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SYSTEM MONITOROWANIA I DIAGNOSTYKI W PROCESIE CIĘCIA TEKTURY

Streszczenie. W pracy przedstawiono system detekcji usterek oraz monitorowania stanu maszyny w procesie produkcji tektury. Dokładność cięcia kartonu istotnie wpływa na jakość produktu, stąd bardzo ważne jest odpowiednio szybkie wykrywanie błędów cięcia oraz innych niesprawności w procesie. Autorzy zaproponowali system diagnostyczny wykorzystujący bieżące pomiary, metody statystyczne oraz klasyfikację opartą na sztucznej inteligencji w połączeniu z estymacją funkcji gęstości pradopodobieństwa błędów cięcia.

MONITORING AND DIAGNOSTIC SYSTEM IN THE CARDBOARD CUTTING PROCESS

Summary. A system for fault detection and condition monitoring in the cardboard production line is presented. Cutting accuracy significantly affects the quality of the product, therefore, it is crucial to detect fast enough cutting errors and any irregularities in the process. The authors proposed a diagnostic system with the use of on-line measurements, statistical process control, and classification based on artificial intelligence combined with estimation of the probability density function of cutting errors.

1. Introduction

The condition of machines and technical equipment has a significant impact on the economic results of industrial companies. The early detection and diagnosis of faults plays an important role in preventing failure of equipment and loss of productivity or quality deterioration. This problem has gained an extensive interest in machine monitoring and Fault Detection and Diagnostics (FDD) is an important element of control and management systems. Modern FDD is based on different artificial intelligence methods, qualitative or quantitative models [9], statistical methods [10], on the so called structural health monitoring [2], and others.

The paper presents a system developed for fault detection and condition monitoring of the rotary cutoff in the cardboard production line. One of the most important production stages, taking place in the final phase of the process, is cutting the cardboard sheet into required formats. Cutting accuracy significantly affects the cardboard quality, so it is extremely important to create a suitable diagnostic and monitoring system that allows for fast and efficient detection of abnormality in the process.

The proposed FDD system consists of five modules, allowing for fast and reliable detection of errors and irregularities in cutting process due to application of on-line measurement of selected signals, statistical process control approach and classification methods based on artificial neural networks [11]. The paper is organized as follows: the cutting process is described together with the main sources of possible malfunctions and the idea of the FDD system; classification of error sources is presented; other elements of the system are described; and final conclusions are drawn.

2. Process description and idea of a diagnostic system

The cardboard cutting is performed on a rotary cutoff machine, where a shearing is obtained thanks to rotary movement of two shafts with knives mounted spirally on them. Fig. 1 presents a rotary cutoff with two cutoffs mounted in a single constructional frame, and sketch of the knife shafts. This type of shears can be used in various industries, like, e.g., in the process of cutting a cardboard, paper, metal sheets, foil, laminate. Nowadays, the cardboard processing line speed may reach up to 450 m/min, and cardboard cutting length may vary from 500 mm to 4000 mm, whereas the required cutting accuracy may be of the order of 0.5 mm for formats shorter than 2000 mm and 1mm for longer formats. Hence, obtaining the adequate quality of the cutting is a real challenge because of many technical problems.

