A fuzzy logic-based approach for predictive maintenance of grinding wheels of automated grinding lines

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***Abstract*—The state of grinding wheels of automated grinding lines can be evaluated by monitoring their vibration and temperature, so that a condition-based approach can be used for their maintenance. However, there are some limitations of condition monitoring, which may conduct to some uncertainty or vagueness in accomplishing diagnostics. Within this framework, the aim of this study is the employment of a fuzzy logic for planning the maintenance policy of the grinding wheels of automated grinding lines.**

Keywords*— *predictive maintenance; vibrations monitoring; fuzzy logic; grinding wheels

I. INTRODUCTION

The automated grinding lines are sophisticated systems, characterized by a higher degree of complexity and the structure of such technical systems conducts to a more difficult planning of their maintenance policies. According to existing literature [1, 2, 3], the maintenance planning has evolved from corrective maintenance policies to preventive maintenance and to predictive maintenance policies.

The rapid development in the fields of data acquisition systems [4] has facilitated the employment of the condition-based maintenance, which is more and more applied in manufacturing industries. In a condition-based maintenance approach, different techniques, such as vibration, acoustic, lubricant or temperature monitoring, may be used to monitor the state of a system [1, 5, 6].

The operating regimes of automated grinding lines are characterized by high speeds, in which some level of vibrations are generated. Since the level of vibrations can be monitored through the use of a data acquisition system, any abnormal change in the amplitude of the vibration spectrum can be detected. For this purpose, a three axis vibration monitoring, which is based on capturing the vibration signal along the (X, Y and Z) axes of the Cartesian coordinate system, may be employed [7, 8].

On the other hand, there are some limitations of condition monitoring [5], which may conduct to some uncertainty or vagueness in accomplishing diagnostics. Within this framework, the aim of this study is the employment of a fuzzy logic approach for planning the maintenance policy of the grinding wheels of automated grinding lines. To achieve this goal, the vibration monitoring approach for the estimation of the technical condition of the grinding wheels is described. Next, a fuzzy logic-based system for the predictive maintenance of grinding wheels of automated grinding lines is developed. Conclusions are presented at the end.

II. ESTIMATING THE TECHNICAL CONDITION OF GRINDING WHEELS OF AUTOMATED GRINDING LINES

An automated grinding line is complex system equipped with a work piece loading station, grinding machine, washing and passivation station, ABB robot and dimensional control station.

Within the automated grinding line, the wear of the mobile abrasive grinding wheel may conduct to the nonconformity of the pieces. Therefore, a three axis vibration monitoring approach was used to estimate their technical condition. For this purpose, the TopMessage device (Fig.1) developed by Delphin Technology AG was used for monitoring the vibration of the mobile abrasive grinding wheel of the automated grinding line. The signal analysis was accomplished by using the Vibrolab software from Delphin Technology.

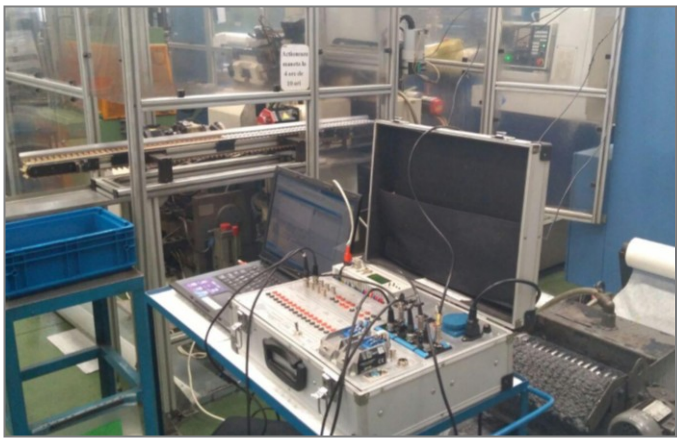


Fig. 1. The TopMessage device

Three piezoelectric accelerometers were employed for vibration measurements along the X, Y and Z axes of a Cartesian coordinate system (X, Y, Z) (Fig. 2), each accelerometer having a sensitivity of 100 mV/g±5% . The operating speed of the mobile abrasive wheel was 420 rot/min.

