Rotating systems misalignment identification using fuzzy clustering method

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Abstract. In the phase of operation, a technical system accomplishes goals which were the reason of the system designing and creation. The execution of operation tasks by the system causes changes in the system state. The changes in the dynamic state of rotating systems can be early identified by means of vibrations measurement. Therefore, the operational tests were performed in order to register time histories of vibrations. Next, characteristics of the collected vibration signals were recorded and the most significant of them were taken as an input for further studies. The studies were performed to formulate a method of identifying the rotating systems misalignment with high reliability. The method consists in fuzzy clustering implementation. According to the method the input signals were used to formulate the fuzzy clusters of the ability and inability states of the system. Thanks to the method, it is possible to identify the operation position of the system on base of the vibration signals analysis. In the paper the proposed method was described. The results of the method application for a gas turbine engine as an example of a rotating system are also presented. It should be emphasized that the reliability of the described operation state identification is higher than other methods implemented by the authors previously.

Keywords: rotating system, misalignment identification, vibration analysis, fuzzy clustering.

1. Introduction

Vibrations of propulsion units of transport means are an important research issue to be explored in terms of their operation processes. They are the main diagnostic symptoms from the point of view of damageability and reliability of these subsystems functioning. They have also effect on the comfort of transport means operators and passengers.

Vibrations and noise produced by rotating subsystems occur in practically all mechanical transport means. Depending on the transport branch and the type of object vibrations are produced by: drive shafts, axes, turbines and fans. On the basis of literature, it was found that early symptoms of rotating systems dynamic changes can be detected mainly by the system vibration measurement in particular its misalignment [1-4].

2. Characteristics of the research object

The research object of this study are eight propulsion systems of selected transport means. Each of them consists of: nominal rotational speed equal to 1550 rpm and nominal power 736 kW, hydro-kinetic clutch with nominal skid 2 % and skid control range 2-98 %, reverse reduction transmission with ratio 3.5:1 and resistance bearing equipped with three rolling bearings.

Vibrations of the main engine shafting were measured in six points of each propulsion system situated on main engine foundation, power end of the engine, a hydro-kinetic clutch, a bearing on the reverse reduction transmission inlet; a bearing on the reverse reduction transmission outlet and a resistance carrier bearing. Three identical accelerometers (B&K 4514B) were used for measurements.

They were mounted on three mutually perpendicular axes. As there was no possibility to use threaded joints the converters were fixed to the tested components of the propulsion system by means of glue. Measurement tracks were calibrated before and after measurements. All the recorded signals were synchronized by means of a four channel measurement gauge [5].

Vibrations were recorded within the range of band 3.2 kHz and for sampling frequency 8192 Hz.

As has already been mentioned the signals were collected from eight objects where vibrations were recorded separately for 4 rotational speeds (850 rpm, 1100 rpm, 1300 rpm and 1500 rpm) and three directions perpendicular to each other. The results were recorded in cvs format files. Each file included values of vibrations for a given transport means, shaft system, measurement point and rotational speed [2, 6].

The above data provided the basis for further studies of this article.

3. Analysis of experimental tests results

The values of registered vibrations were treated as discrete signals expressed in the time domain. For each signal (vs_i) sixteen characteristics ($CH(vs_i)$) were calculated [6-9]:

– the signal integral – $I(vs_i)$,
– the signal mean value – $M(vs_i)$,
– the signal energy – $E(vs_i)$,
– the signal mean power – $P(vs_i)$,
– 1st moment of the signal – $M_1'(vs_i)$,
– 2nd moment of the signal – $M_2'(vs_i)$,
– 1st central moment of the signal – $C_1(vs_i)$,
– 2nd central moment of the signal – $C_2(vs_i)$,
– normalized 1st moment – $N_1(vs_i)$,
– normalized 2nd moment – $N_2(vs_i)$,
– normalized 1st central moment – $NC_1(vs_i)$,
– normalized 2nd central moment – $NC_2(vs_i)$,
– abscissa of signal square gravity centre – $G(vs_i)$,
– the signal square variance – $V(vs_i)$,
– the signal equivalent diameter – $ED(vs_i)$,
– the distance from reference signal – $\delta(vs_i)$.

Next, the mean value and standard deviation of each characteristic were calculated separately for rotating systems remaining in ability state and in inability state in division by measurement point, vibration axis and rotation speed (PAS).

According to the theory presented in [4] characteristics were analysed from the concentration and unequivocally point of view using Eqs. (1) and (2):

$$CH_{CON} \Leftrightarrow \sigma_{CH(PAS)} \leq \overline{CH}(PAS) \cdot 0.15, \tag{1}$$

where CH_{CON} – concentrated characteristic; $\sigma_{CH(PAS)}$ – standard deviation of characteristic CH; $\overline{CH}(PAS)$ – the mean value of the characteristic CH calculated over PAS group of signals.

$$CH_{UE} \Leftrightarrow \{CH \in CH_{CON} \wedge \sigma_{CH(PAS_{IA})} + \sigma_{CH(PAS_A)} \leq |\overline{CH}(PAS_{IA}) - \overline{CH}(PAS_A)|\}, \tag{2}$$

where: CH_{UE} – unequivocal characteristic; CH_{CON} – concentrated characteristic; $\sigma_{CH(PAS)}$ – standard deviation of characteristic CH calculated over PAS group of signals; $\overline{CH}(PAS)$ – the mean value of the characteristic CH calculated over PAS group of signals; PAS_{IA} – PAS group of signals registered on rotating systems remaining in inability state; PAS_A – PAS group of signals registered on rotating systems remaining in ability state.

