 3 consists of life data from six years of firefighting vehicle operation. Provides specific failure times, measured in kilometres, for the initial 30 failures observed in the chassis/cabin of a firefighting vehicle from the start of its operation. Fig. 2 presents all failures recorded for a given subsystem divided into fire departments. At the moment of completion of the investigations, each of the vehicles had different mileages - the lowest was 22 014 km (Kamienna Gora) and the highest was 64 467 km (Zabkowice Slaskie). Failures occurred during the entire period under analysis and their number varied depending on the fire department.

Tab. 4 and Fig. 3 present analogical data for the superstructure; only in this case the data (times) were expressed in work hours. The total time of the vehicles under investigation was 52584 hours for all fire departments, which is equivalent to 6 years of operation; therefore, the time to complete vehicle investigations was the same. In the given case, the failures that occurred throughout the operation and their number depended on the fire department. Additionally, there can be seen a difference in the number of failures between the individual vehicle subsystems. A greater number of failures were recorded for the chassis/cabin compared to the superstructure.

Tab. 3. Example of the 30 first recorded failures for the first subsystem – chassis/cabin of a firefighting vehicle (NF – number of failures, Time – time to failure in kilometres, Fire department – place where the failure occurred).

| No | Time [km] | Fire department | No | Time [km] | Fire department | NF | Time [km] | Fire department |
|---|---|---|---|---|---|---|---|---|
| 1 | 1879 | Polkowice | 11 | 5073 | Jawor | 21 | 9663 | Jawor |
| 2 | 1917 | Polkowice | 12 | 5470 | Lubin | 22 | 10868 | Zabkowice Slaskie |
| 3 | 1923 | Polkowice | 13 | 5780 | Lubin | 23 | 10898 | Jawor |
| 4 | 2606 | Zabkowice Slaskie | 14 | 6740 | Luban | 24 | 11233 | Wolow |
| 5 | 2628 | Polkowice | 15 | 7569 | Luban | 25 | 11754 | Swidnica |
| 6 | 2701 | Polkowice | 16 | 8716 | Polkowice | 26 | 12399 | Lubin |
| 7 | 2706 | Polkowice | 17 | 9223 | Swidnica | 27 | 12921 | Luban |
| 8 | 2775 | Polkowice | 18 | 9304 | Strzelin | 28 | 13719 | Zabkowice Slaskie |
| 9 | 3922 | Luban | 19 | 9308 | Strzelin | 29 | 13864 | Luban |
| 10 | 4552 | Swidnica | 20 | 9309 | Jawor | 30 | 14945 | Wolow |

Tab. 4. Example of the 30 first recorded failures for the second subsystem - superstructure of a firefighting vehicle (No – number of failure, Time – time to failure in hours, Fire department – place where the failure occurred).

| No | Time [hr] | Fire department | No | Time [hr] | Fire department | NF | Time [hr] | Fire department |
|---|---|---|---|---|---|---|---|---|
| 1 | 178,8 | Strzelin | 11 | 2364,1 | Swidnica | 21 | 12657,4 | Swidnica |
| 2 | 307,6 | Jawor | 12 | 3561,4 | Jawor | 22 | 12848,3 | Wolow |
| 3 | 420,9 | Jawor | 13 | 5053,8 | Wroclaw | 23 | 13309,6 | Wolow |
| 4 | 514 | Jawor | 14 | 5268,6 | Zabkowice Slaskie | 24 | 13623,9 | Jawor |
| 5 | 516,1 | Kamienna Gora | 15 | 5532,9 | Luban | 25 | 13788,3 | Wroclaw |
| 6 | 688,6 | Luban | 16 | 5780,2 | Swidnica | 26 | 14843,6 | Zabkowice Slaskie |
| 7 | 1258,6 | Swidnica | 17 | 8796,9 | Luban | 27 | 14844,9 | Swidnica |
| 8 | 1378,4 | Swidnica | 18 | 8916,2 | Wroclaw | 28 | 15280,1 | Wroclaw |
| 9 | 2268,7 | Polkowice | 19 | 11915,4 | Luban | 29 | 17463,4 | Zabkowice Slaskie |
| 10 | 2362,3 | Jawor | 20 | 12153,9 | Swidnica | 30 | 17699,2 | Zabkowice Slaskie |

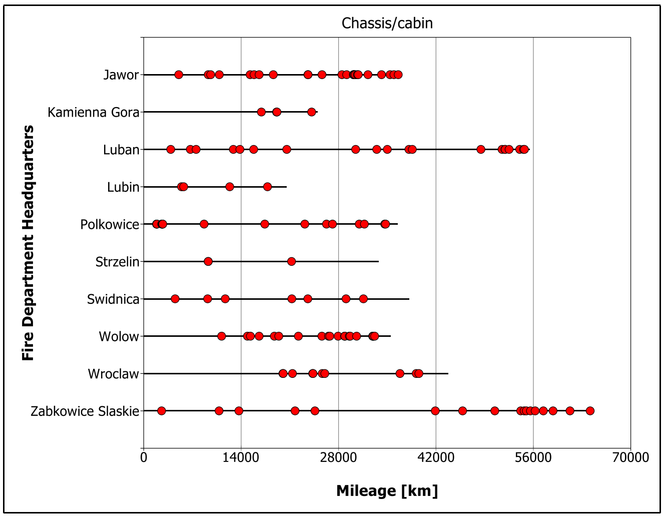


Fig. 2. System operation for the chassis/cabin – exact failure time in kilometres.

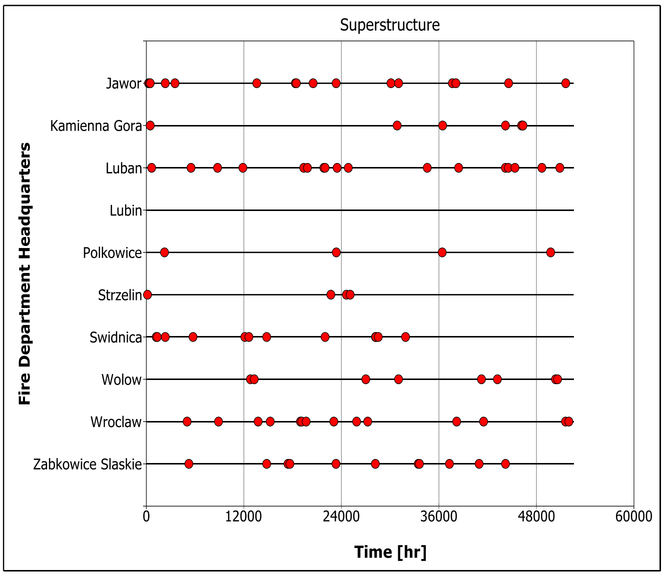


Fig. 3. System operation for the superstructure – exact failure time in hours.

