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ON APPROACHES FOR NON-DIRECT DETERMINATION OF SYSTEM DETERIORATION

METODY POŚREDNIEGO BADANIA STARZENIA SIĘ SYSTEMU

Nowadays the system requirements are set up and evaluated in various manners. We have plenty of excellent options available taking about an item technical state. We can also consider other states by many diagnostic options. The paper deals with the mathematical processing, monitoring and analysis of the oil field data got as a result from the laser spectrography in frame of the tribodiagnostic oil tests. The mathematical methods based on time series and their analysis and calculation processed by suitable method are used in the paper for oil data analysis. Due to the fact that the data sample is classified as fuzzy and uncertain from many reasons the FIS (Fuzzy Inference System) is used.

Keywords: *oil diagnostics, health and condition monitoring, non-destructive diagnostics and prognostics.*

Obecnie wymagania systemu mogą być ustalane i oceniane w różny sposób. Mamy do dyspozycji wiele doskonałych opcji oceny stanu technicznego obiektów. Istnieje również wiele możliwości diagnozowania innych stanów. W artykule przedstawiono proces matematycznego przetwarzania, monitorowania i analizy danych eksploatacyjnych dotyczących oleju uzyskanych na podstawie spektrografii laserowej przeprowadzonej w ramach diagnostyki tribologicznej. Do analizy danych wykorzystano metody matematyczne oparte na szeregach czasowych oraz odpowiednie metody analizy i obliczania szeregów czasowych. Ponieważ dostępne dane sklasyfikowano jako rozmyte i niepewne, zastosowano System Wnioskowania Rozmytego FIS.

Słowa kluczowe: *diagnostyka oleju, monitorowanie stanu technicznego oleju, prognozowanie i ocena stanu technicznego metodami nieniszczącymi.*

1. Introduction

The growing dependability and operation safety requirements of modern equipment together with the increasing complexity and continuous reduction of economic costs of operation and maintenance might be satisfied among others by the consistent use of modern diagnostic systems. At present such systems can be equipped with signal processors related to board computers and with intelligent sensors which are the source of primary information on a technical state in real time. The main task of object technical state diagnostics is not only to find out incurred failures but also to prevent from occurrence the failures with the help of sensible detection and changes localization in the object structure and in its behaviour changes.

A tribotechnical system, friction in it, wear and lubrication is the main subject of this paper. Regarding the tribotechnical system, the basic information on 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 (TTS) is to use the system structure to convert input variables (e.g., input torque, input speed, input type of motion, and sequence of motions) into technically utilizable output variables (e.g., output torque, output speed, output motion) (Fig. 1).

Tribological loads in a TTS are generated by input and disturbance variables' action on the system structure. They chiefly include contact, kinematic, and thermal processes [2]. According to [2], the tribological load represents "the loading of the surface of a solid caused by the contact and relative motion of a solid, liquid or gaseous counterbody." It is introduced via the real contact areas. Plastic deformation and wear can cause the real contact areas to change during TTS operation. When mechanical energy is converted by friction, energy dissipates, which makes itself noticeable by changing the thermal situation. Since the thermal behaviour also continuously adapts to the new conditions as a result of wear, changes to the contact geometry, and resulting changes in the friction, dynamic rather than static influencing variables determine the tribological loading in a real contact. The contact geometry, the processes occurring in the contact, and the thermal behavior of a TTS are influenced by, among other things, the load, the motion conditions, the element properties, and the friction state. While the apparent contact area alone is decisive in fluid lubrication, according to [2], in mixed lubrication, i. e., when the dimensionless film parameter

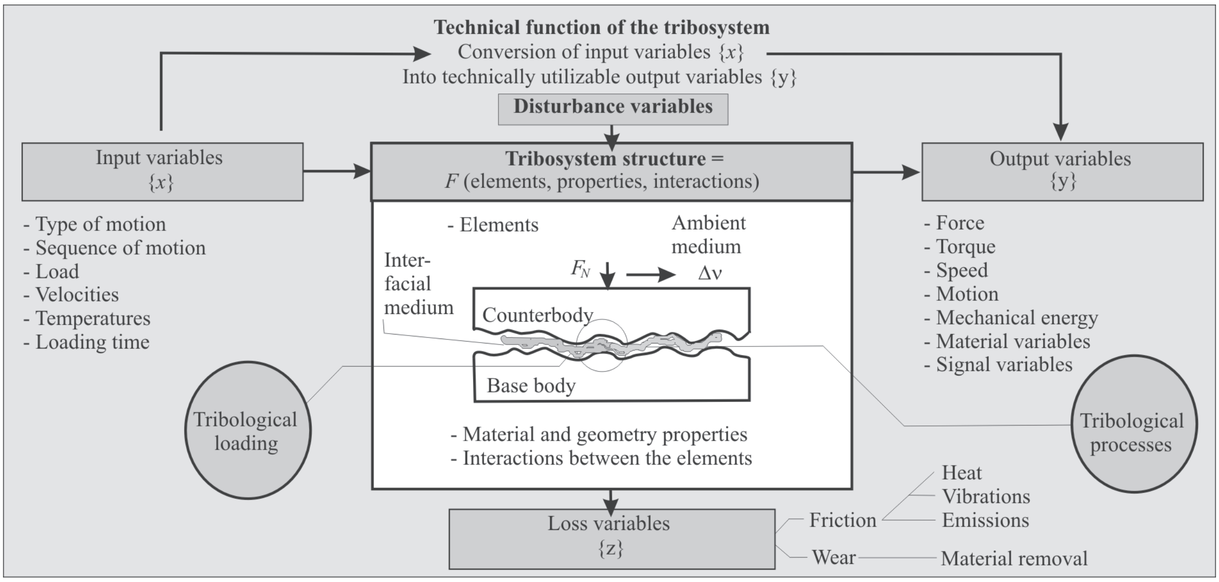

Fig. 1. Expanded representation of a tribotechnical system (TTS) according to [2]

