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Monitoring and Fault Diagnosis in Manufacturing Processes in the Automotive Industry

Roberto Arnanz Gómez, María A. Gallego de Santiago, Aníbal Reñones Domínguez, Javier Rodríguez Nieto and Sergio Saludes Rodil

CARTIF Technology Centre
Spain

1. Introduction

At present production systems in car manufacturing processes are under high demand requirements and maintenance plans are of great importance in order to achieve the production objectives. The main goal of the maintenance is to increase the operativity of the plant and the machines involved in the manufacturing process, avoiding all unexpected stops. Preventive maintenance has been the solution adopted by most factories for years. Based on past experience or on machines suppliers specifications, the maintenance manager decides when to check or replace the machines or some of their components to guarantee their operation without faults until the next maintenance stop. This implies two kinds of costs for the factory: checking a lot of equipment (time and staff costs) and replacing components that may be in good conditions.

That is why knowing the actual state of the different parts and machines of the factory is so important for a good management of the plant. The increasing automation of the plants allows to acquire, store and visualize lots of variables of the process. Most factories have nowadays SCADA systems that allow supervision of processes and equipment giving a valuable information about them. However it is not easy to manage this great amount of information for different reasons. First of all the sample rate of these variables usually hides their dynamic behaviour. Also the complexity of the processes makes it difficult to identify all the relations and dependencies between variables, so it is not possible to determine a wrong operation looking only the variation of a few variables without taking into account how the rest are changing. The number of variables and data acquired in the whole factory makes it impossible for a human supervisor to process all that information, relate it to past data and try to find out if something is going wrong. Although his experience will allow him to detect some problems it is evident that he needs some help to succeed in his work.

Predictive maintenance is a methodology that improves systems availability and contributes to cost reduction and increase of useful life of production assets. It comprises different techniques to process acquired data from the factory to determine machines state and predict how they will work in the future. The variety of problems that must be solved makes the design of a predictive maintenance system be a very complex task where different

knowledge areas must be integrated. It is very important to know the state of the art in all of them and sometimes introduce innovations for applying the solutions to particular cases.

Next sections explain the main components of a predictive maintenance system and how it was implemented in real industrial problems of the automotive industry. An effort has been made in order to choose case studies that offer a wide range of the possible techniques to use, combining classical solutions with newer ones.

2. Structure of a fault detection system for the automotive industry

The core of any predictive maintenance system is a fault diagnosis system able to detect failures not only when they are happening, but also a pre-failure behaviour. It is an advanced solution for the supervision level of the factory where in most cases only SCADAs and alarms based on variables values are considered. One of the main advantages of predictive maintenance is its ability to provide useful information to the human supervisor showing what the real state of a plant or machine is and helping him in the planification of the factory operation. It is also capable of substituting the human operator in some systems taking decisions such as stopping the operation in case of a critical fault or scheduling maintenance operations.

The three main components for any fault diagnosis system are data acquisition, signal processing and decision making. These three components must be designed jointly because the requirements or outputs of one of them will affect the others. Their complexity level will depend on the application and how the symptoms of the faults can be found.

Data acquisition is the first stage of every diagnosis system. This component consists of all the sensors, signal transmission systems, acquisition devices and storage equipment. Sensors are a key component of the fault detection system because they provide all the information the system will have to deal with, although in some cases information coming from production management systems can be useful. In some cases those sensors can be shared with other tasks such as control or supervision and they are included in the machine or plant during its design. But in most cases predictive maintenance is not taken into account during the design of the machines and new sensors are usually required. This occurs specially when predictive maintenance must to be applied to old machines because they start to be a bottle neck in the plant due to their unexpected faults. Electric current, voltage, accelerometers and temperature sensors are of common use for diagnosis systems. Some applications require more specific sensors, like photodiodes and spectrometers. The selection of the appropriate sensor and acquisition system can be determinant for the success of the application because they must guarantee that the collected data have the information of the state of the machine. Capture and synchronize data from sensors of different nature and variables with different dynamics can be an interesting problem to solve and sometimes requires specific programming or storing methods designed ad-hoc.

In the signal processing stage, signals acquired and/or stored by the data acquisition component are processed. This includes common signal treatment like filtering that is used to eliminate noise. However, the most important part in signal processing is feature extraction. Feature extraction consists in looking for a particular behaviour in the signals that allows to identify the faulty or pre-faulty states. There are a wide variety of feature extraction techniques and the one used depends on the problem at hand. For example, one of the most common feature extraction techniques is the Fourier Analysis, which gives information on the distribution of energy power associated to different frequency ranges in

the signals acquired by the sensors. This content changes when a fault occurs or is close to occur. Besides this, feature extraction techniques in the time domain are also useful. Some problems require the use of very specific feature extraction techniques, like the estimation of electron temperature. The final stage is the decision making where the features that have been extracted from the signals generated by the sensors, have to be classified in order to determine the state of the system. The classification is the base of the decision making process, so it has an important role in the fault diagnosis scheme. In some cases, classification can be done by merely checking the features values against a threshold, although selecting the threshold value could be a hard problem to solve. In other cases, more sophisticated non-linear classifiers, like neural networks, neuro-fuzzy systems or support vector machines have to be used. Besides this, features time evolution is also of great importance because it allows to perform trend analysis, which is one of the basis of the fault predictive capabilities of the fault detection systems. The lack of historical data is the main problem that must be solved when designing the decision making component. It can be sometimes a problem to decide what is the optimal classification method to use, and it is always an added difficulty to fix the parameters of the system. Usually conservative strategies are used. This leads to a great number of false alarms during the initial phases of the predictive maintenance system implementation. Human experts supervision and knowledge is one of the main supports for a good design of the decision making system and its configuration.

3. Case studies

3.1 Case study 1: Multitooth machine tool

Machine tools represent one of the main examples of highly automated components (Altintas, 2000). In spite of this automation, the cutting process has an inherent degradation (Astakhov, 2004), which is one of the main problems to be overcome. Other aspects to consider are workpiece tolerance deviations, ensuring a correct evacuation of the chips, changing of worn tools and, if necessary, stopping the machine if abnormal working conditions appear (for example chatter). So, to achieve the desired level of autonomy for this kind of machines, it is necessary to develop the monitoring and diagnosis of the cutting process. Many different kinds of machine tools are used in the automotive industry. Among them, the so called Multitooth Machine Tools represent the most challenging ones, from the diagnosis point of view, due to high number of inserts susceptible to break, and the different machining operations integrated within the same tool. The tools analyzed in this chapter are used in the car industry for mass production of different mechanical parts, such as the crankshaft or the camshaft of car engines. These tools are complex *ad hoc* devices built with many cutting inserts (up to 250, depending on the machine) of different kinds (roughing and finishing) presented in Fig.1(b) and for different operations (turning, milling or broaching) within the same tool, as shown in Fig.1(a). The configuration of the tool is based on multiple tool holders specially designed for the particular operation of the mass production line. Such complexity is necessary to achieve the required high metal removal rate.

3.1.1 Data acquisition in machine tool environment

Regarding the main three components of a fault detection system (data acquisition, signal processing and decision making) an optimal selection of sensors is of paramount importance to obtain valuable information from the environment of the machine tool that should be correlated with the abnormalities to be detected. Different signals susceptible of

(a) Layout of multitooth tools used in the car industry

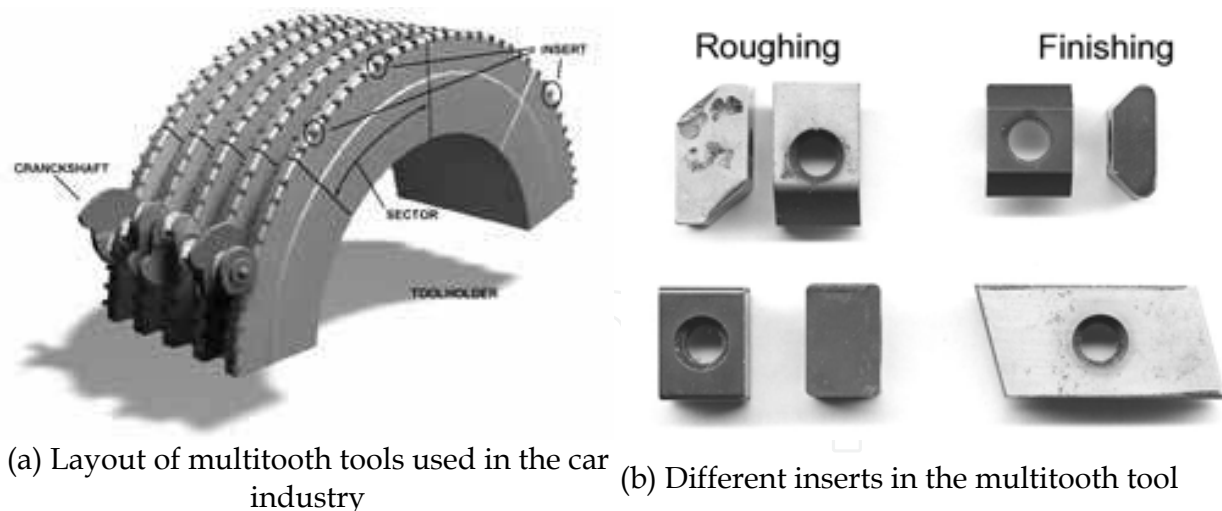(b) Different inserts in the multitooth tool

Fig. 1. Multitooth tools used in the car industry

having correlation with tool wear and the breakage of inserts in the multitooth tool, are shown in Fig.2. Among others the following are the most common in the literature:

Noise: can be measured in the environment of the tool using microphones (Fig. 2(a)). Although noise gathers information coming from the whole machine tool environment, this measure can be very valuable for the first analysis of the machining cycle through the analysis of the time-frequency representation like the spectrogram.

Vibration: measured with accelerometers in one of the main shafts of the machine tool (Fig. 2(b)). As the wear increases in the tool an abnormal increase in the vibration also occurs and can often lead to bad surface quality.

Temperature: the increase of the tool wear causes an increase in the temperature due to an excessive friction. Using sensors like pyrometers, the temperature of the machined surface can be easily measured after the machining has been completed (Fig. 2(c)).

Electrical power consumption: can be measured from the output signals of the frequency converters (for the usual case of AC drives) for every motor that moves the multitooth tool and moves the workpiece (usually rotation movement). Fig. 2(d) depicts the example of rms electrical power consumption of the two drives of an example tool: feed and rotation of the tool holder. These kind of signals show clearly the different parts of the cycle and the grouped attack of the inserts in the tool.