Tab. 5 presents the types of fire truck failures of the fire trucks together with their number and cumulative downtime. The most common causes of engine failure were service/warranty inspections. Their number was at least several times higher compared to other downtimes. Maintenance and failure of the water-foam system was second in the downtime rank. The longest collective downtime was recorded for brake system failure. The longest mean downtime was recorded for the following failures: mechanical failure of the cabin, steering system, and powertrain

Tab. 5. Types of failure for both subsystems.

| No. | Type of failure | Cumulative downtime [h] | Number of downtime [$n_{CD}$] | Cumulative downtime/number of downtime [$h/n_{CD}$] |
|---|---|---|---|---|
| 1 | Service/warranty inspection | 840,0 | 124 | 6,8 |
| 2 | Maintenance | 27,9 | 32 | 0,9 |
| 3 | Water-foam system failure | 811,1 | 32 | 25,3 |
| 4 | Superstructure failure | 48,7 | 25 | 1,9 |
| 5 | Brake system failure | 2330,7 | 25 | 93,2 |
| 6 | Electrical failure | 1085,4 | 24 | 45,2 |
| 7 | Fuel feed system failure | 548,7 | 24 | 22,9 |
| 8 | Pneumatic system failure | 176,3 | 23 | 7,7 |
| 10 | Pump failure | 153,1 | 17 | 9,0 |
| 11 | Other failures | 288,5 | 13 | 22,2 |
| 12 | Engine cooling system failure | 842,2 | 12 | 70,2 |
| 13 | Engine failure | 1685,8 | 10 | 168,6 |
| 14 | Chassis failure | 272,8 | 8 | 34,1 |
| 15 | Suspension failure | 1808,4 | 7 | 258,3 |
| 16 | Cabin failure | 34,9 | 5 | 7,0 |
| 17 | Cabin mechanical failure | 1107,4 | 3 | 369,1 |
| 18 | Drivetrain failure | 3,8 | 2 | 1,9 |
| 19 | Steering system failure | 566,1 | 2 | 283,0 |

### 4.2. Reliability analysis of the two subsystems

A selected sample of heavy firefighting and rescue vehicles operated by the fire departments of Poland was used to carry out research on the failure characteristics. The authors deemed the two-parameter Weibull distribution the best distribution showing the chassis/cabin and superstructure failure data in the 6 year period of firefighting vehicle operation, using aggregated criteria. The resulting values of the three distribution fit tests are shown in Table 6.

Tab. 6. Analysis results: factor values for both subsystems from the fit test.

| **Distribution** | **(*K-S*)** | **(*rho*)** | ***LKV*** |
|---|---|---|---|
| Chassis/Cabin | 24,52 | 2,829 | -1403,513 |
| Superstructure | 83,01 | 3,975 | -1019,414 |

In the next step, the authors estimated its value parameters $\hat{\beta}$ , $\hat{\eta}$ for the chassis/cabin $\hat{\beta}_{cc}$ = 1,6839, $\hat{\eta}_{cc}$ = 31 854,2 and for the superstructure $\widehat{\beta_s}$ = 1,2473, $\widehat{\eta_s}$ = 31150,02 [km]. On this basis, the mean time/distance between failures was calculated from formula 11. Upon substituting the data, the following was obtained:

for the chassis/cabin

$$MTBF_{cc} = 31854{,}2 \cdot \Gamma\left(\frac{1}{1{,}6839} + 1\right) = 28\,440{,}6 \text{ [km]},$$

for the superstructure:

$$MTBF_s = 31150{,}02 \cdot \Gamma\left(\frac{1}{1{,}2473} + 1\right) = 29026{,}8 \text{ [hr]}.$$

An estimation was also made of the reliable life parameter $T_R$ for the required reliability of 0,9, which corresponds to a B10 life indicator, i.e., the time, by which 10% of the objects will fail. Therefore, upon substituting the data the following was obtained:

for the chassis/cabin

$$T_{Rcc} = 31854{,}2 \cdot (-\ln(0{,}9))^{\frac{1}{1{,}6839}} = 8371{,}16 \text{ [km]},$$

for the superstructure.

$$T_{Rs} = 31150{,}02 * (-\ln(0{,}9))^{\frac{1}{1{,}2473}} = 5127{,}8 \text{ [hr]}.$$

In the following steps, we also calculated selected parameters for age ($t$) at the end of the study, that is, after six years of operation, and for the chassis/cabin it was t = 64,467 km and for the superstructure t = 52,584 hours. We estimate the values of the following parameters: the probability of failure $Q$, the failure rate $h$, and the mean residual life $MRL$. From the distribution function formula, the probability of failure was calculated:

for the chassis/cabin:

$$Q_{cc}(64\,467) = 1 - e^{-\left(\frac{64467}{31854{,}2}\right)^{1{,}6839}} = 0{,}96228,$$

and then for the superstructure:

$$Q_s(52584) = 1 - \mathrm{e}^{-\left(\frac{52584}{31150{,}02}\right)^{1{,}2473}} = 0{,}8536.$$

In the next part, the authors calculated the failure rate and the assumed time.

for the chassis/cabin:

$$h_{cc}(64467) = \left(\frac{1{,}6839}{31854{,}2}\right) \cdot \left(\frac{64467}{31854{,}2}\right)^{1{,}6839-1} = 0{,}0000856/\text{km},$$

for the superstructure:

$$h_s(52584) = \left(\frac{1{,}2473}{31150{,}02}\right) \cdot \left(\frac{52584}{31150{,}02}\right)^{1{,}2473-1} = 0{,}0000455/\text{hr}.$$

Then, from formula 10, the mean residual time was calculated after substituting the data for the superstructure:

a) chassis/cabin for t = 64 467 km

$$MRL_{cc}(64467) = 31854{,}2 \cdot e^{\left(\frac{64467}{31854{,}2}\right)^{1{,}6839}} \cdot \Gamma\left(1 + \frac{1}{1{,}6839}\right) \cdot \left(1 - \frac{\Gamma\tau\left(\frac{1}{1{,}6839}\right)}{\Gamma\left(\frac{1}{1{,}6839}\right)}\right) = 10614{,}7 \text{ [km]},$$

b) superstructure for t = 52 584 h

$$MRL_s(52584) = 31150{,}02 \cdot e^{\left(\frac{52584}{31150{,}02}\right)^{1{,}2473}} \cdot \Gamma\left(1 + \frac{1}{1{,}2473}\right) \cdot \left(1 - \frac{\Gamma\tau\left(\frac{1}{1{,}2473}\right)}{\Gamma\left(\frac{1}{1{,}2473}\right)}\right) = 20\,410{,}5 \text{ [hr]}.$$

The estimated parameter values of the $\hat{\beta}$, $\hat{\eta}$ distribution and all calculated characteristics for each subsystem are shown in Table 7. The Weibull shape parameter indicates whether the failure rate is increasing, constant, or decreasing. The estimated values of the shape parameter are greater than 1, which means that the failure rate is increasing. The increase is faster for the chassis/cabin compared to the superstructure. The scale parameter is a measure that represents the time at which approximately 63.2% of the systems or components being analysed are expected to fail. It is closely related to the mean time to failure. A higher value of the indicator was obtained for the chassis/cabin. Table 7 contains all the estimated parameters.

