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PLANOWANIE OBSŁUGI NARZĘDZI DO OBRÓBKI PLASTYCZNEJ NA ZIMNO Z WYKORZYSTANIEM LOGIKI ROZMYTEJ

MAINTENANCE PLANNING OF COLD PLASTIC DEFORMATION TOOLS USING FUZZY LOGIC

W przypadku systemów technicznych, na ogół cechujących się dużą złożonością, ich otwartość można wykorzystać do poprawy niezawodności systemu stosując odnawianie profilaktyczne. Skuteczne zwiększenie niezawodności złożonych narzędzi do obróbki plastycznej na zimno zależy w znacznym stopniu od charakterystyki czynności obsługowych, dlatego też w strategiach odnowy powszechnie stosuje się odnawianie profilaktyczne. W pracy omówiono podejście do planowania obsługi wykorzystujące logikę rozmytą, które można stosować w przypadkach, gdy analityczne wyprowadzenie funkcji niezawodności jest niemożliwe. Przedstawiono oparty na logice rozmytej proces decyzyjny w zakresie planowania czynności obsługowych omawianych narzędzi. Jego zastosowanie zilustrowano w studium przypadku. Wyniki studium przypadku pokazują, że logika rozmyta jest metodą, która może być z powodzeniem stosowana w planowaniu obsługi narzędzi do obróbki plastycznej na zimno.

Słowa kluczowe: *uszkodzenie, monitorowanie drgań, logika rozmyta, planowanie obsługi.*

For technical systems, generally of high complexity, their open feature may be employed to improve system reliability by preventive renewal. The effectiveness of increasing complex cold plastic deformation tools depends considerably on the characteristics of their maintenance actions and renewal policies are widely used to carry out the preventive renewal. If the derivation of an analytical reliability function is impossible, a fuzzy logic approach for maintenance planning is emphasized in this paper. The fuzzy logic decision process for planning the maintenance activities of these tools is presented and a case study illustrates its application. The results of the case study demonstrate that fuzzy logic is a method which can be successfully used in maintenance planning of cold plastic deformation tools.

Keywords: *failure, vibration monitoring, fuzzy logic, maintenance planning.*

1. Introduction

Metal forming is one of the most modern fields in the technology machine building, offering great advantages in terms of rational use of materials, high productivity and cost saving [3, 19]. Increasing complexity of tools used in these processes has conducted to a systematic approach of their function with a special attention to maintain their performances in time. For complex technical systems such as the tools used in cold plastic deformation processes, renewal possibilities are available. Therefore, their effectiveness depends on the reliability, as well as on the fault detection and the planning of the maintenance actions.

The development of a reliability model is based on the notion of failure, when at least one of the cold plastic deformation tool performances exceeds its tolerance limits [4]. The high degree of individualization of each cold plastic deformation tool, the high number of variables of a deformation process and complex interactions between them lead to a lack of accurate information on their failure. The limited and not systemized information about failure of cold plastic deformation tools represent a major impediment in studying the reliability of these tools.

The adoption of distribution law is a fundamental problem of the reliability modeling and in formulating renewal policies of technical systems prior to their failure. Specification of the reliability model requires considerable effort in adoption the law distribution and in estimating its parameters [4]. If the derivation of an analytical reliability function is impossible, the renewal policies cannot be designed. Taking into account that the transition between stage of good function and stage of failure of cold plastic deformation tools is achieved by several intermediate stages characterized by certain levels of performance, the fuzzy logic may be a solution for planning the maintenance actions.

Fuzzy methodology is indicated as an important tool not only to analyze the complex behavior of a system [16], but also to improve a system maintainability using appropriate maintenance practices. Although the idea that fuzzy logic might be used for their maintenance planning is provocative [1, 5, 10, 18], the researches in the field of cold plastic deformation processes are relatively underdeveloped.

