Article citation info:
Lahrache A, Cocconcelli M, Rubini R. Anomaly detection in a cutting tool by K-means clustering and support vector machines. Diagnostyka. 2017;18(3):21-29

DIAGNOSTYKA, 2017, Vol. 18, No. 3

ISSN 1641-6414
e-ISSN 2449-5220

ANOMALY DETECTION IN A CUTTING TOOL BY K-MEANS CLUSTERING AND SUPPORT VECTOR MACHINES

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Abstract

This paper concerns the analysis of experimental data, verifying the applicability of signal analysis techniques for condition monitoring of a packaging machine. In particular, the activity focuses on the cutting process that divides a continuous flow of packaging paper into single packages. The cutting process is made by a steel knife driven by a hydraulic system. Actually, the knives are frequently substituted, causing frequent stops of the machine and consequent lost production costs. The aim of this paper is to develop a diagnostic procedure to assess the wearing condition of blades, reducing the stops for maintenance. The packaging machine was provided with pressure sensor that monitors the hydraulic system driving the blade. Processing the pressure data comprises three main steps: the selection of scalar quantities that could be indicative of the condition of the knife. A clustering analysis was used to set up a threshold between unfaulted and faulted knives. Finally, a Support Vector Machine (SVM) model was applied to classify the technical condition of knife during its lifetime.

Keywords: Knife diagnostics, K-means, Hierarchical Clustering, Support Vector Machines

1. INTRODUCTION

Diagnosis is an important activity which is gaining its value in industrial strategy planning. The supposed possibility of monitoring the technical condition of a complete, although complex, manufacturing line, would enable to reduce the manufacturing costs. In fact, diagnostics allows to plan the replacement of specific machinery's components to avoid sudden and unexpected downtime. It can suggest replacement of the parts only if the component is really damaged, reducing the maintenance costs [9, 15]. There are three main maintenance strategies in literature [17]: the run-to-break, the time-based preventive maintenance and the condition-based maintenance (CBM). In the first strategy, the machines run until they break down and it is suggested only when components are not critical and could be replaced easily and cheaply. The preventive maintenance is done at regular intervals which are shorter than the expected time between failures. Most industries use this strategy to avoid production downtime. The CBM is the most challenging, since it predicts the failure of the component through regular monitoring of specific parameters. Among the others, vibration analysis is probably the most used technique for obtaining information about internal conditions of the machine [17], as proved by the extensive literature available [11]. Unfortunately, the use of vibration signal is not always possible and the CBM must encompass other type of input sensors. The lack of a specific literature can be tackled by the use of more general methodologies [27], e.g. expert systems (like Support Vector Machines [25]) or clustering techniques (e.g. [6, 8]).

Literature is filled with with applications of expert systems to complex systems. For example, Popiolek and Pawlik [16] proposed the diagnosing of planetary gearbox using the artificial neural network. Hadroug et alt. [5] implemented an adaptive hybrid neuro fuzzy inference network to ensure the fault detection in a gas turbine which is presenting a complex system. Marciniak [13] presented the detection of anomalies in controlling the combustion process by using a genetic algorithm. Tabaszewski [24] proposed an optimization of a nearest neighbours classifier for diagnosis of condition of rolling bearings, while Straczkiewicz [22] compared supervised and unsupervised learning process in damage classification of rolling element bearings. Cempel and Tabaszewski [1] successfully forecasted machine condition by means of the grey system theory and first order grey model GM(1,1), starting from the observation of one symptom only. In an interesting paper, Szczurek at alt. [23] determined the influence of room occupancy on indoor air quality, on the basis of CO_2 concentration measurements, as time series, and statistical analysis. The authors examined the similarity between segments of the time series and the pattern of CO2 variability, which represented a selected occupancy profile. The analysis was performed in time domain using moving time window technique. The similarity was judged based on two types of indexes, namely correlation coefficients and distance measures. Regarding the use of pressure sensor for diagnostics of mechanical systems, Sobolewski and Ostapkowicz [20] used flow and pressure data from a SCADA to detect leak in pipelines by means of statistical analysis. Klarecki et alt. [12] measured the pressure pulsation of the gear pump with external gear design and correlated the experimental data to the working condition of the pump. Soylemezoglu at alt. [21] made data fusion of vibration, pressure, temperature, and flow sensors and proposed a Mahalanobis Taguchi System of a hydraulic water pump for the aim of fault detection and prognostics. Ding at alt. [3] proposed a fault diagnosis method for sensor fault based on ensemble empirical mode decomposition (EEMD) energy entropy and optimized structural parameters least squares support vector machine (LSSVM), and proved it on a pressure sensor data. Gajek [4] investigated the influence of different parameters (the vehicle mass, temperature of brakes, aerodynamic drag, etc…) on the efficiency of brakes in cars equipped with pressure sensor. Jiao et alt. [10] proposed a fault diagnosis model based on empirical mode decomposition and probabilistic neural networks for an airborne fuel pump. In particular the authors declare a 100% fault diagnosis by means of only one pressure sensor.

