Application of Machine Learning to Classify Wear Level of Multi-Piston Displacement Pump

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Abstract

This article specifies application of machine learning for the purpose of classifying wear level of multi-piston displacement pump. A diagnostic experiment that was carried out in order to acquire vibration signal matrices from selected locations within the pump body is described herein. Measured signals were subject to time and frequency analysis. Signal attributes related to time and frequency were grouped in a table in accordance with pump wear level. Subsequently, classification models for the pump wear level were developed through application of Matlab package. Assessment of their accuracy was carried out. A selected model was subject to confirmation. The article includes its summary.

Keywords: machine learning, diagnostics, signal analysis, multi-piston pump, vibrations

1. Introduction

Multi-piston pumps make a significant part of the high-power actuator-based hydraulic systems. More than once, proper operation of the entire hydraulic system is made conditional on proper action of the pumps. Wear of individual elements of the pump leads frequently to a drop of its operational pressure, increase of volumetric loss, and as a consequence to a reduction of delivery of pump, increase of vibrations, and increase of pump noisiness. The pump operational vibroacoustic diagnostics is focused on searching symptoms of damages within a vibration signal. In case of high-level noise and mechanical high-complexity (as in the pumps), obtained assessments of wear level of tested elements are burdened with significant uncertainty. The authors of this article specified potentials for application of machine learning for the purpose of classification hydraulic pump wear level on the basis of deliberated vibration signals within typical locations of its body.

2. Pump specification

Figure 1 shows a simplified drawing that includes an axial multi-piston disc-deflected displacement pump. In such a pump, its rotor (2), piston (3), and nose bearing (7) are installed coaxially on a driving shaft (1). Glide shoes (4) on the pistons mate with immovable swashplate (5) deflected at γ angle relative to the pump rotor axis. Pistons along with the rotor rotate and at the same time their shoes (4) that glide on the surface of the immovable swashplate enforce reciprocating motion within the rotor cylinders.

Additionally, the rotor glides on the immovable valve plate (6) which is equipped with suction and pressing openings.

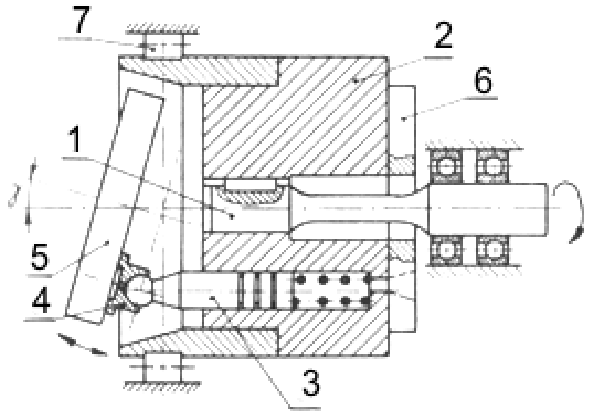

Figure 1. Simplified structural diagram of axial multi-piston disc-deflected pump: 1– shaft, 2 – rotor, 3 – piston, 4– glide shoe, 5 – swashplate, 6 – valve plate, 7 – bearing [5]

Wear of displacement pump elements is caused both by forces that arise during mating its individual parts which make kinematic pairs (e.g. piston-cylinder, valve plate-rotor, piston shoe-swashplate) and inadequate conditions related to pump operation such as exceeding nominal pressure, operation at too low viscosity of working medium, loss or insufficient filtration of working medium.

Abrasive wear is the most frequent type of wear to displacement pump elements. Excessive load on the rotor unit leads to a/o abrasive wear of its elements and increasing radial clearance within piston-cylinder kinematic pairs. It results in increasing volumetric loss and lowering pump general efficiency.

Wear of the deflected disc, which mates with surfaces of rotor piston shoes, leads to occurrence of elliptical notch (Figure 2) on its surface and as a consequence to total wear of this surface. It causes reduction of pump mechanical and hydraulic efficiency. Conversely, wear of the valve plate is caused by a/o decay of lubrication layer between the disc surface and a surface of the rotor face. It results in occurrence of flow micro-conduits (Figure 3) on the surface of the swashplate bridge. Such conduits cause flow of the working medium between suction and pressure zones within the pump; as a result, loss of tightness, reduction in operational pressure and volumetric efficiency of the pump occur.

