Agile diagnostic tool based on electrical signature analysis

Luca Fumagalli*, Stefano Ierace**,
Emanuele Dovere***, Marco Macchi*,
Sergio Cavalieri***, Marco Garetti*

*Department of Management, Economics and Industrial Engineering,
Politecnico di Milano, P.zza Leonardo Da Vinci 32,
20133 Milano, Italy; (email: luca1.fumagalli@polimi.it;
marco.macchi@polimi.it; marco.garetti@polimi.it)

**CELS – Research Center on Logistics and After Sales Service,
Department of Industrial Engineering, University of Bergamo,
Viale Marconi 5, 24044 Dalmine (BG), Italy; (email: stefano.ierace@unibg.it;
emanuele.dovere@unibg.it; sergio.cavalieri@unibg.it)

Abstract: Today, time based maintenance is the most common strategy, to assure a certain level of productivity and reliability in the industrial plants, with a fixed interval length between two maintenance actions. However, given the stochastic nature of the faults, plant equipments and machines usually fail unexpectedly, before the scheduled maintenance action. Therefore, condition based maintenance (CBM) has been introduced, without any fixed interval length between the maintenance actions, as a more efficient maintenance policy. A technique developed for condition based maintenance of electro-mechanical systems is electrical signature analysis. The basic idea behind electrical signature analysis is that, time-dependent load and speed variations in an electro-mechanical system generally induce correlated small variations in the system’s electrical response. Electrical signature analysis analyzes these small variations providing diagnostic information. A tool based on this technique is agile in its adoption since no specific sensors must be installed on the machine, but only power signal must be measured and thus the implementation of such tool can be considered simple and flexible. This paper presents a tool that has such kind of characteristics. The tool processes power signals acquired by transducers installed on the electrical lines of electro-mechanical systems, for machine fault diagnosis. The data acquired are processed through some steps, using some signal indicators developed to understand the machine behaviour.

1. INTRODUCTION

Diagnostics and prognostics tools have been developed during the last years both in research and industrial field. Nevertheless, due to the need of cost reduction, it is necessary not only to develop such kind of tools to prevent failures, but also to implement these tools in a cheap way, i.e. without affecting product/equipment cost and with a low effort of implementation, thus allowing an agile adoption of the tools themselves.

Therefore, the development of an agile monitoring technique may have the potential to greatly influence and enhance the application of CBM practices.

According to Jardine et al. (2006) a Condition Based Maintenance (CBM) program can be separated in three key steps: (1) data acquisition, to obtain data relevant to system’s health; (2) data analysis, to handle and analyze data or signals collected at previous step; (3) decision-making, to provide decision support to maintenance personnel’s decisions on taking actions. Decision-making step is enabled by techniques for diagnostics and prognostics.

Diagnostics focuses on detection, isolation and identification of faults when they occur or while they are occurring. It is a procedure of mapping the information obtained in the measurement space and/or features in the feature space to machine faults in the fault space (Jardine at al. 2006). This mapping process is also known as pattern recognition and traditionally it was done manually by experts using auxiliary graphical tools. Prognostics is the activity that logically follows diagnostics. When information is available to deepen the analysis, in fact, also an estimation of the aging of the components can be considered and thus the Remaining Useful Life (RUL) can be evaluated (see Jardine et al. 2006 for a complete definition of RUL).

Indeed, this paper introduces ESA (Electric Signature Analysis), a novel technique which can act as a cheap and reliable tool for diagnostics and prognostics. Since ESA, unlike techniques such as infrared thermography or vibration analysis, does not require any specific sensor for data acquisition and allows performing diagnostics and prognostics without stoppages, it can give the opportunity to develop very cheap diagnostic and prognostic systems.

Moreover, especially in modern machinery, components such as current/voltage sensors or digital processors are already installed, for non-diagnostic reasons: for example for protection or control of the process. The presence on many machines of a digital processor for control purposes or of
current sensors for current/torque control and over-current protection leads to the possibility of current measurement and digital signal processing at an even lower cost. Current and voltage data can also be acquired directly from the equipment's Motor Control Center (MCC), thus, ESA can be considered as an innovative and cheap tool for the diagnostic and prognostic field.