In order to analyze the sensitivity of every recorded signal, the measurements have to be done over the useful life of several consecutive tools. After that, every set of signals is statistically analyzed to extract global information for comparison and to decide whether there is a correlation with the degradation of the tool, or other abnormalities that could have been recorded. In (Reñones, Rodríguez & Miguel, 2009) are presented the results of such analysis that lead to choose the electrical power consumption as the most appropriate signal for use in the diagnosis of the multitooth tool. This signal showed the best signal-to-noise ratio for the evolution of the wear and was the most cost-effective measure: non-invasive, moderate sensor cost (inexpensive if appropriate signals are available at the drive converter) and high reliability of the measure in comparison with other measures like noise and vibration, because of the high influence of the sensor location. Fig. 3 shows the evolution in electrical power consumption in a particular zone of the analyzed tool. It is clear the increase of the power due to the wear and the abrupt decrease after the tool reaches its useful life and it is changed by a new one.
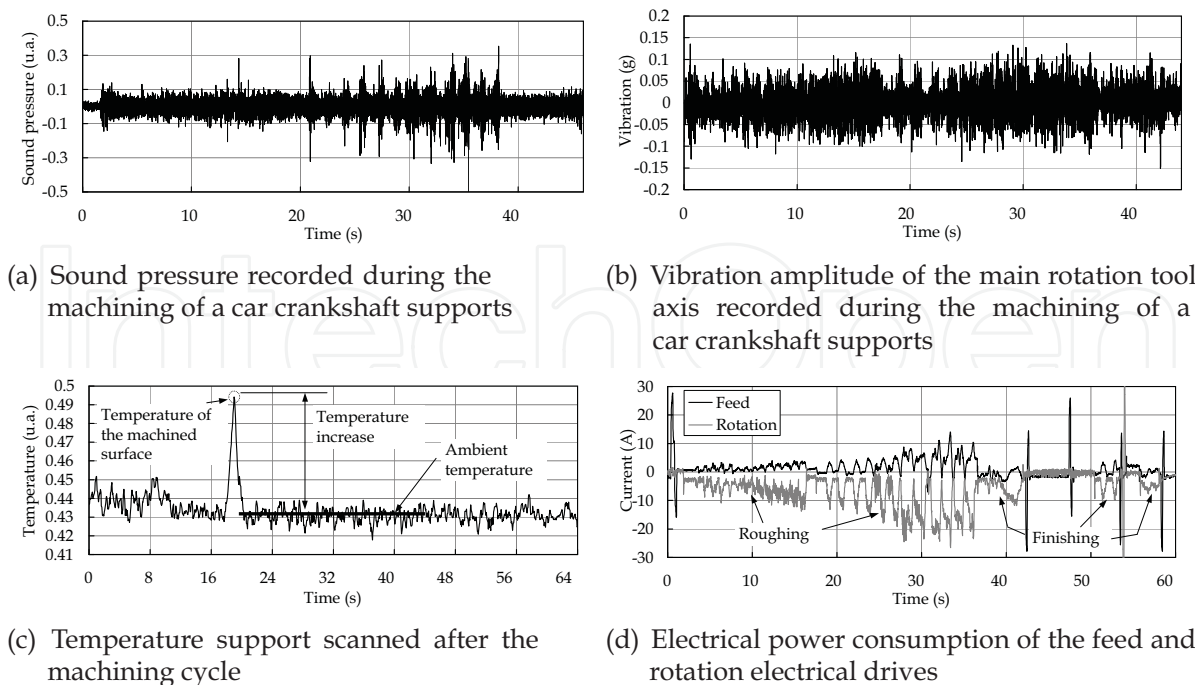
(a) Sound pressure recorded during the machining of a car crankshaft supports

(b) Vibration amplitude of the main rotation tool axis recorded during the machining of a car crankshaft supports

(c) Temperature support scanned after the machining cycle

(d) Electrical power consumption of the feed and rotation electrical drives

Fig. 2. Signal more common in the literature

Fig. 3. Evolution of the tool wear using the electrical power consumption.

3.1.2 Signal processing of the electrical power consumption

Once the electrical power consumption has been chosen as the desired signal for diagnosis of the tool, it is time to extract the part of the electrical power consumption that belongs to each insert or every group of inserts that attacks the workpiece simultaneously. This process is known as signal segmentation and can be formulated as the automatic decomposition of a signal into stationary or transient pieces with a length adapted to the local properties of the signal (Basseville & Nikiforov, 1993).

Firstly, the number of segments that must be extracted has to be defined, taking into account different aspects of the machining process, such as the different kinds of cutting inserts, the workpiece material, changes in the cutting conditions, changes in the PLC programming, different mechanized zones of the workpiece and the layout of the tool.

Among the different alternatives for making the segmentation of the electrical power consumption signals, the use of auxiliary signals not directly affected by the machining, such as, for example, the sampled speed reference of the machining cycle, or its acceleration, ensures a reliable segmentation avoiding false alarms in the detection of a fault in the tool.

Once the different signal segments are extracted, the next step is to obtain the model for every segment that should be sensitive to electrical power consumption changes caused by a

fault in the tool. Another goal of this step is to reduce the amount of information used in the following steps of the diagnosis scheme. There are different methods available to make such reduction (Reñones, Rodríguez & Miguel, 2009). Among them, the calculation of statistical parameters is a straightforward reduction of information. Only those which presented a greater sensitivity to the variations produced by the failures in the tool must be chosen in order to reduce the amount of data for detection of failures in each group of the tool. With the appropriate statistical parameters chosen, the change detection problem can be stated as the detection of a change in a set of random variables. The change detection is usually carried out using a so called *stopping rule*, as presented in (1); that is, a function of the random variables y_k that exceed a preset threshold λ in case of abrupt change. The parameter t_a represents the estimated time of change at which the stopping rule is true for the first time (Basseville & Nikiforov, 1993).

$$t_a = \inf\left\{n : g_n(y_1, \ldots, y_n) \geq \lambda\right\} \tag{1}$$

This problem is frequently solved from a statistical point of view. In Fig.3 an example of abrupt change that must be detected can be seen. The following requirements must be taken into account to solve this change detection problem:

- The segmentations or electrical power consumption trends are non-stationary, so an adaptive detection scheme is needed.
- The changes must be reliably detected, and the false alarms due to occasional electrical power consumption changes must be avoided.
- A mean time between false alarms (MTFA) must be fixed.
- The change detection must be fast enough to avoid serious damage to the whole tool and machine.
- The changes can be abrupt decreases (in case of breakage) but also abrupt increases due to the loss of an insert or an abnormal wear rate caused by the breakage of previous inserts.

Among the different alternatives that can be used to detect abrupt changes (Reñones, Miguel & Perán, 2009), the algorithm based on an adaptive local linear model of electrical power consumption showed the best performance in terms of reliability, and an extremely low computational cost. The algorithm is based on the detection of linear regression outliers. In the present case, the outliers are recorded points with an electrical power consumption out of normal variation due to a breakage (abrupt decrease) or abnormal wear rate (abrupt increase).

Due to the fact that the evolution of the electrical power consumption trends are not linear as the wear increases, this detection scheme must be implemented using a moving data window, let's say of size L.

The outlier detection algorithm is done through the calculation of statistical parameter t_i defined in (2). This statistical parameter follows a Student's t-distribution. Under no fault in the tool and hence no change in the electrical power consumption, the residuals t_i should remain in the interval $\pm t(1 - \alpha/(2L), L - 3)$ of confidence α. These bounds of the interval are also known as the critical level or threshold.

$$t_i = \frac{e_i}{\hat{S}_{R(i)}\sqrt{1 - v_{ii}}} \tag{2}$$

In order to adjust the algorithm in an optimal way, some performance measures must be done and it must be taken into account the variation range of the different parameters for the algorithm (window size L and the critical level or threshold). To make the detection robust, an additional parameter can be added, such as the amount of consecutive detected outliers.

In quality control this is called a *run test*. In fact, this robust mechanism is not particular to this detection scheme and can be applied to other detection algorithms.

In order to optimally adjust the parameters of the detection change algorithm, performance measures must be done, such as (Gusstafson, 2000): MTFA (Mean Time between False Alarms), MTD (Mean Time to Detection) and, MDR (Missed Detection Rate).

The optimal algorithm adjustment is performed by fixing either the performance measure MTFA or MTD, and the parameters of the algorithm are chosen to minimize the other performance measures. The presented algorithm have been evaluated with data coming from the machining of more than 30000 workpieces. As the exploration of the whole range of parameters for the change detection algorithm is unapproachable, some restrictions and assumptions were added to cope with the problem. For the window size L, it seems reasonable to choose a value lower than the mean time between faults. For the test set used, it is approximately 300 workpieces, then the interval for this parameter was set as [40,100] workpieces.

The *run test*, represented as R, influences the speed of detection. After studying historical data and taking into account the protection of the tool, an interval of [2,6] workpieces seems reasonable. The threshold interval was [2,7] and for the residuals was fixed as an interval with a confidence level from 0.1 to 0.001. Two tests have been done to study the relationship between the different parameters, where the threshold is varied in the preset interval and the other two parameters are fixed at the midpoint of their own interval.

In Fig. 4 is presented an example of such performance measures. Detailed analysis of these graphics can be found in (Reñones, Miguel & Perán, 2009). It is straightforward to see that an increase in the threshold (horizontal axis of the graphics) leads to a more reliable detection (higher MTFA) but fewer faults are detected as shown in the third row of graphics. This exploration of parameters influence let to finally make an optimal adjustment in the parameters for the change detection in the different electrical power consumption trends for the different zones of the multitooth tool.

The result of this step is a list of thresholds for every zone of the tool. Positive thresholds can be adjusted to detect abrupt increases of the electrical power consumption due to an abnormal wear rate (called as overload), and also abrupt decreases due to a breakage of one or more inserts in the tool.

3.1.3 Decision making process for the machine tool diagnosis

The last step of the methodology used to detect faults in the multitooth tool is the so-called *Decision-making* process as presented in section 2. In this step, using the information coming from the change detection algorithm and other information of the state of the system, an effective declaration of the fault in some zone in the tool is done. That means, for example, that the machine tool will be stopped at the end of the current cutting cycle, and the operator will fix the problem based on the information of the diagnosis system: the faulty zone of the tool and the type of fault (overload or breakage).