Tab. 7. Estimated model parameters for the two subsystems.

| Parameter | Chassis/cabin | Superstructure |
|---|---|---|
| Shape parameter | $\hat{\beta}$ = 1,6839 | $\hat{\beta}$ = 1,2473 |
| Scale parameter | $\hat{\eta}$ = 31 854,2 [km] | $\hat{\eta}$ = 31 150,02 [hr] |
| Mean time/distance between failures | *MTBF* = 28 440,6 [km] | *MDBF* = 29 026,8 [hr] |
| Reliable life *for t(R=0.9)* | $T_R$ =13 472,1 [km] | $T_R$ = 5 127,8 [hr] |
| **For age (*t*) at end of the study** | ***t* = 64 467 km** | ***t* = 52 584 hr** |
| Probability of failure | *Q* = 0,962285 | *Q* = 0,853612 |
| Failure rate | *h* = 0,0000856/km | *h* = 0,0000455/hr |
| Mean residual life | *MRL* = 10 614,7 [km] | *MRL* = 20 410,5[hr] |

For each subsystem, further figures present the reliability function (Figs. 4 and 5), the failure probability density function (Figs. 6 and 7), the histograms of the number of failures (Figs. 8 and 9) and the mean residual life (Figs. 10 and 11). In Figs. 4 and 5, the blue line represents the calculated probability of failure occurrence based on the two-parameter Weibull distribution model, while the red lines represent the two-sided 95% confidence intervals around this probability estimate. The reliability of vehicles (Figs. 4 and 5) was determined as a function of mileage for the chassis/cabin and a function of time for the superstructure. From the reliability graphs, it can be assumed that, with the passing time, the reliability of each subsystem decreases rapidly and the time until next failure is reduced as the vehicles age.

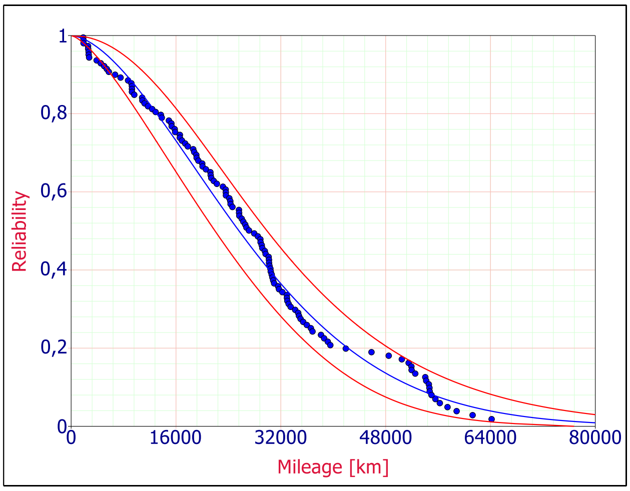


Fig. 4. 2P-Weibull reliability function for the chassis/cabin with the 95% confidence interval.

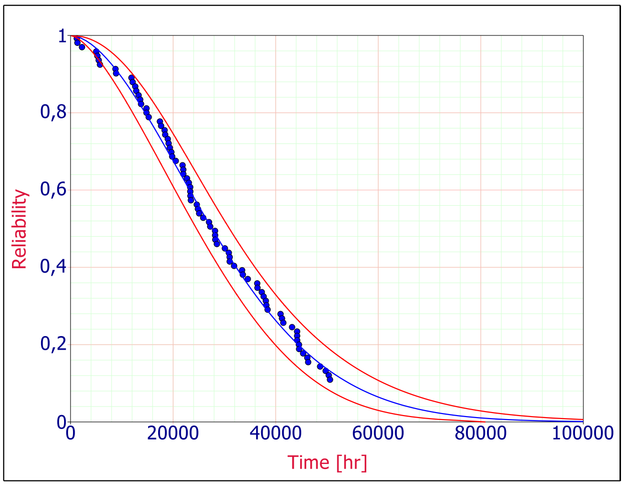


Fig. 5. 2P-Weibull reliability function for the superstructure with the 95% confidence interval.

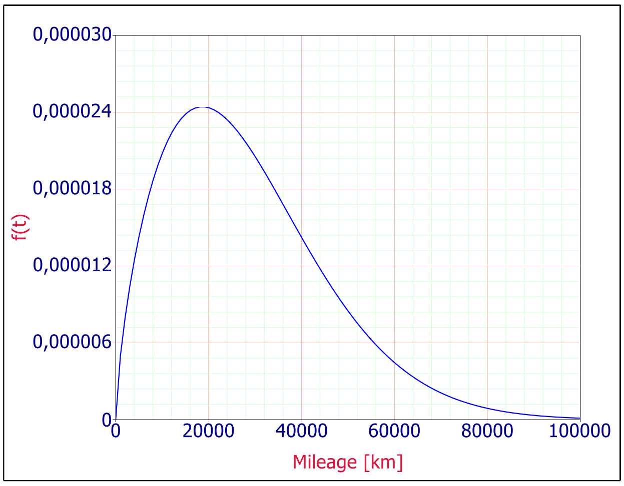


Fig. 6. Probability density plot for the chassis/cabin.

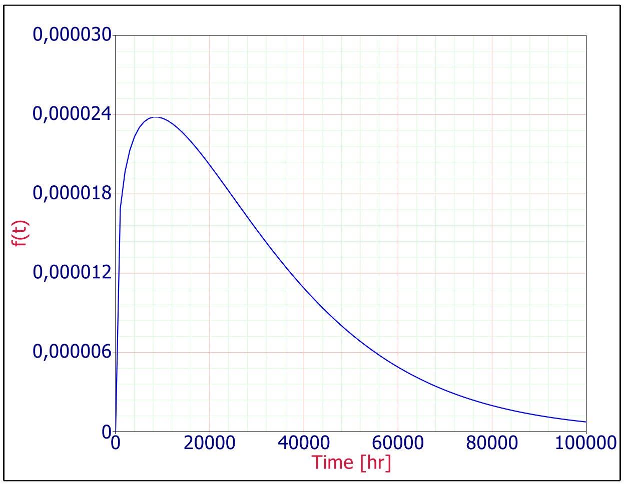


Fig. 7. Probability density plot for the superstructure.

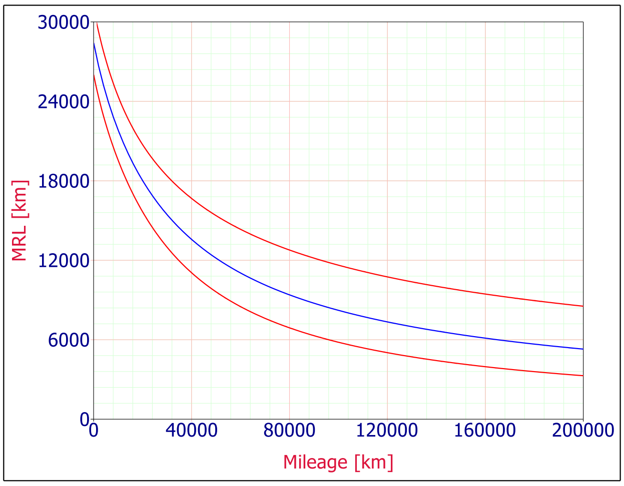


Fig. 10. *MRL* for the chassis/cabin with the CI 95%.

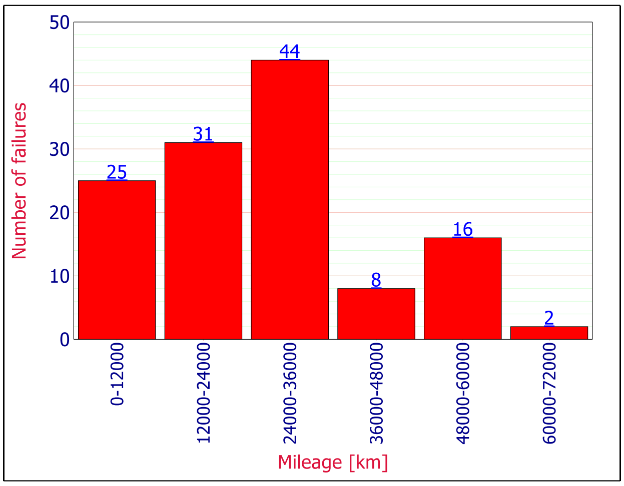


Fig. 8. Histogram for the chassis/cabin.