Figure 2. Demonstration of deflected swashplate wear

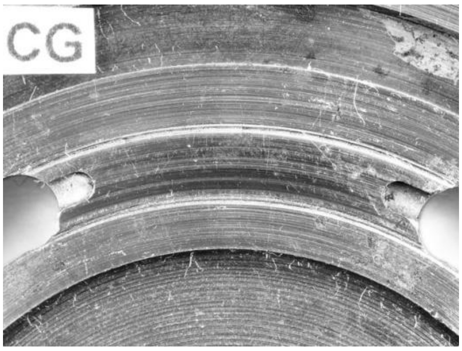

Figure 3. View of flow micro-conduits on worn valve plate

3. Test run

Testing of multi-piston pump wear level was carried out in a special-design laboratory station. One of major purpose of testing was to obtain some wear on the pump elements in a natural way; for this reason, such multi-hour testing was carried out in real operational conditions. In the course of testing, diagnostic signals - such as working medium flow rate, static and dynamic pressure, as well as pump body vibration acceleration - derived from measuring transducers were recorded systematically. Measurements of the body vibration acceleration were carried out on three testing axes (X, Y, Z) upon earlier installation of transducers on the pump body in the vicinity of the valve plate and the swashplate. Frequency of signal sampling was 50 kHz. A simplified diagram of the pump body vibration measurement including vibration transducers is shown in Figure 4. Cumulative root mean square related to short-time Fourier transform from vibration signals recorded on three operational conditions of the pump is shown in Figure 5.

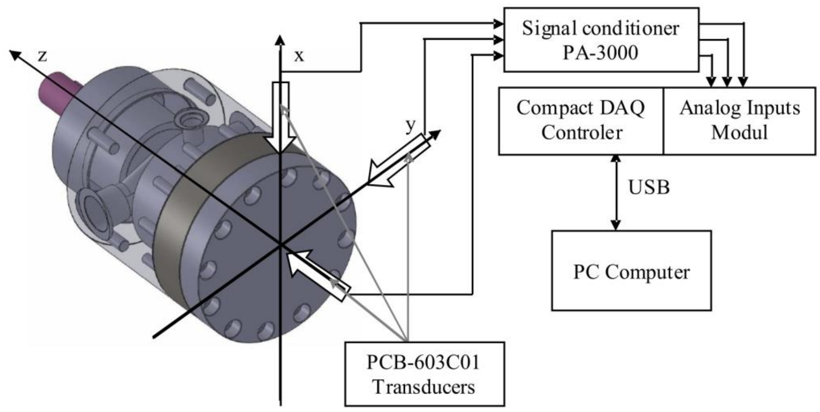

Figure 4. Simplified block diagram related to measurement chain for pump body vibration acceleration on laboratory station

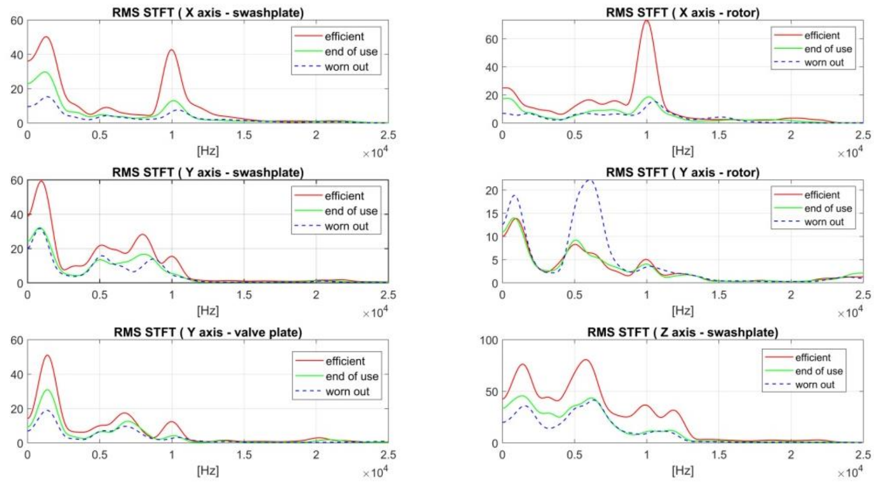

Figure 5. Cumulative root mean square related to short-time Fourier transform from vibration signals recorded on three operational conditions of the pump