The electrical power consumption signal gives the best signal-to-noise ratio to detect faults, as was presented in section 3.1.1. On the other hand, this signal exhibits sensitivity (abrupt changes in the signal) to other phenomena that may cause false alarms which must
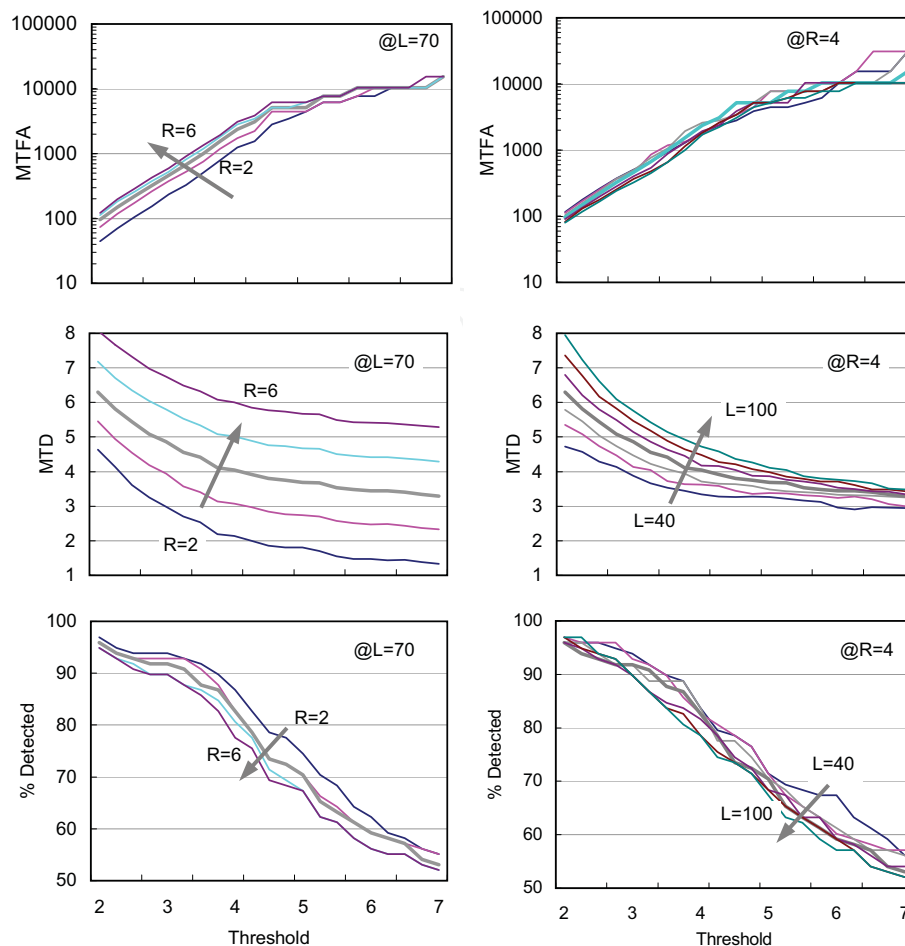
Fig. 4. Performance measures for the linear regression change detection algorithm with
parameters: $L \in [40,100]$, $R \in [2,6]$ and $\lambda \in [2,7]$.

be taken into account, such as a tool changed by a new one, changes in the material of the
workpieces (foundry or steel), compensation adjustments in the inserts made by the
operators to achieve the desired tolerances, the warm up process after a long stop, etc. To
prevent false alarms caused by any of these events, it is necessary to protect or disable the
change detection algorithm. Protective measures that can be taken to avoid false alarms are
to use output signals from the PLC governing the machine tool (new tool, material change,
etc), or to inhibit change detection when changes affect the whole recorded signal or there
are sample points separated too much time.

3.2 Case study 2: Car painting cabinet

This case study shows a predictive maintenance system currently operating in an assembly
car factory, specifically in painting cabinets section. It has been working for thirteen years
now and serves as a valuable tool for anticipating to breakdowns all along the plant,
optimizing equipment performance and reducing unplanned shutdowns and incidents. This
predictive maintenance system is based on mechanical vibrations analysis techniques
applied on the motor-fan sets operating in painting cabinets.

The predictive maintenance for this kind of installations can be performed in two ways.
With online analysis systems or with hand-held, walk-around vibration analyzers. For

extremely large operations and/or very expensive equipment, the first approach is the most cost effective and has repeatedly shown to saving money.

The main advantage of an on-line dynamic vibration monitoring system is that the data acquisition is made continuously. This allows to check past values and to know the evolution of the state of the machine, providing a more reliable diagnosis that off-line data acquisition systems cannot offer. Most of the on-line systems use some kind of acquisition system architecture that involves input channels multiplexing many vibration sensors. This results in a scan rate that varies according to the system scheduler. Another advantage to an on-line dynamic vibration monitoring system is that there is no labour cost to acquiring the data and minimal labour cost for identifying machine faults.

The disadvantages of these systems are that they are the more costly systems to implement and maintain as they include maintaining a full time vibration analyst, and installing a wired network to get the signals from the sensor to the analysis system. Furthermore, the software and hardware that make up the system typically require an extensive maintenance contract as well.

Hand-held, walk around vibration analyzers only provide trending information to identify that a potential problem exists, and do not provide the detailed information necessary to determine the cause of the problem. The supervision is done only at specific moments and it does not provide a trend of vibration levels. Moreover, they require skilled vibration analysts to interpret the data and, without continuous monitoring, problems in between rounds could be costly.

3.2.1 Problem description

The plant under study consists of a series of motor–fans that keep painting cabinets under very strict temperature and humid conditions. In some cases air must be put into these cabinets and in some others air is taken out of them. The target is to keep working atmosphere under control in such a way that safety and sanitary conditions are guaranteed for the staff. Moreover, in order to achieve a good production quality, it is required that air inside the cabinets is at the right temperature, filtered and keeping an adequate relative humidity that prevents varnish thinners from evaporation. It is also necessary to extract the air from the cabinet, in order to eliminate polluting elements.

For each motor-fan the fan is driven by an electric drive whose rotation movement is transmitted to the fan through a couple of pulleys, one attached to the fan and the other one to the drive, together with a belt. Both the electric drive and fan are mounted on an elastic structure that keeps the set isolated from the high frequency excitations of the structure and at the same time, this base structure is not affected by the mechanical vibrations coming from the electric drive and fan.

This assembly plant is able to produce around 1.200 cars every day along three shifts, depending on demand needs. To achieve this, it is mandatory to ensure that every machine is working under optimal conditions avoiding unexpected breakdowns which could lead to stops and subsequent lost of production. Therefore, a predictive maintenance system is needed. A thorough analysis of the related machines has led us to consider the following sources of mechanical vibration that could be the cause of potential failures:

1. Defect related mechanical vibrations: Unbalance, misalignment, looseness, defects in bearings, blade breakage and defects in belts.
2. Mechanical vibrations related to natural frequencies: Natural frequencies of the base structure, natural frequencies from any part of the machine structure and natural frequencies from other elements outside the machine.

3.2.2 Predictive maintenance system

The system consists of an industrial computer in charge of data acquisition, communication protocols and the calculation of spectra and alarms (DCS station in Fig. 5) to which up to four nodes are connected through a LAN. They are multiplexors and receive signals from accelerometers placed on the machines. Analysis and diagnosis tasks are carried out by means of a PC (MD station). This PC has a communication module that allows remote access to the data, so that it is possible to perform the same tasks from a remote computer, outside the factory. Fig. 5 shows the layout just described.
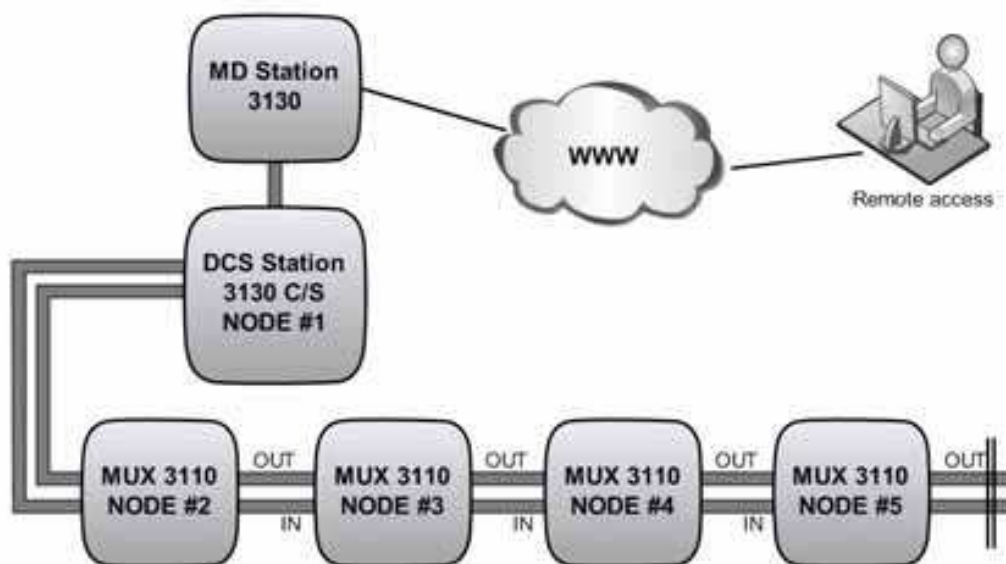

Fig. 5. Predictive maintenance system schema

In each motor-fan two accelerometers have been placed to register mechanical vibrations from the electric drive and the fan, which is the most sensitive part to be monitored in this case. The related bandwidth is 20 kHz, which is enough for the application under study. They have been placed in radial position, as close as possible to the bearings near the pulleys.

The signals from the accelerometers reach one of the four multiplexors (nodes from Fig. 5) inside which they are displayed along 32 channels, and finally get to the industrial computer where they are registered and sent to the PC for further analysis. As soon as an abnormal value is detected, an alarm shows up on the screen so that subsequent actions can be taken in order to solve the problem arising. This scheme is the same for every motor-fan being monitored.

The system is automatically registering data on a daily basis. At the same time, mechanical vibration levels, process variables and alarm levels are being checked for the plant.

It is possible to register three kinds of data: gross scan, spectrum and time signal:

Gross Scan: These data constitute a unique signal taken from a DC stationary signal o calculated from an AC dynamic signal, as for example, a RMS one.

The gross scan measurement from each sensor is compared to a reference value that serves as an alert. After this, the measurement is used to update the related maximum and minimum values that will be finally registered in the database. Whenever any gross scan measurement exceeds the alert value, it is first registered in the database, then it is updated for the DCS, and finally, the related spectrum and time signal are recorded as alarm related data for the specific sensor.

Spectrum: They are calculated from a related time signal and further processed in order to get specific information at certain frequencies associated with the potential defects of the machine being monitored. In this case, this is done through what we call Analysis Parameters Set (APS). Gross scan data are registered for every signal once per each data registered cycle. Spectrum data are recorded for one or two signals once per each data acquisition cycle and time signals are registered simultaneously to the spectra.

Time signal: This software allows the user to visualise data in the time domain, which can be very useful is specific situations, though no further analysis is being performed in the case under study.