The work presented in this paper grounds mainly on a project founded by Regione Lombardia. The project aims at developing the application of ESA on two different problems: prognostics of balancing machine and monitoring of energy efficiency of solar panel. ESA applicability was analysed in a previous work (Fumagalli et al. 2010). Four different industrial cases were studied: aspects such as technical characteristics, maintenance management constraints and features of the companies profile were discussed. Rather than performing a survey, the research was limited on a reduced number of companies, even if a wide range of companies was encompassed, both "user" and "vendor" companies, ranging from power sector to mechanical and automation sector. ESA compatibility with companies profile and its efficacy for established CBM approaches was proved for both users and vendors, as well as technical prerequisites, i.e. components already installed that would allow for low-cost extension. This work aims at deepening the research, by presenting the technical principles of ESA and some experimental results of the use of the Electrical Signature Analysis (ESA) as an approach to condition based maintenance. In particular the paper presents the first release of the tool ProDEST (Prognostics and Diagnostics based on Electric Signature Technique).

The paper should be seen as a research activity, part of a larger research work still in progress. Here the first results of the comprehensive project are mentioned. After a brief description of ESA concept (Section 2), ProDEST is shown (Section 3), instead Section 4 presents the validation using a balancing machine of the proposed approach. Finally, conclusions and future work will be drawn up.

2. ELECTRIC SIGNATURE ANALYSIS

Basically, ESA has the capability of discriminating faults in a machine, starting from the effects of an unbalanced electric supply system. Many examples on the use of this technique can be found in literature: ESA primary application includes the diagnostics of electrical machines and connected mechanical equipments (e.g. Mukhopadhyay & Chaudhuri, 1995, Douglas et al., 2004). ESA is a procedure that enables two main functions: (i) to capture the equipment's input current and voltage signals; (ii) to analyze the signals in order to detect various machinery faults. The idea is that any load and speed variation within an electro-mechanical system generally produces correlated variations or disturbances in current and voltage supply line of the electrical device powering the system. ESA can then be used in order to analyze these small perturbations and to match them to their source. The variations, very small in relation to the average current drawn by the motor, can be monitored and recorded at a convenient location away from the operating equipment. The resulting time and frequency signatures reflect loads, stresses, and wear throughout the system and allow an extensive range of mechanical diagnostic and prognostic information to be obtained from a single sensor installed on an electrical line. The ability to look beyond the electrical machine to the mechanically driven load can be then exploited for a wide variety of electromechanical systems.

ESA is developed based on the approach of pattern recognition, and “pattern” in this case can be used at least for diagnostic purposes, since it allows to identify which equipment and/or machine component causes the change in the signature and why. The comparison between a reference object (e.g. electric signature of an equipment in good condition) and an equipment under monitoring supports fault identification and isolation activities. When some reference objects are available (namely different electric signatures corresponding not only to good condition but also to different degraded conditions of the equipments) it can be assumed that ESA has the capabilities to support diagnostics activities. Moreover, if an evolutionary trend of the degradation may be determined, ESA could be implemented also to support some prognostic activities. The basic principle of Signature Analysis (SA) is that a (measured) effect is the result of a cause (i.e. the machine degradation). SA is only applicable to cases in which this principle is verified. The SA technique requires a mapping process (i.e. pattern recognition): this is based on the notion of similarity between two different “objects” or an “object” and a reference “object”. Pattern recognition has the goal to classify objects into a number of categories or classes. Depending on the application, the objects may be images or signal waveforms or any type of measurement. These objects are usually referred to by using the generic term patterns or, sometimes, signatures.

According to Jain et al. (2000) the best known approaches for pattern recognition can be classified into four categories: (1) template matching; (2) statistical classification; (3) syntactic or structural matching; (4) neural networks. One of the simplest and earliest approaches to pattern recognition is based on template matching. This is a generic operation in pattern recognition which is used to determine the similarity between two entities (points, curves, or shapes) of the same type.

Using the statistical classification, each pattern is represented in terms of d features or measurements and is viewed as a point in a d-dimensional space (Jain et al. 2000). The goal is to choose those features that better describe a certain behaviour and use those to identify a point in a d-dimensional space representing, e.g., the possible health state of a machine.