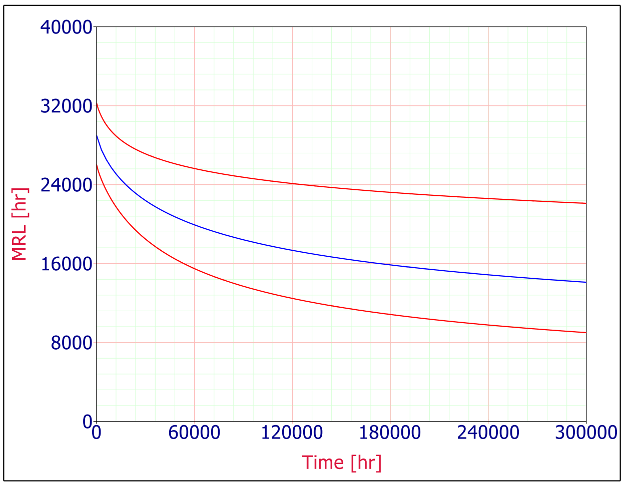


Fig. 11. *MRL* for the superstructure with the CI 95%.

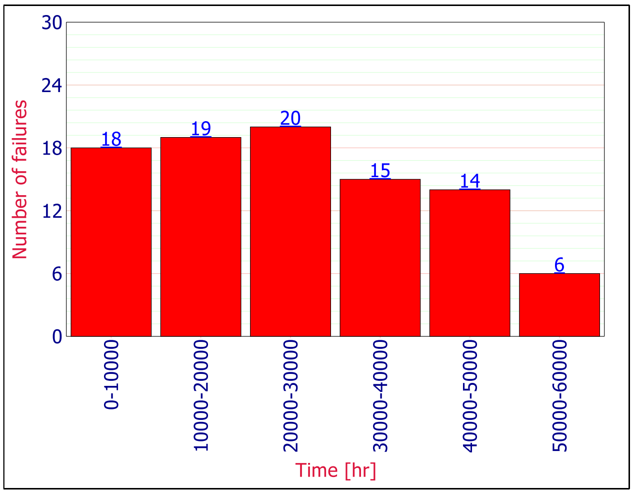


Fig. 9. Histogram for the superstructure.

The fit of the actual data to the two-parameter Weibull distribution is good (Figs. 4 and 5). Most of the results fall within the 95% confidence interval adopted. The number of failures related to the chassis/cab in the initial phase is increasing until a maximum of 36000 km (Figs. 6 and 8). Then, there follows a decrease. The reduction in the number of failures is due to the mileage of the vehicles. The mileage of most vehicles (7 out of 10) did not exceed 39000 km. In the 48000-60000 and 60000-72000 km intervals, only 2 out of 10 vehicles were operated. In the case of the superstructure, in the initial phase, the number of failures is similar, and then it drops and again remains on a similar level until approximately 50000 hours (Fig. 9). In the 50 000-60 000 hour interval, the vehicles operated only for 52584 hours. A longer MRL characterises the superstructure (Figs. 10-11). In the investigated period, it reached approximately 1100 hours for the chassis/cab and 1900 hours for the superstructure.

### 4.3. Reliability indicators of individual vehicles

The time and number of corrective and preventive maintenance for each vehicle individually are presented in Table 8. The selected reliability indicators for individual vehicles are collected in Table 9. The following parameters were included: time to first failure, mean time between failures, mean time to repair, mean time between maintenance, mean maintenance downtime, inherent availability, and operational availability. In addition, to better illustrate and interpret the results, the most important indicators have been presented in graphs (Figs. 12-18).

Tab. 8. Operating time and failure data for fire departments.

| **Fire department** | **Uptime** | **Downtime corrective maintenance** | **Downtime preventive maintenance** | **Cumulative downtime** | **Number of failures** | **Number of preventive maintenance** |
|---|---|---|---|---|---|---|
| **Acronym/Unit** | ***UT* [hr]** | ***CM* [hr]** | **Downtime *PM* [hr]** | ***CM+PM* [hr]** | ***NF*** | $N_{PM}$ |
| Jawor | 51580,8 | 861,8 | 140,9 | 1002,6 | 41 | 18 |
| Kamienna Gora | 52305,9 | 25,8 | 251,6 | 277,5 | 10 | 21 |
| Luban | 50191,2 | 2220,4 | 171,8 | 2392,2 | 37 | 25 |
| Lubin | 52512,8 | 24,5 | 46,1 | 70,6 | 4 | 5 |
| Polkowice | 50908,8 | 1644,5 | 30,1 | 1674,6 | 20 | 7 |
| Strzelin | 50931,5 | 809,2 | 842,7 | 1651,9 | 7 | 21 |
| Swidnica | 51723,3 | 650,2 | 209,8 | 860,1 | 19 | 28 |
| Wolow | 51832,7 | 694,0 | 56,7 | 750,7 | 28 | 24 |
| Wroclaw | 48907,7 | 1482,0 | 2193,8 | 3675,7 | 24 | 16 |
| Zabkowice Slaskie | 49514,9 | 2389,1 | 679,4 | 3068,5 | 28 | 26 |

Tab. 9. Reliability metrics for fire departments.

| **Fire department** | **Time to first failure** | **Mean time between failures** | **Mean time to repair** | **Mean time between maintenance** | **Mean maintenance downtime** | **Inherent availability** | **Operational availability** |
|---|---|---|---|---|---|---|---|
| **Acronym/Unit** | ***TTFF* [hr]** | ***MTBF* [hr]** | ***MTTR* [hr]** | ***MTBM* [hr]** | ***MMD* [hr]** | $A_I$ **[%]** | $A_o$ **[%]** |
| Jawor | 307,6 | 1258,1 | 21,0 | 874,3 | 17,0 | 0,9836 | 0,9809 |
| Kamienna Gora | 516,1 | 5230,6 | 2,6 | 1687,3 | 9,0 | 0,9995 | 0,9947 |
| Luban | 688,6 | 1356,5 | 60,0 | 809,5 | 38,6 | 0,9576 | 0,9545 |
| Lubin | 15141 | 13128,2 | 6,1 | 5834,8 | 7,8 | 0,9995 | 0,9986 |
| Polkowice | 2268,7 | 2545,4 | 82,2 | 1885,5 | 62,0 | 0,9687 | 0,9681 |
| Strzelin | 178,8 | 7275,9 | 115,6 | 1819,0 | 59,0 | 0,9844 | 0,9686 |
| Swidnica | 1258,6 | 2722,3 | 34,2 | 1100,5 | 18,3 | 0,9876 | 0,9836 |
| Wolow | 12848,3 | 1851,2 | 24,8 | 996,8 | 14,4 | 0,9868 | 0,9857 |
| Wroclaw | 5053,8 | 2037,8 | 61,7 | 1222,7 | 91,9 | 0,9706 | 0,9301 |
| Zabkowice Slaskie | 2558,9 | 1768,4 | 85,3 | 916,9 | 56,8 | 0,9540 | 0,9416 |

The first failures of the investigated vehicles occurred during different periods (Tab. 9) starting from a month (Jawor) ending at almost 18 months (Wolow) after the onset of the operation. Interestingly, in the case of the vehicle operated in Jawor, the shortest time between failures was recorded. An almost 10-fold longer time (at the same time the longest) time was recorded for the vehicle operated in Lubin. For the given vehicle, the highest operational availability was also observed; similar availability was observed for the vehicle operated in Kamienna Gora. The lowest availability had the vehicle operated in Wroclaw, The mean repair time varied from several hours (Kamienna Gora, Lubin) to several days (Luban, Polkowice, Strzelin, Wroclaw, Zabkowice Slaskie).