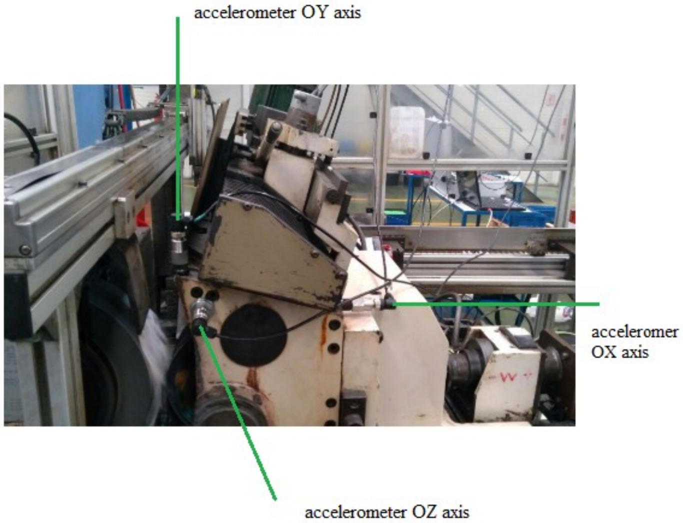
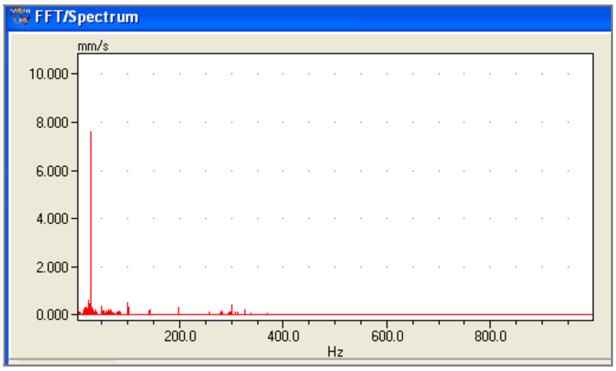


Fig. 2. The accelerometers placement in the trihedral Oxyz

Fig. 3, 4 and 5 depict the amplitudes of vibrations expressed in terms of root-mean-square (rms) velocity in the FFT spectrum for a new, respectively a fault wheel related to sensors placed along the OX, OY and OZ axis.



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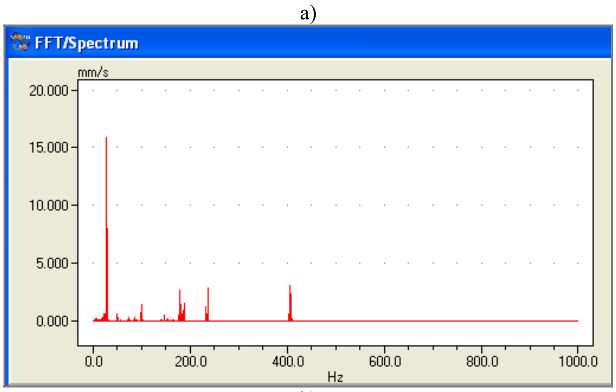
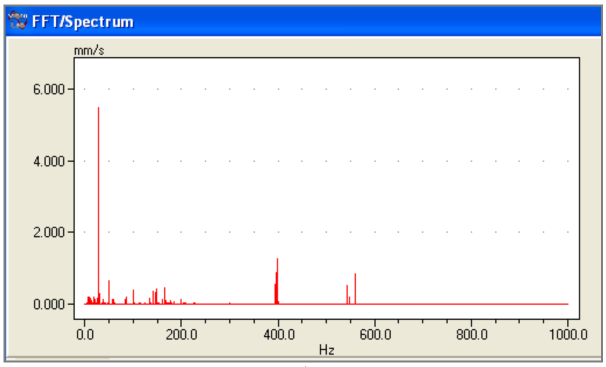


b)

Fig. 3. Amplitudes of vibrations in the FFT spectrum related to the accelerometer placed along the OX axis corresponding to: a) new wheel; b) fault wheel



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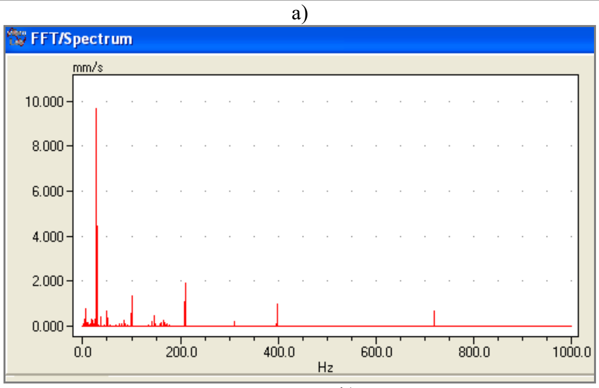