In this paper those methodologies are applied to diagnose a specific component in a packaging machine. Among several functions, the focus of the paper is on the cutting process that divides a continuous flow of packaging paper into single packages. The cutting process is made by a steel blade driven by a hydraulic system, in particular two small cylinder which pulled the knife outside its frame, allowing to cut the package. At the end of the cutting the pressure is reduced and the knife goes back in its frame thanks to a spring placed on the bottom part of the knife. The cutting process is driven by a PLC without any kind of closed loop control. This working condition requires a sharp blade, otherwise it will cause a rip of the paper instead of a clear cut. The packaging machine was provided with pressure sensor that monitors the hydraulic system driving the blade.

The paper is structured as follows: Section 2 briefly describes the expected pressure signal in the working conditions. Section 3 details the scalar parameters describing the working conditions of the knives. Sections 4 and 5 describe and show results of the proposed methodology. Conclusions are at the end of the paper.

2. EXPERIMENTAL SETUP

A pressure sensor was chosen and inserted in the hydraulic system driving the knife. The setup is free from moving cables and could be mounted on the machine without drawbacks regarding the working conditions.

The data acquisition is done with a PCB pressure sensor. Preview tests were done to assess the differences in the pressure signal with or without the presence of the paper material. Results are shown in Fig. 1, but without the y-axis values due to an NDA with the customer.

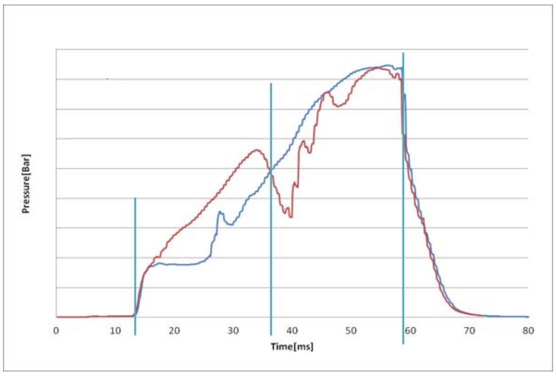

Fig. 1. Pressure signal difference: with paper (red) and without paper (blue)

As shown in Fig. 1 we can divide the knife's cycle into four parts:

- **No Pressure** [0-12 ms]: The valve is just opened and the pressure is near to 0 bar, because the oil from the pump has not encountered any obstacle yet.
- **Over-Pressure** [12-37 ms]: For both signals (with and without paper) the pressure starts to increase due to the resistance in the hydraulic circuit. It is important to see that in this step two signals are different.
- **Under-Pressure** [37-60 ms]: The brake of paper seems to reduce the pressure signal to a lower value than the case without it. Probably there is a return of elastic energy due to the first deformation of the paper.
- **Final pressure** [60-80 ms]: In this last step both signals are equal, because pressure values are only defined by the spring action that is the same for both cases.

The effect of the cutting is shown by the oscillation of pressure signal at the middle of the cycle, thus the step 2 and 3 can be a good reference to monitoring the knives' damage.

- Typical pressure signal is characterized by:
- sampling frequency (Fs=20 kHz),
- acquisition time (T=0.13 seconds),
- number of samples (N=2600 points).

The acquisition system starts to acquire when the PLC sends an acknowledgement to the valve and stops acquiring after 0.13 seconds.

According to the maintenance policy, the customer company has to keep the historical list of all technical operations, like the substitution of a faulted knife. The list reports the code of the repaired machine, the date of substitution, the name of the customer, the number of knives replaced and the total machine working hours.

The list allows identifying complete lives of the knives, and separate the corresponding data from the historical. It must be noted that an operator updates the list manually. It cannot be excluded that it happens rarely that some knives' changes are not logged. Moreover, the choice of the replacing time is based only on the opinion of the single technician, who looks at the production, by visual inspection, and decides that the knives are damaged and have to be replaced. Finally, both knives are often replaced at the same time to avoid the second stop of a production to substitute the other knife. Therefore, a complete life of the knife is not the same as a complete uptime of the knife, which can be replaced even if it is still working well.

3. DATA ANALYSIS

Figures 2 and 3 show a comparison between the pressure data for a knife at an early (just replaced) and late stage (just before the replacement), in time and frequency domain respectively. Since no previous analysis was available, the choice of the physical parameters for data analysis is arbitrary, either in the type or in the number. In a preliminary stage, several parameters could be suggested, based on the experience of the authors or the expected descriptors of data distribution in physical phenomena (e.g. mean value, standard deviation, skewness, etc…). Afterwards, the number of these parameters will be reduced, according to some rules that will be defined later in the paper.

The choice of preliminary dataset is done on two different domains: time domain and frequency domain.