Graph 12 presents the total corrective maintenance downtime of the chassis/cabin (heavy firefighting and rescue vehicles). In this case, the highest values were recorded for Zabkowice Slaskie (2079,6 hours), then Luban, Polkowice, and Wroclaw, respectively. The shortest downtimes were recorded for Kamienna Gora (8,5 hours) and Lubin (24,5 hours).

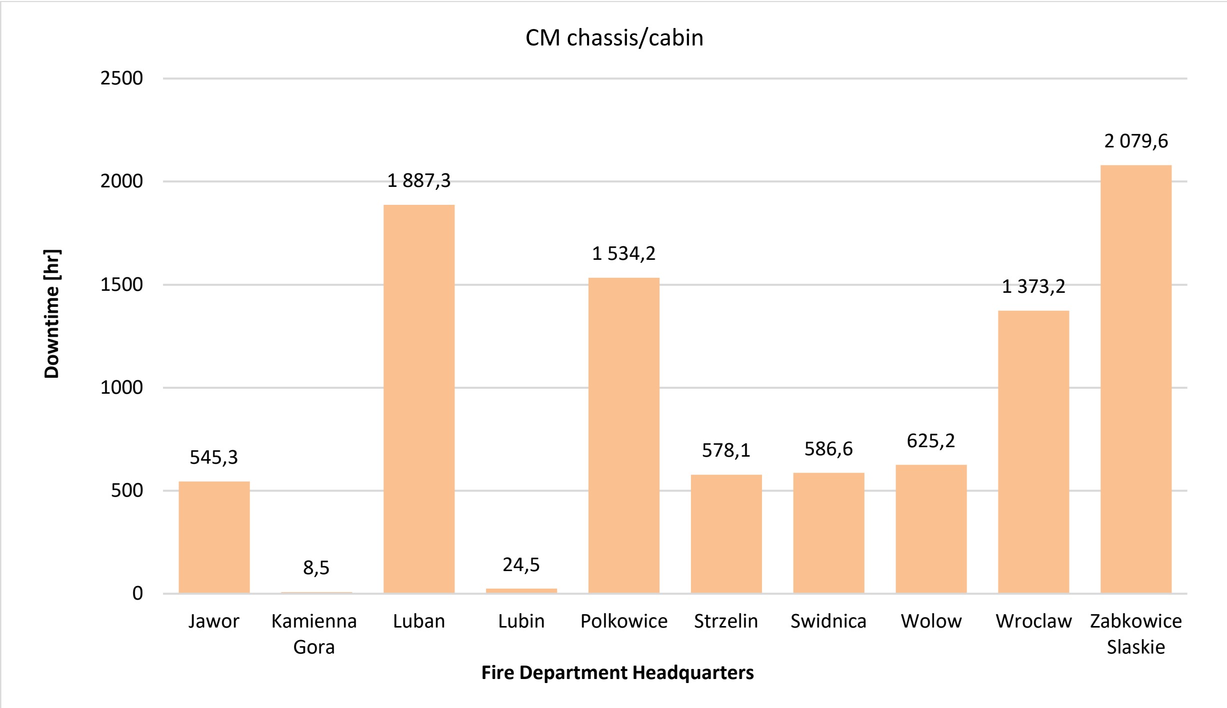


Fig. 12. Corrective maintenance downtime for the chassis/cabin.

The next graph (Fig. 13) presents the superstructure subsystem downtime. In this case, high values were obtained for three fire departments (Jawor, Luban, and Zabkowice Slaskie) and the lowest for Kamienna Gora. It should be noted that for Lubin, no superstructure repair downtimes were recorded.

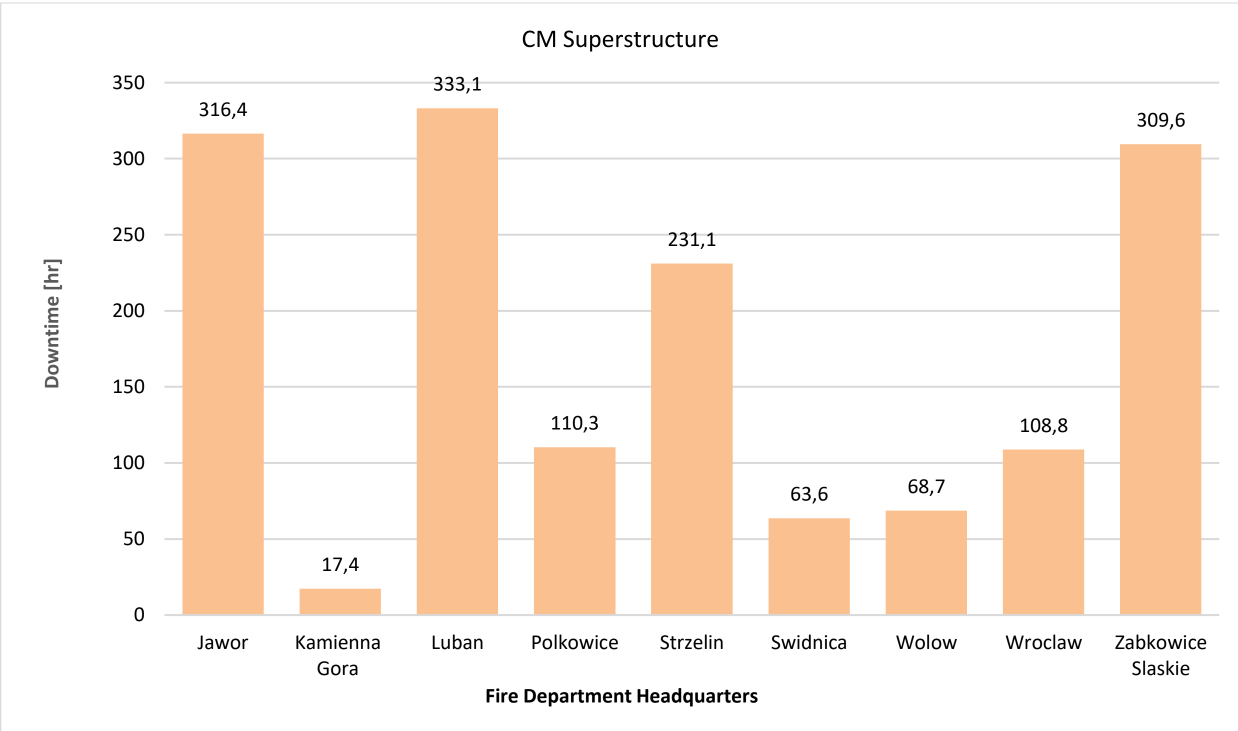


Fig. 13. Corrective maintenance downtime for the superstructure.

Figure 14 presents the total system corrective maintenance downtime (both chassis/cab failures and superstructure failures were taken into account). The longest repair time was recorded for the two investigated subsystems for Zabkowice, Slaskie, and Luban, which is the result of the sum of times presented in the two previous graphs. The shortest subsystem downtime, in this case, was recorded for Kamienna Gora and Lubin.

