INDUSTRY 4.0: Predictive Intelligent Maintenance for Production Equipment

Susana Ferreiro[1], Egoitz Konde[2], Santiago Fernández[3] and Agustín Prado[4]

[1,2,3]*IK4-TEKNIKER, Intelligent Information Systems Unit, Eibar, Gipuzkoa, 20600, Spain*
susana.ferreiro@tekniker.es
egoitz.konde@tekniker.es
santiago.fernandez@tekniker.es

[4] *Goratu Maquinas Herramientas, Elboibar, Gipuzkoa, 20870, Spain*
aprado@goratu.com

ABSTRACT

In manufacturing, users increasingly demand comprehensive maintenance service in their production equipment in order to ensure high availability and to prevent downtimes in critical phases of the production processes, affecting customer delivery times. From the manufacturer's point of view, it is vital to optimize and to improve the service provided to the final users, allowing appropriate maintenance planning and responding to the demand.

Contrary to the classic preventive maintenance programs in use today, predictive maintenance improves the performance of the equipment, strengthening the business model of companies. Thanks to the inclusion of a set of sensing, condition monitoring, predictive analytics and distribute systems technologies, it is possible to perform and provide a remote technical assistance based on continuous monitoring and maintenance support from a distance.

This paper shows the benefits and advantages to be achieved by the development of a comprehensive predictive maintenance, through the concept of Industry 4.0, and focuses on remote monitoring and self-diagnosis function of health condition for the equipment. However, the main emphasis of the work presents the data acquisition and analysis processes to develop predictive algorithms for machines in production.

1. INDUSTRY 4.0: THE FUTURE OF MANUFACTURING FOR MACHINE-TOOL SECTOR

In view of the current trends in the machine tool sector and what it entails from a manufacturing point of view according to the concept of Industry 4.0, the future of the machine tool sector is that it will become a Cyber-Physical System (CPS) integrated into the global production system.

However, for this to happen, some improvements are needed related to:

- Integration of embedded systems.
- Development and integration of cognitive models.
- Increased decision-making ability of the machine, aided by sensors and models.
- The interconnectivity of the machine with other machines and global production system.

Furthermore, CPS can be applied at lower level in the machines in order to enhance their abilities. In this way, machine-tool concept (commonly considered passive), will be turned into an active production environment, integrated into the global production chain and with the decision-making ability to:

- Optimization of machining process.
- Monitor and assess the health to define and carry out maintenance actions before the failure occurs.
- Optimize operational parameters and conditions for energy optimization.
- Deal with unexpected events.
- Connect not only with other machines and production resources, but also with staff involved in the production, taking advantage of the amount of available information/data.

1.1. Opportunities and challenges for the machine-tool sector

The first significant driver for the advance of Industrial Internet solutions lies in the opportunity to integrate and better manage horizontal and vertical value chains. Companies surveyed expect more than 18% higher productivity over the next five years. While today only one fifth of industrial companies have digitized their key processes along the value chain; in five years' time, 85% of these companies will have implemented Industry 4.0 solutions in all important business divisions.

The digitization and interconnection of products and services (Internet of Things/Services) is a second important driver. It will contribute strongly to ensuring competitiveness and promises additional revenues of 2% to 3% per year on average (Koch et al, 2014).

A third major driver is the newly emerging, often disruptive, digital business models that offer significant additional value to customers through tailor-made solutions. These new business models are characterised by a considerable increase of horizontal cooperation across the value chains, as well as the integrated use and analysis of data. They are therefore capable of better fulfilling customer requirements.

The various opportunities, the large extent of change and the elevated need for investments make the Industrial Internet one of the most important topics for corporate management. However, the numerous challenges that the transition entails are also not to be underestimated.

The fourth industrial revolution has begun and offers attractive opportunities for industrial companies. However, the Industrial Internet is not an end in itself. It is closely tied to clear economic objectives and holds the potential for clearer differentiation in global competition.