The system allows to define up to 12 parameters directly related to the frequencies or selected ranges of them that are of interest in order to characterize (detect) certain types of machine failures. There are many possibilities to choose different types of Analysis Parameter Sets and the most widely used are briefly described next:

Total Energy: This value represents all of the energy of a signal. Because of the nature of the FFT, the first two points of the spectrum are excluded from this summation.

Energy within a Frequency Range: The energy between the two specified points of a spectrum will be summed.

Non-Synchronous Energy within a Frequency Range: The energy between the two specified points, which is not an integer multiple of turning speed, is summed.

Synchronous Energy within a Frequency Range: The energy between the two specified points, which is an integer multiple of turning speed, is summed.

Synchronous Peak: The signal is synchronously sampled to determine the energy at harmonic of running speed. In order to use this parameter, the sensor must have a tach pulse defined for it.

HFD (5k-20kHz) High Frequency Detection: An additional collection of vibration data is made from which the energy from 5.000 Hz to 20.000 Hz is computed. HFD sometimes useful in detecting bearing faults at an early stage.

RPM: This field displays the RPM for this sensor. A good way to ensure that the tachometer definition is set up correctly and the RPM ratio is correct is to compare the reported RPM with the expected value.

3.2.3 Practical example

Next, an example of a fault is showed. In this case, a progressive defect in the fan bearings has been detected. As soon as the pre-alarm level is reached all the related parameters are supervised, and once the system indicates the alarm level has been exceeded, the faulty bearings are replaced. This kind of fault is best detected using the energy within a frequency range parameter. For this kind of defect several frequency ranges have been selected in order to assess the degree of severity of the fault. When a bearing defect is first detected (just within a unique frequency range), the machine will still be able to work under acceptable conditions long before it is advisable to replace the damaged bearings. Therefore, when some ranges are affected simultaneously the fault is considered severe enough so as to recommend the replacement of the faulty pieces. Fig. 6 shows the trend followed by mechanical vibrations for five related consecutive frequency ranges. They all have the same performance, giving precise information on the very moment when the failure first appeared. Then, it became more and more important until the alarm level was reached, and finally it can be seen the level of vibration once the faulty bearings were replaced by means of a planned intervention, not affecting production by any means.
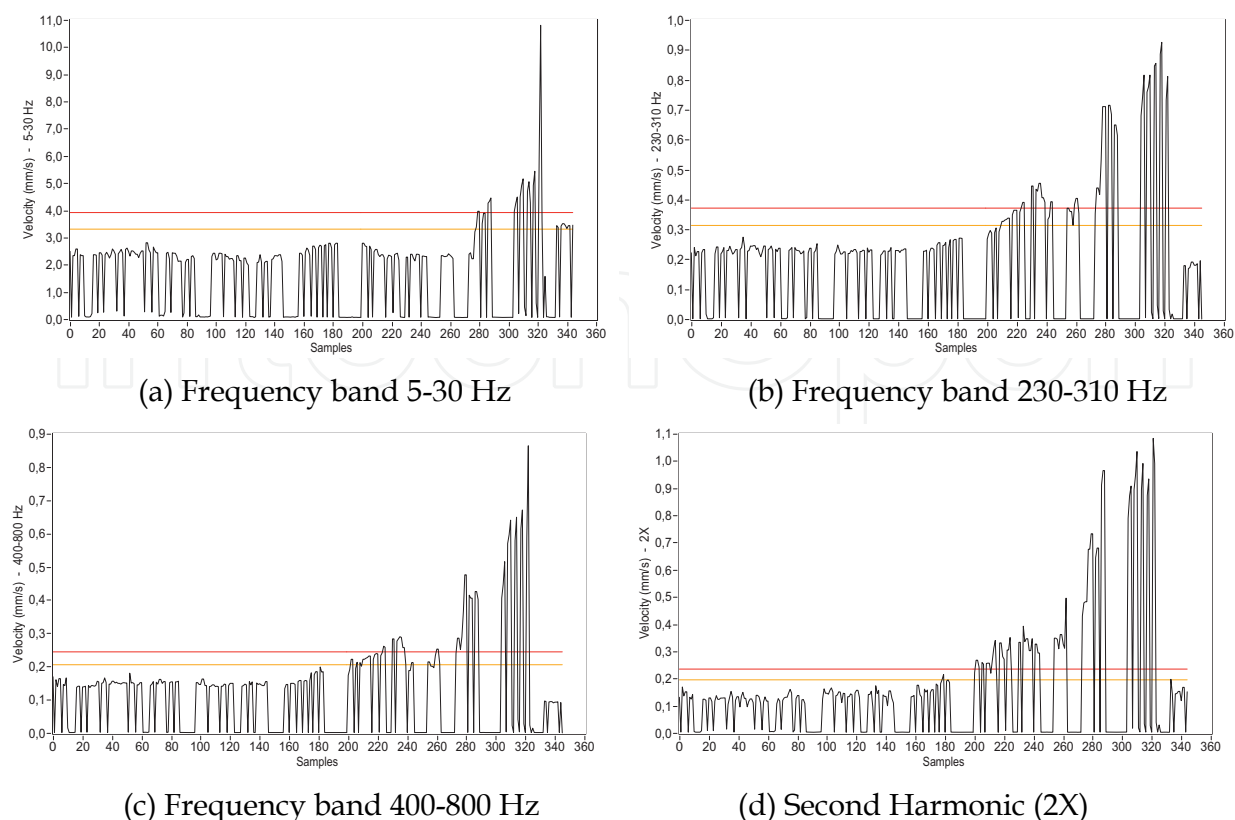
(a) Frequency band 5-30 Hz

(b) Frequency band 230-310 Hz

(c) Frequency band 400-800 Hz

(d) Second Harmonic (2X)

Fig. 6. Fault detected in the bearings of the fan

3.3 Case study 3: Electric motors diagnosis in non-stationary processes
3.3.1 Predictive maintenance of electrical motors

Electrical motors are one of the most crucial components of production, and many of them are of vital importance for factories to be operational. For this reason a great number of diagnosis methods have been developed during years in order to detect motor faults. Some of this methods can only be applied off-line because the motor needs to be disconnected and isolated. This is the case of hipot analysis, partial discharges, isolation test or surge comparison testing. These are well-known techniques in the field of maintenance of electrical motors and are widely used in industry, especially for high power machines. There are another group of techniques that can be used on-line such as thermography or vibration and spectral current analysis. All of them can be considered as predictive methods because allow to detect incipient faults and predict the time until a critical fault is declared. The problem with the off-line methods is that a fault can produce damages in the system before it is detected. This happens when its evolution is faster than the period between analysis. On the other hand, spectral analysis methods (current and vibration) allow on-line detection of mechanical faults besides electrical ones. Bearings faults, mechanical unbalance, eccentricity, windings or coils short-circuits and electrical unbalance are the faults than can be diagnosed using vibration or current spectrum. To obtain good results with these methods it is important to have the adequate precision in the analized spectrum, what is related mainly with the data acquisition rate, acquisition time and speed variation. Though there exist processing techniques to use spectral analysis in case of speed variation, they require the use of an encoder and have a limit in speed variation.

In this section, two industrial applications will be presented:
- Diagnosis of DC motors of stamping presses
- Diagnosis of master-slave synchronized AC motors in metal cutting machine

In both cases it will be explained why it is not possible to use any of the previous detailed methods and how other fault detection techniques can be used instead. It is intended to show the application in the industry of methods validated in laboratory and widely present in scientific literature.

3.3.2 Diagnosis of DC motors of stamping presses

Stamping presses are machines used for metal processing with an important role in the automotive industry. They usually work forming a line of stamping presses in which the piece of metal is sequentially processed along it to acquire its final shape. The movement of the press punch is generated with an electrical motor and transmitted trough several gears that transform the rotation of the motor in a lineal displacement of the punch with the appropriate speed and force to process the metal. The high power of the motor makes that in many cases, specially in old machines, it be a DC motor. In these cases it is not possible to apply current spectral analysis because fault frequencies appear as side bands of the fundamental frequency of the AC motor. Vibration analysis could be used to diagnose faults in bearings or other mechanical faults but electrical faults need another diagnosis method.

In this case a model–based diagnosis system were used to detect faults in motor windings. Model-based diagnosis uses the differences between the real system and a model of it to detect possible faults and locate their origin. Since it was first proposed by (Chow & Willsky, 1984), model–based diagnosis has been object of a great number of publications. Many theoretical and practical studies have been carried out along these years, but it is not easy to find it in the industry. The main reason for this is the complexity of most systems and machines and the difficulty to obtain a model that represents them in all the operating conditions. Multiple techniques and solutions have been proposed to solve non-linearity problems or model uncertainties. The advantage of applying model-based diagnosis to a DC motor is that it has a well-known linear model. In this case the difficulty is the identification of the model, because in an industrial environment it is not easy to develop all the required experiments and only production data were available.

The motor model is defined using two electrical equations, one for field winding and another for armature winding:

$$U_f = R_f \cdot i_f + L_f \frac{di_f}{dt} \tag{3}$$

$$U_a = E + R_a \cdot i_a + L_a \frac{di_a}{dt} \tag{4}$$

being U the source voltage, i the current through the winding, R the winding resistance and L its inductance. Subscripts f and a refers to field and armature windings respectively. Finally, E is the electromotive force and it is proportional to the field current and motor speed ω:

$$E = K \cdot \omega \cdot i_f \tag{5}$$

Identifying a closed–loop system is difficult due to correlation between inputs and outputs what makes impossible to use some of the usual identification methods of linear systems. In this case, the armature and field source voltage are generated with a controlled rectifier so the feedback between output (speed) and input (voltage) is made controlling the firing angle. This means that during the period between commutations of the power electronic switches an RL circuit is established and it can be seen as an open–loop system between voltage and current. Fig. 7 shows measured voltage and current for field and armature windings. Induced voltage E can be easily calculated because it is the value of armature voltage when current armature is zero. From Equation 5, K can be obtained using measured field current and speed. The identification of R and L in each of the windings is made considering intervals of operation when a RL circuit between voltage and current can be assumed. In these intervals the relation between output (current) and input (voltage) is a first order system that can be easily identified calculating the attenuation and lag between signals. A mean of all the values of R and L is obtained as DC motor parameters. For parameter armature identification only data with $i_a > 0$ is used. In the case of field winding the continuity in i_f allows to use all the acquired data for identification. Parameter values are those showed in Table 1.
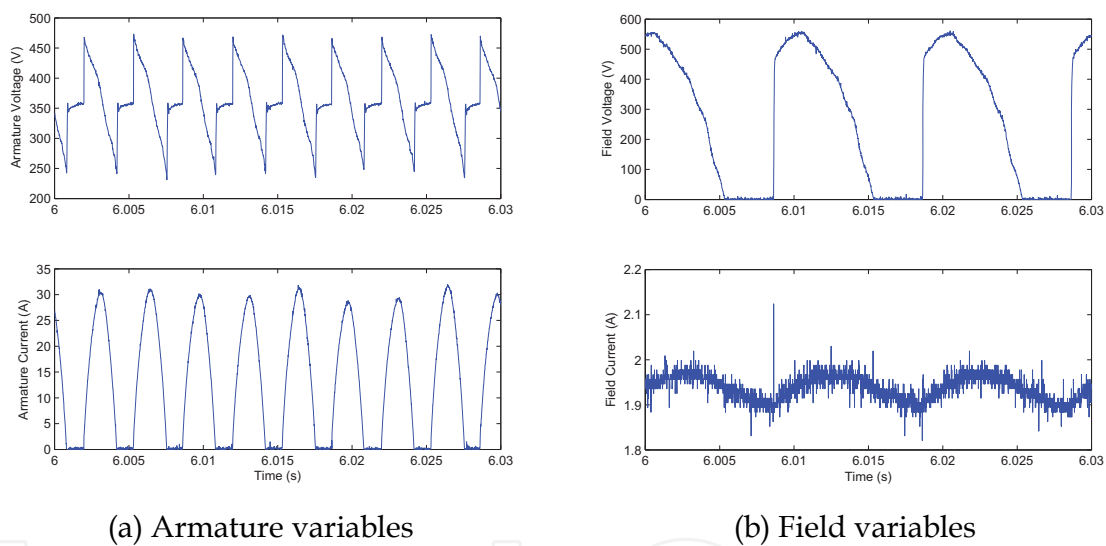

| (a) Armature variables | (b) Field variables |

Fig. 7. Identification data for DC motor

R_a	0.425Ω
L_a	0.00233 H
R_f	138.67Ω
L_f	27.57H
K	1.358

Table 1. DC motor parameters

Using the identified model it is possible to define two equations, called residuals, that take a value different from zero when a variation in the model happens. This two equations are:

$$r_1 = U_f - R_f \cdot i_f - L_f \frac{di_f}{dt} \tag{6}$$

$$r_2 = U_a - K \cdot \omega \cdot i_f - R_a \cdot i_a - L_a \frac{di_a}{dt} \tag{7}$$

The system could have been completed with the mechanical equation of the motor including ω as a variable. As only electrical faults are going to be studied, it is assumed that there will be no faults in the encoder. The considered faults are:

- Brushes faults: can be modelled as a decrease in the armature voltage source respect the measured voltage
- Armature winding short-circuit: this can be turn-to-turn or commutator bar-to-bar faults. In both cases RL circuit change its parameters
- Field winding shot-circuit: also a change in RL circuit is the result of the fault
- Fault in armature voltage rectifier: one of the power switches fails and remains opened
- Fault in field voltage rectifier: one of the power switches fails and remains opened

These five faults have been simulated using the identified model of the motor fed with a controlled rectifier in each of the circuits. The simulation allows to observe how the residuals change with each of the faults. Six and seven intervals have been defined for the values of r_1 and r_2 respectively. The limits of intervals have been fixed using simulation results allowing the use of this two residuals as directional residuals to isolate four type of faults. This is shown in Fig. 8.

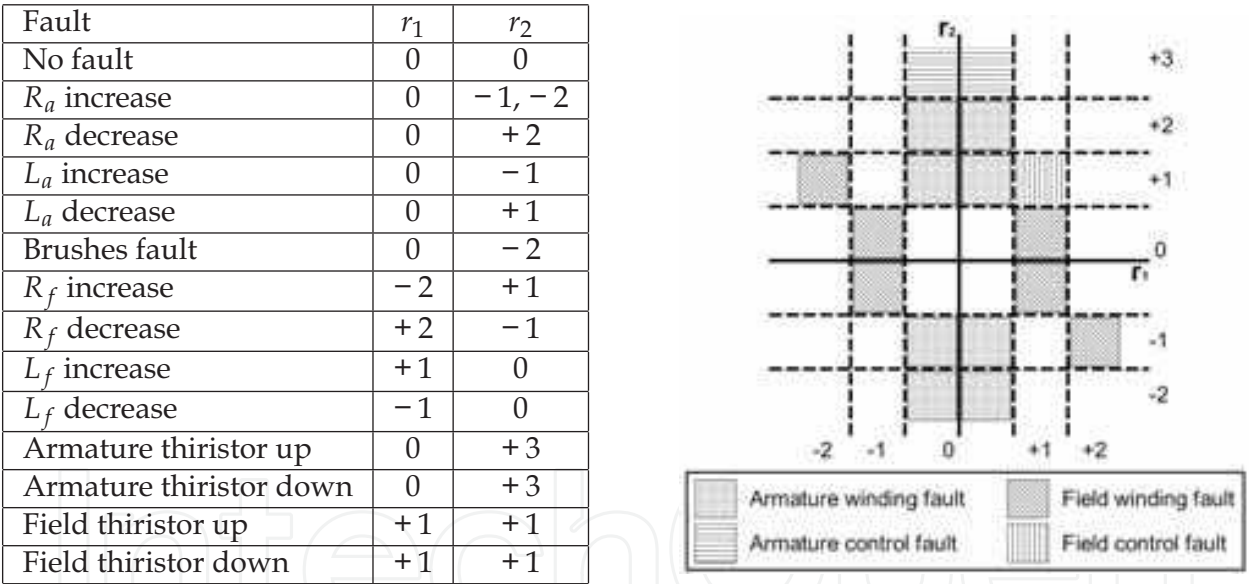| Fault	r_1	r_2
No fault	0	0
R_a increase	0	$-1, -2$
R_a decrease	0	$+2$
L_a increase	0	-1
L_a decrease	0	$+1$
Brushes fault	0	-2
R_f increase	-2	$+1$
R_f decrease	$+2$	-1
L_f increase	$+1$	0
L_f decrease	-1	0
Armature thiristor up	0	$+3$
Armature thiristor down	0	$+3$
Field thiristor up	$+1$	$+1$
Field thiristor down	$+1$	$+1$

Fig. 8. Structural residuals for DC motor diagnosis

A DC motor diagnosis system was also presented in (Isermann, 2006) using different approaches. Four structured residuals were defined to identify and isolate sensor and motor faults. The limitations in the system identification are the main difference between both case studies. So a different identification method has been proposed in this case and only two residuals have been included in the diagnosis system. This imply that sensor faults cannot be considered.

3.3.3 Diagnosis of AC motors using space current vector

In the case of AC motors, the use of a model-based diagnosis method is more difficult due to non-linearities. But other signal analysis techniques can substitute current spectral analysis

when this cannot be used. Next example studies an AC motor in a cutting machine where speed variation is so high in such a short time that Fast Fourier Transform (FFT) cannot differentiate spectrum lines for fault detection. The cutting machine has two tilting knifes (one at the bottom and one at the top of the machine) that allow cutting trapezoidal pieces alternating between two angles of the knife. The reference position must be reached in one or two seconds. In this time both knifes must change their speed form zero to maximum speed and to zero again. Each knife is moved with an AC motor that are known as master and slave. The knifes are mechanically joined so the motors must be synchronized and generate always the same torque to avoid problems in the mechanical joint. Master motor receive the speed reference that makes possible to achieve the required angle in the specified time. This speed reference is prefixed as a function of the rotating angle and line speed (time to achieve the required angle), but there is no feedback of the knife angle during the movement. The controller of the master motor generates a torque reference -equal to the torque it is producing- that is used in the control of the slave motor. If the torque of both motors is not the same, it will originate medium-term mechanical faults. But the most obvious problem will be the oscillation in the knife control and the uncertainties in the cutting angle that this imply.

To detect problems in the motor windings or in the inverter that controls the motors, current space vector analysis is used. Space vector is constructed from the three phase currents using the next equation:

$$\bar{i}_S = \frac{2}{3}(i_R + a \cdot i_S + a^2 \cdot i_T) \tag{8}$$

being $a = e^{j \cdot \frac{2\pi}{3}}$. The result is a rotating vector that for a balanced system has a constant modulus equal to the amplitude of the current of each phase and whose rotating frequency is the frequency of the currents. When an electrical fault occurs in any of the windings it will produce an electrical unbalance whose effect is that current space vector will not be centered in origin or will loose constant modulus. The fault can be detected using the spectral analysis of the space vector modulus (Cardoso et al., 1999; Acosta et al., 2006) or pattern recognition of the space vector representation during one or several cycles (Nejjari & Benbouzid, 2000; Diallo et al., 2005).

Fig. 9(a) shows a capture of the master and slave motor angle during 50 seconds of cutting process. In Fig. 9(b) a detail of the negative angles can be seen. This difference between angles is a repetitive pattern during the production of this type of piece. To find the origin of this problem current space vector is analized during the movement of the knife at $t = 240s$ and $t = 280s$. Fig. 10(a) and 10(b) presents the three currents of master motor in each of the cases, Fig. 10(c) and 10(d) the current space vectors and Fig. 10(e) its modulus. As the desired movement of the knife is always the same (constant time and angle references) it is expected that the control actions were identical for every piece. This means that current consumption pattern during the movement of the knife should be repeated continuously. Two points have been selected along this movement to compare current space vector. These are noted as points C and D in Fig. 10(c), 10(d) and 10(e). Points A and B are the start and end of the movement in both cases. It can be seen that when the reference point is at the left side of the plane, the modulus of the current space vector is higher that when it is at the right side. This imply that for the same reference, the generated current and then the generated torque are different. The problem is that the expected torque in both cases is the