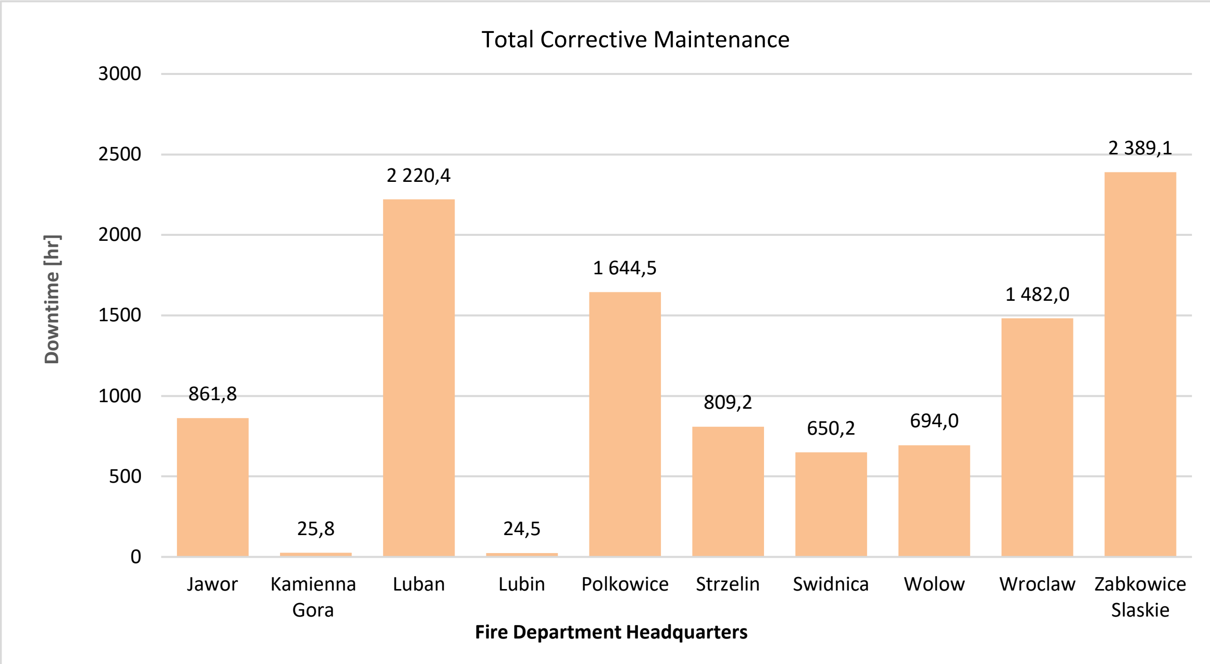


Fig. 14. Total corrective maintenance downtime for the chassis/cabin and the superstructure.

Figure 15 presents the downtimes related exclusively to the maintenance of the entire vehicle, this is the cumulative downtime, that is, the chassis/cabin and the superstructure maintenance. These times result from the maintenance of the vehicle (chassis/cabin), The highest value in this case was recorded for Wroclaw and the lowest for Polkowice, Lubin, and Wolow, These differences are related to the specificity of the operation of the vehicles in their many aspects (technical, organisational, or economic) and result from the operational intensity.

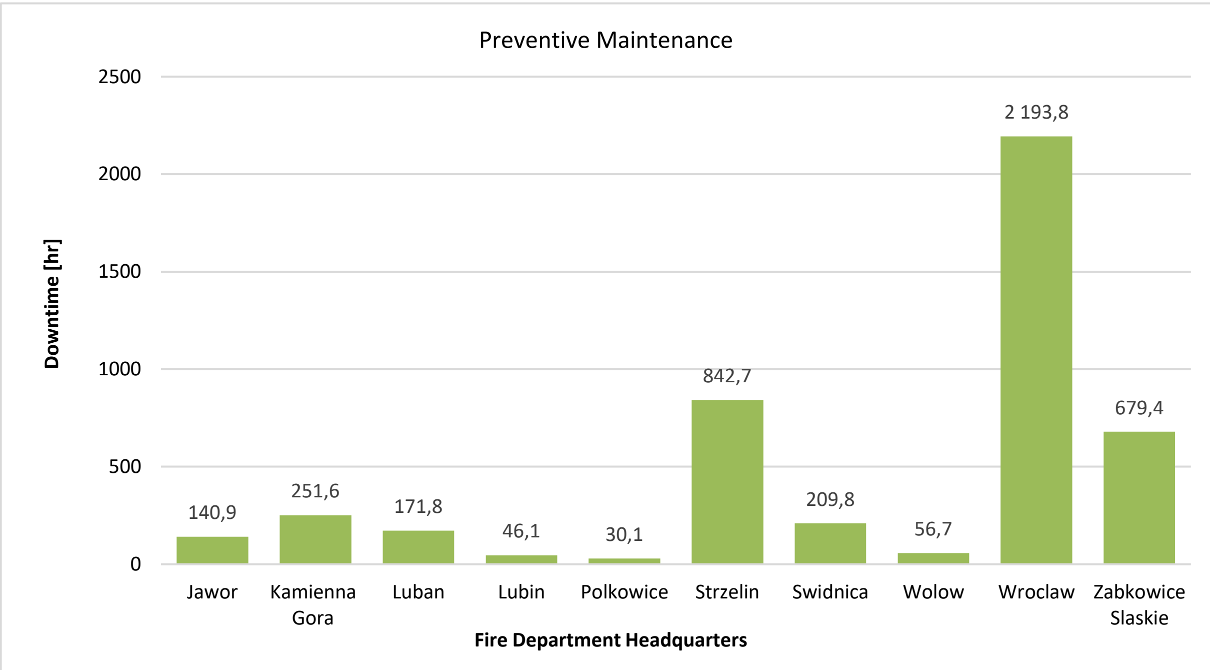


Fig. 15. Preventive maintenance downtime.

The total system downtime (including the corrective and preventive maintenance of both subsystems) is presented in Figure 16. This value impacts the system availability, therefore, is very important in terms of vehicle command in the SFS, In this case, the highest values were recorded for Wroclaw, then Zabkowice Slaskie and Luban.