Upon completion of laboratory testing, the pump was subject to assessment in relation to wear of its components. Basing on visual inspection, wear of the rotor unit and wear of the valve plate were confirmed. Neither the swashplate surface nor the piston foot surfaces were worn. Such kinematic pair was not obtained due to the pump static operational conditions as the effect of decay of lubricating surface between mating surfaces of the swashplate and the piston foot did not occur. Wear of the rotor unit consisted in (on average) approx. 10 μm enlargement of radial clearance in each piston-cylinder pair. Additionally, wear of the rotor end face mating with surface of the valve plate was confirmed. Degradation of the rotor end face was measured with a profile measurement gauge [4] within three selected directions (Fig. 6). Upon comparison of profile courses, identical wear of the rotor end face was confirmed with its average depth approximately 50 μm.

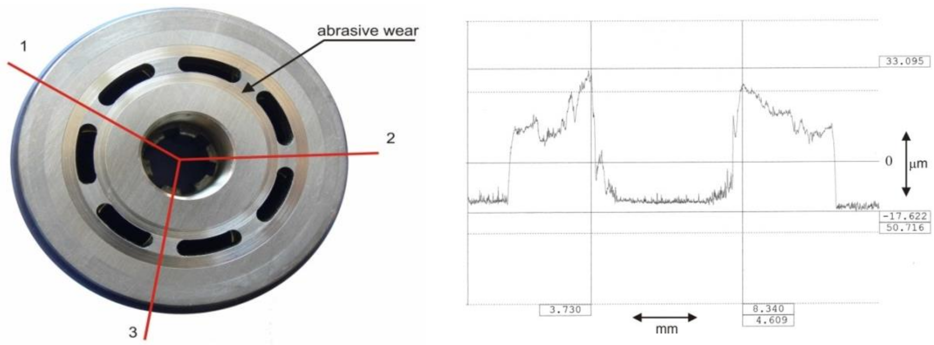

Figure 6. View of wear of rotor end face and a wear profile

Wear of surfaces on the valve plate caused occurrence of flow micro-conduits on the surfaces of the transition zones (so-called bridges) between suction and pressure conduits, Fig. 7. Upon measuring profiles on A transition zone (transition from suction side to pressure side) and B transition zone (transition from pressure side to suction side) uneven wear of the transition zones was confirmed (Fig. 7). However, surface of A transition zone (transition from suction to pressure side) was subject to increased degradation.

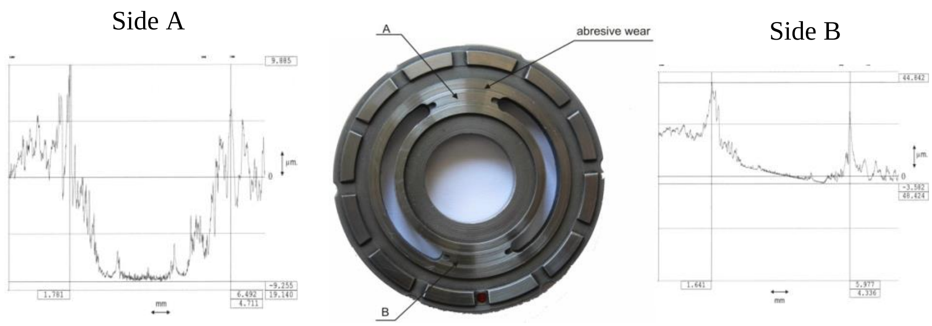

Figure 7. View of worn surface on the valve plate and wear profiles on transition zones

Obtained courses of the pump body vibration were grouped in accordance with the pump efficiency level and attributed with the following grades (labels): *efficient*, *end of use*, *worn*. The next stage of testing included creation of models related to classification of the pump efficiency on the basis of vibration courses that have been grouped.