$$\Lambda = \frac{h_{\min}}{(R_{q1}^2 + R_{q2}^2)^{1/2}} \qquad (1)$$

with the minimum lubrication film thickness h_{min} and the root-mean-square (rms) surface roughnesses R_{q1} and R_{q2} of the base body and counterbody is in the range $\Lambda<3$, in boundary lubrication with $\Lambda<1$ and for dry friction both the apparent contact area and the real contact areas must be allowed for (Fig. 1). When there are contacts between the friction bodies, *interactions* occur in the real contact areas and in the near-surface zones. *Atomic/molecular* interactions occur on the one hand and *mechanical* interactions on the other. Whereas the former cause adhesion on solid–solid boundary layers are extremely important technically in the form of physisorption and chemisorptions on solid–fluid boundary layers, the latter lead to elastic and plastic contact deformations and to the development of the real contact areas.

The type of interaction that primarily occurs depends greatly on the friction state. Thus, when a lubricant is present the atomic/molecular interaction can be disregarded more often than the mechanical. Friction and wear in a given TTS ultimately depend on the interactions between the elements. The friction state, the effective mechanisms of friction and wear, and the contact state can be used to describe the interactions. The tribological loads occurring in the real contact areas produce *tribological processes*. These subsume the dynamic physical and chemical mechanisms of friction and wear and boundary-layer processes that can be attributed to friction and wear.

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2. Objects on diagnostics and diagnostics methods

The assumed objects of diagnostics, i.e. the tank engines T-72M4CZ, TATRA 810 and PANDUR II have not been ready yet in terms of design to use the ON-LINE system, though in practice similar possibilities for other applications have already existed. It results from the information stated above that we are still supposed to use OFF-LINE engine diagnostics system when sampling lubrication fluid at certain intervals, and using known and optimised special tribodiagnostic methods [4-9].

Recognition of a technical state is a basic assumption for making a diagnosis used for determining either operability or non-operability, or for the detection, recognition, distinction, and localization of system parts faults. Although the data on the object condition obtained from a lubrication fluid is available, little importance is attached to it when changing the oil. If the condition of a lubrication fluid affected not only evaluation of the object condition but also modification and optimisation of exchange dates, it would be notably positive in terms of economic optimisation.

When evaluating data, the information is transformed many times and provides only estimated reality which might be different from reality itself. That is why the pattern recognition is an important and very complex area of technical diagnostics. Generally the recognition is divided into two groups depending on which methods are used - syntactic or signature.

Parsing/Syntactic Method – is based on recognizing a qualitative way. A word or a symbol string represents the pattern reflecting an object, an event or a process.

Signature Method – is based on recognizing objects, events, or processes with the help of an arranged set of numbers which describe the object characteristics.

Technical state patterns are given by n-dimensional vectors of numerical values of diagnostic quantities recorded in different parts of a diagnosed object at the same time. In matrix form the technical state pattern might be defined by a column vector [7]:

$$x = [x_1, x_2, \ldots, x_n]^T \tag{2}$$

where numbers $x_1, x_2, \ldots, x_n$ are diagnostic characteristics magnitudes, or calculated characteristics determining vector coordinates in n-dimensional space.

Single process recognition classes correspond with single diagnoses of technical states of a diagnosed object. The diagnoses set *D*:

$$D = \{D_1, D_2, \ldots D_R\} \tag{3}$$

is explicitly classified as belonging to a diagnoses indicators set D.

Then the decision rule $D_i = s(x)$ matches each specific signature vector with a corresponding diagnose – state indicator. In practice the diagnose indicator is transformed into a formulation or a corresponding diagnose – state code.

In practice, when applying a signature recognition method, it is necessary to:

- select an optimal number of diagnostic characteristics so that the necessary resolution capability of a classifier could be obtained using minimum number of quantities and measured data;
- set an algorithm, i.e. the rules used when classifying into single diagnoses.

In diagnostics in many cases there is no exact line between an up state and fault, i.e. there is no mutually explicit representation among points spaces and points classes spaces and corresponding technical states – diagnoses. The failure classes intersect which means that the same magnitudes of measured characteristics might correspond with different diagnoses. If the vagueness in classes distribution is not given by a stochastic character of measured characteristics but by the fact that the exact line among states classes does not exists, it will be good to use fuzzy set theory and adequate multi-criteria fuzzy logic.

Note:

The obtaining of functional – process diagnostic parameters which will be explicitly matched with an appropriate technical state in real time is the basic problem of modern tools, e.g. formal logic, expert systems, neural networks, fuzzy logic, and many other methods available nowadays. It is about the parameters which form the line among good, acceptable, limit, and disrepair state, or between an up state and fault in binary logic. It results from the example of an engine diagnostics that the usage of multi-criteria fuzzy logic can be appropriate in decision process when analyzing diagnostic information, e.g. applying the analysis of lubrication oil which contains relatively complex, more dimensional information on states, events, and a course of wearing. Moreover, the oil can be found in complex mechanical closed systems such as an engine, a gear box, a hydraulic system, etc. Regarding complex usage of lubrication oil it will be necessary to monitor and assess other parameters while analyzing machine wear. One of the most important information sources might be the results of ferographical analysis (a type, a size, material composition, distribution, morphology, speed of generation, etc.) and particles wear in real time, or lubrication oil degradation got by the methods FTIR (Furier Transform Infrared Spectroscopy), etc. However, it has not been possible to get this information in real time yet.