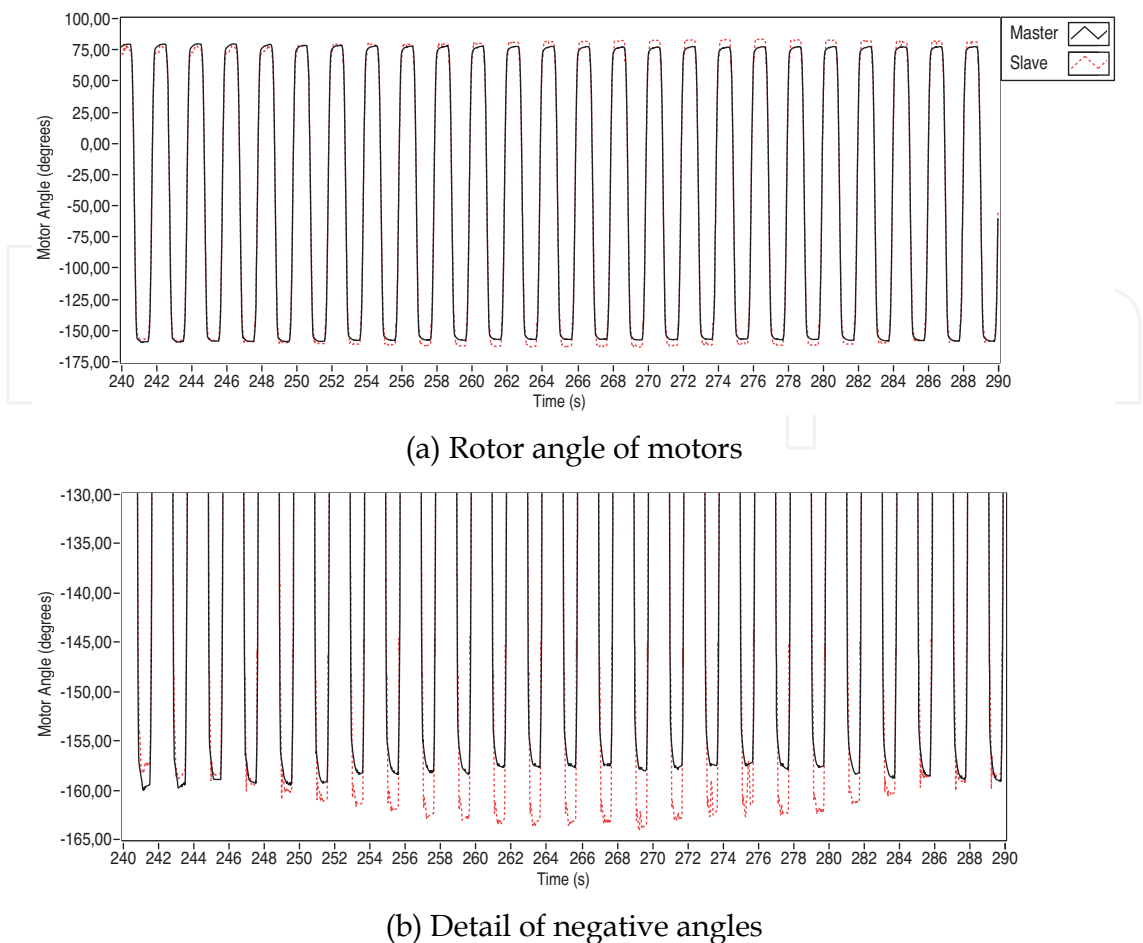(a) Rotor angle of motors

(b) Detail of negative angles

Fig. 9. Master and slave angle for 25 pieces production

same but not the actual torque. That is why the difference between master and slave angles varies along time depending on the origin and final point of the current space vector.

The detected fault is caused by the unbalance of the electric circuit that can be caused by a fault in the motor windings or in the voltage source inverter. The other possible cause that is a fault in the current sensor is rejected because the sum of the three currents is zero. To identify the origin of the fault it would be necessary to find a constant speed and constant torque operation of the motor and then compare the pattern of the current space vector with known fault patterns.

An example of operation with constant torque can be seen in Fig. 11 where it is constant during almost a cycle of the current signal. The current space vector (Fig. 11(d)) is again displaced to the left side of the plane.

Taking into account all the data shown, it can be concluded that the origin of the fault is located in the voltage source inverter. Probably the actual duty cycle of one of the switching devices is slightly different to the desired, what makes that the voltage generated is not balanced.

Looking at this example it can be understood that the main challenge to use current space vector for diagnosis is the automation of the method that could allow using it without expert supervision. If the process under research would be stationary, the task will be only a pattern recognition problem. In a case like the showed tilting knife, the pattern recognition should also have into account the torque variation.
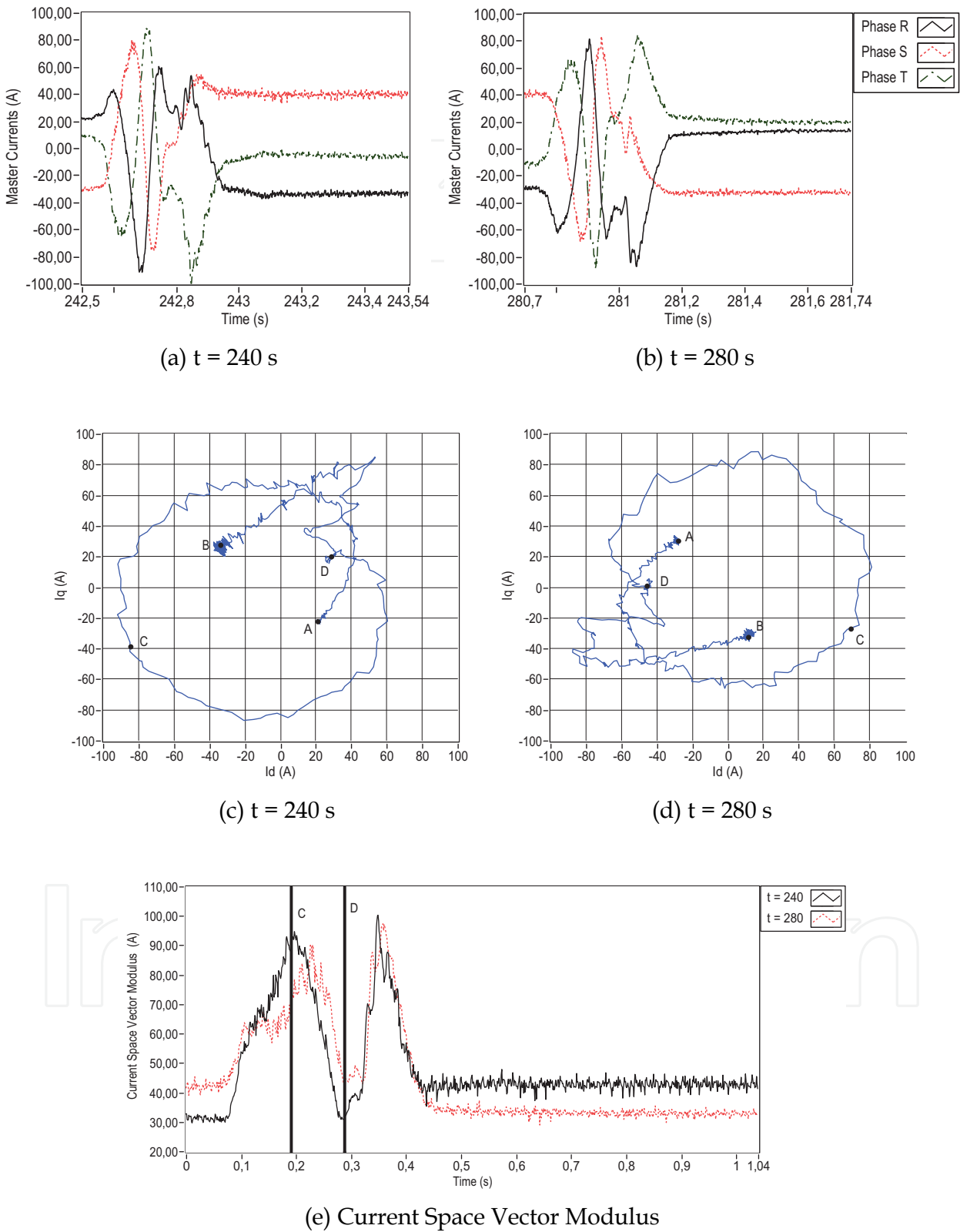
(a) t = 240 s

(b) t = 280 s

(c) t = 240 s

(d) t = 280 s

(e) Current Space Vector Modulus

Fig. 10. Current Space Vector Analysis of master motor at different times

(a) Three phase currents of master motor

(b) Current Space Vector modulus

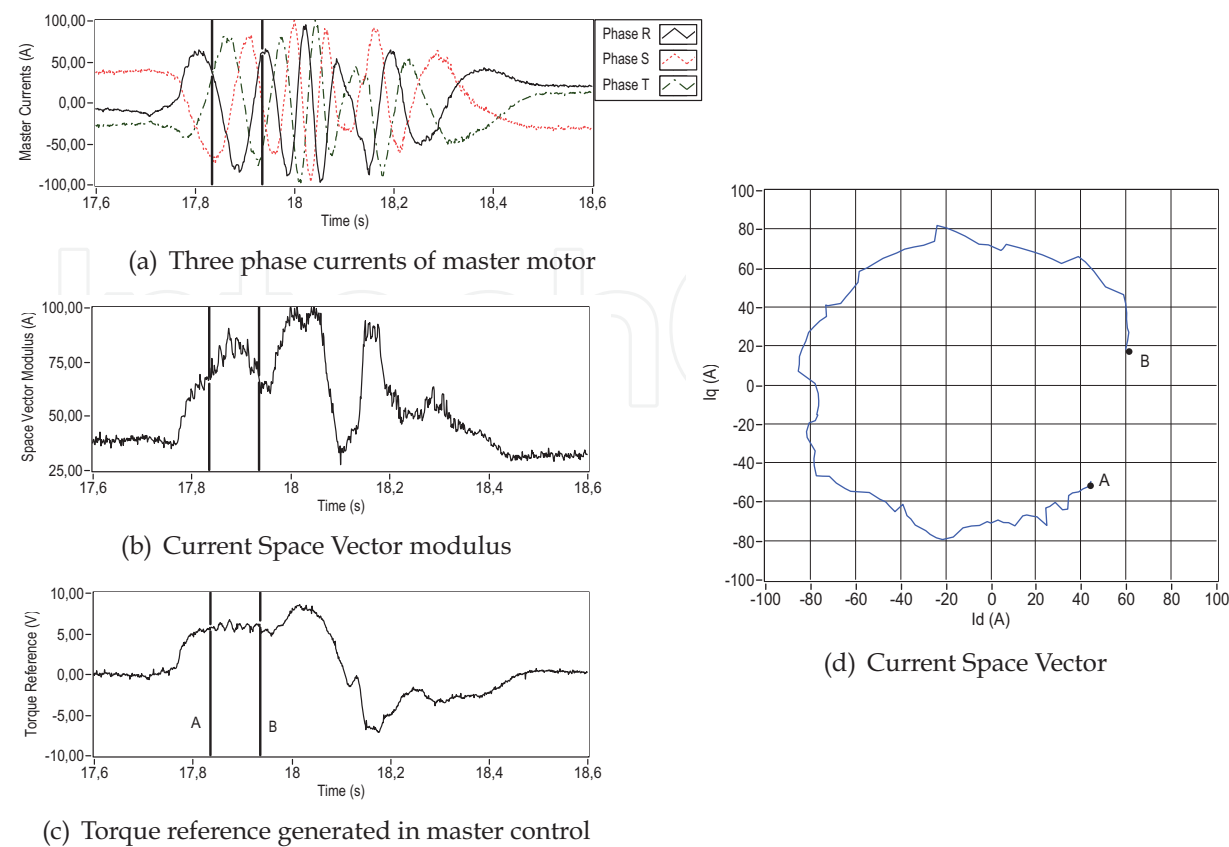(c) Torque reference generated in master control

(d) Current Space Vector

Fig. 11. Example of constant torque reference

3.4 Case Study 4: Laser welding defect detection

In this section, two approaches to the problem of defect detection in laser welding are presented. The first is based on analyzing the signal generated by a photodiode in both the time and frequency domain. The second consists of relating variations in the plasma electron temperature with weld quality.