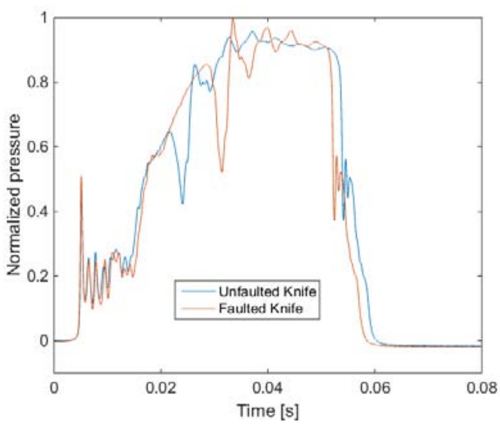

Fig. 2. Comparison between the pressure profile in time domain, measured at an early (blue) and late (red) stage

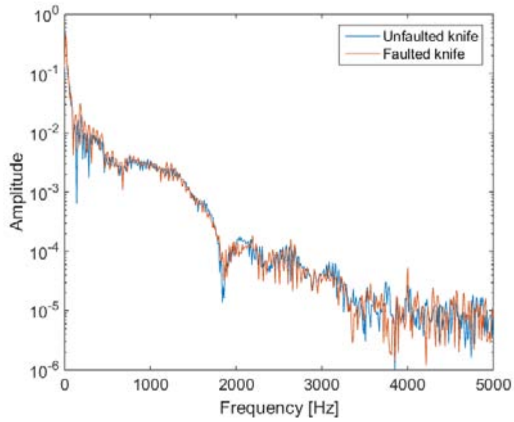

Fig. 3. Comparison between the pressure profile in frequency domain, measured at an early (blue) and late (red) stage

3.1. Time domain parameters

The pressure signal in Figure 1 was originally described with 16 scalar parameters, such as the maxima, the kurtosis values, the main percentiles, etc... A preliminary analysis was done by means of the Pearson product-moment correlation coefficients [26], as a measure of the degree of linear dependence between two variables. Parameters with high Pearson coefficient were removed since the information carried was linearly dependent.

Only two parameters have been considered at last:

1. The third quartile of all sampled points (***Q3***), which trend over time is shown in Figure 4.
2. The time interval between the start of acquisition and the maxima of the derivative of pressure signal when it is going to achieve the maximum (***It_der_max***). The trend is shown in Figure 5.

The third quartile is a measure of the data dispersion in a single acquisition. As soon as the cutting edge of the knife is not sharp, the pressure in the circuit increases during the cutting profile, as shown in Figure 4. Another consequence is a small delay in the cutting time, which is measured by the feature *It_der_max* and shown in Figure 5.

With reference to Figures 4-6, there are clear falls in the signal at different intervals, highlighted with black arrows. The falls almost correspond to the data of knife's replacement by the maintenance service. Sometimes the falls are related to specific value of the signal only (like outliers). The length between falls is not meaningful since the acquisition schedule had not constant timing. Similar behaviour will be present in the trend of other features. Clear falls are also evident in Fig.7, but there are no arrows not to hinder the readability.

Another data processing technique which is used is the Empirical Mode Decomposition (EMD). It is a procedure to decompose a signal into a series of components with specific characteristics. The mathematical background could be found in [7]. These components are called Intrinsic Mode

Functions (IMFs). The sum of all these components is equal to the original signal, i.e. it works in time-domain as a decomposition. It was developed to study non-stationary signals and the extracted components have a frequency content decreasing from the first one to the last [18].

Since we are interested into high frequency components rather than lower ones, the first two IMF are considered and added together. The main advantage of the EMD is that resulting IMFs have a zero-mean value which makes it easier to identify the local minima/maxima.

In particular, the phase of the second minima, labeled ***It_min_imf***, has been taken as a third parameter in time domain. The trend of the It_min_imf over time is shown in Figure 6. The feature *It_min_imf* gives information similar to the *It_der_max*, since it is related to the delay in the cutting time due to the faulted edge of the knife. Compared the *It_der_max*, the *It_min_imf* works on the IMF output that acts like a high-pass filter on the pressure signal.