3. Oil field data assessment and system health determination

Having enough field data obtained from a statistically important set of diagnosed objects is a basic assumption for solving this problem successfully (e.g. the engines themselves, etc.). We have assumed so far that the signatures belonging to a certain diagnosis – state are known, or that it is possible to suggest and set up a classifier which classifies a pattern into a right diagnosis. In practical applications the signatures are of the nature of deterministic variables with a stochastic part. As a result of this a signature vector changes and single diagnoses are not disjunctive in a signature space. When using deterministic classification methods it is not possible to decide explicitly into which diagnosis a signature vector should be classified. In such cases statistical methods are used.

Technical state diagnostics and engine monitoring includes system approach which deals with sampling, analysis and information utilisation which is important in relation to a mechanical or thermodynamic engine state. Generally it is about monitoring and assessing wearing particles and pollution in life fluids (e.g. hydraulic and engine oils), or metal wearing particles monitoring, non-metal polluting particles monitoring, products of burning process by high or low temperatures, soft pollutants of organic origin which form oil resin, so called cold sediments, oil and fuels oxidation products, hard-solid pollutants of inorganic origin, dust particles of silicon origin, etc. The monitoring covers a life fluid sample collection and its off-line analysis using easy, standard or special – instrumental methods. The increased forming of metal magnetic wearing particles is usually monitored too, using magnetic detectors with recording and signalization. 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.

3.1 Utilisation of regression model

For the sake of the analysis there were used engine oil samples where, depending on cumulative operation time, it was possible to monitor the concentration of wearing specific particles. It was about soot particles as a burning process product as well as abrasive metal particles as fatigue process products, cutting abrasive processes, and sliding abrasive processes. In the Tables below there is a list of these particles.

a) Soot particles data

We start from the presumption, which is not always consistent with reality, that local minima correspond to oil change. We intended to straighten courses between oil changes by the help of regression. It might be expected that tangents will be constant or they will show a small growth which can be interpreted by return as increasing wearing. As an experiment it could be possible to set tangents or intervals and the corresponding oil change intervals. The real state would be diagnosed by field data on the basis of which (using statistical hypothesis testing) the intervals between oil changes would be modified (increasing tangent – shortening intervals).

Table 1. Input data of soot particles

Sample	Soot (%)	Sample	Soot (%)	Sample	Soot (%)	Sample	Soot (%)
1	0.031771816	16	0.185519338	31	0.131379321	46	0.298258215
2	0.103316583	17	0.235333502	32	0.164228171	47	0.314934731
3	0.125431612	18	0.250645906	33	0.198963374	48	0.125000909
4	0.1473445	19	0.263931781	34	0.214886084	49	0.109051809
5	0.168435231	20	0.282059491	35	0.249506742	50	0.116552792
6	0.13423948	21	0.32115677	36	0.274932355	51	0.129438415
7	0.137344524	22	0.322607964	37	0.301216871	52	0.035240542
8	0.138561517	23	0.357020229	38	0.203418538	53	0.040360887
9	0.182563171	24	0.399251908	39	0.097838856	54	0.054815382
10	0.240091324	25	0.367105871	40	0.15223287	55	0.087472059
11	0.234781966	26	0.36917761	41	0.187827662	56	0.128711835
12	0.256827921	27	0.377272516	42	0.220623925	57	0.141270027
13	0.107033946	28	0.399431527	43	0.23116672		
14	0.166212305	29	0.035686743	44	0.242863998		
15	0.193901226	30	0.119831741	45	0.264045507		

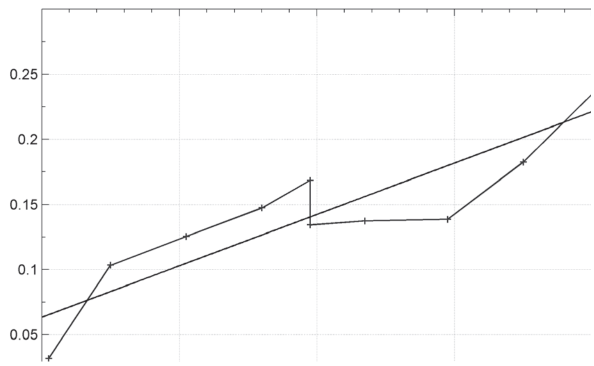

Fig. 2. Soot concentration to the first change

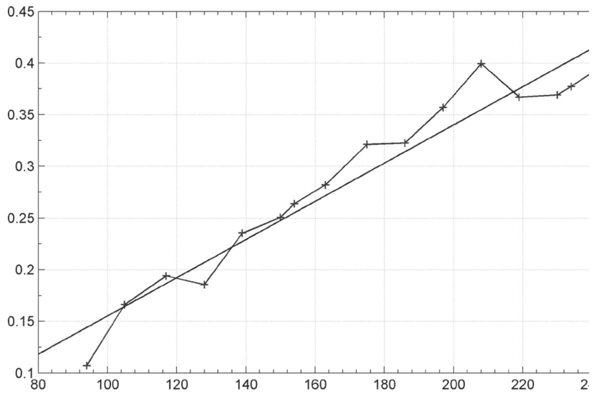

Fig. 3. Soot concentration to the second change: regression by the line y = 0.018x + 0.0296, determination coefficient R = 0.97

