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DETERMINATION OF SYSTEM OPERATION HISTORY BASED ON OIL FIELD DATA

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The paper is to apply regression analysis methods with confidence intervals in order to analyse field data with the aim of finding the dependence of Fe particles occurrence on operating time. When comparing the results of the method/approach the authors believe that they can estimate the real operating profile of observed technical systems as well as its operating history. The results might be used for optimizing during an operation and maintenance phase.

Keywords: *Maintenance optimization, tribo-diagnostics, field data, regression analysis, fuzzy logic*

INTRODUCTION

The growing dependability and operation safety requirements for modern equipment together with the increasing complexity and continuous attempts to reduce operation and maintenance costs might be satisfied, among other things, by the consistent use of modern diagnostic systems. The main task of object technical state diagnostics is not only to find out incurred failures, but also to prevent from the failure occurrence with the help of sensible detection and changes localization in the object structure and in its behaviour changes.

A tribotechnical system (TTS), friction in it, wear and lubrication, and especially its outcomes, are the subjects of our major concern. Regarding the tribotechnical system, the basic information about the tribological process, operating and loss variables are provided. Tribology is the science and technology of interacting surfaces in relative motion. The function of a tribotechnical system is to use the system structure to convert input variables (e.g. input torque, input speed, the input type of motion, and the sequence of motions) into technically utilizable output variables (e.g. output torque, output speed, output motion) [1, 2].

Owing to the TTS, there is plenty of diagnostic oil data. In view of tribo-diagnostics, these data are considered to be the final outcome. These data can tell one a lot about lubricants/life fluids quality itself as well as about system condition. From the reliability, maintainability and safety point of view, such data are considered very valuable. We distinguish between various methods for oil/life fluids samples analysing. Since the system operation, taking the oil samples and the outcomes themselves are very fuzzy, we later expect to adapt some approaches from the fuzzy logic theory to help. The procedure and results presented below are based on standard mathematical principles: the regression function and the regression analysis. Later these will be supported by fuzzy logic approaches. We present results which contribute to the general approach when considering both the maintenance procedures and the cost analysis optimisation. From both presumptions we expect some cost savings. As for the military point of view, we would like to determine remaining "time units" in order to perform the mission. Following the regression analysis, it is possible, among other things, to assess the operating history of an observed vehicle.

1. OBJECTS OF DIAGNOSTICS AND DIAGNOSTICS METHODS

The assumed objects of diagnostics, i.e. the tank engines T-72M4CZ, TATRA 810 and BMP II were not ready yet in terms of design to use the ON-LINE system, though in practice similar possibilities for other applications already existed. It results from the information stated above that we are still supposed to use the OFF-LINE engine diagnostics system when sampling lubrication fluid at certain intervals, and using known and optimised special tribodiagnostic methods [3, 4, 5]. When evaluating data, the information is transformed many times and provides only estimated reality which might be different from reality itself. If the vagueness in classes distribution is not given by the stochastic character of measured characteristics but by the fact that the exact line among states classes does not exist, it will be later good to use the fuzzy set theory and the adequate multi-criteria fuzzy logic. In our case we use the results and information from atomic emission spectrometry. Following this analysis, we can obtain the information about the presence of the elements of specific kind and the amount of elements. However, we cannot identify their real origin, e.g. as a result of fatigue, cutting or sliding. Therefore, in our further research we attempt to identify where the elements might come from.

2. OIL FIELD DATA ASSESSMENT

Having enough field data obtained from a statistically important set of diagnosed objects, there is a basic assumption that we will solve this problem successfully (e.g. the engines themselves, etc.). Since the data sets are very extensive, we are not going to introduce them here except for a part/example of ferrum particles found in an infantry fighting vehicle engine shown in Table 1. But we deal with dozens of samples taken and analysed at different types of observed engines. In certain aspects we consider an engine in an infantry fighting vehicle II to be a reference object, because the event of a failure type occurred in it. All the tribodiagnostic processes related to the failure occurrence were recorded [10-12].

Using the on-line diagnostics based on a laser particles analyser appears to be a very progressive method. This method enables us to find wearing particles according to a corresponding wearing mechanism (fatigue), adhesion, abrasion, cavitations, corrosion, vibration, combination of the situations mentioned above together with expressing the state, prognosis, trends calculations, etc., supported by intelligent software in the future in real time [5].