4. Machine learning

Considering complexity of physical phenomena during the unit operation (usually intensely non-linear and intensely non-stationary), modelling of multi-piston pumps is a hard task in terms of mechanics. Current mathematical models usually constitute approximation of phenomena that occur within pumps during their operation [3]. As part of the operations engineering, machine learning systems have been applied more and more frequently; these form conditions for industrial process or its elements (e.g. machines) only on the basis of available measurement data ascribed to the process conditions (grade). Machine learning systems have been widely used in multiple industries. These are applied a/o in finance, power energy, machine vision, and (broadly defined) operations engineering for the purpose of anticipation of machine wear level and discovery of their damages. In particular, machine learning is applied in all locations where (considering complex conditions within the testing item) it is not possible to provide a full mathematical description of phenomena that occur inside the unit (as such a description does not exist or it could be inaccurate), and the signals recorded at the output (which are responses to input function) make the only available information to be provided.

Considering methods of learning, machine learning can be divided into supervised and non-supervised systems. Supervised learning includes creation of a process model (an issue) on the basis of input data only (collected earlier) and reference output data (labels, grades). This is widely applied to classification in order to use obtained model to classify input data (e.g. recognition of sounds, speech, illness in a patient) as well as regression for the purpose of continuous anticipation of changes to a certain output value induced by alteration of input value. Non-supervised learning, however, is based only on input data, collected earlier, and their grouping as well as interpreting. Such systems are applied for the purpose of data grouping and detecting hidden properties [1]. In case of classification of wear of displacement multi-piston pump, supervised learning algorithms are to be used.

4.1. *Arrangement of data for machine learning system*

Recorded measurement signals that have been obtained every day during the experiment related to operation of the multi-piston pump were subject to qualitative assessment in order to recover potential major error resulting from a/o unpredictable faults (interference) in the course of recording. Subsequently, constant component was removed from the signals and then subject to wall filtration at cut-off frequency $f = 20$ kHz. Bearing in mind that during signal measurement, a signal related to pump shaft rotation marker was also recorded, all recorded signals were divided as per such marker signal. Matrices related to a single-rotation length were obtained in that manner.

Considering hydraulic oil temperature growth during test, input data of the machine learning system constituted only courses obtained at temperature $T = 50°$ [C] at which oil viscosity does not undergo alteration and may be accepted as a constant. 429 courses of the pump body vibration signals were recorded in total, whereby signals measured for an *efficient* pump constituted 144 of these and signals measured for a pump in transition condition (*end of use*) constituted 144 of these courses. Last 141 courses were obtained from operation of a *worn* pump. A consecutive stage related to arrangement of data for machine learning system was its division into data applied in the process of learning classifier model and data for its later attestation. 25% of general data were used for testing of operation accuracy of the classifier model that has been obtained. Data received in such a manner were read in to the operational space of Matlab package [2], where further analysis was carried out in the following way:

- selection and calculation of signal properties,
- selection of classifier model,
- assessment of the applied classifier efficiency.

4.2. *Selection of signal properties*

Another important issue related to a structure of machine learning system is selection of signal features on which the learning system will be basing. Quantity of calculated features is theoretically countless, but practically it is aimed at obtaining a minimum number of properties to describe signal features. It favours obtaining a dense model including accurate mating. Signal property selection optimisation may be carried out with one of available methods [1], that is Correlation Matrix, Principal Component Analysis (PCA), and Sequential Feature Reduction.

For each of obtained matrices related to the pump body vibration signals, time and frequency-feature signals were determined. In case of time-feature signals, standard deviations, entropies, and root-mean-square values were calculated. In case of frequency-feature signals, signal spectrum entropy, maximum power spectral density, and frequency at which maximum power spectral density occurred were accepted. 56 features were obtained in total.

Calculated features of vibration signals were grouped in the table in which pump operational grades (labels) were specified in its last column i.e. *efficient*, *end of use*, *worn* pump. Basing on a cumulative curve including standard deviations related to 56 features (of each pump efficiency grade), their quantity was narrowed to 19 most separative towards individual grades (Figure 8).