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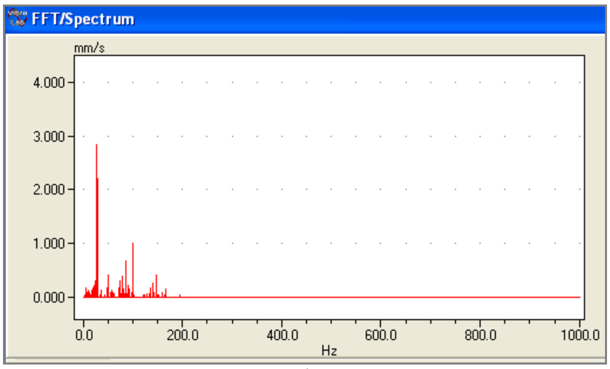
Fig. 4. Amplitudes of vibrations in the FFT spectrum related to the accelerometer placed along the OY axis corresponding to: a) new wheel; b) fault wheel



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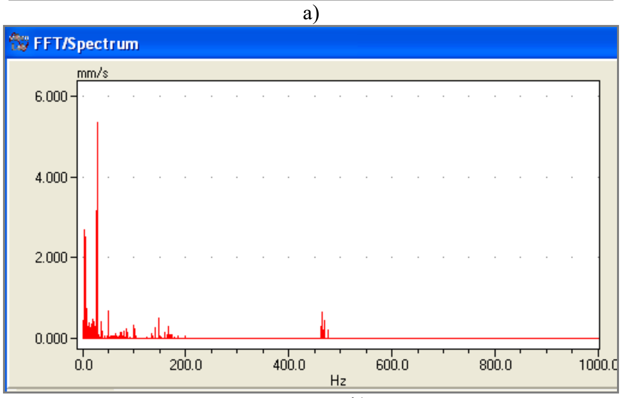

b)

Fig. 5. Amplitudes of vibrations in the FFT spectrum related to the accelerometer placed along the OZ axis corresponding to: a) new wheel; b) fault wheel

III. A FUZZY LOGIC-BASED SYSTEM FOR THE PREDICTIVE MAINTENANCE OF GRINDING WHEELS OF AUTOMATED GRINDING LINES

A fuzzy logic approach for planning the maintenance activities was presented in [9,10,11]. This approach will be adapted for predictive maintenance of grinding wheels of automated grinding lines, in order to determine the number of parts that the abrasive wheel can grind until its reconditioning.

1) The vibration amplitudes $\{AV_X, AV_Y, AV_Z\}$ on the OX, OY and OZ axis, respectively were considered as the input linguistic variables in the fuzzy decision system ([mm/s] rms).

2) The domain values for the input linguistic variables were defined considering the amplitudes of vibrations for a new and a fault wheel, respectively (Fig. 3, 4 and 5):

$$\begin{aligned} AV_X &: D_{AV_X} = [7.625, 16.755] \\ AV_Y &: D_{AV_Y} = [5.612, 9.742] \\ AV_Z &: D_{AV_Z} = [2.840, 5.393] \end{aligned} \quad (1)$$

3) The linguistic terms for the input linguistic variables $\{AV_X, AV_Y, AV_Z\}$ were defined as:

$$AV_X: \quad LT^{AV_X} = \begin{Bmatrix} AV_X\_verysmall \\ AV_X\_small \\ AV_X\_medium \\ AV_X\_big \\ AV_X\_verybig \end{Bmatrix}$$

$$AV_Y: \quad LT^{AV_Y} = \begin{Bmatrix} AV_Y\_verysmall \\ AV_Y\_small \\ AV_Y\_medium \\ AV_Y\_big \\ AV_Y\_verybig \end{Bmatrix} \quad (2)$$

$$AV_Z: \quad LT^{AV_Z} = \begin{Bmatrix} AV_Z\_verysmall \\ AV_Z\_small \\ AV_Z\_medium \\ AV_Z\_big \\ AV_Z\_verybig \end{Bmatrix}$$

4) The Gaussian functions are frequently used as the membership functions [12, 13] and will be employed in our approach. According to [12, p.26], their expressions are:

$$\begin{aligned} mf_i^{AV_X}(x, c_{AV_{X_i}}, \sigma_{AV_{X_i}}) &= e^{-\frac{1}{2}\left(\frac{x-c_{AV_{X_i}}}{\sigma_{AV_{X_i}}}\right)}, \; i = \overline{1,5} \\ mf_j^{AV_Y}(x, c_{AV_{Y_j}}, \sigma_{AV_{Y_j}}) &= e^{-\frac{1}{2}\left(\frac{x-c_{AV_{Y_j}}}{\sigma_{AV_{Y_j}}}\right)}, \; j = \overline{1,5} \\ mf_k^{AV_Z}(x, c_{AV_{Z_k}}, \sigma_{AV_{Z_k}}) &= e^{-\frac{1}{2}\left(\frac{x-c_{AV_{Z_k}}}{\sigma_{AV_{Z_k}}}\right)}, \; k = \overline{1,5} \end{aligned} \quad (3)$$

where c and σ represent the center and width of each Gaussian membership function.