In this case we will focus not only on the regression analysis itself, but comparison too. We will compare confidence intervals for a motor to destruction with common operation motors. However, in order to set confidence intervals for a single vehicle as well as for a group and correlation, some standard tools of the regression analysis are used and will be introduced below. Following the previous conclusions, we put in the graph the overall courses of Fe particles generated for all three examined vehicle types – see Figure 1. From these dependencies we might judge under what conditions a single type of vehicles was operated.

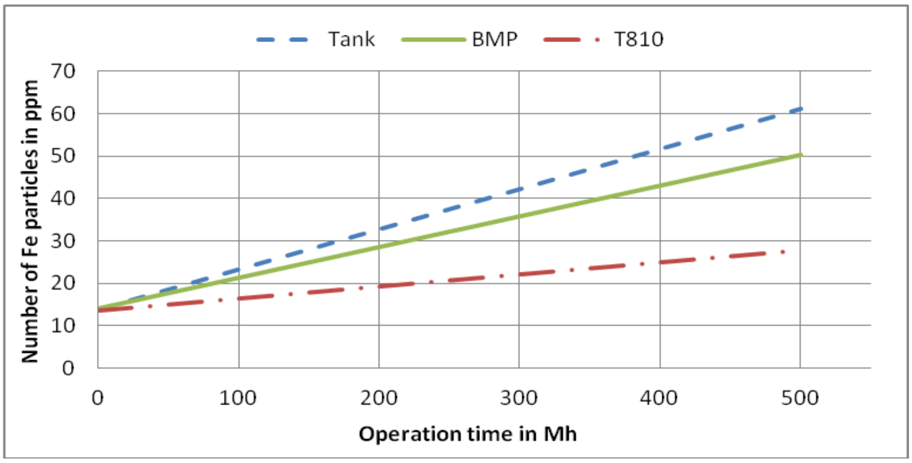

Fig. 1. Basic courses of Fe linear regression in the oil of a single examined vehicle type

Source: Own elaboration

2.1. Utilisation of regression model

Exploring and analysing variable dependencies, the values of which are obtained when performing an experiment, is considered to be an important statistical task. In view of their random character, a random vector X = ($X_1,\ldots,X_k$) represents independent variables and a dependent variable is represented by a random variable Y.

When describing and examining the dependence of Y on X, we use the regression analysis, and this dependence is expressed by the following regression function:

$$y = \varphi(\mathbf{x}, \boldsymbol{\beta}) = E(Y \mid \mathbf{X} = \mathbf{x}), \tag{1}$$

where:

$\mathbf{x} = (x_1, \ldots, x_k)$ vector of independent variables, y is a dependent variable, $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_m)$ vector of regression coefficients β_j.

For our data we will look for the regression function in a linear form and we will apply a linear regression model:

$$y = \sum_{j=1}^{m} \beta_j f_j(\mathbf{x}), \tag{2}$$

where:

$f_j(\mathbf{x})$ are well-known functions where $\beta_1, \ldots, \beta_m$ are not involved.

This model is based on the following assumptions:

1) Vector $\mathbf{x}$ is non-random, so the functions $f_j(\mathbf{x})$ take non-random values $f_{ji} = f_j(\mathbf{x}_i)$ for $j = 1,...,m$ and $i = 1,...,n$.
2) Matrix $\mathbf{F} = \begin{pmatrix} f_{11} & \cdots & f_{1n} \\ \vdots & \ddots & \vdots \\ f_{m1} & \cdots & f_{mn} \end{pmatrix}$ of the type (m, n) with elements f_{ji} is of a $m < n$ rank.
3) Random variable Y_i, where $E(Y_i) = \sum_{j=1}^{m} \beta_j f_{ji}$ and $D(Y_i) = \sigma^2 > 0$ for $i = 1,...,n$.
4) Random variables Y_i are non-correlated and have a normal probability distribution for $i = 1,...,n$.