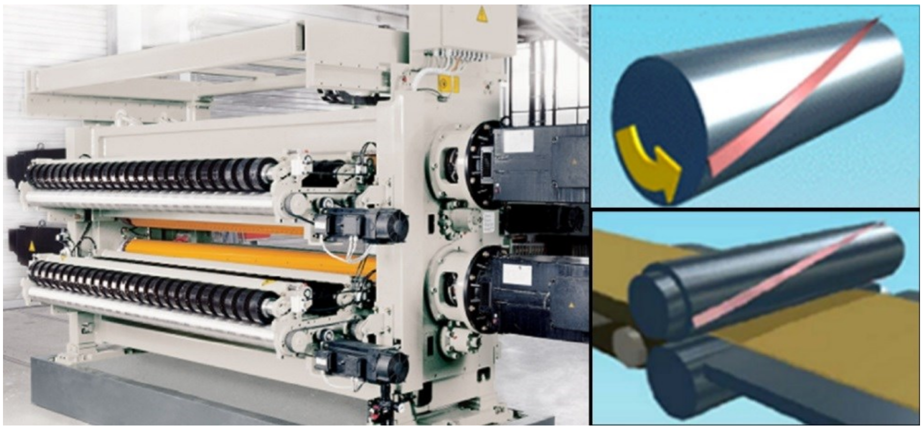

Fig. 1. A rotary cutoff machine (duplex type) and knife shafts

Incorrect cutting can result from various causes. They can be caused by the cutoff itself, or they can lie on the side of its surroundings in the production line. In the first case the errors may be induced by improper fastening of the encoder when its zero marker does not correspond to the mechanical position of the knife, improper controller settings, irregularities in the power transmission system, etc. Another group of sources of errors includes, e.g., instabilities of the production line speed, play in the cutoff input rolls, changes of the cardboard quality. Examples of cardboard stacks for incorrect and correct cutting are shown in Fig. 2 .

Fig. 2. Examples of cardboard cutting errors, the last photo is a cut in the norm

In order to build a diagnostic system, a preliminary analysis of cutting fault classification was performed using the Ishikawa diagram, see Fig. 3. Ishikawa diagram is a set of causes and effects known as the Fishbone diagram [7]. The analysis starts from the observation of the effect and is guided towards identifying all the possible reasons that caused it. Then, each of these components can be considered individually as a problem to be solved. Next, using the Pareto chart [10] error sources were hierarchically classified in descending order of incidence. It was stated that encoder knife cutting phase, the occurrence of slippage phenomena, the transport system, the control system and temperature have a dominant impact on the cutting errors.

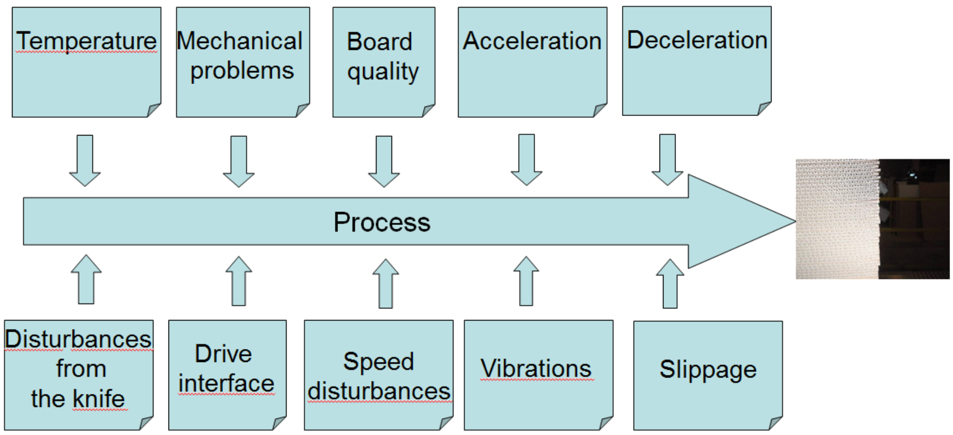

Fig. 3. Ishikawa diagram of the major causes of irregularities in the cardboard cutting

Diagnostics is defined as a process of detecting and distinguishing object malfunction as a result of the collection, processing and analysis of diagnostic signals. Generally, it can be based on continuous monitoring of the process parameters, or on testing the product quality to assess the condition of the machine. The disadvantage of the first solution is the high cost of installation of measurement systems and the need for support by appropriately trained personnel. On the other hand, in the second approach a malfunction can be noticed after the decline in the quality of the product, so it is associated with economic losses.

Here, both options are used. Taking into account the analysis of the Ishikawa diagram, as well as the existing measurement capabilities, it was proposed to build a diagnostic system consisting of five modules.