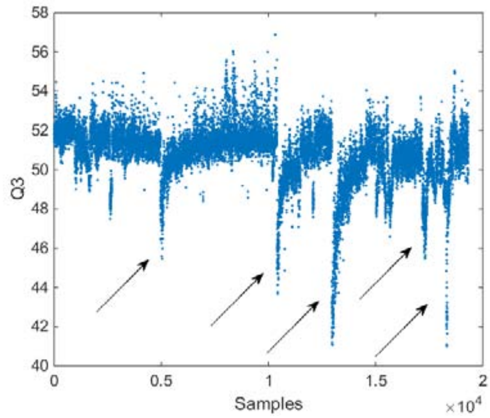

Fig. 4. Trend of the third quartile (Q3) over time

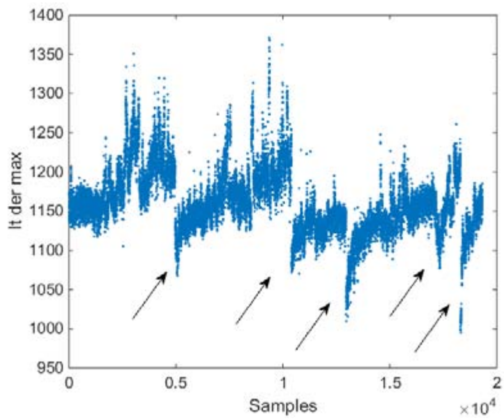

Fig. 5. Trend of the It_der_max parameter over time

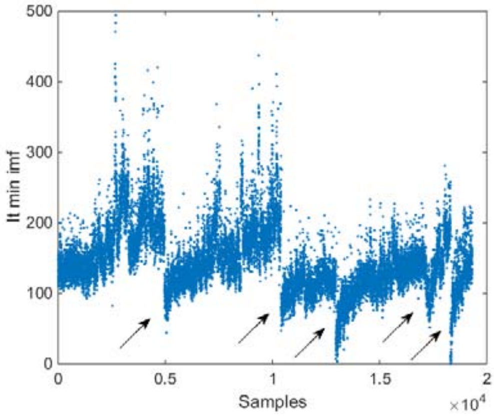

Fig. 6. Trend of the It_min_imf over time

3.2. Frequency domain parameters

Since the cutting process induces hammer`s effects in the oil pressure, with visible harmonics, the choice of some physical parameters from the frequency domain seems promising.

All the spectra of the available signals were taken into account in the preliminary study. Subsequently the spectra components were reduced to the first 20 harmonics of cyclic frequency, i.e. the frequency of the cutting process. Finally, the comparison of the trend of the amplitudes of these harmonics, with reference to different lives of the knife, leads to identify just 4 components:

1. **A3**: amplitude of the 3rd spectrum component,
2. **A4**: amplitude of the 4th spectrum component,
3. **A5**: amplitude of the 5th spectrum component,
4. **A6**: amplitude of the 6th spectrum component.

Figure 5 shows the trend of the amplitude harmonics. The number of selected harmonics points to phenomena that repeat from 3 to 6 times in the cutting time. Probably they are related to oscillations of the knife due to the release after the cutting.

A list of dates of the knives' replacement was available. The trend of the physical parameters over time was compared with that list in order to assess the sensitivity of the parameters. An example is given in Fig. 4, where the dates of knives' replacement overlay the signal. Figures 4–7 show the trend of the third quartile, the *It_der_max* parameter, the *It_min_imf* parameter, and the third to sixth harmonics respectively. The trend of these parameters clearly highlights discontinuity corresponding to a precise time instant (the replacement of the knife). The trend could be different, e.g. the A3 parameter has a higher value after the replacement that decreases during the lifetime of the knives, while the A5 parameter has the opposite behaviour. It must be noticed that the behaviour of the parameters is not relevant by itself, the key point is that the trend must have a discontinuity before and after the replacement, since it means that the parameter is sensitive to the technical condition of the knife. Indeed, the logarithmic behaviour of all the data in figures 4–7 makes it difficult to assess the deterioration of the knife over time, since the trend tends to be flat as the wear increases. An ideal behaviour would be the exponential one, increasing the output value over time, but unfortunately none of the tested parameters demonstrated that trend.

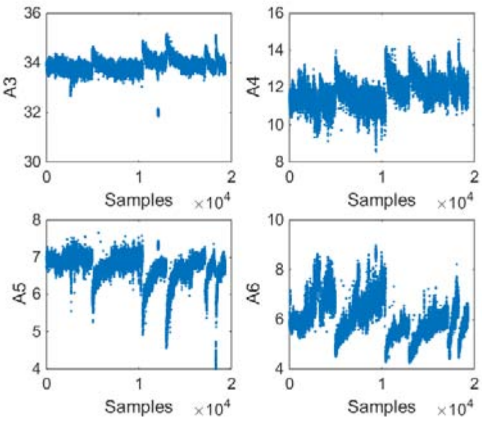

Fig. 7. Trend of the amplitude of the third to sixth harmonics

4. CLUSTERING ANALYSIS

Clustering analysis classifies a set of data in terms of similarity among the elements of the dataset. A vector of seven components, the physical parameters identified in the previous section, substitutes each element of the dataset.

Clustering analysis should highlight if the ensemble of the chosen parameters changes according to the life of the knife.

The data available for this analysis was divided into four datasets, covering the period from July 2014 to February 2015. The resulting complete lives of the knives collected are 16. A complete life is given by the data when the technical engineer substituted the knife in the ordinary maintenance.

The clustering techniques have been used in this paper in order to compare the results: the K-means clustering and the hierarchical clustering.

4.1. K-means clustering

The K-means algorithm distributes data into K clusters, minimizing the variance inside each cluster. The K-means algorithm used requires as input the number of clusters (N), the metrics to measure the similarity among data elements (Distance), the input matrix (X) each column lists the dataset for all the observations.

The output of the cluster has two elements: the cluster's number for each observation (Idx), i.e. the labelling of data into a specific cluster; a vector giving an information (a number between -1 and +1) about the quality of the clustering for each data (Silhouette) [19].