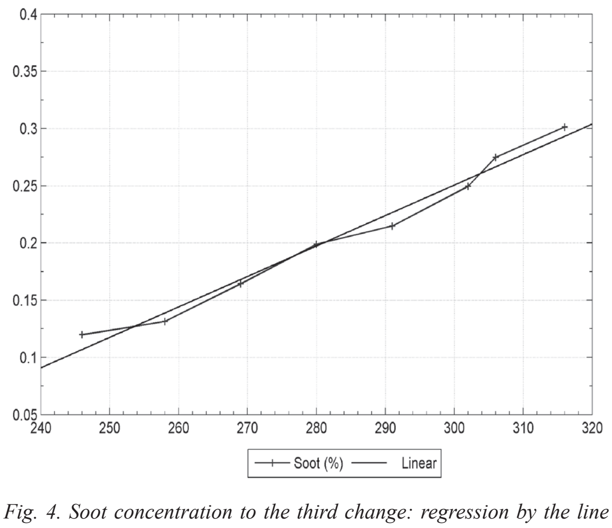

Fig. 4. Soot concentration to the third change: regression by the line y = 0.0027x + 0.5474, determination coefficient R = 0.99

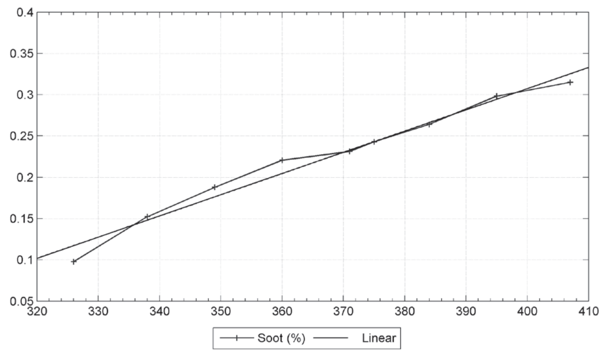

Fig. 5. Soot concentration to the fourth change: regression by the line y = 0.0026x + 0.72, determination coefficient R = 0.99.Regression by the line y = 0.0026x + 0.72, determination coefficient R=0.99

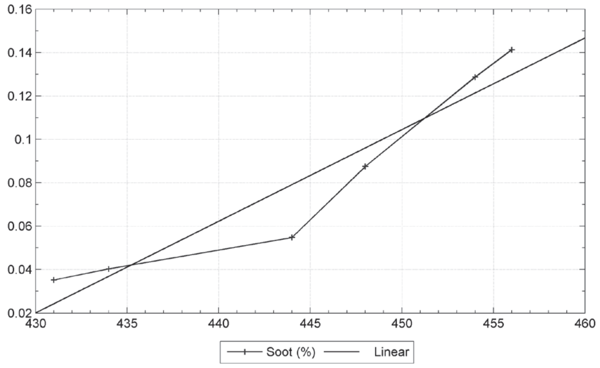

Fig. 6. Soot concentration to the fifth change, regression by the line $y = 0.0042x - 1.79$, determination coefficient $R = 0.95$

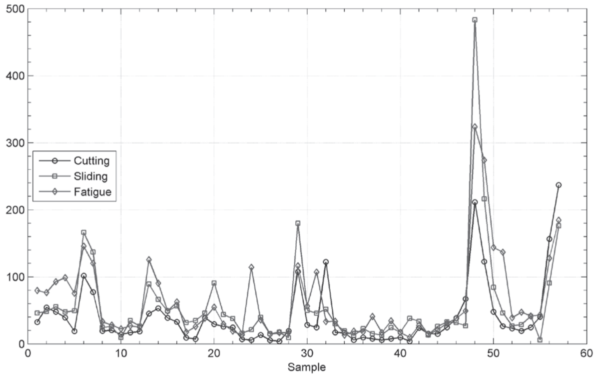

Fig. 7. Total course of cutting, sliding and fatigue particles

Table 2. Input data of cutting, sliding, fatigue particles

Sample	Cutting	Sliding	Fatigue	Sample	Cutting	Sliding	Fatigue
1	32.3381511	46.19006729	79.69317579	30	28.51932859	49.71670866	56.26627159
2	54.43107224	48.15056419	76.42622399	31	24.65869081	45.84933078	107.1173915
3	47.7745769	55.48026347	92.84393597	32	122.2669096	51.72775424	33.3818934
4	39.31019068	47.45829821	98.55917168	33	17.08991575	29.84530449	33.77119803
5	18.86055315	49.26862264	75.44025481	34	16.55065846	19.24586105	13.0867945
6	101.8758668	166.3172793	145.8493638	35	5.773758411	12.7022686	18.86094451
7	77.18351507	136.9976914	120.0213284	36	9.638239861	22.74575508	17.73239851
8	19.23974991	24.62658668	33.09119701	37	7.700790524	15.40158081	40.81693268
9	20.3872683	25.77249193	28.08072448	38	5.771924973	13.46782494	16.54559851
10	14.22187865	9.49721241	22.54989433	39	7.695899963	24.24149847	34.24646163
11	16.94164109	34.65355778	26.95227838	40	9.622930765	17.32127523	16.93596685
12	18.48091865	26.56723869	24.64204156	41	3.850395441	38.12156081	9.625988245
13	45.42258263	89.30431986	125.4877148	42	23.86369467	33.48662567	27.71286666
14	53.08758593	66.16782999	90.39810944	43	15.40647697	13.48066711	14.63811278
15	38.88133812	48.88801241	48.50426865	44	15.01138079	26.17358899	20.78513956
16	32.70757484	56.56398487	62.71806693	45	24.65330708	32.73876286	30.81295347
17	9.248981953	31.60101461	17.34331131	46	38.52843809	31.59361362	38.14325213
18	7.315261722	34.65355682	25.79618037	47	67.08244026	26.98707104	48.96461153
19	38.93652487	45.87753093	38.16693771	48	211.2935009	483.2885046	323.3624358
20	29.67515659	90.95250392	54.72660637	49	122.9303293	216.4200897	273.7473412
21	25.81434846	43.92251658	29.66719174	50	47.77693057	84.38728714	143.7644463
22	24.65829825	37.7580657	18.87903285	51	26.56841278	46.20474243	136.6924605
23	6.927727699	16.16534972	13.47210288	52	23.10237217	26.95276642	38.88703585
24	5.775592804	21.17717361	114.2053576	53	19.23974991	28.85962486	47.32773209
25	13.48066711	39.67050409	35.8188839	54	24.65134203	41.21526575	41.60434842
26	5.386788368	15.38691235	14.23700106	55	40.39064407	5.77009201	43.0862869
27	3.847949982	17.31577492	16.54559851	56	156.7627567	90.79354894	127.6534103
28	19.24586177	9.23762238	16.55065835	57	236.9066696	175.971869	184.4765167
29	107.8546431	179.933398	116.3448297				