The essential Module #1 includes a neural network (NN) classifier, which basing on the probability density function (pdf) of the cardboard length specifies the class that describes the state of the machine. In the event of cutting errors, the classifier determines the possible causes of these errors. The frequency of the calculation depends on the signals from the second and third modules, or on the reaction of staff in the case of noticing a deviation from the set value.

The other four modules play an auxiliary role. Module #2 establishes the bivariate distribution of the position and speed of the cutter knives. Module #3 is responsible for the on-line acquisition of the selected physical signals from the sheeter. Module #4 is activated in the order change, when there is a change of format cartons. Module #5 performs a statistical study of the process and visualization. If irregularities are detected, the classification module is invoked.

3. Classification of error sources

Classification is a general process of identifying to which of a set of categories, a new observation belongs, on the basis of a training set of data containing instances whose category membership is known [1]. Idea of classification of possible faults in cardboard cutting follows from a long-term experience in maintenance of corrugators and analysis of cutting precision. It was noticed that information left in a length histogram of a cut cardboard stack allows for identifying a type of disturbance in a cutting process. Thus, it was proposed to diagnose the state of the machine and its peripheries basing on probability density function (pdf) of errors of cardboard length. Here only the sketch of this approach can be presented. The more detailed description of the classification method can be found in [11].

Prior to the procedure of classification, data for pdf estimation should be prepared. Deviations from the set value are calculated and the data should be normalised to improve the possibility of separation between the classes. Besides, in order to increase the generalization properties of the classifier, data were subjected to randomization before they were used for pdf estimation. Having regard to the precision of manual measurement of the sheet length, random noise with uniform distribution within the interval +/- 0.25mm was added to the data. Then the kernel density estimator [13] is used to calculate the pdf from the length histogram.

Various methods of classification are known, like, decision tree methods, Bayesian algorithms, neural networks (NN), rough sets, linear discrimination, etc. On account of the nonlinear relationship between pdf and belonging to a certain category, a multilayer perceptron (MLP) was chosen as a nonparametric approximator used in the classification procedure [6]. Here, the number of nodes in the input layer depends on the number of points, for which pdf values are fixed. The number of neurons in the output layer corresponds with the defined number of classes. The final response of the network should be equal to 1 to that output which corresponds to the class from which the pdf comes from, and 0 for all other classes. Values between 0 and 1 can be interpreted as a suggestion of degree of belonging the examined pdf to a given class.

Years of experience and the detailed analysis of the relationship between different shapes of cardboard and miscellaneous sources of cutting error have made it possible to define 20 main classes of faults. Fig. 4 shows the exemplary pdf of cutting errors for the class 7 and 12. These data were then used to train the NN classifier.

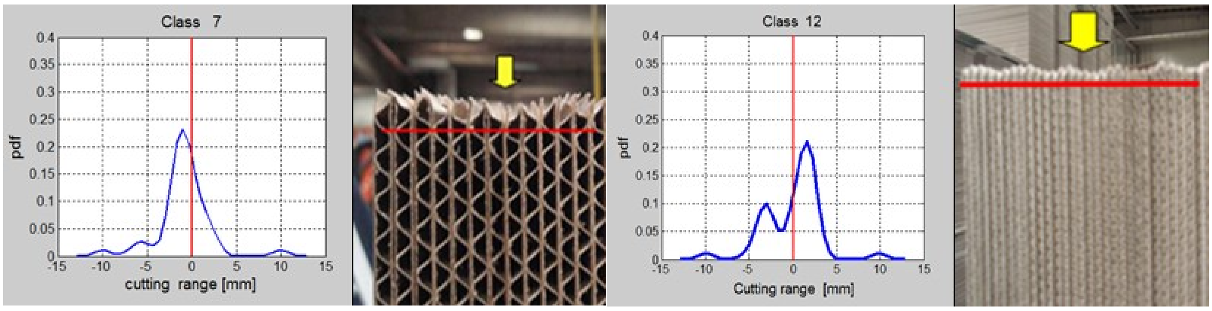

Fig. 4. Examples of pdf of errors and view of a cardboard stack for class 7 (vibration of the measuring wheel) and class 12 (incorrect value of the speed of the transporter)