Within this framework, this article focuses on developing a fuzzy approach for maintenance planning of cold plastic deformation tools and is organized as follows. First, a data acquisition system based on vibration analysis for monitoring the failure of cold plastic deformation tools is described. Then, the fuzzy logic decision process for planning the maintenance activities of these tools is depicted. A case study demonstrates the application of the fuzzy logic system in the case of a combined shearing for fine mechanics. Several conclusions and a recommendation for future research are presented at the end of the study.

2. Failure identification of cold plastic deformation tools

The knowledge of influences and determination of causal phenomena of cold plastic deformation tools failure is confronted with the reduced volume of experimental data. This leads to a relatively high level of uncertainty in the estimation of proper function of the tools. On the other hand, the methods of diagnosing failure do not have a universal character, so depending on the nature of processes, equipments or systems, specific methods must be put into practice each time. The vibration monitoring is indicated as an important technique for failure diagnosis [8, 12, 13, 15].

The wear of the active elements of cold plastic deformation tools, which are moving relatively, is one of the main cause of their failure and vibration spectrum analysis may be employed for the failure identification. Each active element generates a particular signal and any change in frequency can be measured and identified with monitoring vibration devices.

For failure identification of active elements, a data acquisition system based on vibration amplitude monitoring was used. The vibration amplitude is expressed in velocity units [mm/sec] and comparing the vibration amplitude value at a moment with its reference value, the failure can be detected. The data acquisition system is composed by sensor-TopMessage device-personal computer.

The data acquisition system was developed around a notebook with extension slot for TopMessage device. The signal from sensor is transferred to the TopMessage device, which include the AMDT/V module for vibration monitoring. The Vibrolab software is employed for vibration analysis and monitoring. Both TopMessage and Vibrolab are made by Delphin Technology AG (Germany).

3. A fuzzy approach for maintenance planning of cold plastic deformation tools

The capacity of cold plastic deformation tools to accomplish their mission depend on their intrinsic reliability and on the characteristics of the maintenance actions. Therefore, their effectiveness groups both reliability and maintainability, because they treat the same design elements and use the same mathematics base in their approaches.

Within this context, the reliability modeling of cold plastic deformation tools must be performed. Because of the complexity of physico-chemical phenomena that lead to the degradation of their specified function, phenomena that are not subject to deterministic laws, the reliability analysis must be carried out by the probability theory and mathematical statistics.

The central problem of reliability modeling of cold plastic deformation tools is the adoption of the distribution law, using a goodness-of-fit test based on the theory of hypothesis testing. The Kolmogorov-Smirnov test is one of the best known goodness-of-fit tests, in which the distribution law is accepted if and only if [4, p.34]:

$$\max_{1\le i\le n}\left| F(t)-\hat{F}(t)\right| < d_{1-\alpha}(n) \tag{1}$$

where $F(t)$ and $\hat{F}(t)$ are the true and estimated cumulative distribution function, α is the risk of first order, n is the sample and $d_{1-\alpha}(n)$ is the 1-α percentile of the Kolmogorov-Smirnov distribution. The parameters of the proposed distribution law must also be estimated from the experimental data. The reliability measures estimated in the reliability studies are used as input data in the design of the renewal polices to improve the tool effectiveness. The periodic and non-periodic are the main types of renewal policies and several criteria can be used in designing renewal policies [4, 7, 9]. The periodic renewal policy is described by the same time interval between two successive preventive renewals, while the non-periodic renewal policy is based on system age. Therefore, the block replacement policy is a deterministic policy and the age replacement policy is a random one.

The main problem appears when the available distribution laws are rejected by the goodness-of-fit test. A combination or succession of exponential distributions can be used to approximate the true distribution law, at any level of accuracy [4]. However, is very difficult or even impossible to design the renewal policies for a such distribution.