The standard Euclidean distance is used as metrics and the number of clusters is chosen to be 10 (N = 10). Result for one of the chosen input parameters (*It_der_max*) is shown in Figure 8. The ten clusters gradually change one each other from the beginning of the life (left part of the figure) to the end (right part of the picture). The clustering could recognize the technical condition of the knife and could assign a proper label to it.

In particular, the clusters bounded with a new/good knife are in red colour, while the cluster bounded to old knife is in green (cluster 1), yellow and violet (clusters 8-10). The *x* points are the centroids of each cluster.

It seems that the progression of the wear of the knives is fast at the beginning and then decreases. This behaviour is in accordance with the trends of physical parameters (logarithmic trend).

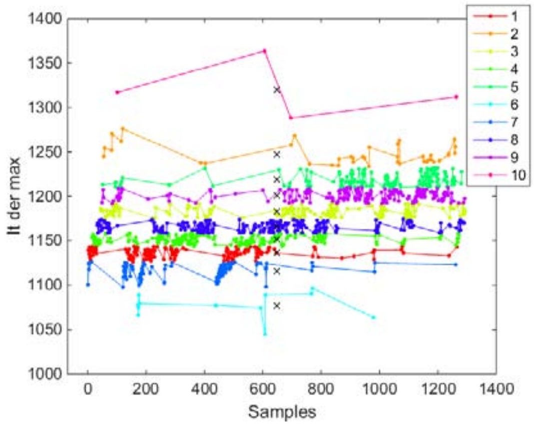

Fig. 8. K-means clustering of the *It_der_max* values with N = 10

4.2. Hierarchical clustering

The hierarchical clustering is similar to the K-means but it gives quantitative information about how close the clusters are to each other. In particular, the hierarchical cluster returns a dendrogram, which is a hierarchical tree and the branches are placed in different positions depending on similarity between the clusters.

Hierarchical clustering algorithm needs as input the number of clusters (N), the metrics to measure the similarity among data elements (Distance), the input matrix (X) each column lists the dataset for all the observations and the method of linkage to connect different observations (Linkage).

The output of the cluster has two elements: the cluster's number for each observation (Idx), i.e. the labelling of data into a specific cluster; the cophenetic coefficient (c), that is similar to silhouette in the K-means algorithm, i.e. it is a number between 0 and 1 giving an information about the quality of the clustering.

In this paper, the standard Matlab's functions of the Statistics and Machine Learning Toolbox have been used. In particular the distance chosen is the **Euclidean metric** and the linkage type is called ***complete linkage*** or ***farthest neighbour clustering***. The linkage method joins together clusters based on the maximum distance between their elements.

For clarity, figure 9 shows, the output of the hierarchical classification of the knives into 10 clusters. Figure 10 shows the corresponding dendrogram. Results are similar to the k-means method.

Note: the colours of the map in the k-means and hierarchical clustering are not related to each other, it is just a graphical representation of the software.

Dendrogram shows that three clusters are close to each other (linking to the technical condition of the knife), while clusters 6, 7 and 9 are similar to each other but different from the others (linking to a faulted condition of the knife).

The final number of clusters has been chosen by trial and error approach. A small number of clusters may not provide the sufficient discrimination among different knife's conditions, while a large number makes the clustering classification not so robust.

In the next section the hierarchical clustering of the data into 10 clusters will be compared with the results of the k-means algorithm (with N=10) as defined in section 4.1.

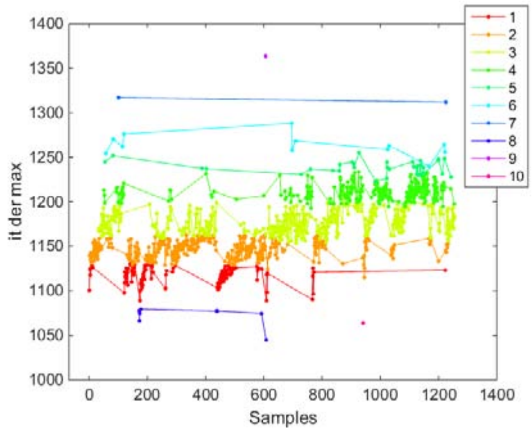

Fig. 9. Hierarchical clustering of the It_der_max values with N = 10

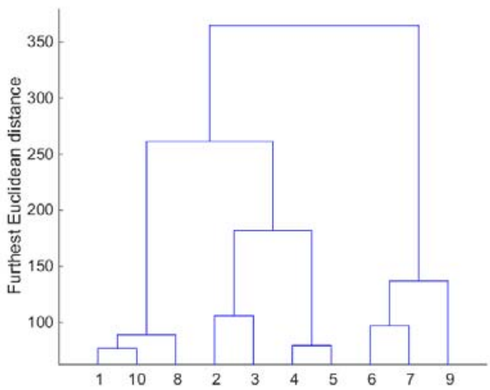

Fig. 10. Dendrogram in the hierarchical clustering

5. CLASSIFICATION BY SVM

The Support Vector Machines (SVM) belong to the algorithms of machine learning. In particular, they are a class of supervised algorithms, which means it requires a training step where both unfaulty and faulty cases are needed. Supervised machine learning tools are very useful when a lot of historical data are available for training, and a physical and detailed model of the system is not necessary.