b) Data – cutting, sliding, fatigue

The obtained field data show smoothly increasing tangent – see figures 2 – 6. Regression to the first change by the line $y = 0.002x + 0.0635$, determination coefficient $R = 0.93$, regression to the second change. The total course of observed particles (cutting, sliding and fatigue) is further presented in figure 7.

3.2 Utilization of FIS (Fuzzy Inference System)

A Fuzzy Inference System (FIS) is based on the terms *fuzzy set* and *fuzzy relation* which were introduced by Lotfi A. Zadeh in 1965 following the [14]. The fuzzy set is one of the possible generalizations of the term set. The fuzzy set is a pair ($\mathbf{U}$, μ_A) where $\mathbf{U}$ is universe and μ_A: $\mathbf{U} \rightarrow \langle 0,1 \rangle$ is a function describing that U elements belong to A fuzzy set. The membership is marked with $\mu_A(x)$. The fuzzy set is the generalization of a "typical" set because the following formula applies for a "typical" set A membership

μ_A: $\mathbf{U} \rightarrow \{0, 1\}$ and $x \in \mathbf{A} \Leftrightarrow \mu_A(x) = 1$ and $x \notin \mathbf{A} \Leftrightarrow \mu_A(x) = 0$.

Let $\mathbf{U}i$, $i = 1, 2, ..., n$ be universes. Then the fuzzy relation R over the universe $\mathbf{U}$ is regarded as the fuzzy relation $\mathbf{U} = \mathbf{U}_1 \times \mathbf{U}_2 \times ... \times \mathbf{U}_n$.

Nowadays one of the most widely used applications is a *Fuzzy Inference System* – FIS (once used as a term "fuzzy regulator"). The FIS is considered to be a fuzzy relation which gives resultant values when put together with input values. There are several types of the FIS. In this paper we applied the type P: $u = R(e)$ where an output quantity value depends only on the magnitude of an input quantity.

Let $\boldsymbol{E_i} = (E_i, \boldsymbol{T}(E_i), \mathrm{E}_i, \mathrm{G}, \mathrm{M})$, $i = 1, ..., n$ be input language variables, and $\boldsymbol{U} = (U, \boldsymbol{T}(U), \mathrm{U}, \mathrm{G}, \mathrm{M})$ be an output language variable. E_i, U are the names of variables, $\boldsymbol{T}(E_i)$, $\boldsymbol{T}(U)$ is a set of language values, E_i, U are relevant universes, G is grammar, M represents the meaning of language values. The FIS is considered to be:

$\mathbf{R} = \mathbf{R}_1$ otherwise $\mathbf{R}_2$ otherwise, ... , otherwise $\mathbf{R}_p$,where $\mathbf{R}_k$, $k = 1, \dots, p$ is as follows:

$\mathbf{R}_k$ = **if** E_1 **is** $X_{E1,k}$ **and** E_2 **is** $X_{E2,k}$ **and** ..... **and** E_n **is** $X_{En,k}$**, then** U **is** $Y_{U,k}$ $X_{Ei,k} \in \boldsymbol{T}(Ei)$, $Y_{U,k} \in \boldsymbol{T}(U)$ for each $i = 1, ..., n$, for each $k = 1, ..., p$.

The meaning of the statements $\mathbf{R}$ is expressed by $\mathrm{M}(\mathbf{R}_k) = \boldsymbol{R}$, and $\mathrm{M}(\mathbf{R})$ is a fuzzy relation above E1×E2×...×En×U which

$$R = M(\mathrm{R}) = \bigcup_{k=1}^{p} M(\mathrm{R_k}) \tag{4}$$

is defined as follows:

Regarding other rules $\mathbf{R}$ is considered as unification, and $\mathrm{M}(\mathbf{R}_k)$ is defined $\mathrm{M}(\mathbf{R}_k) = A_{E1,k} \times A_{E2,k} \times ... \times A_{En,k} \times A_{U,k}$, $A_{Ei,k} = \mathrm{M}(X_{Ei,k})$ which is a fuzzy set above the universe E_i, $i = 1, \dots, n$ and = M() is a fuzzy set over the universe U, $k = 1, \dots, p$. $\mathrm{M}(\mathbf{R}_k)$ is a fuzzy relation over the universe $\mathrm{E}_1 \times \mathrm{E}_2 \times ... \times \mathrm{E}n \times \mathrm{U}$.