For the data we will select gradually the following regression functions:

– m=1, $f_1(x)$=1, regression function: $y=\beta_1$
– m=2, $f_1(x)$=1, $f_2(x)$=x, regression function: $y=\beta_1+\beta_2$
– m=3, $f_1(x)$=1, $f_2(x)$=x, $f_3(x)$=x^2, regression function: $y=\beta_1+\beta_2x+\beta_3x$

For the expected dependence we select the model which will follow the data and will also be the simplest. We will proceed the following way:

– gradually we will look for the models for m=1,2,3
– regarding the models $y=\beta_1+\beta_2x$ a $y=\beta_1+\beta_2x+\beta_3x^2$ we will test whether the highest power coefficient is not equal to zero.
– for each model we will search for a multiple correlation coefficient:

$$r = \sqrt{1 - \frac{S^*_{\min}}{\sum y_i^2 - n(\bar{y})^2}}, \text{ where } S^*_{\min} = \sum_{i=1}^{n}\left(y_i - \sum_{j=1}^{m} b_j f_{ji}\right)^2. \tag{3}$$

This coefficient will be squared and it will show its suitability for approximation/data spacing with a relevant regression function. With the coefficient getting bigger, the regression analysis reflects the assessed data better.

When applying the regression analysis, we will look for the dependence which would be able to differentiate among the particular types of vehicles. Moreover, we would be able to compare these dependencies.

Using the collected data we will first analyse one individual measurement. It is necessary to calculate here the confidence intervals estimation of an individual value y at a confidence level $1 - \alpha$:

$$\left\langle \sum_{j=1}^{m} b_j f_j(x) - t_{1-\alpha} s\sqrt{h^* + 1};\ \sum_{j=1}^{m} b_j f_j(x) + t_{1-\alpha} s\sqrt{h^* + 1} \right\rangle \tag{4}$$

where:

$h^* = \mathrm{f(x)^T H^{-1} f(x)}$, and $\mathbf{f}(\mathbf{x}) = \begin{pmatrix} f_1(\mathbf{x}) \\ \vdots \\ f_m(\mathbf{x}) \end{pmatrix}$, H= FF^T and $t_{1-\alpha/2}$ is $\left(1-\dfrac{\alpha}{2}\right)$- student´s distribution quintile S(k) with $k = n - m$ degrees of freedom.

The calculated intervals will form confidence levels.

If we want to work with a group of vehicles, for selected data and a relevant regression model the confidence intervals estimation of a mean value y at a confidence level 1 – α might be calculated:

$$\left\langle \sum_{j=1}^{m} b_j f_j(\mathbf{x}) - t_{1-\alpha/2} s\sqrt{h^*};\ \sum_{j=1}^{m} b_j f_j(\mathbf{x}) + t_{1-\alpha/2} s\sqrt{h^*} \right\rangle, \tag{5}$$

where:

$h^* = \mathrm{f(x)^T H^{-1} f(x)}$, and $\mathbf{f}(\mathbf{x}) = \begin{pmatrix} f_1(\mathbf{x}) \\ \vdots \\ f_m(\mathbf{x}) \end{pmatrix}$, H= FF^T and $t_{1-\alpha/2}$ is $\left(1-\dfrac{\alpha}{2}\right)$- student´s distribution quintile S(k) with $k = n - m$ degrees of freedom.

The calculated intervals will form confidence levels.

In the analysis we focused on ferrum Fe particles as the mechanical process product of fatigue processes, cutting abrasive processes, and sliding abrasive processes. In the tables below there is a short list of these particles [4].

– Ferrum – [Fe] particles at BMP

Table 1. Input data of Fe particles – an example of set

Sample/Mh	**Fe (ppm)**	**Sample/Mh**	**Fe (ppm)**
1/0	1.29	21/179	21.87
2/8	20.53	22/188	23.70
3/11	21.36	23/200	24.90
4/22	25.93	24/211	24.87
5/26	20.59	25/222	25.74
6/35	16.49	26/233	27.98
7/46	18.64	27/244	24.44
8/57	18.08	28/255	25.22
9/64	21.03	29/259	27.07
10/72	18.73	30/269	27.51
11/84	17.00	31/271	16.69
12/95	23.89	32/283	16.12
13/106	23.34	33/294	16.92
14/109	21.72	34/305	16.26
15/119	22.71	35/316	16.18
16/136	15.24	36/327	17.70
17/142	20.16	37/331	18.47
18/153	18.24	38/341	21.71
19/164	18.88	39/351	7.41
20/175	20.12	40/363	11.46

Source: Own elaboration

Single statistical sets have more than 80 recorded items, but we are not going to fill the paper with them.