Last but not least, artificial neural networks (ANNs) are a popular Artificial Intelligence technique (Expert Systems are another, see Jardine et. al 2006). ANNs can be viewed as massively parallel computing systems consisting of an extremely large number of simple processors with many interconnections. The main characteristic of ANNs is that they have the ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data. The training process – needed for adaptation – involves updating the connection weights so that...
the ANN can efficiently perform a specific classification / clustering task. The increasing popularity of ANN based models to solve pattern recognition has been primarily due mainly to their low dependence on domain-specific knowledge (relative to model-based and rule-based approaches). It is then worth considering that many of the adopted ANN based models are practically equivalent or similar to classical statistical pattern recognition methods.

In this work the statistical approach is used to build statistical indexes that represent signal shape and characteristics of the signal in diverse ways. It is foresee that ANN approach will be used to carried out and complete the research work here presented as discussed in Section 5.

3. ESA TOOL ARCHITECTURE

Appendix A shows the part of ProDEST proposed in this paper. This tool allows implementing ESA for diagnostics purposes. According to MIMOSA standard, diagnostics is a three steps process: (i) detection, (ii) isolation and (iii) identification.

The following paragraphs will present the model. In this work, the tool is developed using LabView environment for diagnostic purposes. Indeed, the software runs some routines developed in Matlab for data analysis and exploits LabView capabilities for user interface and connection with the Data Acquisition systems.

Indeed, the first step is data acquisition of the measurement system, usually developed under a virtual instrument environment (e.g. a software like LabView) on a PC hosting the ADC board. The key idea is to associate the measure not to a specific hardware but to the algorithm that implements the required measure (Cristaldi et al., 2008).

In data filtering step, transitory and non-stationary power signals acquired in the data acquisition step both for healthy condition and normal operating condition of the machine are filtered down to high and low frequency components. Indeed, the main tasks described in the figure (Annex 1) are the ones related to a Diagnostic Analysis Toolbox. They depict a flow chart whose details are provided in the following paragraphs.

There are four main steps in the flowchart (Annex1): Data Acquisition, Detection, Isolation, Identification. Data Acquisition is mainly related with hardware solutions and data filtering, while the software part here presented is related with the other steps of the flow. The flow through the last three steps, namely detection, isolation and identification is explained in the following sections.

The tool operates through comparison of time-domain indicators. Different data sets of power signals are acquired in the healthy working condition of the system and in the unhealthy conditions so to have a database of indicators at disposal for the comparisons. Time-domain indicator values for condition based maintenance are calculated for each of these data sets and also for the power signals acquired during the normal operation condition of the machine. As time-domain indicators are commonly used in the literature for machine fault diagnosis, five time-domain indicators, namely Mean value, Kurtosis coefficient, Skewness coefficient, Crest factor and RMS value are used in the proposed tool, for machine fault diagnosis by using algorithms developed on Matlab. The comparison of time-domain indicators is done according to the control chart principles, explained in the remainder.

3.1. Detection

In this step of the flowchart, the approximations or details of the power signals obtained in the data filtering step are processed. In detection step, the decomposed power signals acquired during the machine operation are compared to the decomposed reference power signals acquired during the healthy operation condition of the machine. The comparisons are carried out by means of time-domain indicators that are discussed in the following sections. If the reference power signals and the power signals acquired during the machine operation are similar, the machine is in good operation condition. On the other hand, any dissimilarity between the signals is the indication of a component fault in the system. In this case, the second step, namely isolation is carried out.

3.2. Isolation

In isolation step, firstly, the power signal is divided into segments according to the different operations performed on the machine, thus according to the components working in each operation. This is feasible thank to the structure of the database of the signatures where some information are recorded about the timing of the segments of the working conditions, provided by a synchronization between the acquisition system with the PLC of the machine. The aim of the isolation step is to locate the faulty component in the machine.
Secondly, each segment is compared to its reference segment signal. The comparisons are carried out in the same way as in the isolation step, namely by means of time-domain indicators. The segments that are dissimilar to their reference segments indicate that there is a faulty component of the machine, working in the corresponding segment of the power signal identified as the one with unhealthy conditions. Therefore, the faulty components in the machine are isolated. After isolation step, the identification step is carried out for the faulty components.