On this basis the characteristics which fulfil the concentration and unequivocal conditions to relatively high degree, were chosen for further analysis. These were the signal energy, the signal mean power, abscissa of the signal square gravity centre, the signal square variance and the signal distance from the reference one.

The characteristics formulated five-dimensional space in which fuzzy clusters of ability and inability states can be identified. In the space each signal was expressed as a point and their coordinates were the values of the characteristics. The identification procedure was carried out according to the FCM (fuzzy c-means) method [10].

Analysing the signals, it was stated that ranges of the dimensions of the formulated space were completely different. Therefore, prior to the clusters identification the minimum and maximum values for each dimension was calculated and on this basis the values of each signal coordinates were normalized according to Eq. (3):

$$CH(vs_i) = \frac{CH(vs_i)}{\max\big(CH(VS)\big) - \min\big(CH(VS)\big)}, \tag{3}$$

where: VS – the set of vibration signals, $\max(CH(VS))$ – maximum value of the characteristic CH of VS; $\min(CH(VS))$ – minimum value of the characteristic CH of VS; vs_i – vibration signal no. i, $CH(vs_i)$ – value of the characteristic CH of the vibration signal vs_i.

Thanks to the coordinates normalisation each dimension of the space has the same influence on the clusterisation process.

In the first step of identification the signals were divided into two groups. One group consisted of 17792 signals recorded on rotating systems remaining in ability state and 2854 signals recorded on rotating systems remaining in inability state. This group, called learning set, was used in centre of clusters identification process. The second group consisted of 5670 signals recorded on rotating systems remaining in ability state and 1386 signals recorded on rotating systems remaining in inability state. This group, called testing set, was used for testing the misalignment identification method reliability. Next, the FCM method was applied with the learning set.

The method requires three starting parameters to be set. The number of clusters (cno), coefficient which define the fuzziness of the cluster membership function (q) and ε – procedure stop condition. At the beginning, the initial random values of the membership matrix are generated. The matrix defines the membership degree of each signal to each cluster. Later, the clusters centre points were recalculated according to for Eq. (4):

$$c_{j,k} = \frac{\sum_{i=1}^{I} \mu_{i,j}^{q} \cdot CH_k(vs_i)}{\sum_{i=1}^{I} \mu_{i,j}^{q}}, \tag{4}$$

where: $c_{j,k}$ – the dimension no. k of the cluster no. j, I – the amount of the signals vs, $\mu_{i,j}$ – the membership degree of the signal no. i to the cluster no. j, q – the coefficient which define the fuzziness of the cluster membership function, $CH_k(vs_i)$ – value of the characteristic CH no. k of the vibration signal vs_i, vs_i – vibration signal no. i.

Then the membership matrix values are recalculated according to Eq. (5):

$$\mu_{i,js} = \frac{1}{\sum_{j=1}^{cno} \left[\frac{\sqrt{\sum_{k=1}^{chno} (c_{js,k} - CH_k(vs_i))^2}}{\sqrt{\sum_{k=1}^{chno} (c_{j,k} - CH_k(vs_i))^2}} \right]^{\frac{2}{q-1}}}, \tag{5}$$

where: $\mu_{i,js}$ – the membership degree of the signal no. i to the cluster no. js, cno – amount of clusters, $chno$ – amount of dimensions, q – the coefficient which define the fuzziness of the cluster membership function, $c_{j,k}$ – the dimension no. k of the cluster no. j, $CH_k(vs_i)$ – value of the characteristic CH no. k of the vibration signal vs_i, vs_i – vibration signal no. i.

The calculations are performed until the stop condition, described by the Eq. (6), is met:

$$\sum_{j=1}^{cno}\sum_{i=1}^{vsno}\left|\mu_{i,j}(t)-\mu_{i,j}(t-1)\right|<\varepsilon, \tag{6}$$

where: $\mu_{i,j}$ – the membership degree of the signal no. i to the cluster no. j, cno – amount of clusters, $vsno$ – amount of signals vs, t – iteration number, ε – procedure stop condition.

During the research the clusters identification was performed several times using different values of the cluster number and the membership function fuzziness coefficient in order to account for the signals noisiness and the signals arrangement in the space. The parameters of the identification process were accepted only if the cardinality of the weakest cluster found was not lower than 30 % of the strongest cluster cardinality Eq. (7):

$$\begin{aligned}&\forall c_j \in C_{ident}: card(c_j) \geq 0.3\cdot \max\left(card(C_{ident})\right),\\&card(c_j)=\sum_{i=1}^{I}\mu_{i,j},\end{aligned} \tag{7}$$

where: c_j – the cluster no. j, C_{ident} – the set of the identified clusters, $card(c_j)$ – cardinality of the cluster no. j, $max(card(C_{ident}))$ – maximum value of the cardinality among the clusters from set C_{ident}, I – the amount of the signals vs, $\mu_{i,j}$ – the membership degree of the signal no. i to the cluster no. j.