2.2. Analysis results: estimating and specifying confidence and correlation intervals

At first, using the equations stated above (1)-(4), we will estimate individual confidence intervals for each type of a vehicle with the regression analysis – see Figures 2-4. A confidence level α was set at 0.05. This interval enables us to determine the real operating history of a single vehicle, no matter if we know its operating past. When no more than one sample of oil is taken, it will demonstrate that real operation complies with the set operating conditions.

Confidence intervals of Fe particles for a single vehicle – a tank:

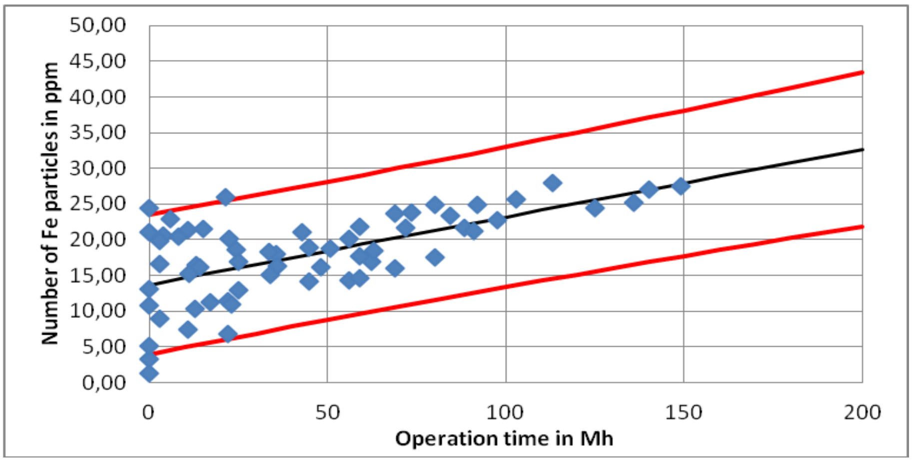

Fig. 2. Course of the confidence intervals of Fe particles for a single vehicle – a tank

Source: Own elaboration

Confidence of Fe particles for a single vehicle – a medium lorry:

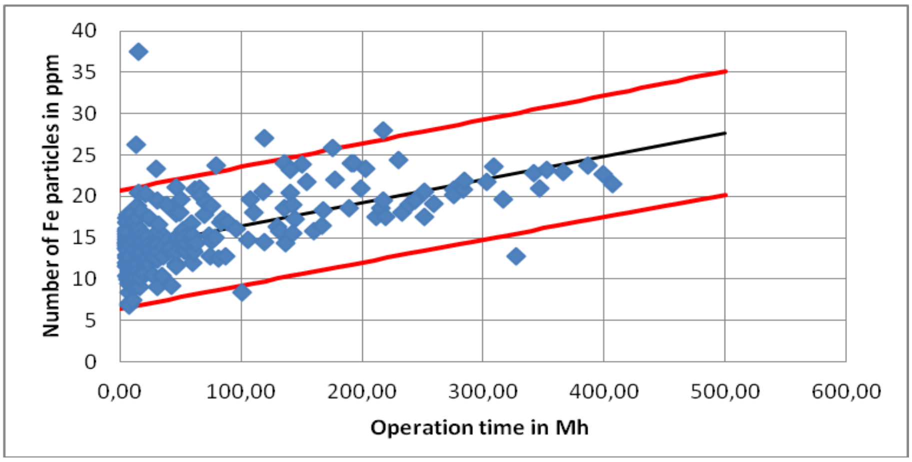

Fig. 3. Course of confidence intervals of Fe particles for a single vehicle – T810 - a medium lorry

Source: Own elaboration

Confidence intervals of Fe particles for a single vehicle – an APC:

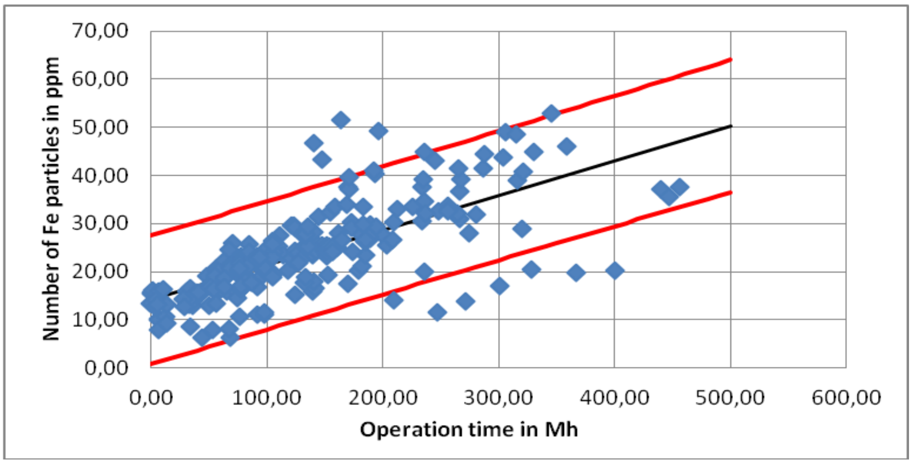

Fig. 4. Course of confidence intervals of Fe particles for a single vehicle – an APC

Source: Own elaboration

Next, confidence intervals for the group – mean values of Fe particles – will be estimated and determined with the equations (1-3; 5) and the regression analysis. A confidence level α was set at 0.05. The calculation has been done for each type of a vehicle separately – see Figures 5-7. These intervals, however, take into account the group of certain type vehicles and work with an average Fe particles value within this group. The intervals enable us to determine the real operating history of vehicle groups, no matter if we know the past of an assessed sample. We want to demonstrate that real operation complies with the determined operating conditions.

Confidence intervals for the mean value of Fe particles for a vehicle group – a tank:

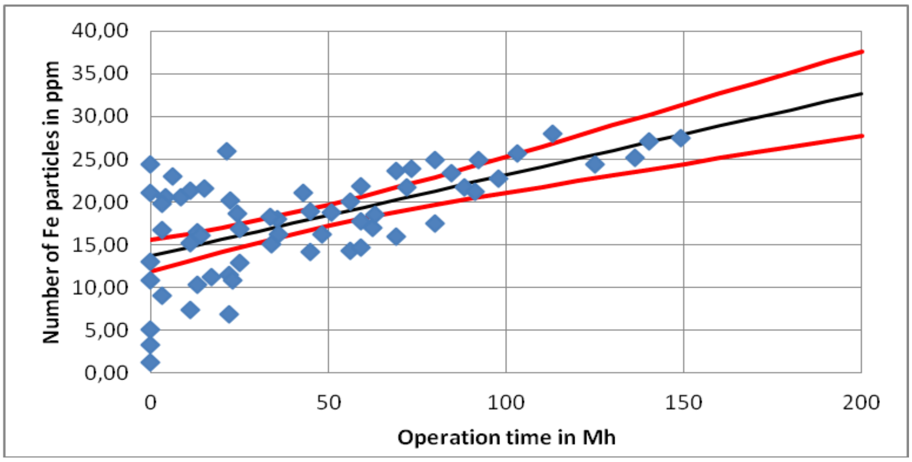

Fig. 5. Course of confidence intervals for the mean value of Fe particles for a vehicle group – a tank

Source: Own elaboration

Confidence intervals for the mean value of Fe particles for a vehicle group – a medium lorry:

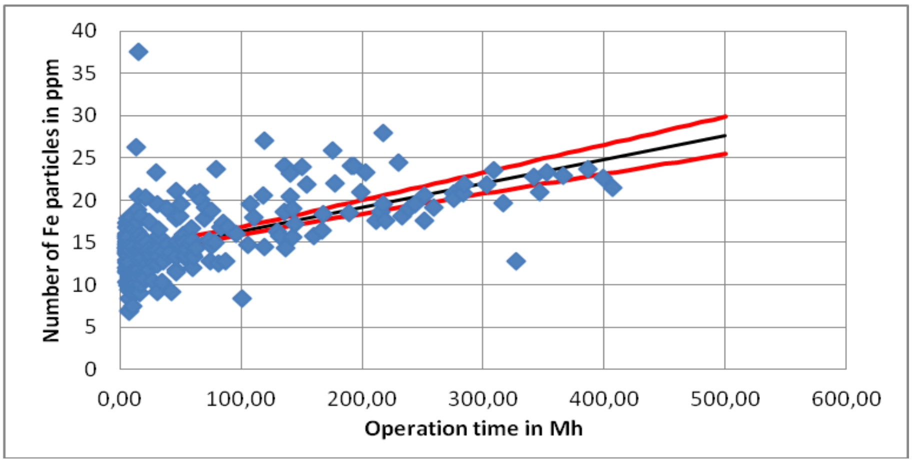

Fig. 6. Course of confidence intervals for the mean value of Fe particles for a vehicle group - T810 - a medium lorry

