Automated defect detection in oil-lubricated parts and units of D30KP/KP-2 aircraft gas turbine engines by results of microwave plasma method

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Abstract. Classifier between states of "normal/high maintenance/defective" for oil-lubricated parts and units of D30KP/KP-2 aircraft gas turbine engines is developed. The classifier is based on "random forest" machine learning algorithm. It is trained on results of microwave plasma measurements of metallic admixture in oil filter wash samples of engines. Technical state for train set was determined earlier by expert method and was confirmed by factory disassembly study. Classifier result for states "normal/high maintenance/defective" matches expert method in 73 %, 52 %, 66 % respectively.

1. Introduction

Microwave plasma method was developed at Applied Physics Institute of Irkutsk State University and is used for technical state evaluation of oiled parts and units of gas turbine aircraft engines. Diagnostic decision is taken according to measurements of parameters of metallic impurity in oil and oil filter wash samples. Defect can be localized up to assembly unit while using this method.

Large quantity of measured parameters necessitates high proficiency of the evaluator. Hence, automation of the process is preferable.

Diagnostic decision-making algorithm that could be implemented in software was not formalized. Decisions were carried out expertly by comparison of measured values with reference values of statistical model of normally operating engine.

The purpose of this research is the development of an algorithm and machine learning system that determine technical state by results of microwave plasma measurements.

2. The Data

Initial data contains oil filter wash samples from D30KP/KP-2 aircraft gas turbine engines analyzed through 2000-2019. The engines in the data have operating time from 0 (fresh from the acceptance tests) up to 5000 hours. The data contains both engines with regular 50-hour sampling beginning from engine operation and samples, taken after external defect manifestation.

Sample distribution by technical state shown in Table 1.

To summarise, the data contains information about defects of back and frontal drive box (FDB, BDB); inner and outer rings and seperator of high pressure turbine (HPT) roller bearing (r/b); intershaft r/b; high pressure compressor (HPC) ball (b/b) and roller bearings. "High maintenance" state
means that expert was not able to localize the defective unit, but there were abnormal values in measurements and undetermined defect was possible.

Table 1. Sample distribution by technical state

| №  | Engine state             | Sample quantity |
|----|--------------------------|-----------------|
| 1  | Normal                   | 532             |
| 2  | High maintenance         | 292             |
| 3  | Roller bearing HPT       | 30              |
| 4  | FDB units defect         | 33              |
| 5  | BDB units defect         | 3               |
| 6  | ISB defect               | 2               |
| 7  | HPC r/b defect           | 1               |
| 8  | HPC b/b defect           | 1               |

3. Diagnostic features
Microwave plasma method gives the following notable parameters of metallic impurities in samples:

1. Content of element in form of submicron admixture or discrete particles of size up to 2 μm, Cs (ppm);
2. Content of element in discrete particles more than 2 μm in size, Cp (ppm);
3. Discrete particles quantity of specific elemental composition (Al-Cu, Fe-Ni etc.), from 8 possible elements (Al, Cr, Ni, Cu, Fe, Ag, V, Mg), N (cm\(^{-1}\)). Particles from one element are called "simple"; two and more – "complex";
4. Average size of particle for each measured element, D (μm);
5. "Rating" of particles of specific elemental composition, R (%). The rating is ratio of specific particles to total measured particle count. Usually are used:
   1. Ratings of simple particles, containing specific element, \(R_{\text{simple}}\) (%), 8 parameters total;
   2. Total rating of particles, containing specific element, \(R_{\text{all}}\) (%), 8 parameters total;
   3. Ratings of complex particles, \(R\) (%), \(2^8 - 8 - 1 = 247\) parameters total.

The work [2] shows, that most information about wear processes is contained in particles, deposited in main oil filter. To measure them, oil wash sample is prepared.

Ratings were developed to account for filter operation time, which correlated with particle counts. Thus, ratings were used almost exclusively in current work. Out of 247 possible complex particle ratings, 221 appeared in the data. It is clear that accounting for such large number of features in a small dataset requires dimensionality reduction, which is done through feature engineering.