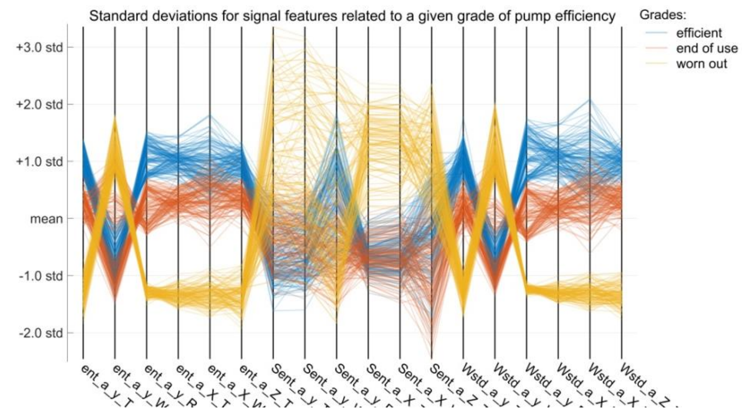

Figure 8. Distribution of standard deviations for signal features related to a given grade of pump efficiency

Vibration signal entropy and their standard deviations were selected as the most convenient. An example of distribution of vibration signal entropy measured in the vicinity of the pump swashplate (along Y and Z measurement directions) that properly separate grades related to pump efficiency are specified in Figure 9.

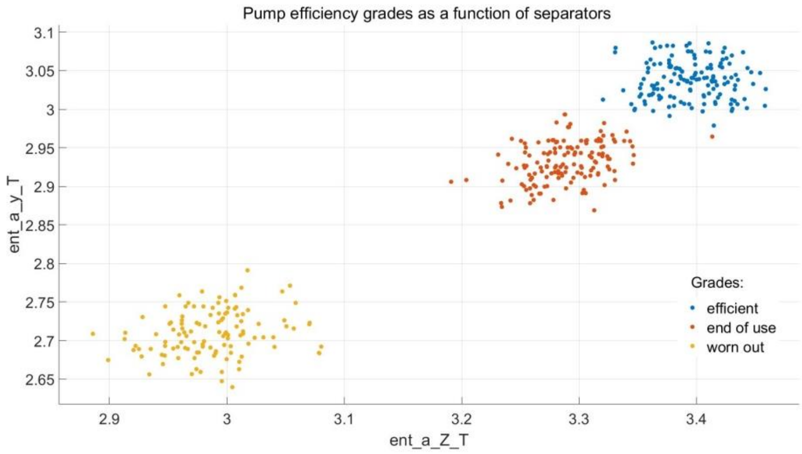

Figure 9. Example of separation of efficiency grades on the tested pump with application of entropy from swashplate vibration signals along Y and Z measurement directions

4.3. *Selection of classification algorithm*

Both in case of systems that use supervised and non-supervised learning, there is a large group of learning algorithms; selection of the most convenient algorithm is subject to multiple factors. First of all, in order to select an appropriate learning algorithm, it is necessary to determine properly a relevant task for a model (classification, regression, grouping). The next issue is related to the type and quantity of input data which has an impact on learning rate, load of computer memory (controller) as well as accuracy of output data prediction (model response). Selection of an appropriate type of algorithm is not explicit; only an experienced researcher is able to quickly determine an exact algorithm. Usually, selection of the most relevant algorithm of classification is carried out on the basis of multiple type tests as well as provision of assessment related to classifiers that have been obtained in terms of action swiftness, accuracy of classification, and memory load of a computing unit.

A group of algorithms that meet classification requirements related to wear of multi-piston pump include [1]:

- *Decision Trees*

Within this algorithm, in order to classify data, a decision tree is based on a starting point and branching which make a binary decision system; its end branches make a result of attributing data to a specific grade.

- *Discriminant Analysis*

It is based on analysis of signal Gaussian distribution received from observation (input) set. The classifier provides estimation of parameters of Gaussian distribution received from observation set; on such a basis the classifier will ascribe those to a relevant grade.

- *Support Vector Machines*

It classifies data through finding the most relevant hyperplane which separates data of a grade from another grade. The most convenient hyperplane to be considered is the one that separates data with the biggest possible margin.

- *Nearest Neighbour Classifiers*

It determines affiliation of a new data (received from an input set) to the specified grade on the basis of location of anticipated number (*K* Nearest Neighbour) related to nearest (neighbouring) input set data in relation to this data. However as a position measure, a measure of distance related to classified data from neighbouring data is accepted.

- *Naive Bayes Classifiers*

It makes a probable classifier in which mutual independency of input variables is assumed (naively). Following the Bayes' theorem, this classifier is used to calculate probability related to affiliation of input data to a specific grade.