In this paper, the aim of SVM is to assess the faulted knife. Among 16 lives of knives available for training and test, 11 lives are used in the training part, the remaining 5 lives are applied in the test. The test data are not used in any step of the SVM computation, in order to not bias the results. The ratio between training and test data is the consequence of the limited number of available trials. In this work, 2/3 of data is used for the training step due to uncertainties on the real technical condition of the knife at the end of useful life. A discriminant analysis on SVM training data has been done, in order to avoid biased results due to the specific data used for training [26].

Support vector machines try to define a separation plane (or hyper-plane) between two groups. The exact dimension of this plane depends on the dimension of the input array [2]. As described in the previous sections, the array used is made of 7 scalar values, i.e. the separation surface becomes a 7-dimension hyper-plane. Support vector machines are able to separate two groups at a time, while the clustering techniques classified data into 10 different clusters in the previous section 4. As a consequence, data reduction is necessary before using the SVM and could be done using the results of clustering algorithms. The ten clusters resulting from the previous step are divided into two classes only: the first 6 clusters are labelled as healthy, while the remaining 4 are labelled as faulted. The initial clustering into 10 clusters gives the customer a larger degree of freedom, which is the possibility to move the threshold according to experimental results. Flowchart of the data processing is given in Fig. 11.

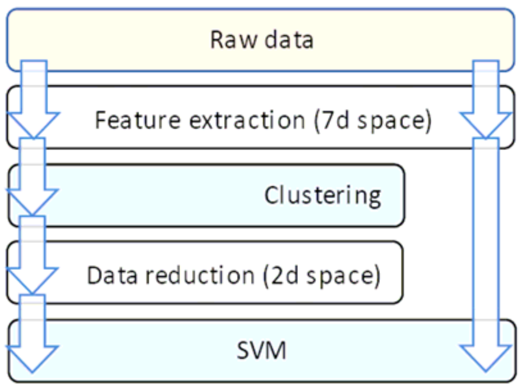

Fig. 11. Flowchart of the data processing. Flow data of the training step on the left, testing on the right

Two types of SVM were developed, according to the previous clustering methods:

1. SVM with k-means clustering;
2. SVM with hierarchical clustering.

5.1. SVM with k-means clustering

The k-means clustering is applied on the averaged cutting cycle over a single acquisition. Data are reduced and the physical parameters are not so sensitive to transitory effects.

Figure 8 shows the classification of data before this clustering reduction, while Figure 12 shows the final classification into two classes only for one of the input parameter (*It_der_max*).

Figure 13 compares the classification of the SVM for test data with the classification provided by K-means clustering. The percentage of success for the SVM equals 99.34%. It must be noted that test data are not taken into account during the training phase.

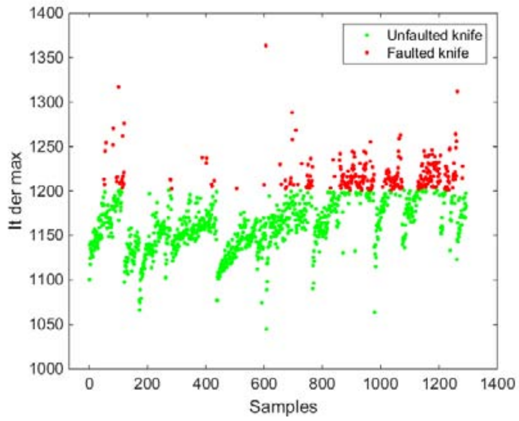

Fig. 12. Classification between unfaulted and faulted knives

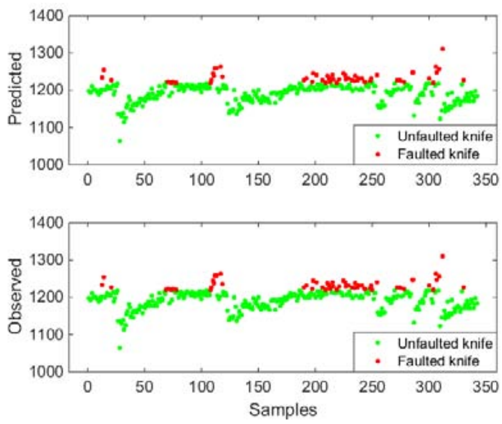

Fig. 13. Difference between predicted and observed outputs with k-means

5.2. SVM with hierarchical clustering

The same process to determine the SVM model is repeated, considering the hierarchical clustering instead of the k-means method.

Figure 14 shows the data classification corresponding to the dendrogram shown in Fig. 10.