When entering into the FIS, any fuzzy set will be above E_i (a_{Ei}). Then the magnitude of an actuating quantity a_U is determined by the formula $a_U = (a_{E1} \times a_{E2} \times ... \times a_{En})^\circ \boldsymbol{R}$. A_U consists of the fuzzy relation ($a_{E1} \times a_{E2} \times ... \times a_{En}$) above the universe $\mathrm{E}_1 \times \mathrm{E}_2 \times ... \times \mathrm{E}_n$, and the relation $\boldsymbol{R}$ defined above the universe $\mathrm{E}_1 \times ... \times \mathrm{E}_n \times \mathrm{U}$. The fuzzy set above the universe U is the result of this composition.

In many cases the fuzzy set is not required to be an output from the FIS, but a specific value $u_0 \in U$, i.e. we want to carry out *defuzzification*. The centroid method is the most widely used defuzzification method. The FIS specified this way is called *Mamdani* FIS [6].

If we do not know how the process works (i.e. FIS rules cannot be set), but the sufficient amount of input and output data is available, we can use the modification of Mamdani-FIS Sugeno (Takani-Sugeno FIS) [6] and [11]. This FIS is described by suitable parameters during tuning performed on well-known data. Sugeno FIS input language values are similar to Mamdani-type FIS, but the output quantity value is expressed by a different formula:

$\mathbf{R}_k$ = **if** E_1 **is** $X_{E1,k}$ **and** E_2 **is** $X_{E2,k}$ **and** ... **and** E_n **is** $X_{En,k}$, then $U = F_k$,

where F_k describes the value in the universe U for k-th rule.

This value depends on the magnitude of inputs (a_{E1}, a_{E2},..., a_{En}) into FIS: $F_k \equiv F_k(a_{E1}, a_{E2},..., a_{En})$. If E_1, E_2, ..., E_n, are the subsets of the universe U of real numbers, it can be stated that $u_k = f_k(\mathrm{defuzz}(a_{E1}), \mathrm{defuzz}(a_{E2}), \dots, \mathrm{defuzz}(a_{En}))$.

The function f_k is mostly considered to be a function in a constant form and it is expressed by the following way:

$f_k(\mathrm{defuzz}(a_{E1}), \mathrm{defuzz}(a_{E2}), \dots, \mathrm{defuzz}(a_{En})) = \alpha_k$,

or a linear form expressed as follows:

$f_k(\mathrm{defuzz}(a_{E1}), \mathrm{defuzz}(a_{E2}), \dots, \mathrm{defuzz}(a_{En})) =$
$= \alpha_k + \beta_{1,k}\ \mathrm{defuzz}(a_{E1}) + \beta_{2,k}\ \mathrm{defuzz}(a_{E2}) + \dots + \beta_{n,k}\ \mathrm{defuzz}(a_{En})$,

where α_k, $\beta_{i,k}$, $i = 1, 2, \dots, n$, $k = 1, 2, \dots, p$ are suitable invariables. The magnitude of these invariables is set during FIS tuning. In most cases the fuzzy sets are not considered as an input into Sugeno FIS, but only the values from E_1, E_2, ..., E_n.

Let us take into account the input denoted by $(x_1, ..., x_n) \in \mathbf{R}^n$. Then

$f_k(x_1, \dots x_n) = \alpha_k$,

$f_k(x_1, \dots x_n) = \alpha_k + \beta_{1,k}\, x_1 + \beta_{2,k}\, x_2 + \dots + \beta_{n,k}\, x_n$.

The rules are put in the following equation:

$\mathbf{R}_k \equiv$ **if** x_1 **is** $X_{E1,k}$ **and** x_2 **is** $X_{E2,k}$ **and** … **and** x_n is $X_{En,k}$, then $u_k = f_k(x_1, \dots x_n)$.

This means that if the input $(x_1, ..., x_n)$ belongs to the area specified by the language values $X_{E1,k}$ up to $X_{En,k}$, then the output is found by the function f_k. The weighted value u_k of the input z_k is determined the same way as the FIS of Mamdani-type using the level of conformance between the inputs $(x_1, ..., x_n)$ and the fuzzy sets $A_{E1,k}$ up to $A_{En,k}$. When applying the rules $\mathbf{R}_1$ up to $\mathbf{R}_p$ we get for the input $(x_1, ..., x_n)$ the values u_1, up to u_p, and using weighted values w_1 up to w_p and a weighted average we obtain a resultant output value u.

3.3 Searching for a proper FIS form used for the prediction of a time series

In order to predict successfully a time series by the FIS of Sugeno-type, it is necessary to select appropriately the n-number of FIS input variables and the p-number of language values for each input variable. The time series is divided into *tuning data* and *checking data*. Regarding the tuning data we stabilized the FIS for a different number of input variables and a different number of input variable values. The number of input variables n specifies how many members of a time series enters into the FIS before predicted values, and therefore affects the prediction. We gradually selected different n-s. Using the time series we matched the following member as an output quantity to the input set of n elements, thereby getting the time series into $n + 1$ dimensional space. Applying a cluster analysis we found clusters. Relevant language values and one FIS rule of Sugeno-type were made for each cluster. This rule was selected in a linear form $Z_k = \alpha_j + \beta_{1,k}$ defuzz(a_{E1})+$\beta_{2,k}$ defuzz(a_{E2}) + … + $\beta_{n,k}$ defuzz(a_{En}). By means of optimization over tuning data we found invariables α_j, $\beta_{i,j}$ i= 1, 2, …, n, k = 1, 2, …, p (where n is the number of language variables, and p is the number of language values).