In the course of classification of the pump wear level, it was decided to test two of previously mentioned algorithms, i.e. algorithm of decision trees and algorithm of *K* Nearest Neighbour.

4.4. *Classification of pump wear level*

With application of previously specified data, vibration signal features provide the best possible separation of efficiency grades; decision tree classifier was applied in the course of classification process.

Accuracy of the classifier was estimated through application of Confusion Matrix which is shown in Figure 10. From amongst 144 input signals received from vibrations of *efficient* pump body, the model was able to recognise 142 signals accurately and remaining 2 signals were incorrectly ascribed as *end of use*. Within *end of use* grade the model recognised 142 observations correctly and 2 observations were incorrectly classified as *efficient* pump. All signal observations as part of *end of use* grade were recognised properly. Obtained model is used to classify the pump wear level at 99.1% accuracy; relevant learning time was 0.95 s.

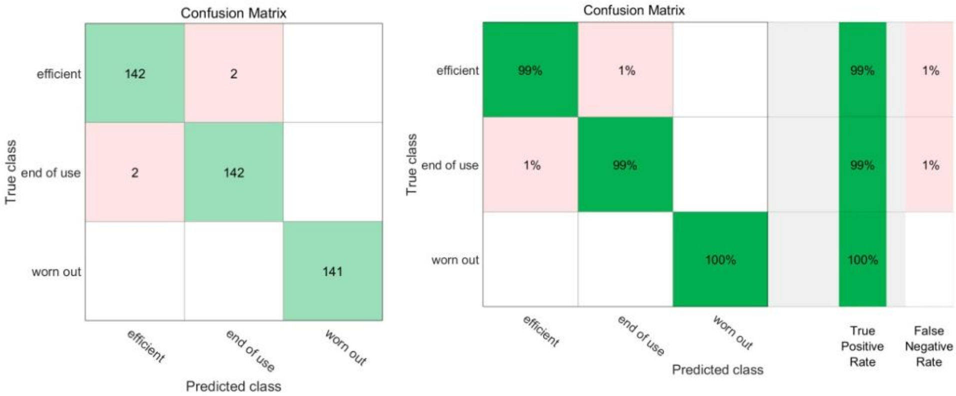

Figure 10. Confusion matrices for pump wear level
with application of decision tree model

In order to reduce the dimension of the obtained model (which is to prevent against its overtraining and to ensure better physical implementation), Principal Component Analysis (PCA) was applied. From amongst 19 signal features that has been applied for the purpose of determination of initial classifier model, only those that totally circumscribe 95% of signal variance value within the optimised model were retained. Within examined model, the features that circumscribed 95.9% of signal variance were constituted by entropy of recorded vibrations at the pump swashplate along Y measurement direction and vibration entropy recorded at the pump rotor along Y measurement direction. Accuracy of the pump efficiency grades (as per optimised model) was estimated with confusion matrix; its shown in Figure 11.

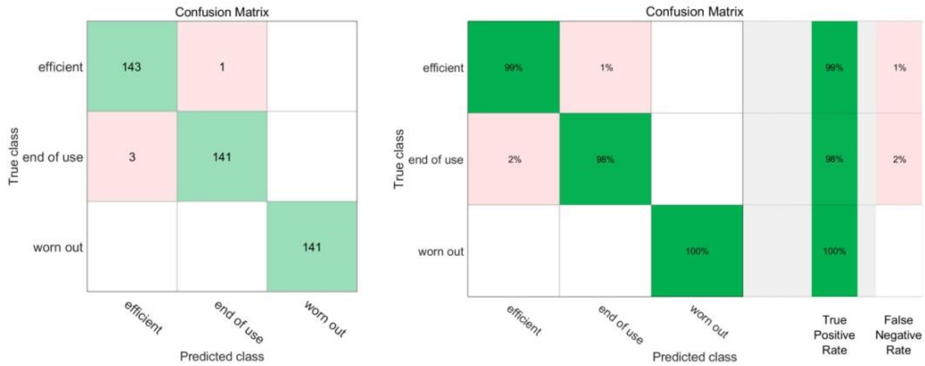

Figure 11. Confusion matrix for pump wear level
with application of optimised decision tree model

The obtained model provides classification of the pump wear classification at 99.1% accuracy. From amongst 144 input signals that have been obtained from vibrations of efficient pump body 143 were properly recognised by the model and 1 was recognised incorrectly as *end of use*. Within *end of use* grade, the model recognised 141 observations correctly, and 3 observations were qualified incorrectly as *efficient* pump. Similar to the basic model, all 141 observations (as part of *worn* pump grade) were recognised properly. A model prediction of the pump deflection gear vibration signal entropy (along Y and Z measurement directions) obtained through estimated model of decision tree is shown in Figure 12.