Unlike the K-means method, the cluster reduction of data into two main classes (unfaulted and faulted knives) is straightforward, since the dendrogram itself suggests which clusters should be jointed together (see Fig. 10). It is worth mentioning that the clustering into 10 clusters reminds a cophenetic coefficient of 0.71, while usually a good classification has a cophenetic coefficient greater than or equal to 0.8. In fact, the cophenetic coefficient value increases with the decrease of the observations.

Figure 14 shows the prediction of knives technical condition for test data. Unlike the case with K-means the hierarchical clustering gives a late classification of faulted knives, just in the very last instants before the supplier replaced them. As a consequence, the K-means method seems more conservatives, since it suggests the knife replacement earlier than the hierarchical method.

Comparing Fig. 13 with Fig. 14 it seems that the hierarchical methods allocate too few data in the faulted cluster. Probably the calculation of the SVM with a larger set of data for training could improve the hierarchical approach.

6. SUMMARY

This section summarizes the results of the paper. The aim of the paper was proposing a condition monitoring algorithm to assess the wearing condition of a cutting tool. The analysis has been done on pressure data in the hydraulic system that drives the knife. The main steps and results are collected in the following list:

- Based on available experimental data, an initial set of features on both time and frequency domain has been selected.
- The list of features has been reduced by means of Pearson's correlation coefficients, that measures how close to each other were the information provided by features.
- A final set of 7 features has been selected. Namely *Q3, It_der_max, It_min_imf, A3, A4, A5, A6*. Chapter 3 of the paper details the chosen features.
- Three of the selected features are given in time-domain, while four are given in frequency-domain.
- The real wear condition of the knives at the time of replacement were not known. Then a clustering step was used to assess the status of the knives in each data set.
- Two type of clustering techniques were tested: the K-means and the Hierarchical clustering.
- Both methods recognize differences in feature array from early to aged knives.
- The output clusters are divided in two classes: unfaulted and faulted knives. The threshold is arbitrarily chosen among the K-means clusters, while it is straightforward from the dendrogram in the Hierarchical clustering.
- Support Vector Machine is trained based on the two classes of the previous step.
- The SVM based on K-means recognizes a fault knife earlier than the replacement time. Nevertheless, it could be used by the company for supplying the new knife and scheduling the maintenance.

- The SVM based on Hierarchical clustering gives a late classification of faulted knives, just in the very last instants before replacement by the supplier.

Based on the results the K-means based SVM is suggested for the condition monitoring of the wearing condition of knives. The main advantage is the arbitrarily choice of the threshold used in data reduction step before the SVM. It is a degree of freedom that the user could change to adapt the procedure to different situations, like changes in environmental conditions. It must be noted that the clustering itself could make the classification of faulted knife, without any further step. The introduction of SVM is proposed to ease the condition monitoring on field. Indeed, the clustering techniques need all the historical data in order to calculate distances and classify data. In this paper, the SVM is computed and validated once then could be used alone, without any need of historical data.

7. CONCLUSIONS

This paper details a condition monitoring procedure to assess the technical condition of a cutting blade. The knife is driven by a hydraulic circuit whose pressure is measured by the acquisition system. The methodology involves the use of both clustering and Support Vector Machines. Pre-processing of data is necessary to reduce the number of scalar quantities used to describe the status of the system. In particular, the Pearson product-moment correlation coefficient is used to measure the degree of linear dependence between two variables. The clustering of the remaining quantities allows to identify the most significant thresholds to distinguish a class from the other. Finally, availability of acquired data makes advisable to use supervised expert systems like SVM to classify the incoming signal. A rate of 99% of success in the testing makes the proposed methodology promising. It is worth noting that the clustering step is made necessary by the uncertainties on the real status of the knife at the date of replacement. Try to link together uncertainties, condition monitoring and pattern recognition will be the focus of future researches.

ACKNOWLEDGMENTS

The authors want to acknowledge Davide Borghi and Luca Capelli of Tetra Pak Packaging Solutions SpA for suggestions, fruitful discussions and technical support.

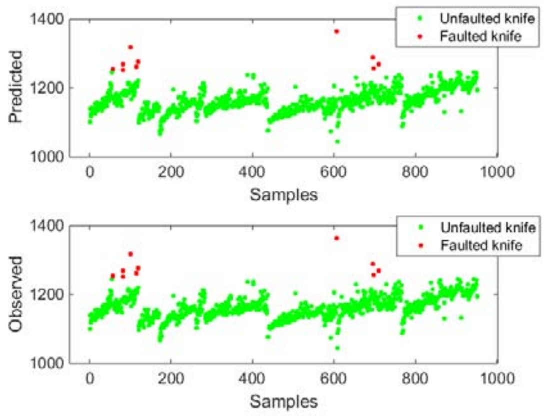

Fig. 14. Difference between predicted and observed outputs with hierarchical clustering (1: faulted knife in red; 2: unfaulted knife in green)