Concerning the machine-tool sector, the major challenges are focused on:

- Machine sensoring and monitoring: data acquired from sensors is used to define correction actions, to increase the knowledge about the use, reliability and efficiency of the equipment/process.
- Predictive modelling based on data: predictive models can predict the behaviour of the machines and processes so that both can be optimized.
- Cloud solutions: this allows the manufacturer to manage the fleet of machines for the customers. Collecting and saving non-confidential information about the use of the machines allows the manufacturer, through predictive analytics techniques, to anticipate the remaining useful life (RUL) of some of the components, and to establish predictive maintenance plans for their customers, providing services with additional value (Servitization).
- Interoperability: standards-based interface to communicate and collaborate with other machines or CPS and cloud, and to get useful services from them.

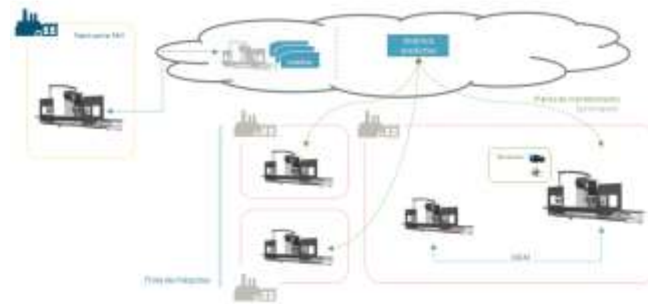

Figure 1. Major challenges graphic representation.

Our work is intended to demonstrate solutions for successful Industry 4.0 implementation. It is mainly focused on the design and development of an embedded smart system to assess the health of the machine using power based information. The information will be analysed for feature extraction and to develop predictive algorithms which will help in the prevention of failures.

2. MAJOR REQUIREMENTS FOR THE MACHINE-TOOL SECTOR

The European machine-tool industry is concentrated on customized and small-scale production of high value-added and high-precision machines. GORATU, in particular, is designing and developing its products to cover the more demanding requirements of the customers, focusing on machines capable of producing extremely large parts with high accuracy requirements as a differentiator factor of its business.

The fact that the customer buys a higher value-added product also means that those machines are used in critical processes, and therefore the customer expects a failure-free machine. The breakdown of such critical equipment in the production chain at the customer's site is something to be fully avoided. So, the way that maintenance operations are carried-out is critical to maintain the accuracy and productivity of those machines at the required levels.

Installation and support to the end user of the machine is also more and more demanding, since products are more complex and different from one another. Not less demanding is the technology related to the machine tool such as the Numerical Control (NC) that continually changes and which makes the technicians' work more difficult, requiring more resources from the machine tool builder.

Concerning the sales network, as a general rule, manufacturers of machine tools have two ways to construct it. On the one hand, companies set their own offices according to their possibilities, taking their target markets into consideration. The remaining countries are covered by sales representatives, usually local companies, which establish business relationships with the client and are responsible for sales and technical assistance during the life of the machine. For example Goratu has its own offices, apart from the headquarters in Spain, in the UK, Germany, Italy, India and China.

Usually customers have their own maintenance staff, which are trained by the manufacturer to perform routine maintenance and diagnosis and to solve the most frequent problems. When the problem requires specialized knowledge, the client contacts the manufacturer or dealer for the solution.

Nowadays, tools such as tele-service, are frequently used by manufacturers and customers to solve problems, but this has been effective only in the last years. Goratu today sells all the machines with this option installed. Most of the connections to the machine available today are still made by analog modem and rarely by Ethernet connection through VPN.

2.1. Proactive and Predictive Maintenance: A value-added service

This scenario requires the application of proactive maintenance strategies from the machine tool builders and users, predicting the potential failures and scheduling maintenance operations in convenient periods to avoid unexpected equipment failures.

The machine tool manufacturer should be able to evaluate the machine tool "health" and have a proactive attitude towards the customer, solving problems before a breakdown or failure occurs.

Along with the customer's satisfaction with the prevention of breakdowns, the more precise knowledge of the health of the machine will also bring improvements to the planning of technical assistance department.