Source: Own elaboration

Confidence intervals for the mean value of Fe particles for a vehicle group – an APC:

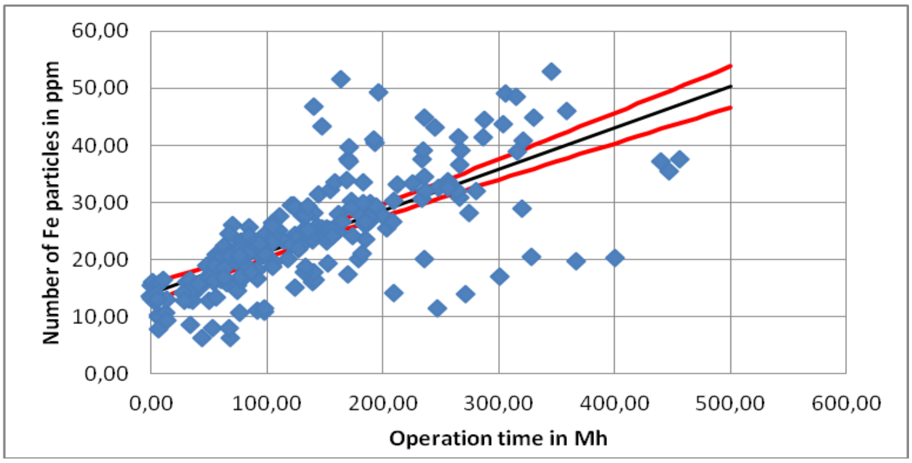

Fig. 7. Course of confidence intervals for the mean value of Fe particles for a vehicle group – a BMP

Source: Own elaboration

CONCLUSION

The aim of the paper is to shed light on the area of tribodiagnostics, including the mathematical calculation method, which is applicable and suitable for oil analysis.

The data regarding lubrication fluid, which is available due to the performed analyses, is a good source of information when considering the cost savings, provided that oil is changed systematically [8, 9, 10, 11]. It would also be good to see the results of the analysis in a broader context as an interesting reflection of the actual state of a technical object from where the oil was taken.

The paper is to point out that some tribodiagnostics data, which are generally not taken into account, can be used anyway. They might be used when verifying "declared" operating modes, or reviewing introduced and performed maintenance schemes. We suppose that although we introduced a tool for analysing three essential elements (Fe, Pb and Cu, and Fe is considered to be the most interesting), the conclusions are definitely interesting and important, especially those regarding the reference object – an engine which may have achieved a limit state.

Some specific classifications of failures are also used in relation to risk sources and they are recognised due to oil and other life fluids diagnostics [13, 15-17].

The results shown in the figures above demonstrate quite clearly that it is possible to assess the state of a system depending on oil data. Therefore the system history might be estimated. It is obvious that the type of motor data corresponds to the obtained results of the analysis and the assumed operating profile.

We believe that later in our research we will determine the recommended optimum period for changing oil. With the help of fuzzy logic [14] we expect to specify our information about operating history or the estimation of remaining operating units.

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GENEZOWANIE STANU TECHNICZNEGO SYSTEMU NA PODSTAWIE BADAŃ WŁAŚCIWOŚCI OLEJU REALIZOWANYCH W WARUNKACH POLOWYCH

Streszczenie

W artykule wykorzystano metodę analizy regresji w określonych przedziałach ufności do badania systemów uzbrojenia eksploatowanych w warunkach polowych. Metoda ta posłużyła do przeanalizowania zależności występowania cząsteczek żelaza od czasu eksploatacji badanych systemów. Analiza porównawcza otrzymanych rezultatów wskazuje, że wykorzystana metoda daje możliwość oszacowania realnego trybu i czasu pracy badanych systemów. Otrzymane wyniki mogą być wykorzystanie do optymalizacji faz użytkowania i utrzymania rozpatrywanych systemów uzbrojenia.

Słowa kluczowe: *Optymalizacja eksploatacji, trybo-diagnostyka, dane eksploatacyjne, analiza regresji, dane rozmyte*