Using the FIS designed and stabilized this way we predicted other members of the time series. Comparing the predicted data to the checking data we determined the quality of the prediction. This comparison was made applying mainly two criteria – MAPE – an average error, and MAX – a maximum error. Let (R_1, R_2, …, R_k) be the real members of the time series, and (P_1, P_2, …, P_k) be the time series predicted members, where k is the

$$MAPE = \frac{1}{k}\sum_{i=1}^{k}\frac{|P_i - R_i|}{R_i} \quad (5)$$

$$MAX = \max_{i=1,\dots,k}\frac{|P_i - R_i|}{R_i} \quad (6)$$

number of members under examination. Then

The design and stabilization of the FIS Sugeno along with the comparison was performed in Matlab 5.3 – FuzzyToolbox program.

The FIS can be viewed as a device which for the n members of a time series determines next time series members. However, this device is not a "black box" as it is for neural networks for example. If we generate all possible inputs into the FIS and calculate output values from the FIS for them, the FIS activity can be shown as a FIS area. If we have n inputs (n members of a time series), and m outputs (we predict m members of a time series), the FIS area can be displayed in $n + m$ dimensional space. It is convenient to display the area in the form which shows the dependency of output quantities on input ones. The shape of the FIS area helps us to assess which input (a time series member) affects a selected output most. In *Fig. 1* and *2* there is a FIS with three inputs and one output. We obtain a four-dimensional space which can be displayed in three pictures showing the dependency of an input value on the combination of two input values. The FIS was designed so that it could predict only one following member of a time series. If we want to predict more steps, we repeat the calculation m-times using the FIS, whereas the predicted value is considered to be real and will be applied as an input into the FIS to calculate another value. In order to predict a time series correctly it is necessary to choose the appropriate number of inputs into the FIS (n), and the number of values for each input (when dealing with the FIS of Sugeno-type the number of values at all levels is the same (p) and equals the number of the FIS rules). The prediction depends on the number of inputs (n) and the number of values (p) which is noticeable especially in the series showing a trend and periodic unit. These series usually occur right in the area of mechanical systems´ operation. If there are too many FIS rules, the FIS is too sensitive to small changes. If there are few of them, the FIS is not able to describe changes. Some dependencies are introduced in Figure 8 below.

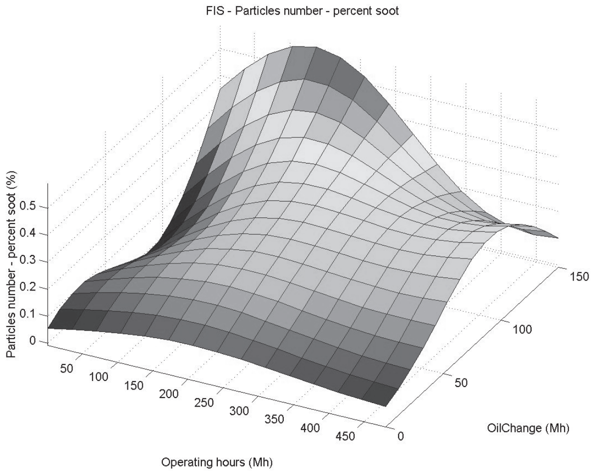

Fig.8. Course and correlation of soot particles onto operating hours

4. Proposals for system health condition calculation based on the results from tribodiagnostics

In case of taking single oil samples it is about a time line which might be possibly not stationary, and before making next calculation it needs to become stationary (non-constant mean value and dispersion); standard transformations do not provide satisfactory results.

Cumulative series of the quantities mentioned above show a linear course (determination coefficient higher than 0,97), so by analogy the linearization could be used for soot particles as an indicator for interval length modification between oil changes.

However, the analysis results detected from the oil provide a potential space for the modification of oil exchangeable date considering the number of particles present in the oil before the actual change. The situation is interesting especially with regard to the velocity of their occurrence. A recognized number of particles before the actual change would not necessarily mean a critical number which could threat reliable engine function or cause an accident. However, the exchange date is determined by an oil producer, and the time period in which the exchange is performed might be significantly affected by other characteristics. The presence and the number of particles which occurred in a lubricating system by mechanical processes should be viewed in the future as one of the most important factors in the process of lubrication fluid state assessment.

However, regarding the dependence courses of single particles occurrence between individual performed changes it is possible to observe slow increase in the particles number with a cumulative number of operational units. When using [5] we can apply the formula expressing velocity of wearing particles occurrence m.

$$m = m_o + at \quad (7)$$

Where $a = \frac{d_m}{d_t}$ is a coefficient of increase trend – second derivation of regression curve

m_o is a velocity of wearing products occurrence (oil degradation) – first derivation of the regression curve while crossing the applicable state limit [mg.Mh^{-1}]. The limits and criteria used for determining an up state are usually based on a statistical analysis, and some possible forms of it are to be found in [5] and [8].

Since the number of oil particles is fuzzy itself we have to create a rule of unacceptable increase of that number. This fact is presented by the acceleration factor of oil particles creation. Variation of that number alongside with the possible failure consequences comes to modifications of total risk number.

Fuzzy logic seems to be one of the good tools for determining the importance of the acceleration factor magnitude. Following approaches represented in figure 8 are to be adapted according to the degradation processes and limit states got by the observation. The outcome and suitable variation of the fuzzy number represents our strategy in maintenance or mission planning. These facts overcome only such possibilities since we have strict cuts of all expenses spent not only on the armed forces. Economical and costs optimization plays significant role in the life cycle costing and many other decisions made during complex system in service operation.

Outcomes from FIS calculation present oil quality development.

These results can be used for:

the setting of an observed item – engine condition;

the identification of a risk source – the occurrence of a possible dangerous event – failure.