To know the health of the machine, it is not only necessary to define the procedure to measure it, but also it is very important to know the characteristics that have generated that health situation. For the machine tool builder a good diagnosis will enable better knowledge. This will serve for improvement in new designs that consider the different categories of customers using the machines. This will help to give a better solution during maintenance works by adjusting the machine according to the type of use. For example, it is possible to give a bigger preload to the spindle bearings if the customer uses the machine for roughing for long periods.

From the point of view of the machine tool manufacturer, Goratu, the business opportunity is shown in two ways. The first one is to be able to offer customers added value and dependable services, along with actually selling the product. The second one is that offering this added value will improve the brand reliability definition which, in such a competitive market, could be the difference between selling new machines or not.

The incorporation of intelligent predictive technologies into the machines could contribute to these objectives, but these techniques are not widely used in the production environment. Sensors and other monitoring techniques required for the production environment are not so standard and require costly implementations.

The research work described in this paper focuses on the spindle, the most relevant and faulty component in a machine-tool. How the changes of different parameters can be used to detect an incipient failure has been studied for machine tool (Jardine et al, 2006; Martin, 1994). Techniques for condition monitoring are mainly related with acoustic and vibration techniques, and some are centered on spindle failures detection (Saravanan et al, 2006). Acoustic techniques have as their main drawback the influence of background noise, and vibration requires a set of accelerometers mounted in the machine structure, which is impractical for most applications.

Key features for successful predictive technologies are:

- The use of non-intrusive monitoring techniques.
- Affordability in terms of cost.
- Effectiveness.

3. DESIGNING AND DEVELOPING AN EMBEDDED SMART SYSTMEM TO ASSESS THE HEALTH OF THE MACHINE USING POWER BASED INFORMATION

Following these requirements, specified in the sections above, (Power-OM Consortium, 2102) has been working on how to apply motor current signature analysis for the spindle condition monitoring. This approach is described in next sections.

3.1. Data Analysis Approach

The aim of this work is to test on a controlled environment the different approaches for the development of a condition monitoring system for spindles. Taking into consideration that our intention is to study the response in power and current signals, the proposed technique is the Electric Signature Analysis. The idea behind it is that any load and speed variation within an electro-mechanical system produces correlated variations in current and voltage. The resulting time and frequency signatures reflect loads, stresses, and wear throughout the system but this requires a mapping process or pattern recognition. The comparison between a reference, electric signature of equipment in good conditions (the fingerprint), and equipment under monitoring supports that fault identification.

Signature Analysis will be applied to cases in which the principle cause-effect is verified and modelized. So, the first step was to carry out a lab research using test benches and the proper design of experiments to characterize the problems to be predicted, using the power and current signals. A high number of measurements have been performed to correlate parameters in order to compare features of abnormal signals of failure with healthy signals.

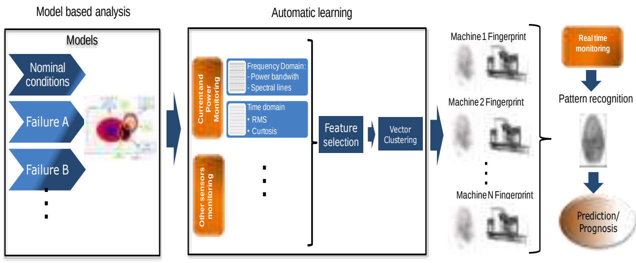

Figure 2. Power based health assessment approach.

To obtain the fingerprint, machines will run a pre-defined test cycle in no-load condition in order to achieve better failure detection and to remove the noise that the normal machine process load could introduce. In this way, the resultant method will be easily adapted to other similar machines and it could prevent adaptation problems, since most of the time developed models only work properly with the machine from which the data for the training method was collected. This is the case of machine learning algorithms, for which it is necessary to repeat the training/learning process to conform to the particularities of each machine.