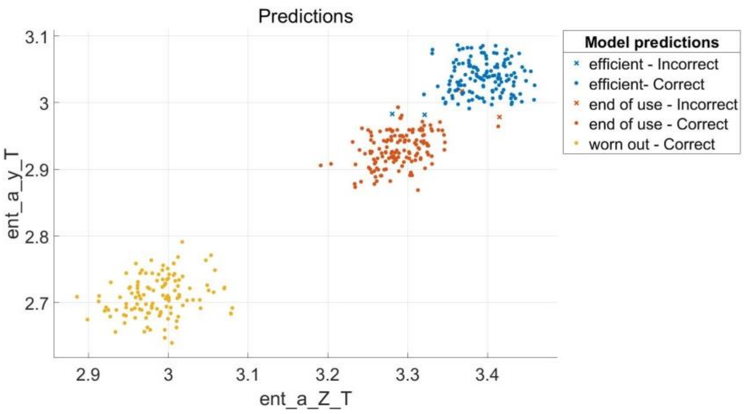

Figure 12. Example of prediction of the pump swashplate vibration signal entropy obtained through optimised model of decision tree

The subsequent algorithm used to classify efficiency of the tested pump was *K* Nearest Neighbour. As in case of the previous classifier, 19 vibration signal features were used; those were separating individual grades of pump efficiency in the best possible way. Correctness of the classifier operations were estimated through application of Confusion Matrix, which is shown in Figure 13. The obtained model classifies the pump wear level at 100% accuracy; learning time was 3.77 s.

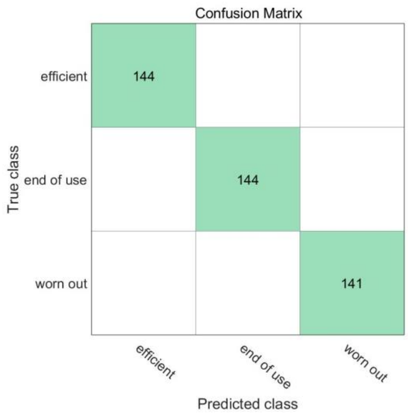

Figure 13. Confusion matrix for pump wear with application of *K* Nearest Neighbour

The optimisation of the obtained model with application of Principal Component Analysis caused reduction of its dimension. As part of the optimised model, features that describe totally 97.7% of signal variance are entropy of vibrations measured at the deflected gear along Y measurement direction and entropy of vibrations measured at the impeller along Y measurement direction. Results of estimations for parameters of optimised model were determined through application of Confusion Matrix; these are shown in Figure 14.

The obtained model classifies the pump wear level at 99.5% accuracy; the training time was 1.76 s. From amongst 144 input signals received from vibrations of *efficient* pump body, 143 were recognised correctly by the model and 1 was incorrectly recognised as *end of use*. As part of *end of use* grade, 143 observations were recognised correctly while 1 observation was incorrectly qualified as *efficient* pump. Similar to the basic model, all 141 signal observations as part of *worn* pump grade were recognised properly.