5) The number of parts that the abrasive wheel can grind until its reconditioning NPR ([pieces]) was considered as the output linguistic variable in the fuzzy decision system

6) The domain values for the output linguistic variable was defined as:

$$NPR: D_{NPR} = [0, 6800] \quad (4)$$

7) The linguistic terms for the output linguistic variables NPR were defined as:

$$NPR: \quad LT^{NPR} = \begin{Bmatrix} NPR\_verysmall \\ NPR\_small \\ NPR\_medium \\ NPR\_big \\ NPR\_verybig \end{Bmatrix} \quad (5)$$

8) The Gaussian function was also used as the membership function for the output linguistic variable NPR. Its expression is [12, p.26]:

$$mf_l^{NPR}(x, c_{NPR_l}, \sigma_{NPR_l}) = e^{-\frac{1}{2}\left(\frac{x-c_{NPR_l}}{\sigma_{NPR_l}}\right)}, \; l = \overline{1,5} \quad (6)$$

where c_{NPR_l} and σ_{NPR_l} represent the center and width of the Gaussian membership function.

9) The fuzzy rules base includes 125 rules, as follows:

$$\begin{aligned} &R1: \; IF(AV_X = AV_X\_verysmall) \; AND (AV_Y = AV_Y\_verysmall) \\ &AND\ (AV_Z = AV_Z\_verysmall) \; THEN (NPR = NPR\_verybig) \\ &\ldots\ldots \qquad (7) \\ &R125: \; IF(AV_X = AV_X\_verybig) AND (AV_Y = AV_Y\_verybig) \\ &AND\ (AV_Z = AV_Z\_verybig) THEN (NPR = NPR\_verysmall) \end{aligned}$$

10) The centroid method [14] was employed as defuzzification method.

The development of the fuzzy decision system was achieved through the use of the Fuzzy Logic Toolbox™ of Matlab® software and it is depicted in Fig. 6. The inference rules are shown in Fig. 7.

As an example of the employment of the fuzzy decision system, the values of the $\{AV_X, AV_Y, AV_Z\}$ were measured as {14.10, 9.04, 4.88} mm/s rms. Considering these values, the NPR was determined with the fuzzy decision system as 1770 pieces.