3.3. Identification

In the third and last step, namely identification step, the power signal segments of the faulty components are compared to various types of failure mode signatures of the corresponding components. The aim is to identify the failure mode of the faulty component. When there is a match between the failure mode signature and the faulty segment, the failure mode of the corresponding component is identified. The comparisons are carried out in the same way, by means of time-domain indicators. Database of signatures related with faulty components is needed. To make the tool more effective as possible the database must be created with the signatures of critical components that must be identified by proper preliminary analysis. In the following paragraphs the time-domain indicators used by this tool are described.

3.4. Indicators used in the tool

- Root mean square (RMS), also known as the quadratic mean, is a statistical measure of the magnitude of a varying quantity. The meaning of this index is the average power of a signal. Average power of a signal can give diagnostic information for condition based maintenance since it estimates how efficiently the machine is working and if something makes the machine working in a different condition.
- The Kurtosis coefficient, also known as flatness factor, determines the relative amplitude of a distribution, if compared to the Gaussian distribution. Kurtosis coefficient is used as a time-domain indicator in order to estimate the shape of the signal. A negative Kurtosis means a flatter distribution than the normal and a positive Kurtosis means a sharper distribution than the normal.
- The Skewness coefficient, also known as asymmetry factor, defines any distribution asymmetry around the signal’s sample mean value. In case of a negative skew, the left tail is longer than the right tail, the mass of the distribution is concentrated on the right of the figure. In case of a positive skew the shape of the distribution is the opposite.
- The Crest factor (CF) is a measurement of a waveform, calculated from the peak amplitude of the waveform divided by the RMS value of the waveform, that is, the maximum absolute value of the differences between the signal data points and the signal’s mean, divided by the root mean square value of the signal.

3.5. Control chart interval

Control charts are tools used to determine whether or not a manufacturing or business process is in a state of statistical control. The analysis of the control chart can indicate that: i) a process is currently under control (i.e. it is stable, with some known variation) ii) the process being monitored is not under control. A more detailed analysis can determine the sources of variation, that for what concern the scope of this research, it is generally a failure. Although control charts are mainly used in quality control area, control chart intervals with 3-sigma limits are used in the tool here proposed. Control charts are defined for each indicator value, with the purpose of machine fault diagnosis. For each indicator, mean of indicator values obtained from different data sets of power signals for healthy operating condition of the machine and standard deviation of indicator values obtained from different data sets of power signals for healthy operating condition of the machine are considered.

4. CASE STUDY

A case study is carried out to test the developed tool. The case study is carried out in conjunction with a company. The company has consolidated its presence into two competence areas that currently identifies the company offer: automatic, semiautomatic and manual machines employed in the electronic final tests and in the balancing of armatures and rotating bodies, and measurement and auxiliary control systems for machine tools. Customers mainly belong to electric motors industry, car industry, aeronautics, railway sector and their suppliers; there are also fan and turbo-compressors manufacturers, grinding machines, spindles and tool-holders, bearing and dies manufacturers.

A balancing machine is selected as test case for the tool here presented. The balancing machine operates according to a working cycle that can differ considerably for each part that is worked. This is due to the fact that the work needed to balance a part can be different according to the unbalance that has to be corrected. For this reason the definition of a standard test cycle was necessary to define repeatable conditions. In order to define the test cycle, analysis of criticality of the machine was carried out in order to identify the critical components to be stressed during the standard cycle. This preliminary analysis was carried out thanks to a FMECA analysis. Indeed FMECA analysis was customized for the specific purpose to be preparatory for application of electric signature analysis. To this end a method for criticality analysis was developed and called MAFE, that stands for (Metodologia di Applicazione della Firma Elettrica – Methodology of Adoption of Electric Signature). Nevertheless this criticality analysis is out of scope of this paper and thus it is not presented here.

The test cycle that has been defined is thought to stress all the components that are deemed critical according to FMECA and whose degradation can be identified by the analysis of the electric signature. For the test cycle no working condition are considered, because working conditions present a high variance for the electric signature due to the balancing operations that the machine for the case study does.
Moreover other diagnostic tools have been already developed to predict the degradation of the cutting tool and so this was a further reason to keep this issue out of the scope of the test of our tool.