Table 1. The parameters of the clusters identification process

	Number of clusters $clno$	The coefficient which define the fuzziness of the cluster membership function q	Procedure stop condition ε
Signals collected on rotating systems remaining in ability state	2	3	0.1
Signals collected on rotating systems remaining in inability state	2	2	0.1

Table 2. The cardinality and coordinates of the identified clusters

	Cardinality	Coordinates
Signals collected on rotating systems remaining in ability state	8084,79	0,068; 0,067; 0,479; 0,451; 0,934
	9707,2	0,025; 0,024; 0,481; 0,457; 0,956
Signals collected on rotating systems remaining in inability state	1026,88	0,176; 0,175; 0,484; 0,459; 0,979
	1827,12	0,078; 0,077; 0,482; 0,458; 0,983

As a result, the value of identification process parameters where chosen (Table 1). Using them, the clusters for learning set were identified. The cardinality and the coordinates of the clusters are presented in Table 2.

For each subgroup, according to the FCM method, one cluster was identified. Next, the obtained clusters were analysed. For each of them, the distance from the clusters identified for the learning set of signals collected on rotating systems remaining in ability state and the distance from the clusters identified for the learning set of signals collected on rotating systems remaining in inability state were calculated according to Eq. (8) and (9):

$$d_{as}(ctst_{ls}) = \sum_{j=1}^{cano} \sqrt{\sum_{k=1}^{chno} (ca_{j,k} - ctst_{ls,k})^2}, \tag{8}$$

where: $ctst_{ls}$ – the cluster identified for the test set no. ls, das – distance from clusters identified for signals collected on rotating systems remaining in ability state, $cano$ – amount of clusters identified for signals collected on rotating systems remaining in ability state, $chno$ – amount of dimensions, $ca_{j,k}$ – the dimension no. k of the ability state cluster no. j, $ctst_{j,k}$ – the dimension no. k of the test cluster no. j:

$$d_{ins}(ctst_{ls}) = \sum_{j=1}^{cinno} \sqrt{\sum_{k=1}^{chno} (cin_{j,k} - ctst_{ls,k})^2}, \tag{9}$$

where: $ctst_{ls}$ – the cluster identified for testing set no. ls, $dins$ – distance from clusters identified for signals collected on rotating systems remaining in inability state, $cinno$ – amount of clusters identified for signals collected on rotating systems remaining in inability state, $chno$ – amount of dimensions, $cin_{j,k}$ – the dimension no. k of the inability state cluster no. j, $ctst_{j,k}$ – the dimension no. k of the test cluster no. j.

If the distance between specified test cluster and the ability state clusters was bigger than the distance between the cluster and the inability state clusters, then the signals of the analysed test cluster were interpreted as signals of the rotating system remaining in inability state Eq. (10). Otherwise, they were interpreted as signals of the rotating system remaining in ability state:

$$d_{as}(ctst_{ls}) > d_{ins}(ctst_{ls}), \tag{10}$$

where: $ctst_{ls}$ – the cluster identified for testing set no. ls, d_{ins} – distance from clusters identified for signals collected on rotating systems remaining in inability state, d_{as} – distance from clusters identified for signals collected on rotating systems remaining in ability state.

In Table 3 the results of the testing set analysis are presented.

Table 3. The results of the testing set analysis

	Number of signals tested	Number of signals identified as signals collected on rotating systems remaining in ability state	Number of signals identified as signals collected on rotating systems remaining in inability state
Signals collected on rotating systems remaining in ability state	5670	4536 (80 %)	1134 (20 %)
Signals collected on rotating systems remaining in inability state	1386	126 (9 %)	1260 (91 %)

Presented results indicates that the efficiency of the proposed method is higher in case of the signals collected on the rotating systems remaining in the inability state than in case of signals collected on rotating systems remaining in ability state. Comparing the efficiency of the method with the earlier works of the authors [4] in can be noticed that the efficiency of the inability state identification is slightly lower but still relatively high (higher than 90 %) and the efficiency of the ability state identification is much higher. The overall efficiency of the rotating systems misalignment identification is higher – over 82 %.

4. Conclusions

The conclusions of the carried out research can be expressed in the following list:

– the signal energy, the signal mean power, abscissa of the signal square gravity centre, the signal square variance and the signal distance from the reference one can be used to formulate the method of the rotating systems misalignment identification,

– the efficiency of the presented identification method is – 80 % for signals collected on rotating systems remaining in the ability state and 91 % for signals collected on rotating systems remaining in the inability state,

– the total efficiency of the proposed method is higher than of other methods used in previous works of the authors.

It should be emphasized that the presented method can a universal tool to be used for analysis of any rotating system vibrations.

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