A fundamental problem of NN modelling is the determination of network size and topology, i.e., the number of hidden layers and the number of neurons within individual layer. Generally, it is supposed to determine a total number of neurons as a geometric mean of the number of inputs and outputs of the neural network, but their distribution into specific layer is performed empirically. In this research many different MLP structures were investigated, consisting of 1, 2 or 3 hidden layers with up to 100 neurons. Taking into account the effectiveness of classification and the ability to generalize, the best results were obtained for two hidden layers with 28 and 20 neurons respectively. Besides, RBF (Radial Basis Function) networks [4], PNN (Probabilistic Neural Network) [14], and a two-class classifier of type ”one against all others” using a single layer MLP were tested.

The number of patterns and their selection have a big impact on the learning outcomes. According to [15], good generalization of the classifier can be obtained if the number of data is at least 10 times greater than the Vapnik-Chervonenkis measure VCdim. Taking into account dimensions of the tested NN, it was assumed that data sets for network learning should contain 600 vectors for each class. Hence, the total number of data was 12 000 vectors, each containing 40 measurements of the carton length. Because for some classes no adequate amount of measurements were available, the bootstrap method [5] was used to supplement the data.

Beyond the classical evaluation of classifiers like the coefficient of efficiency defined as the ratio of the number of correctly classified data vectors to the total number of vectors, ROC (Receiver Operating Characteristic), etc. [3], the classifiers were also tested in terms of the ability to generalize. Three types of tests were performed:

- For data obtained from the arbitrary substitution of the measurements;
- For data generated by adding a Gaussian noise to a training sample;
- For data generated by the bootstrap method.

Recently, multiple classifier systems (MCS) have gained popularity as a powerful tool for difficult pattern recognition problems involving large class sets and noisy input [16]. Hence, finally, MCS based on five best classifiers obtained in the former studies was built and extensively tested on new data sets obtained from the industrial processes. In all cases examined, MCS correctly detected the cause of the cutting errors.

4. Modules supporting the classifier

NN classifier allows for determining sources of errors in the rotary cutoff operation based on measurements of the final product. To accelerate the ability to detect errors in the machine operation and improve the efficiency of the diagnosis, the diagnostic system is complemented by four additional modules. These modules monitor the state of the machine and invoke the alert in the case of detecting any irregularities and support the classifier in the case of doubts.

Module #2 establishes the bivariate distribution of the position and speed of the blade cutters [8]. The operator can see the phase plane of the position and velocity errors on the monitor. Two examples of such plots are shown in Fig. 5. Ellipses calculated for 1, 2 and 3 standard deviations, respectively, are drawn around a mean value of errors, and a square marks the central point characterized by (0,0) coordinates. The marginal histograms for both errors are also shown in the plots. This module may suggest where one should look for errors in the process. After finding the deviations, the operator may start the cutoff alone, without the production cycle, and assesses its technical condition on the grounds of the analysis of ellipses of errors, restricting a set of possible causes for irregularities.