The methods presented have been tested in an industrial facility under real production conditions, exposing them to conditions more requiring than those found in laboratory experimentation. Detailed description can be found in (Saludes et al., 2010).

3.4.1 Problem description

Laser welding is used to weld the tailored welded blanks due to its advantages: a high processing speed, flexibility, low heat input and ease of automation. However, it is possible that some defects could appear in a laser welded seam that can also appear in seams welded using other techniques.

The defects that have to be detected are lack of penetration, pores, inner pores, holes and drop–outs.

The methods described here have been tested on an industrial facility equipped with a Trumpf Turbo 8000 CO_2 laser with output power of up to $8000W$ and operated in a continuous–wave regime. The installation is completely automated and capable of welding up to 20,000 seams a day.

The specimens welded in this installation were galvanized steel sheets whose thicknesses were different and, in both cases, less than 1 mm. Taking into account the sheets thickness and

according to (ISO, 1997), the minimum size of the defects is 200 μm. Beam–on–plate welding was carried out at a power ranging from 6 to 8 kW. The welding head displacement speed was between 6 and 10 m/min. The shielding gas used was Helium at a flow rate of 40 l/min.

3.4.2 Radiation based methods

Two 1.5 mm diameter optical fiber EH 4001 type were used to collect and transmit the plasma–emitted and melted–emitted radiation to two different photodiodes. The first was a Siemens SFH203FA IR sensor, sensitive to the 800–1100 nm range, intended to detect variations in the shape of the pool of molten material. The second was a Centronic OSD5,8-7 Q UV and visible light detector, sensitive to the range 200–1100 nm. The signals generated were amplified by means of two Femto LCA-400K-10M amplifiers. A National Instruments PCI 6034E data acquisition board was used to measure and collect data using a PC with a sampling frequency of 10000 Hz. The detectors' visual line was 25° above horizontal.

3.4.2.1 Time domain method

As the measured radiation is related to the melting of the welded metals, it is expected that defects in the welding process will produce changes in the signal to be analyzed. If the width and depth of the keyhole is constant, and the laser power is also constant, the quantity of melted metal at each point will be the same and the radiation produced will be constant throughout the process. In the case of a lack of penetration or porosity occurs at any point of the seam, the radiation will instantaneously decrease.

Defect detection will be based on the idea that the changes in the signals generated by the photodiodes are related to the defects. Thus, the location of changes in the signals can lead to defect detection. This issue can be included in what is called detection of abrupt changes (Basseville & Nikiforov, 1993b).

The algorithm used in this case is a CUSUM RLS adaptive filter that combines an adaptive least squares (LS) filter with a CUSUM test for change detection (Gusstafson, 2000).

The time domain fault detection method is intended for finding small defects that can be present in the seam. These faults are typically holes, both trespassing and not trespassing, with sizes ranging from 0.5 mm to 2 mm.

In order to simulate such kinds of defects, small scrapes have been removed from the edge of the thinnest of the workpieces to be welded. These scrapes have been done in such a way that they are not visible when the workpiece is looked at from above, i.e., from the side the laser hits the workpiece. Then, the workpieces have been welded under normal conditions. Afterwards, visual inspection has been carried out. Finally, the visual inspection findings have been compared to the ones obtained through the time–domain algorithm. The ratio of detected holes versus induced holes is 55.1% and the ratio of false alarms is 2.04%. The detected holes ratio seems to be very low but this can be explained by considering how the detection algorithm works. As it is based on a polynomial fit of the signal, to decide if a signal change is a fault or not, the number of valleys in the signal corresponding to holes will affect the threshold used. So the presence of various defects with great changes in the same signal can move the polynomial to a limit for which small holes with low changes do not overpass. If the number of seams with some hole detected is counted instead of every detected hole, the ratio of faulty seams detected is 100% and the false alarm ratio is 0%.

3.4.2.2 Frequency domain method

The authors found in previous work that, in the frequency domain, the signal energy decreases significantly in the case of a partial penetration fault (Rodríguez et al., 2003). Based
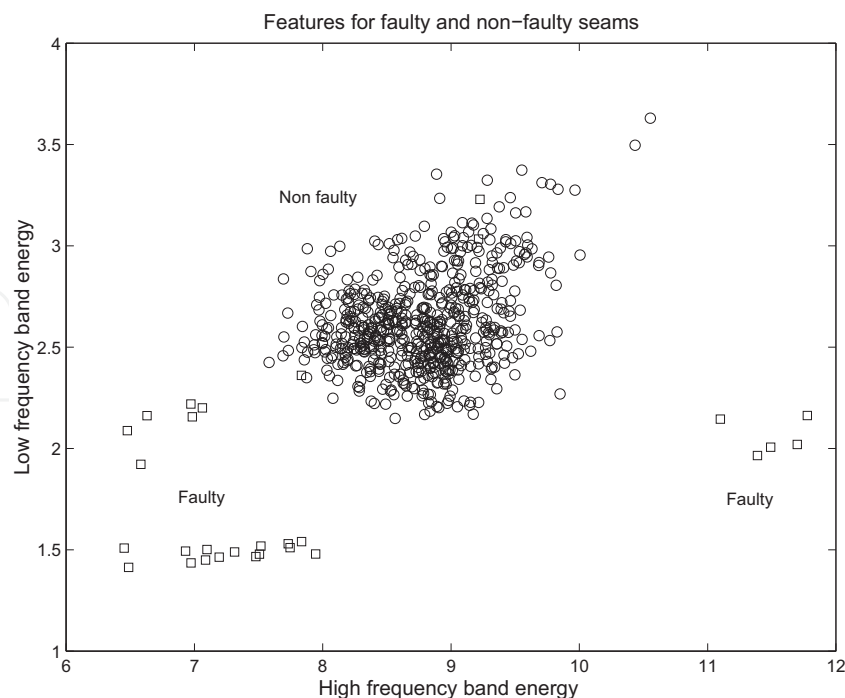
Fig. 12. Features associated to faulty and non–faulty seams

on this result, a method for detecting lack of penetration has been developed. The method comprises two parts. In the first, some features are extracted from the signals generated by both photodiodes. In the second, these features are classified by means of a multilayer perceptron neural network. The two steps are summarized below.

1. Feature extraction. The signal coming from both sensors is divided into *N* equal–size segments and the Fast Fourier Transform (FFT) is used to perform a frequency domain transformation for each segment. Then, the RMS value for four frequency bands is obtained. Also, the RMS for the whole frequency range is computed. The bands range from 500 *Hz* to 1500 *Hz* and from 4000 *Hz* to 5000 *Hz*. The features can be seen in Fig. 12. Finally, a normalization for each segment is done obtaining the relative harmonic distribution for each frequency band. After all this calculation, four parameters for each sensor and for each segment are obtained: normalized and noise-free data of RMS values for the two frequency bands, global weld RMS and global noise RMS.

2. Decision making. The extracted features are classified using a multilayer perceptron neural network (Haykin, 1999).

The results obtained show that 93.9% of the normal seams were classified as normal and 97.1% of the faulty seams were classified as faulty.

3.4.3 Plasma electron temperature based method

During laser welding, a plasma is formed inside the keyhole. The electron temperature is related to the energy of the electrons that are in the plasma. In the following sections, the estimation of the electron temperature and how to correlate it with weld quality is explained.

3.4.3.1 Electron temperature estimation

Plasma electron temperature T_e can be determined by using the Boltzmann equation (Griem, 1997), which allows the population of an excited level to be calculated by means of the equation (9):

$$N_m = \frac{N}{Z} g_m \exp\left(\frac{-E_m}{kT_e}\right) \tag{9}$$

where N_m is the population density of the excited estate m, N is the total density of the state, Z is the partition function, g_m the statistical weight, E_m the excitation energy, k the Boltzmann constant and T_e the plasma electron temperature. Equation (9) can be used when the plasma is in local thermal equilibrium (LTE), a condition that is assumed to be valid when (Griem, 1997)

$$N_e \geq 1.6 \times 10^{12} T_e^{1/2} \left(\Delta E\right)^3 \tag{10}$$

where N_e is the electronic density and ΔE is the largest energy gap in the atomic level system. Equation (10) can be determined by considering that a necessary condition for LTE is that the collision rate has to exceed the spontaneous emission by a factor of ten. The assumption of LTE implies that the different particles within the plasma have Maxwellian energy distributions.

In optically thin plasmas, the intensity of a given emission line I_{mn} induced by a transition from level m to level n, can be related to the population density of the upper level N_m through

$$I_{mn} = N_m A_{mn} h\gamma_{mn} \tag{11}$$

where A_{mn} is the transition probability, and $h\gamma_m$ is the energy of such a transition.
Combining equations (9) and (11), T_e can be obtained from the following expression:

$$\ln\left(\frac{I_{mn}\lambda_{mn}}{A_{mn}g_m}\right) = \ln\left(\frac{hcN}{Z}\right) - \frac{E_m}{kT_e} \tag{12}$$

The plot resulting from using various lines from the same atomic species in the same ionization state and representing the left–hand side of equation (12) versus E_m has a slope inversely proportional to T_e. This technique is usually referred to as a Boltzmann–plot.

3.4.3.2 Spectroscopic lines identification

There are several conditions spectral lines must fulfil in order to be valid candidates for electronic temperature estimation. Selected lines must verify that $\Delta E > kT$ on the upper energy levels to ensure they don't belong to the same multiplet. Moreover, the line must be free of self–absorption; one can prove that this condition has been fulfilled by verifying that the optical depth (Griem, 1997) τ of the plasma for the selected spectral lines is $\tau < 0.1$.

Measurements were performed during normal welding. Radiation emitted by plasma plume was gathered by means of a 3 mm diameter optic fiber. This optic fiber fed light to a high resolution Oriel MS257 spectrometer fitted with an Andor ICCD–520 camera. The spectral lines suitable for electronic temperature estimation found in this way are shown in table 2.

All the spectral lines shown in table 2 come from iron electronic transitions. The wavelength, transition probability, low level energy and its degeneration are all shown in this table. Wave- length is a measured feature, while the remainder come from the NIST (National Institute for Standards and Technology) atomic spectra database.