Fuzzy methodology is one of widely applied expert system methodologies in many fields [11] and the studies available in the literature demonstrate the importance of fuzzy logic in maintenance actions. Kobbacy [10] points fuzzy logic as an important tool in the applications of artificial intelligence techniques in the maintenance field. The choosing of the most adequate maintenance approach based on a fuzzy multiple criteria decision making methodology is shown in [1], while Sudiarso and Labib [18] present a fuzzy logic algorithm to an integrated maintenance/ production scheduling. Using the fuzzy set theory, an algorithm for specifying the best type of maintenance has been developed in [5].

In the case of cold plastic deformation tools, the fuzzy logic decision process for planning the maintenance activities is based on:

1) Setting up the inputs in the fuzzy decision system

$$C=\{C_1,C_2,...,C_j,...,C_m\} \tag{2}$$

These inputs represent the evaluation criteria set in relation to which the maintenance planning will be determined.

2) Defining the domain of values for each evaluation criterion

$$\begin{aligned} &C_1 : D_1 = [L_1^{\inf}, L_1^{\sup}]\\ &\vdots\\ &C_j : D_j = [L_j^{\inf}, L_j^{\sup}]\\ &\vdots\\ &C_m : D_m = [L_m^{\inf}, L_m^{\sup}] \end{aligned} \tag{3}$$

where $L_j^{\inf}, L_j^{\sup}$ are the lower respectively the upper limit of the domain of values associated with the criterion C_j , $j=\overline{1,m}$

3) Defining linguistic variable associated with each evaluation criterion

Each evaluation criterion is associated with a linguistic variable. For simplicity, the linguistic variable will have the same name as the evaluation criterion. Thus C_j criterion will become the linguistic variable C_j, $j=\overline{1,m}$.

4) Establishing linguistic terms associated with each linguistic variable

For each linguistic variable, the linguistic terms are defined [6, 14]. They serve to fuzzy characterize the crisp information. The set of linguistic terms associated with each linguistic variable C_j is:

$$\begin{aligned} &C_1 : GL_1^C = \left\{GL_{1\,1}^C, GL_{1\,2}^C, ..., GL_{1\,k}^C\right\} \\ &\vdots \\ &C_j : GL_j^C = \left\{GL_{j1}^C, GL_{j\,2}^C, ..., GL_{j\,k}^C\right\} \\ &\vdots \\ &C_m : GL_m^C = \left\{GL_{m\,1}^C, GL_{m\,2}^C, ..., GL_{m\,k}^C\right\} \end{aligned} \tag{4}$$

5) Establishing of membership functions associated with each linguistic term of relation (4)

$$\begin{aligned} &C_1 \rightarrow GL_1^C \rightarrow FA_1^C = \left\{fa_{1\,1}^C, fa_{1\,2}^C, ..., fa_{1\,k}^C\right\} \\ &\vdots \\ &C_j \rightarrow GL_j^C \rightarrow FA_j^C = \left\{fa_{j1}^C, fa_{j2}^C, ..., fa_{j\,k}^C\right\} \\ &\vdots \\ &C_m \rightarrow GL_m^C \rightarrow FA_m^C = \left\{fa_{m1}^C, fa_{m2}^C, ..., fa_{m\,k}^C\right\} \end{aligned} \tag{5}$$

Several membership functions are available, and they are shown in [6, 17].

6) Defining the outputs of the decision process. For the maintenance planning of cold plastic deformation tools, the scheduled time when preventive renewals should be carried out T is proposed as output.

7) Defining the domain of values for the output T

$$T : D_T = [L_T^{\inf}, L_T^{\sup}] \tag{6}$$

where $L_T^{\inf}, L_T^{\sup}$ are the lower respectively the upper limit of the domain of values associated with the output *T*.

8) Defining linguistic variable associated the output: for simplicity, the output T will become the linguistic variable T.