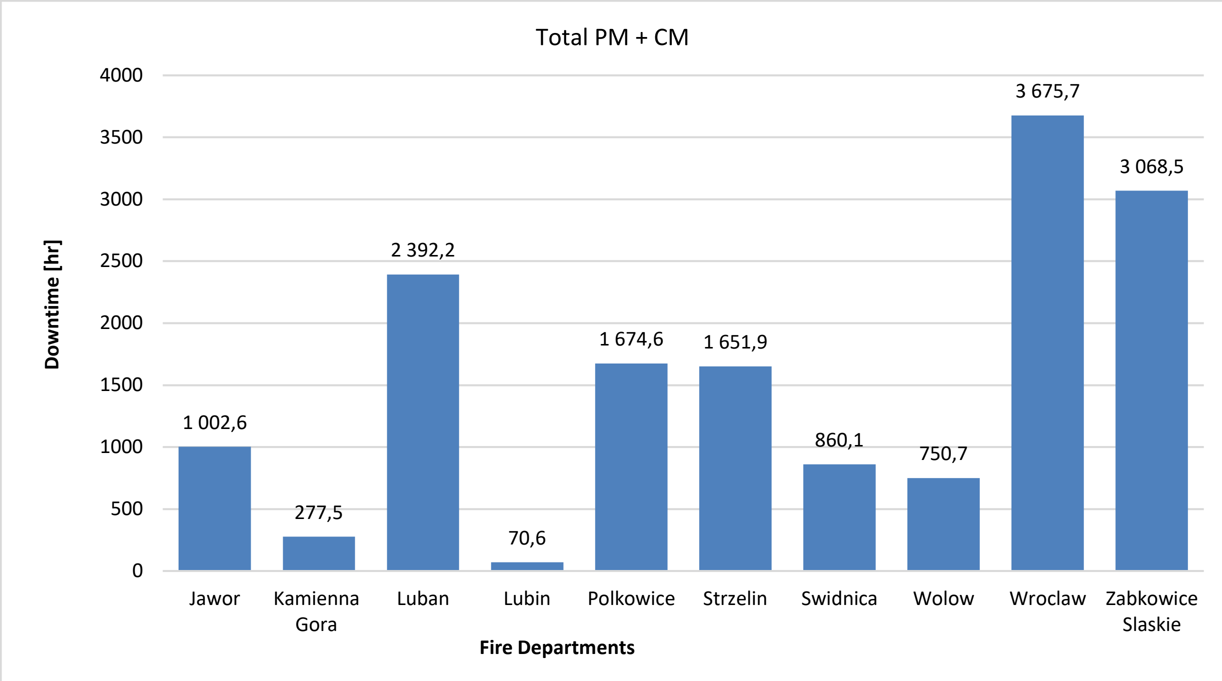


Fig. 16. Cumulative downtime for preventive and corrective maintenance for the chassis/cabin and the superstructure.

Figure 17 presents the vehicle inherent availability indicator, that is, the mean time share, in which the vehicle remains in its roadworthy condition (except corrective maintenance). Based on the value of this quantity, it can be inferred that the lowest availability exhibited by the fire departments in Zabkowice Slaskie and Luban was 95,40% and 95,76%, respectively. Relatively low values were also recorded for Polkowice (96.87%) and Strzelin (98,76%). The highest values of these indicators were calculated for the fire departments in Kamienna Gora and Lubin.

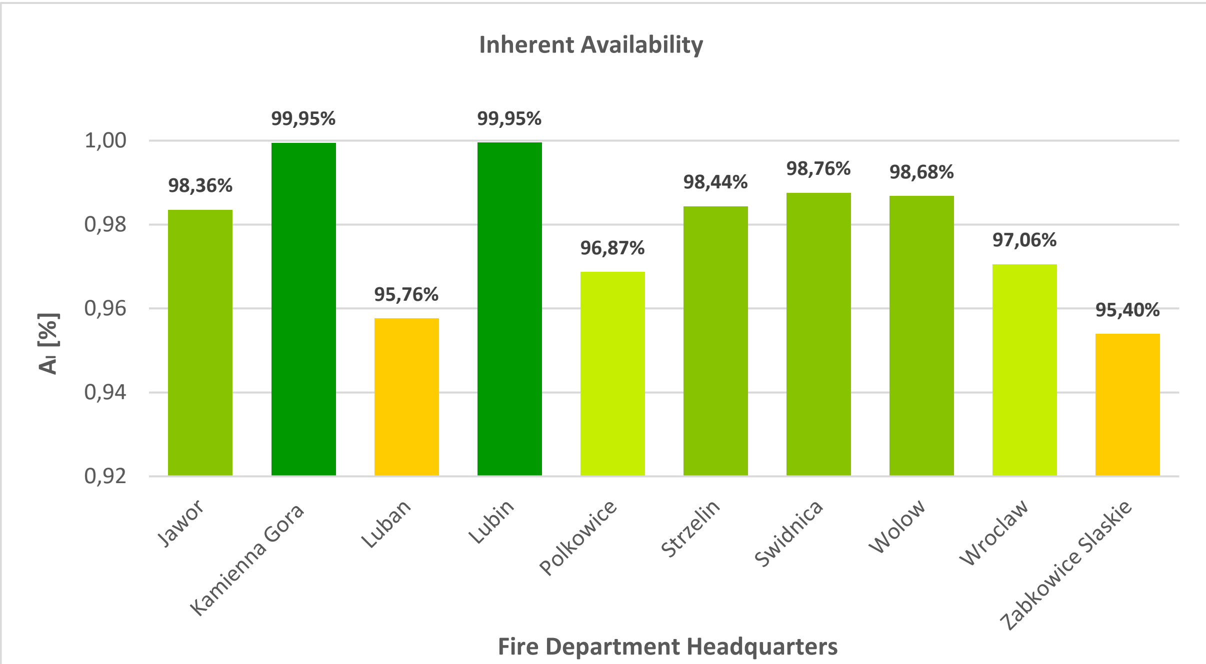


Fig. 17. Inherent availability for fire departments.

The operational availability values for individual fire departments are shown in Figure 18. These graphs show that the lowest availability was recorded for Wroclaw and amounted to 93,1%. Very low availability was also recorded for Zabkowice Slaskie and Luban. On the other hand, very high availability values were recorded for Lubin (99,68%) and Kamienna Gora (99,47%).

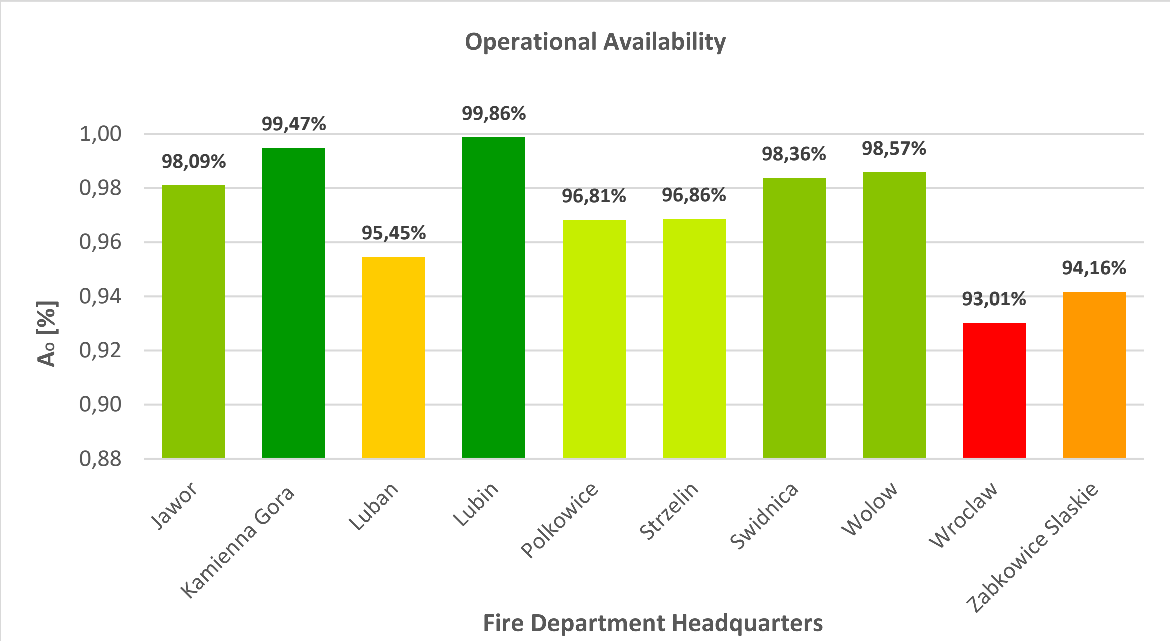


Fig. 18. Operational availability for the fire departments.