The spectrometer used during on–line monitoring was an Ocean Optics HR4000, fitted with a 2400 *lines/mm* diffraction grating and a 5 *μm* aperture slit. The spectrometer features a 3600 pixels CCD, a 0.05 *nm* spectral resolution and an 80 *nm* spectral range. Due to that the

λ (nm)	A_{mn} (s^{-1})	E_k (cm^{-1})	g_k
411.85	$5.80 \cdot 10^7$	53093.52	13
413.21	$1.20 \cdot 10^7$	37162.74	7
414.39	$1.50 \cdot 10^7$	36686.16	9
425.01	$2.08 \cdot 10^7$	43434.63	7
426.05	$3.20 \cdot 10^7$	42815.86	11
427.18	$2.28 \cdot 10^7$	35379.21	11
430.79	$3.40 \cdot 10^7$	35767.56	9
432.58	$5.00 \cdot 10^7$	36079.37	7
438.35	$5.00 \cdot 10^7$	34782.42	11
440.48	$2.75 \cdot 10^7$	35257.32	9
441.51	$1.19 \cdot 10^7$	35611.62	7
452.86	$5.44 \cdot 10^7$	39625.8	9

Table 2. Spectral lines associated to Fe I

device is able to take data at a rate of 200 Hz and the welding speed ranges from 6 m/min to 10 m/min, the distance travelled between spectra is two or three times the size of the smallest defect that must be detected. Since at least one spectrum must be gathered during a defect occurrence, this will be a drawback of the proposed method unless a strategy based on the synchronization of several spectrometers is adopted.

3.4.3.3 Results

The defect detection method based on electronic temperature has been tested in the industrial facility described in section 3.4.1. The conditions under which experiments were carried out are the same as those found during normal industrial production: electrical noise, mechanical vibrations and steel sheets to be welded covered by an oil film. During experiments, the laser power was set to 8000 W and welding speed was 4.5 m/s.

Experiments can be classified into two classes: Those that have been performed during normal operation and those in which defects have been forced.

Experiments carried out during normal operation are those in which the manufacturing cadence was the usual in the car factory where the experiments were done. The purpose of these experiments were twofold: to estimate the electronic temperature during normal operation and to observe its variation between seams.

The electronic temperature variation between seams can be seen in Fig. 13(a), in which the electronic temperature of 70 consecutively welded seams is shown. The electronic temperature represented is the mean value of the temperatures estimated in 180 points along each seam. Moreover, the standard deviation is also represented by means of error bars. All the welds were made with the same process parameters. Worth to be noted is the sudden increment in the mean value of the electronic temperature in seam number 21, which decreases in seam number 40. The standard deviation remains constant along all the seams, although it can be seen that it is greater between seams numbers 39 and 40, just during a drop in the electronic temperature. The seams numbers 1 and 28 presents a huge standard deviation, but no differences were found in the seams, with respect to the other seams, that can explain this behaviour. A decreasing trend can be observed, specially from seam number 40. Again, no differences in quality terms, penetration depth in this case, were found. Since no changes in the process parameters were introduced, these fluctuations can only be related to some internal state of the laser welding machine.

(a) Electronic temperature variation between seams

(b) Electronic temperature along a seam in which three holes have been produced
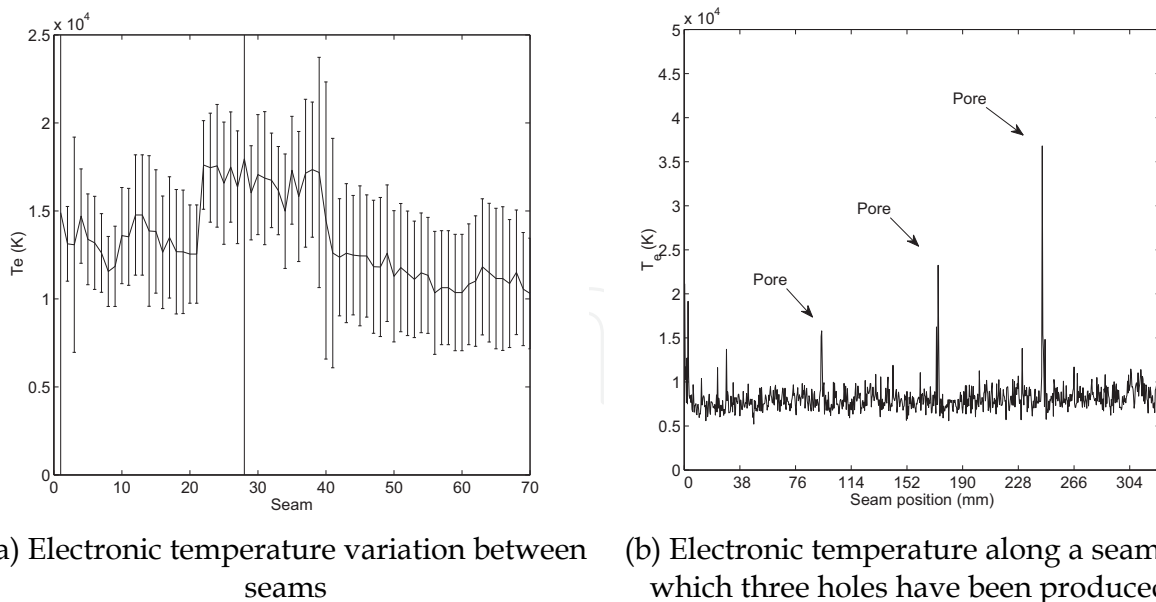
Fig. 13. Electron temperature results

Besides the estimation of electronic temperature during normal welding, some experiments intended to generate defect have been carried out. The class of detect used in such experiments was holes and pores. The difference between a pore and a hole is that the former does not go through the seam while the latter does.

In Fig. 13(b), the electronic temperature associated to a seam in which three holes were forced is shown. Worth of be noted are the three peaks that appear at the same positions the holes were induced. They can be seen at positions between 76 *mm* and 114 *mm*, 152 *mm* and 190 *mm* and 228 *mm* and 266 *mm* in figure 13(b).

4. Conclusions

Fault detection methods in the automotive industry have a great complexity due to the differences between the different machines and processes involved. This complexity makes difficult or even impossible the human supervision of all the processes, although the available technology are of great help in this task. The difficulties found in process supervision came from the huge amount of variables that have to be taken into account and the overwhelming information available.

Nowadays, the correct operation of any plant is more than keeping all the devices in good shape. It also means to know the state of all the devices and machines in order to avoid disruptions in manufacturing production originated by faults or unexpected stops.

In this chapter, it has been shown that predictive maintenance can be applied to very different equipment. This maintenance approach provides the operator with valuable information about equipment status and its future behaviour. The implementation of any predictive maintenance strategy is subject to the importance of the process to be supervised. This also will determine the diagnosis to be performed. Moreover, the economical analysis of the design and implementation of the diagnosis system will determine the adoption of any predictive maintenance strategy.

Any diagnosis system can be broken down into three main modules: data acquisition, signal processing and decision making. Through the case studies presented in this paper, several implementation ways of each component have been presented.

In this way, data acquisition has been illustrated by the case of a machine tool in which the data needed to perform diagnosis is the same data the controller commanding it uses. In this case no more sensors are required. The opposite situation is found in the case of laser welding. In this case, very specialised sensors, like spectrometers, are required to gather data. In the other two study cases, conventional sensors have been installed. Current transducers and accelerometers are common in industrial applications. Their costs depends on precision, range and other requirements. Acquisition hardware to which sensors will be connected is not usually a critical element. This is due to the variety of devices commercially available. However, it could be necessary to develop tailored solutions for specific applications, although it will never be the most critical step in the implementation of a diagnosis system.

Through the case studies, several approaches to the signal processing module are shown. They range from classical frequency analysis to plasma physics. Also, complex techniques have been used to process signal in the time domain or to detect abrupt changes. The most suitable technique is always determined by the pursued target. In same cases it would be possible to chose between several techniques that pursues the same objective. This is the case of defect detection in bearings, where vibration analysis and current analysis are both suitable. Nevertheless, usually only one technique provides the information required to detect the defects. For this reason, the designer has to have a deep knowledge of the processing techniques in order to find the most suitable for the problem at hand. In some cases this will not be enough, and the designer has to develop the processing techniques. This is the situation in the study case related to the machine tool, where segmentation techniques had to be developed in order to find the exact defect location.

Decision making usually is the most difficult step, due to the lack of information about system behaviour when it is in faulty state. This information can be gathered along time once the data acquisition and signal processing modules are installed. The most simple case presented is the motor–fans in a car painting cabinet. In this case, the decision making is carried out by means of a threshold set whose values are set through observation. This is a process that has to be repeated every time a major maintenance task is done. A very different situation is found in the case of laser welding, where decision making is performed by a machine learning method, like neural networks, whose training is done only when significant information has been collected. In this case there is no need for an operator performing supervision tasks.

It is important to note that process expert knowledge is basic in the design of any diagnosis system. A deep understanding of the physical principles involved in the process is the main clue to choose the best strategy to extract features indicating the presence of a fault. The expert is who will be able to know or to deduce which signals are the most affected by the presence of a fault and how they can change in this situation. For example, part of the failures will have an effect on the signal harmonic content, while others will affect the evolution in the time domain. Moreover, they will play a key role when assessing any other kind of dependencies among the data. Frequently it is advisable to analyse correlations among variables or along the evolution of any variable in the time domain. This can be done by means of mathematical methods that can also offer information on the changes associated with failures. The expert will be able to confirm if that information is relevant or is just a mathematical result coming from particular cases.

To sum up, automotive industry can improve their processes through predictive maintenance and the automatic defect detection methods that can be integrate into it. The vast majority of these techniques have reached a mature state and have been successfully implemented. There are also new promising techniques that can improve new processes in the automotive industry, like laser material processing. The implementation of any of these

techniques needs of qualified technicians whose knowledge and expertise will make possible success in their implementation.

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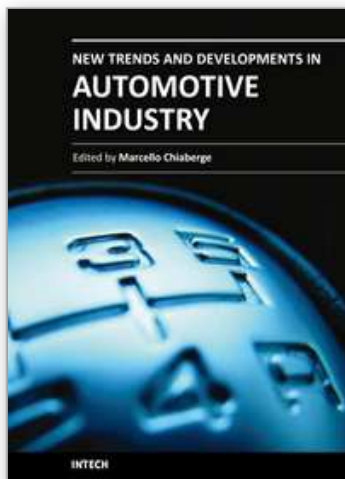
New Trends and Developments in Automotive Industry

Edited by Prof. Marcello Chiaberge

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