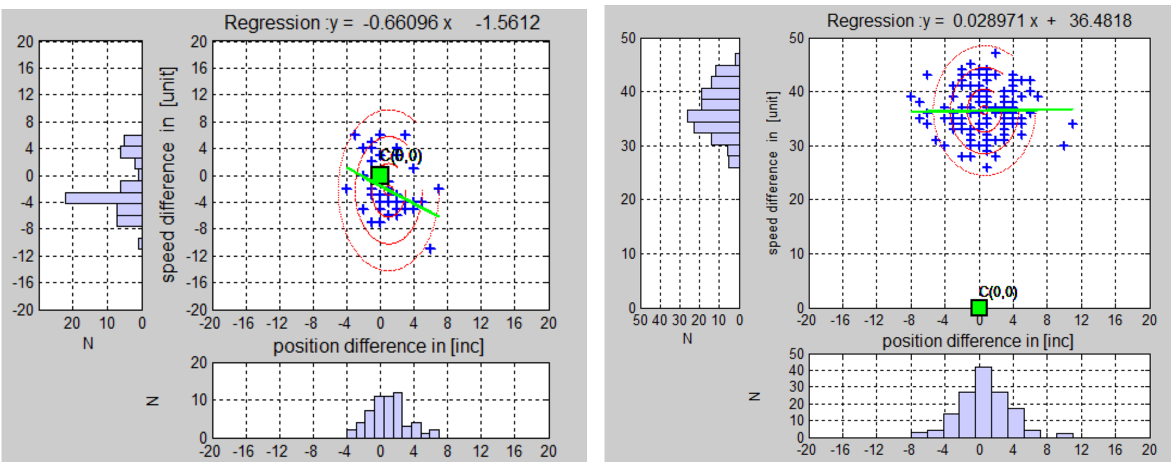

Fig. 5. Examples of correct operation of the cutoff and with high velocity error

However, it should be noticed that these results represent measurements obtained from the encoder located on the knife shaft of the cutoff – they are not the physical measurements of the cut cardboard. In reality, this length may be different, which may result from causes existing outside the cutoff, e.g., line velocity measurement errors resulting from the wear of the measuring wheel or the contamination with glue, slipping caused by the different paper quality or coated structures, or others. Hence, despite proper adjustment of the cutoff's control system and statistical results suggesting that the process runs properly, there may still be deviations of the cardboard length. But the presented analysis of bivariate distribution makes it possible to ascertain unambiguously, whether the causes lie on the cutoff's side (if the distributions are incorrect), or outside the cutoff (distributions are correct although cardboard is cut improperly).

The task of Module #3 is to inform about emerging irregularities in the process. Taking into account the main sources of irregularities, six additional measurement signals have been selected: temperature of the cutoff bearings, the moment in the phase of cutting, line speed, vibration of the measuring wheel and the knife shaft, the position of the knife in a cutting phase, and vacuum in the cardboard transport system. Exceeding the limit value of one of the signals triggers an alarm warning about deviations in the process. This modification entails increasing the cost of installation, so it is treated as an option.

The process of changing cardboard formats, called OC (Order Change), is a very difficult part of the production process because it begins with the rapid acceleration of the upstream part of the corrugator. Thus, the last 20 meters of cardboard for the order may appear uncertain cut. Module #4 is designed to indicate at which position deviations occur and which section of the corrugator is responsible for them. On the basis of the timing diagram of deviations, and knowing the length of the consecutive sections of the machine, it is possible to assign error to the corresponding item.

The task of Module #5 is the visualization of statistical parameters to indicate if the process is correct, stable and centralized, and to what extent the process differs from the normal operation. After the measuring cardboard, the operator inputs data to the module. The module calculates basic statistical parameters such as mean value, standard deviation, histogram and the probability density function of cutting deviations which are presented in a graphical form.

5. Conclusions

Automatic fault detection and diagnosis are always a challenge when monitoring complex machinery. In this paper an example of a diagnostic and condition monitoring system is proposed for the cutoff in the corrugated board production line. The system consists of five modules which use both modern measurement techniques and sophisticated methods of data processing, based on the artificial intelligence and statistics.

Implementation of some modules (e.g., Module #2 or Module #4) does not involve high costs, because it does not require direct interference in the control system of the machine. It is sufficient to introduce suitable functions directly into a controller or into a supervisory control system, combining them with the possibilities of documenting and visualization of that system, or using an operating panel. The most expensive part is the introduction of the new measurement system, so it can be considered as an option in older machines.

The proposed diagnostic system has been tested in the corrugated industry on a variety of machines - a new generation or older - and it demonstrated its usefulness alike for process operators, service technicians, as well as for the higher technical personnel. The proposed method for determining defects in corrugator was patented by the Polish Patent Office [12].

Acknowledgement

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