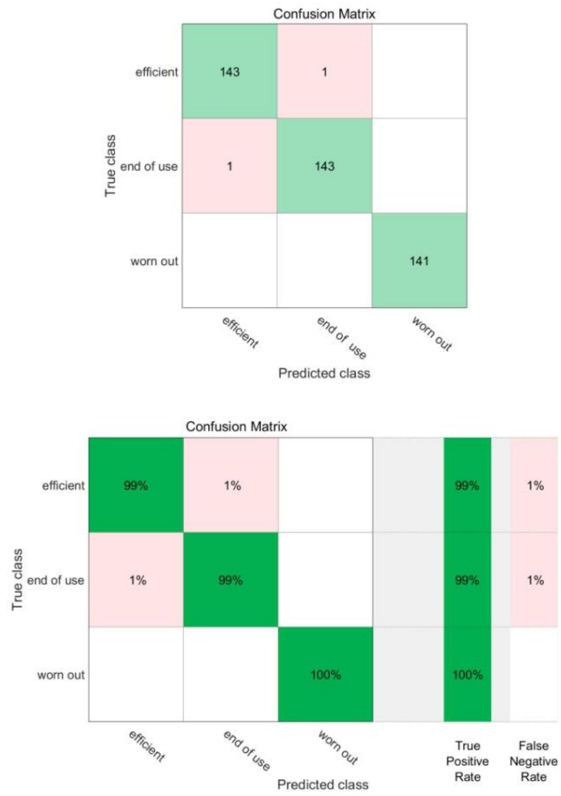

Figure 14. Confusion matrix for pump wear classification with application of *K* Nearest Neighbour

An example distribution of the pump deflected gear vibration signals (along Y and Z measurement directions) obtained through application of *K* Nearest Neighbour is shown in Figure 15.

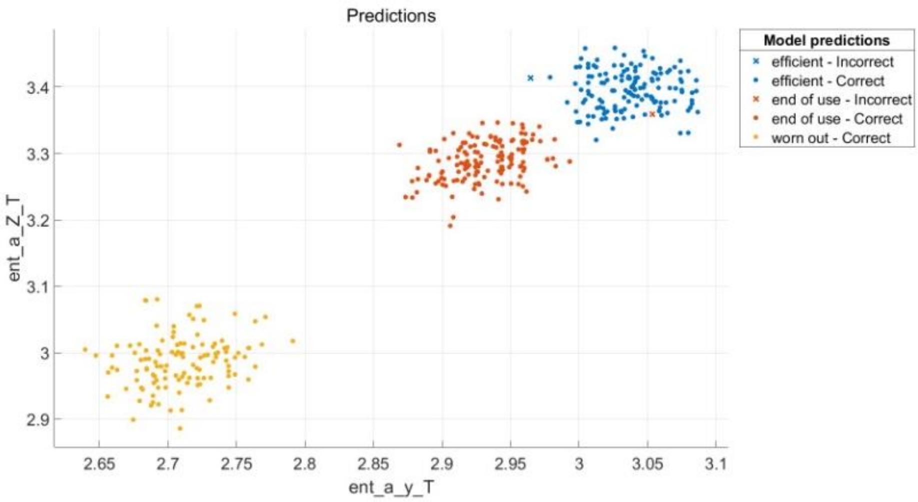

Figure 15. An example of deflected gear vibration signal entropy distribution with application of *K* Nearest Neighbour

On the basis of analysis of obtained results related to classification of the pump wear level with application of engineered model set it was confirmed that *K* Nearest Neighbour separates the pump efficiency grades at the highest possible accuracy. This model was subject to further verification that included check of accuracy of the classification related to new measured pump body vibration signals in three levels of efficiency. Basing on pre-calculated features of measured signals the classifier model (exported to Matlab) recognised the pump efficiency grades at 90% accuracy.

5. Summary

As part of issues related to classification of damages to machines and equipment which operations are determined by occurrence of complex mechanical and fluid phenomena (as in case of displacement pumps) the major factor is to carefully arrange input data for machine learning system. Relevant selection of signals and locations for the purpose of measurement provision makes reception of highly informative data possible. With reference to classification of displacement pumps, input data sets that contain measured signals should be as numerous as possible. Input data must include operation courses within entire range of operational pressure changes as well as operational medium viscosity that changes in accordance with temperature fluctuations. It has an impact on the training of obtained classifier model and obtained efficiency during classification of the pump wear level. The next important issue is a selection of such signal features which separate efficiency grades or machine damages in the best possible way. In case of classification of multi-piston pump, features which separated its efficiency grade in the best way were entropies related to vibration signals. Minimum number of applied features during classification process has an impact on the classifier learning time and prevents against its overtraining. Selection of relevant machine learning algorithms is decisive in relation to obtained accuracy of classification. Basic and modified algorithms of decision tree and nearest neighbours confirmed their usefulness for the purpose of classification of the displacement multi-piston pump wear level at a satisfactory accuracy.

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