REFERENCES

1. Cempel C, Tabaszewski M.The application of the grey series theory to modeling and forecasting in machine diagnostics. Diagnostyka. 2007; 42: 11-18.
2. Cortes C, Vapnik V. Support-vector networks. Machine Learning 1995; 20 (3): 273-297.
3. Ding G, Wang L, Shen P, Yang P. Sensor fault diagnosis based on ensemble empirical mode decomposition and optimized least squares support vector machine. Journal of Computers, 2013; 8 (11): 2916-2924.
4. Gajek A. Diagnostics monitor of the braking efficiency in the on board diagnostics system for the motor vehicles, IOP Conference Series: Materials Science and Engineering, 2016; 148 (1).
5. Hadroug N, Hafaifa A, Kouzou A, Chaibet A. Faults detection in gas turbine using hybrid adaptive network based fuzzy inference systems. Diagnostyka 2016; 17 (4): 3-17.
6. Hu W, he Pan Q. Data clustering and analyzing techniques using hierarchical clustering method. Multimedia Tools and Applications 2015; 74 (19): 8495-8504.
7. Huang NE, Shen Z, Long SR, Wu ML, Shih HH, Zheng Q, Yen NC, Tung CC, Liu HH. The empirical mode decomposition and Hilbert spectrum for nonlinear and non- stationary time series analysis. Proceedings of the Royal Society A 1998; 454: 903-995.
8. Jain AK. Data clustering: 50 years beyond K-means. Pattern Recognition Letters 2010; 31 (8): 651-666.
9. Jardine AKS, Lin D, Banjevic D. Review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing 2006; 20 (7): 1483-1510.
10. Jiao X, Jing B, Huang Y, Liang W, Xu G. A Fault Diagnosis Approach for Airborne Fuel Pump Based on EMD and Probabilistic Neural Networks, Prognostics and System Health Management Conference (PHM-Chengdu), 2016: 1-6.
11. Lee J, Wu F, Zhao W, Ghaffari M, Liao L, Siegel D. Prognostics and health management design for rotary machinery systems - Reviews, methodology and applications. Mechanical Systems and Signal Processing 2014; 42 (1-2): 314-334.

12. Klarecki K, Rabsztyn D, Hetmańczyk M. Influence of setting the selected parameters of hydraulic systems on pressure pulsation of gear pumps. Diagnostyka 2015; 16(2): 49-54.
13. Marciniak J. The detection of anomalies in controlling of the combustion process by using a genetic algorithm. Diagnostyka 2016; 17 (1): 21-25.
14. McLachlan G. Discriminant Analysis and Statistical Pattern Recognition, John Wiley and Sons, 2004.
15. O'Connor PDT, Kleyner A. Practical reliability engineering. 5th ed. Chichester: John Wiley & Sons; 2012. DOI: 10.1002/9781119961260.
16. Popiolek K, Pawlik P. Diagnosing the technical condition of planetary gearbox using the artificial neural network based on analysis of non-stationary signals. Diagnostyka 2016; 17 (2): 57-64.
17. Randall RB. Vibration-based condition monitoring. 1st ed. Chichester: John Wiley & Sons; 2011. DOI: 10.1002/9780470977668.
18. Rilling G, Flandrin P, Goncalves P. On empirical mode decomposition and its algorithms. Proceedings of IEEE EURASIP Workshop on Nonlinear Signal and Image Processing 2003, Jun 2003, Grado, Italy.
19. Rousseeuw PJ. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. Computational and Applied Mathematics 1987; 20: 53-65.
20. Sobolewski A, Ostapkowicz P. Leak detection in liquid transmission pipelines using statistical analysis. Diagnostyka 2013; 14(1): 71-77.
21. Soylemezoglu A, Jagannathan S, Saygin C. Mahalanobis-Taguchi system as a multi-sensor based decision making prognostics tool for centrifugal pump failures, EEE Transactions on Reliability, 2011; 60 (4): 864-878.
22. Straczkiewicz M, Czop P, Barszcz T. Supervised and unsupervised learning process in damage classification of rolling element bearings. Diagnostyka 2016; 17 (2): 71-80.
23. Szczurek A, Maciejewska M, Wylomanska A, Zimroz R, Zak G, Dolega A. Detection of occupancy profile based on carbon dioxide concentration pattern matching. Measurement, 2016; 93: 265–271.
24. Tabaszewski M. Optimization of a nearest neighbors classifier for diagnosis of condition of rolling bearings. Diagnostyka, 2014; 15 (1): 37-42.
25. Widodo A, Yang BS. Support vector machine in machine condition monitoring and fault diagnosis. Mechanical Systems and Signal Processing, 2007; 21 (6): 2560-2574.
26. Wilcox RR. Introduction to robust estimation and hypothesis testing. 3rd ed. Burlington: Elsevier Academic Press; 2005. ISBN 9780123869838.
27. Worden K, Staszewski WJ, Hensman JJ. Natural computing for mechanical systems research: A tutorial overview. Mechanical Systems and Signal Processing, 2011; 25 (1): 4-111.

Received 2017-03-20
Accepted 2017-06-24
Available online 2017-07-31

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