9) Establishing linguistic terms associated with the linguistic variable T

$$T : GL^T = \left\{ GL_1^T, GL_2^T, ..., GL_k^T \right\} \tag{7}$$

10) Establishing the membership functions associated with linguistic terms of relation (7)

$$T \rightarrow GL^T \rightarrow FA^T = \left\{fa_1^T, fa_2^T, ..., fa_k^T\right\} \tag{8}$$

11) Setting up the method of connecting the different values of membership functions (the inference rules)

In the case of cold plastic deformation tools, the AND operator is used and the inference rules have the following form:

$$\begin{aligned} &RIN_1 : \text{IF } (C_1 = GL_{11}^C \text{ AND ... AND } C_m = GL_{m1}^C) \text{ THEN } (T = GL_1^T) \\ &RIN_i : \text{IF } (C_1 = GL_{1j}^C \text{ AND... AND } C_m = GL_{mj}^C) \text{ THEN } (T = GL_j^T) \\ &RIN_r : \text{IF } (C_1 = GL_{1k}^C \text{ AND... AND } C_m = GL_{mk}^C) \text{ THEN } (T = G_k^T) \end{aligned} \tag{9}$$

12) Establishing the defuzzification method

Several methods are available for defuzzification and the centroid method is employed in this paper. Its expression is presented in [14, p.101; 17, p.98] and can be written as:

$${}^0T = \frac{\int_T T \cdot {}^0 fa_{rez}^T(T) \cdot dT}{\int_T {}^0 fa_{rez}^T(T) \cdot dT} \tag{10}$$

4. Case study

The maintenance planning using fuzzy logic was applied for active elements of a fine mechanics plastic deformation tool (a combined shearing tool). We assumed that after each corrective repair, the active elements are brought to the same state, eliminating the wear accumulated since the preceding failure.

The times-to-failure were achieved employing the data acquisition system. Comparing the amplitude of vibration with the situation when the active elements are in a good state (figure 1), respectively in a failure state (figure 2), the times-to failure can be identified.

Using the data acquisition system, the following times to failure of the tools were obtained (in cycles): 12943, 14959, 15714, 17137, 18011, 19822, 22117, 24148, 26997, 28889, 29783, 34315. Taking into account a first risk α=0.1, the more widely used laws in reliability modeling of cold plastic deformation tools, respectively alpha and power laws [2], are rejected by the Kolmogorov-Smirnov goodness-of-fit test.

The maintenance planning can be achieved in this case based on the fuzzy logic decision process depicted in section 3. A fuzzy decision system called Fuzzy_maintenance_Combined_Shearing was developed using Fuzzy Logic Toolbox of Matlab software (figure 3).

The amplitude of vibration C_1[mm/s] and the distance (break clearance) between the active elements of the combined shearing tool C_2 [mm]) are adopted as inputs. The number of

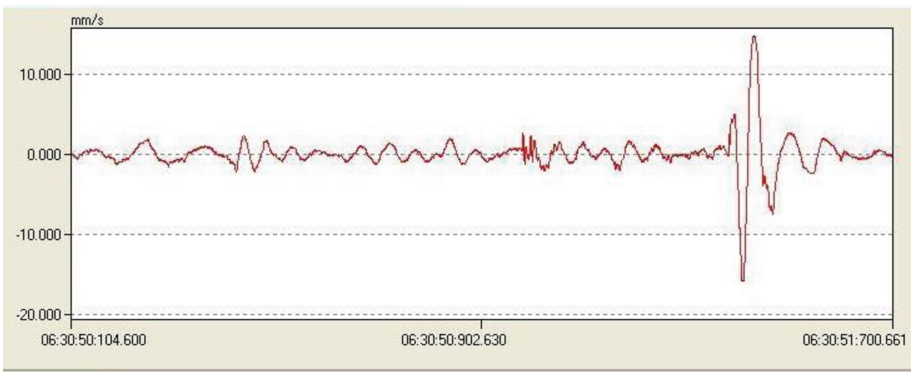

Fig. 1. The vibration amplitude for the good state of the active elements

cycles to the preventive renewal O_1 [cycles] is used as output. The domain of values of each input is: C1:D1=[16.75;20.45]; C2:D2=[1.40;1.65], while for the output is O1:DO1=[0;22500]. The inference rules are shown in figure 4.