Table 1 - Time-domain indicator for the detection phase

<table>
<thead>
<tr>
<th></th>
<th>Mean values</th>
<th>Kurtosis coeff.</th>
<th>Skewness coeff.</th>
<th>Crest factor</th>
<th>RMS values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data set 1</td>
<td>1.71</td>
<td>19.11</td>
<td>0.19</td>
<td>28.6</td>
<td>0.252</td>
</tr>
<tr>
<td>Data set 2</td>
<td>18.25</td>
<td>11.86</td>
<td>-0.47</td>
<td>21.1</td>
<td>0.265</td>
</tr>
<tr>
<td>Data set 3</td>
<td>-4.84</td>
<td>24.18</td>
<td>-0.28</td>
<td>29.5</td>
<td>0.2305</td>
</tr>
<tr>
<td>Data set 4</td>
<td>-1.23</td>
<td>24.48</td>
<td>-0.05</td>
<td>29.1</td>
<td>0.2385</td>
</tr>
<tr>
<td>Control chart intervals</td>
<td>lower limit</td>
<td>lower limit</td>
<td>lower limit</td>
<td>lower limit</td>
<td>lower limit</td>
</tr>
<tr>
<td>-11.84</td>
<td>11.05</td>
<td>-0.58</td>
<td>21.1</td>
<td>0.2234</td>
<td></td>
</tr>
<tr>
<td>upper limit</td>
<td>upper limit</td>
<td>upper limit</td>
<td>upper limit</td>
<td>upper limit</td>
<td></td>
</tr>
<tr>
<td>18.79</td>
<td>28.76</td>
<td>0.28</td>
<td>33.1</td>
<td>0.2703</td>
<td></td>
</tr>
</tbody>
</table>

Herein the part related with the use of the control chart is presented, through a test with real data captured on the balancing machine used as test-bench. Indexes are shown in the Table 1, where values for an healthy signal and control chart intervals for each of the indicator values obtained are showed (unit of measure of the indicators is not mentioned because meaningless for this data where the proper gain is not considered).

5. FUTURE DEVELOPMENT

![Fig. 2. Vision of development of the tool ProDEST](image)

Nowadays the stage of development of ProDEST allows to carry out the diagnostic activity through the detection, isolation and identification steps, namely the complete development of the Diagnostic Analysis Toolbox (considering the picture in Figure 2). This is done thanks to the proper development of the Electric Signature Toolbox that has been already prepared and whose tuning is ongoing for the preparation of a proper cheap hardware. Next steps will be the development of the Prognostic Analysis Toolbox thanks to the adoption of ANN and the definition of a Maintenance Policy Optimization Toolbox that will work as support of the decision maker and will allow to effectively improve maintenance policy based on real time data coming from the field. Moreover the comprehensive project will aim at further improving the MAPE method, previously mentioned, to be able to provide, beside the agile tool, ProDEST, an agile methodology for its implementation.

6. CONCLUSION

The objective of this work was to develop an agile diagnostic tool based on electrical signature analysis for condition based maintenance of electro-mechanical systems. The use of the ESA as a diagnostic and prognostic tool can give the ability to detect and quantify mechanical / electrical malfunctions and degradation phenomena in electromechanical equipment. In fact ESA allows the extraction of information about healthy, faulty and incipiently faulty operating conditions from the electric supply line of the equipment in a cheap way.

Limitations of the proposed approach are related with the time and resources that have to be spent in order to set up the tool, defining the control charts limit for good condition of the machine as well as for other faulty conditions. This is the main weak point of the proposed tool, that does not allow it to be used directly on a machine, without a proper set up of the software.

Eventually, it is worth considering that obtained results show that a tool based on statistical indicator can be developed to analyse electric signature analysis. This allows considering that simple algorithms combined with a cheap hardware can effectively build up an agile tool to diagnostic failures. Furthermore vision of the future developments of the proposed tool has been provided.

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Appendix A. FIRST APPENDIX

![Flowchart Diagram]