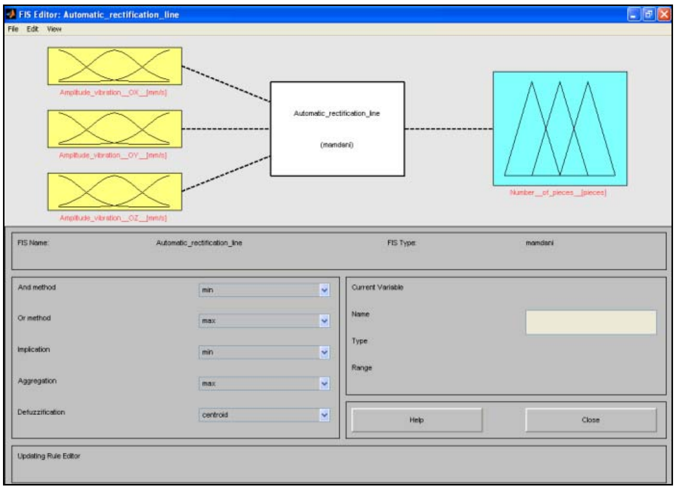

Fig. 6. The fuzzy decision system
Automatic_rectification_line.fis

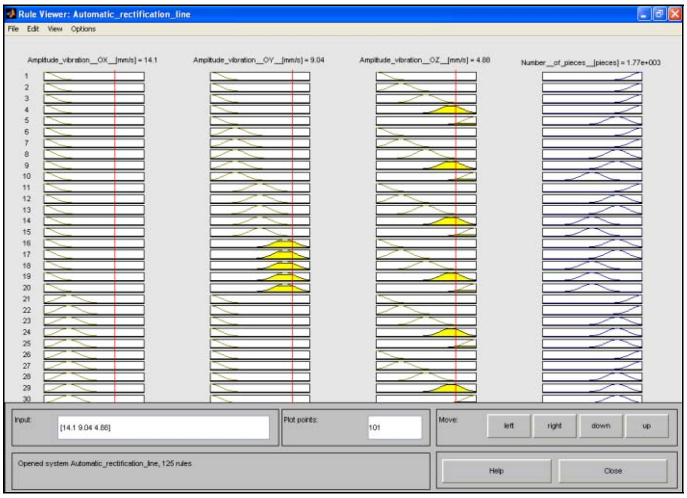

Fig. 7. The inference rules of the fuzzy decision system fuzzy system
Automatic_rectification_line.fis

IV. Conclusion

The predictive maintenance can be used for an adequate maintenance of grinding wheels of automated grinding lines prior to their failure. Considering some limitations of condition monitoring, a fuzzy decision system for planning the maintenance policy of the grinding wheels of automated grinding lines was presented. The Fuzzy Logic Toolbox™ of Matlab® software was employed for the development of the fuzzy decision system. Based on a three axis vibration monitoring approach, this fuzzy decision system allows the determination of the number of parts that the abrasive wheel can grind until its reconditioning.

References

[1] R. Ahmad and S. Kamaruddin. “An overview of time-based and condition-based maintenance in industrial application”, Computers & Industrial Engineering, vol. 63, issue 1, pp. 135–149, 2012.

[2] S.H. Ding, and S. Kamaruddin. “Maintenance policy optimization-literature review and directions”, International Journal of Advanced Manufacturing Technology, vol 76, issu 5-8, pp. 1263-1283, 2015.

[3] K.F. Martin. “A review by discussion of condition monitoring and fault diagnosis in machine tools”, International Journal of Machine Tools and Manufacture, vol. 34, issue 4, pp.527-551, 1994.

[4] R.B. Chinnam and P. Baruah. “A neuro-fuzzy approach for estimating mean residual life in condition-based maintenance systems”, International Journal of Materials and Product Technology, vol. 20, issue 1–3, pp. 166–179, 2004.

[5] A.K.S. Jardine, D. Lin, and D. Banjevic. “A review on machinery diagnostics and prognostics implementing condition-based maintenance”, Mechanical Systems and Signal Processing, vol. 20, issue 7, pp.1483–1510, 2006.

[6] Pratesh Jayaswal, S.N. Verma and A.K. Wadhwani. “Machine Fault Signature Analysis”, International Journal of Rotating Machinery, vol. 2008, pp.1-11, 2008.

[7] P.A. Delgado-Arredondo, D. Morinigo-Sotelo, R.A. Osornio-Rios, J.G. Avina-Cervantes, H. Rostro-Gonzalez and R.D. Romero-Troncoso. “Methodology for fault detection in induction motors via sound and vibration signals”, Mechanical Systems and Signal Processing, vol. 83, pp. 568-589, 2017.

[8] 8. J.Z. Zhang and J.C. Chen. “Tool condition monitoring in an end-milling operation based on the vibration signal collected through a microcontroller-based data acquisition system”, International Journal of Advanced Manufacturing Technology, vol. 39, issue 1-2, pp.118-128, 2008.

[9] C.F. Baban, M. Baban and M.D. Suteu. “Using a fuzzy logic approach for the predictive maintenance of textile machines”, Journal of Intelligent & Fuzzy Systems, vol.30, issue 2, pp. 999–1006, 2016.

[10] M. Baban, C.F. Baban, C., Bungau, G. Dragomir and R.M. Pancu. “Using Fuzzy Logic for the Estimation of the Technical State of Automotive Disc Brakes”, International Journal of Computers, Communications & Control, vol. 9, issue 5, pp. 531-538, 2014.

[11] 11. M. Baban, C.F. Baban and F.S Blaga. “Maintenance planning of cold plastic deformation tools using fuzzy logic”, Eksploatacja i Niezawodnosc-Maintenance and Reliability, nr. 3, pp. 21-26, 2010.

[12] J.-S.R. Jang, C.T. Sun, and E. Mizutani. Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, Upper Saddle River, NJ: Prentice-Hall, 1997.

[13] N. Siddique and H. Adeli. Computational Intelligence: Synergies of Fuzzy Logic, Neural Networks and Evolutionary Computing, Chichester: John Wiley & Sons, 2013.

[14] T. Ross. Fuzzy Logic with Engineering Applications, 3rd ed., Chichester: John Wiley & Sons Ltd., 2010.