Rating of complex particles, containing a particular element, was proposed \(R_{\text{complex}}\). Next, two groups of features were formed. The first contained ratings of simple particles \(R_{\text{simple}}\) and ratings of complex particles containing particular element \(R_{\text{complex}}\). The second contained ratings of complex particles less than of 5 elements \(R\).

All features were normalized with mean 0 and standard deviation 1 using Yeo-Johnson method (scikit-learn package implementation was used [3]). The distribution parameters were calculated on a subsample of engines with over 500 operating time, 2, 2.5, and 3 standard deviation outlier counts in each group became new features.

Most features have significant dispersion, caused by engine operating conditions [4]. For demonstration purposes, sample dot distribution to rating of complex particles which contain copper is shown on figure 1.
Figure 1. Sample dot distribution relative to rating of complex particles which contain copper.

The dots represent quantity of samples within particular parameter value by technical states; from top to bottom – "normal", "high maintenance", "HPT r/b defect", and "other defects". It is clear that there is significant mixing between the states which makes the classification problematic.

4. Results
The data containing new features was used to train random forest-based classifier (again, scikit-learn implementation was used). Algorithm was chosen due to faster training while offering the same results in comparison to xgboost / neural nets of simple architecture (consisting of several dense layers).

Conditions "normal", "high maintenance", "defective" were chosen as classes. The samples of "high maintenance" class without first or second group 2-standard deviation outliers (20 samples) were transferred to "normal" class.

Train and test set contained half of each class respectively. The samples of rare defects (BDB, ISB, HPC) were transferred to test set from the start.

Confusion matrix averaged on hundred models is shown in table 2.

| According to expert method | Classified |          |          |          |
|----------------------------|------------|----------|----------|----------|
|                            | Normal     | High maintenance | Defective | Total samples |
| Normal                     | 73 [10] %  | 25 [10] % | 2 [2] %  | 288      |
| High maintenance           | 36 [12] %  | 52 [10] % | 12 [6] % | 124      |
| Defective                  | 8 [8] %    | 27 [14] % | 66 [14] % | 39       |

Train-test set splitting was done separately for each model of the hundred. Square brackets contain confidence interval (\(\alpha=0.95\)).

According to the table, for classes "normal", "high maintenance", "defective" state can be accurately classified in 73 %, 52 % and 66 % cases respectively. In 8 % cases defect can not be
detected by algorithm at wear level, when defective unit can be localized by the expert. In 2 % cases "normal" engine is classified as "defective".

For comparison, Table 3 shows confusion matrix ratings of two-element complex particles.

Table 3. Averaged confusion matrix for model based on ratings of two-element complex particles.

| Classified          | Normal | High maintenance | Defective | Total samples |
|---------------------|--------|------------------|-----------|---------------|
| Normal              | 75 [8] % | 23 [8] %         | 2 [2] %   | 288           |
| High maintenance    | 42 [8] % | 51 [8] %         | 7 [6] %   | 124           |
| Defective           | 18 [10] % | 39 [14] %       | 43 [14] % | 39            |

This model detects defects accurately 23 % less often on average, and "misses" it altogether 10 % more often. Using extra non-engineered features for this model does not result in higher classifier accuracy, even with model tuning. This suggests that most of the features have high measurement error, reduction of which is crucial for classification result.

5. Conclusion
The results of the developed classifier match expert method in 73 %, 52 % and 66 % cases for classes "normal", "high maintenance", "defective" respectively. The algorithm uses 2, 2.5, 3 standard deviation outliers of two groups of ratings only.

In 8 % cases defect can not be detected by algorithm at wear level such that defective unit can be localized by expert. In 2 % cases "normal" engine is classified as "defective". Incorrect classification in these cases can be explained by adjustment of statistical model as time passed resulting in variance in margins used by experts. Previously obtained results, evidently, were never revised. This is also corroborated by appearance of "high maintenance" and "defective" classes without statistical outliers in dataset. The same could be said for low (52 %) accuracy of "high maintenance" classification.

Since incorrect classification for said cases is relatively rare (2 % and 8 %), the classifier can be used as rough automated technical state evaluator for oil-lubricated parts and units of D30KP/KU-2 aircraft engines. The decrease in error of measurement of complex particles quantity using microwave plasma method and revision of expert evaluation for the dataset would be primal means to increase the classification result of the algorithm.

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