Figure 5 presents the graphical representation of the $O_1=f(D_1,D_2)$. As an example, if C1= 17.9 mm/s and C2=1.51 mm, O1=15200 cycles. Therefore, the number of scheduled cycles to the next renewal of the combined shearing tool is 15200 cycles.

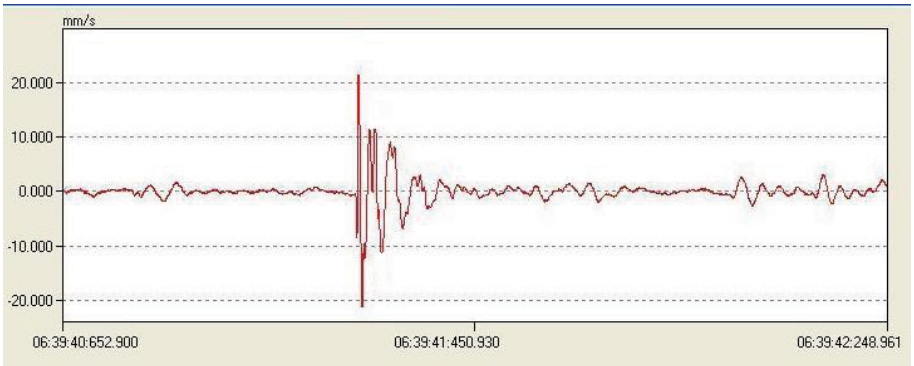

Fig. 2. The vibration amplitude for the failure state of the active elements

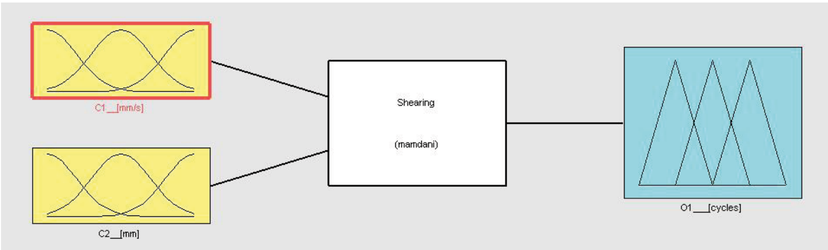

Fig. 3. The fuzzy decision system Fuzzy_maintenance_Combined_Shearing.fis

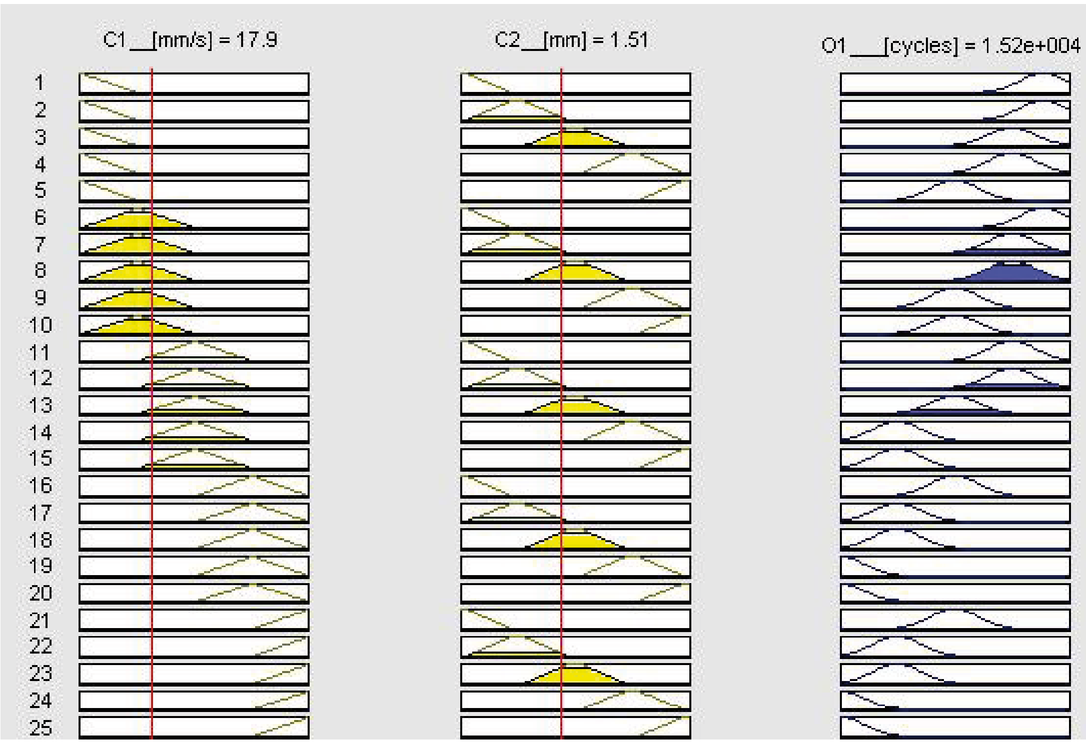

Fig. 4. The inference rules

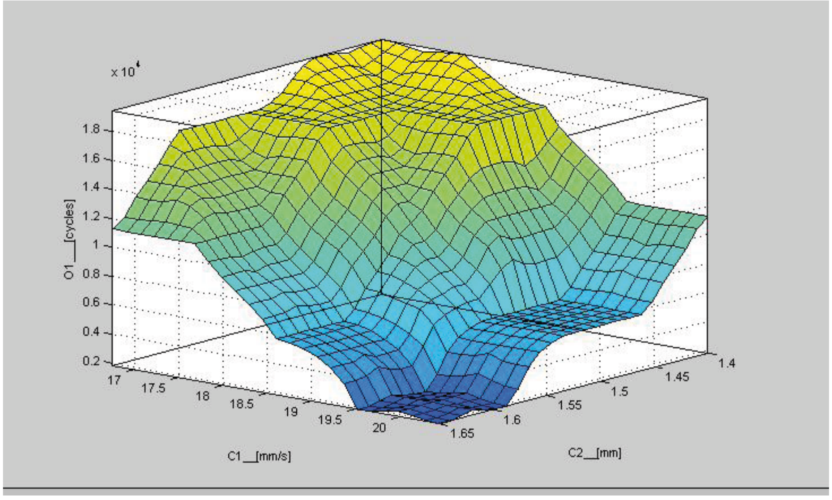

Fig. 5. The graphical representation of the $O_1=f(D_1,D_2)$

5. Conclusions

Adequate maintenance actions of complex technical systems to prevent failures has become increasingly important. Renewal policies are generally the major maintenance actions carried out in the case of cold plastic deformation tools. For this purpose, the reliability modeling of cold plastic deformation tools must be performed by a goodness-of-fit test. Kolmogorov-Smirov test was proposed to adopt the reliability model and a data acquisition system was developed for the identification of the times-to-failures.

However, after testing the available distribution laws against the experimental data the possibility to reject some of the most used laws can appear, while for other distribution laws is very difficult or impossible to design renewal policies. In such a situation, we emphasize fuzzy logic for maintenance planning.

The studies available in the literature demonstrate the importance of fuzzy logic in maintenance actions, but not so much work has been done on applying fuzzy logic for maintenance planning of cold plastic deformation tools. A fuzzy logic decision process for planning their maintenance activities is depicted and a fuzzy decision system developed using Fuzzy Logic Toolbox of Matlab software demonstrates its application for a fine mechanics plastic deformation tool.

In conclusion, fuzzy logic for maintenance planning provides a proactive method to renewal cold plastic deformation tools prior to their failure. The results of the case study demonstrate that the fuzzy logic is a method which can be successfully used in maintainability planning of these tools. The combination of fuzzy logic with neural networks or genetic algorithms for maintenance planning of cold plastic deformation tools is an important area for future researches.

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