Some dependencies are introduced in Figures 9 below:

The output of the FIS method application:

Procedure: **hours=soot_enginehours([0.1 0.2 0.5 0.55 0.9 1.1], soot_FIS)**

Input: [0.1 0.2 0.5 0.55 0.9 1.1]

Output: 0 3.6905 35.2711 45.1254 .91.3312 . 97.6548
5.6635 8.8995 45.4304 51.7286 107.8874 161.2406

Example based onto the graph: The soot content input e.g. 0,5 indicates number of operating hours between 35.27 and 45.43. We understand one operating hour as approximately 15 kilometres of drive for tracked vehicles.

Practically it means that the higher number of particles in oil represented by increasing acceleration factor the more significant decrease of the system performance may occur and in fact it may represent higher risk of system failure. Such failure might have more outcomes and consequences some of which

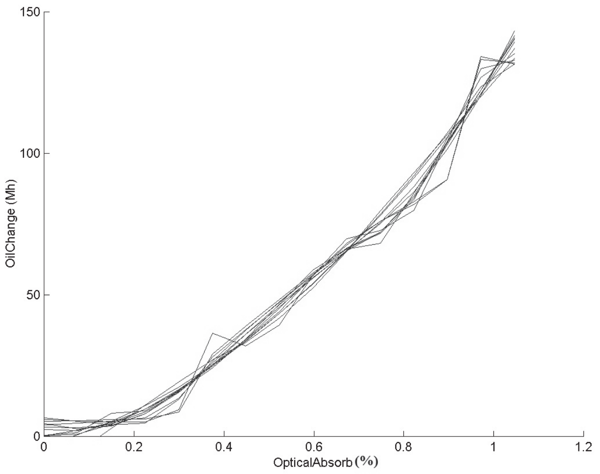

Fig. 9. Course of soot contents relation upon number of operation hours.

are not welcome in system operation especially in the area of military systems like battle vehicles for instance [12].

Possible expressions of acceleration factor increase based on magnitude of particles number is represented in Figure 10 bellow.

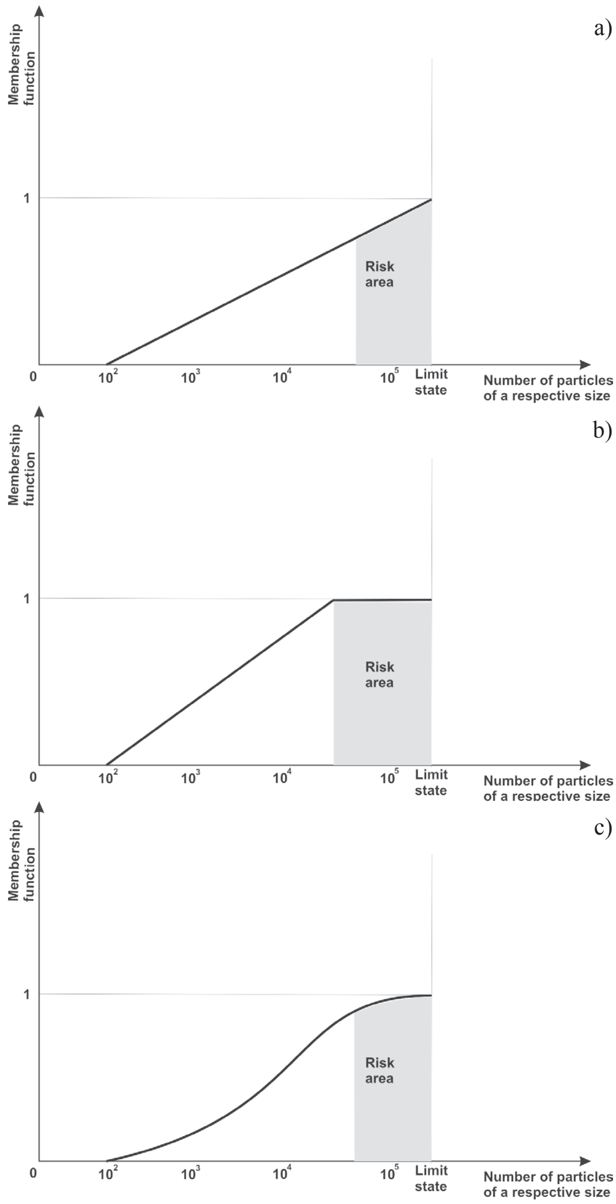

Fig. 10. Possible expressions of acceleration factor increase based on magnitude of particles number. a) Triangular shape of fuzzy number, b) Trapezoidal shape of fuzzy number, c) Progressive shape of fuzzy number

5. Conclusion

The aim of the paper contents is to shed light on the area of tribodiagnostics including the methods which are applicable and suitable for oil analysis. Results of the analysis can be used in a much better way and the impact they made on operation characteristics of a technical object might be perceived much strongly. The data regarding lubrication fluid which is available due to performed analyses is a good source of information when considering the cost savings in case the oil is changed systematically [8-9]. It would be also good to see the results of the analysis in a broader context as an interesting reflection of an actual state of a technical object from where the oil was taken. When taking into account the results of the tribological analysis, the cost savings might be manifested as extension of time of oil changes and relating maintenance costs and downtime resulting from object unavailability by extraneous causes [14]. Since there is a wide spectrum of suitable methods while analysing an immediate state and prognosis (PHM – Prognostics and Health Monitoring), and because the area falls very deeply into interdisciplinary studies, the specification of relevant dependencies of the analysis results on a real technical state is not at all an easy task to do.

Having this tool we are capable to understand of mechanisms of failures better. Such procedures enable to be prepared for coming failures and progression to faults. The diagnostics is cheaper than on-line assets and failure mechanisms are determinable in advance. Some specific classifications of failures are also used in relation to risk sources which are recognised due to oil diagnostics [13].

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