## 5. Discussion

The rescue equipment, in particular the most important active safety means of a fire department, is the firefighting and rescue vehicles. They perform key tasks for effective rescue operations. Among their tasks are the following: emergency transport of firefighter rescuers, equipment, and extinguishing agents, reaching injured and allowing evacuation, providing the necessary power supply, and generating and delivering effective extinguishing streams and lighting to the scene of the incident [32]. Damage to such vehicles leads to their temporary downtime and unavailability in the operational resources of the rescue system. It is obvious that a rescue system based on firefighting and rescue vehicles is characterised by redundancy. In fire departments, there are first response vehicles and those kept in reserve, but they are usually not equivalent. Firefighting vehicle failures occur randomly, so their type and quantity during operation can be treated as a random variable. Regarding the number of failures from a certain set, it is described using a discrete random variable [46]. The reliability function reflects the trend of the behaviour of the object studied in the event of subsequent failures during operation. By determining the required reliability values, it is possible to establish reliability either at the design stage or during operation (through corrective changes, such as replacing components with reduced reliability). New measures can serve as a tool to support the implementation of the operation process according to a supervised reliability strategy.

However, presenting the estimated functional characteristics (reliability, probability density, mean remaining life) graphically, along with the histogram of the number of failures, can aid in identifying the nature of the damage or failure patterns. This information is important in predicting the course of failures and can also facilitate the attempt to determine the costs incurred from corrective maintenance in the future [2].

In fire departments, the main approaches to performing the maintenance of fire equipment are reactive and preventive. In the first case, maintenance is based on maintaining a system only after a functional failure. Unscheduled activities are usually time consuming (lack of spares) and cost consuming [5]. The authors of other papers demonstrated such scenarios in their research. Due to wheel failures, the firefighting vehicle was unavailable for more than 2750 hours, which is 114 days [30]. The second approach assumes that maintenance is performed on a scheduled basis. Preventive maintenance checks and services are conducted regularly. It leads to a reduction of catastrophic failures, but it can also result in an excess number of maintenance actions, which can contribute to excess maintenance labour hours. The paper demonstrates that approximately 33% of all downtimes were caused by service/warranty inspections. In the given case, the average downtime did not exceed 7 hours. However, the average downtime in the event of a failure of a particular component exceeded 6 days. Therefore, it can be inferred that service/warranty inspections do not significantly extend the downtime of firefighting vehicles.

Each vehicle consists of subsystems [47]. The reliability of the overall system depends on the reliability of these individual subsystems and how they are interconnected or configured [35]. In the analysed structure of the firefighting and rescue vehicle, the subsystems are connected in series. The failure of one of the subsystems will render the entire vehicle nonfunctional. Therefore, it is crucial that both subsystems exhibit high reliability. It has been observed that 58% of all failures are due to chassis/cabin failure. This means that this particular subsystem is less reliable. This difference does not appear to be significant, yet in some characteristics and parameters, it appears more diverse (Figs. 5-11, Tab. 7). Firefighting vehicles analysed are characterised by higher reliability compared to those presented in [12]. The estimated reliability indicators presented there have been shown in the tab. 10. The average time between failures was nearly 75 days shorter, the average repair time was almost 2 days longer, and the mean availability indicator was 0.017% lower than the vehicles analysed in [12] (comparison to the values obtained for vehicles built on the MAN chassis).

Tab. 10. Reliability indicators of firefighting vehicles [12].

| Fire department | Number of vehicles | Mean time between failures | Mean time to repair | Operational availability |
|---|---|---|---|---|
| **Acronym/Unit** | **nV** | **MTBF [hr]** | **MTTR [hr]** | **$A_o$ [%]** |
| Mercedes-Benz Econic CAS | **14** | 1394,4 | 82,1 | 0,941 |
| Tatra 815-2 4x4 CA | 28 | 1192,8 | 66,0 | 0,945 |
| Tatra 815-7 6x6 CAS | 15 | 3681,6 | 121,2 | 0,967 |
| Scania | 5 | 2210,4 | 115,9 | 0,948 |

The source of data used for the reliability analysis presented in this work is also noteworthy. These data are confidential in nature, and only specially trained and authorised officers of the State Fire Service are allowed to input and retrieve data sets from the DSS-ST system. Due to limitations, in some other services, vehicle operating documentation is typically maintained in paper form and the practice of creating electronic databases encounters organisational barriers [9]. However, the State Fire Service has implemented one of the first systems of this kind in our country (collection of operational data). Importantly, it is integrated at the level of all fire departments throughout the country, from central to regional levels. The data contained in this system are so-called 'from practise' data. There is a list of reasons for the inability to help the user qualify for adverse events [6]. The problem is the correct filling in of the description field, which is supposed to indicate the current technical condition of the vehicle. Often, the description is too laconic or ambiguous. For example, the breakdown of temporary unavailability in the DSS-ST, related to service/warrant inspections, is difficult to qualify as preventive or corrective action based on user-drawn descriptions of the reasons for unavailability. Therefore, some of the analyses presented in this paper in this respect can be considered conceptually and treated as a proposal by the authors. The DSS-ST system is continually being improved. This system is continually being improved. The intention of the authors of this article was to prepare a study that aligns with this trend. Methods and analytical tools of utilitarian importance were proposed and used. In this way, significant variations in reliability parameters between units from different regions within the same province were demonstrated. The likely reason for this situation is the lack of a uniform maintenance management system and maintenance policies in individual fire departments. Guidelines in this regard may include standards developed in other countries, such as NFPA 1911 [27], which includes, *inter alia*, recommended operational practice. It is also important to emphasise the importance of implementing appropriate maintenance policies [13] and actions that can reduce total operating costs by implementing proper preventive maintenance and maintenance [40] in a fire department by a team of adequately trained firefighters.

## 6. Conclusions

The study focused on the maintenance of a critical and critically reliable transportation system such as firefighting and rescue vehicles. The article conducted an analysis of failures and reliability using actual operational data obtained through real-world operation until failure occurred. Accurately determining the reliability, availability, and serviceability parameters is crucial to preventing multiple vehicle and rescue equipment failures, which is essential for the effective functioning of life-saving firefighting services. Since the data on which the prediction was built come directly from a real-world operation system, the results obtained take into account the conditions and operational routines of a given firefighting and rescue vehicle operation system. Reliability analysis is mainly used if the operation time of the components is known and the mean time to failure is easily predicted based on the presented analysis. Estimation of parameters for failure models is necessary for an accurate prediction of the expected number of component failures over a period of time based on operating conditions in order to develop cost-effective maintenance strategies. This paper is based on the collection and analysis of maintenance data over a six-year period for parameter estimation for probabilistic models predicting two subsystems. The Weibull statistical distribution plays a key role in determining the reliability parameters. Using shape and scale parameters, along with graphical methods such as reliability and density function plots, histograms, and *MRL* plots, a deeper understanding of the data can be achieved. This methodology is invaluable to comprehend the reliability of a system and predict potential future failures of firefighting vehicles. The results of the research provided here convey unusual knowledge that is seldom encountered in the academic literature. There is a huge scope for future work in this area in terms of development of decision models related to the inspection and replacement of selected components of complex technical objects. Failure prediction is essential for predictive maintenance due to its ability to prevent failure occurrences and reduce maintenance costs. Predictive analysis results are crucial in firefighting systems, mainly due to life-saving work carried out by fire services.

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