3.2. Monitorization and Data adquisition

There are different test benches which will be used to provide relevant information for the project. In each of them the objectives of the tests are different, but they all have specific functions for the final task of the health assessment of the machines. Listed below are, the test benches and machine tools which will be used on the work package:

- The Gearbox Prognostic Simulator (GPS) test rig from IK4-TEKNIKER: Understands the capacity of current analysis.
- The test bench for spindles at Goratu: Compares repaired and damaged spindles
- New machines fabricated at Goratu: Ensures the repeatability of the signals with different machines
- The machines in production installed at Goratu: Controls evolution of the signals during the time

3.3. Design and development of prediction algorithms

3.3.1. GPS test rig

The main advantage of the GPS is the capacity to run gears and bearings with failures, so it could work in a controlled failure environment. It will help to see the capacity of current and power signal analysis and better understand how the different features of failure could appear. Also, it would help to check the set of test that should be carried out to extract the fingerprint of machines.

Figure 3. GPS test rig Lab.

Mainly, the first part of the analysis has been oriented to detect and diagnose if the mounted gears were healthy or not. But it also helped to select the best type of test, at this point, a first fingerprint (or a group of candidate fingerprints) formed by a combination of signals that maximize results. The expected results are significant differences in the current signal. The vibration signal should act as a reference signal. Also, it will be possible to control the dependence of the measured signal with different speeds or loads.

Selected preprocessing techniques and features are extracted for identification and comparison of the gears. The features extracted from sensor signals are used to characterize properties of the condition of the components. The techniques implemented are commonly used for vibration analysis (Robert 2004, Wang et al 2001) and in motor current signal analysis (Arellano et al 2009, Kar et al 2006, Bonaldi et al 2008). Most used methodologies are applied to the signal in the time domain and in the frequency domain.

Once the features were extracted, classifiers were applied to detect failure condition. Each algorithm could maximize the use of features or select the main features for the results. So, once a set of features has been extracted, an optional feature selection step can be considered. The aim of the selection of variables as stated in (Nilsson, 1998) does not involve analyzing the variables because this task was carried out in a previous section, but this is a second selection and it determines which are the most influential variables and which of them improve the model. This Feature Subset Selection has some advantages:

- Noise elimination, increasing data precision and predictive and explanatory ability of the model.

- Irrelevant data elimination, decreasing acquisition cost and computational cost of the data base.
- Redundancies elimination, avoiding problems of inconsistencies and duplications.
- Dimensionality reduction, in order to deal with the so-called curse of dimensionality.

Supervised techniques have been tested in order to reduce the dimension of the number of features and to obtain the most relevant ones, only those necessary to detect the fault. After having the relevant features determined by the set of combination of pairs (criteria, search algorithm), a post-manual selection has been performed for vibration and current signal, keeping only the most relevant features. That is, the features identified by the majority of the algorithms as the most important.

Once the relevant features were clear for the GPS, this knowledge was used to determine their potential in a real environment (Spindle test-bench and real machines) to detect and predict failures in gears.

3.3.2. Spindles Test Bench

The test bench for spindles at Goratu will mainly provide information about the difference in the signal characteristics between failed and repaired spindles. Here it is possible to run faulty spindles, so we will be able to extract the main features of signals to distinguish between "good" and "bad" components.

The main objective has been to check if the features selected in the GPS were able to distinguish problems in the spindles. Thus, comparing the features of spindles which have arrived to Goratu with the same spindles after being repaired, gives an idea of the capacity of the system to assess the health. The main restrictions to obtain an algorithm giving the health of the spindles will be the number of spindles which have arrived and are going to arrive at Goratu. It can be difficult to develop an algorithm working on good enough accuracy without having a group of samples of which the majority is statistically significant.

So the first algorithm to determine the health of the spindle will be basic, but the procedure exists to improve and upgrade the algorithm in mind to address the problem.

As shown in the GPS, checking the frequency domain, some differences have been found between faulty and healthy spindles, but variations are clearer when the faulty spindles are very deteriorated:

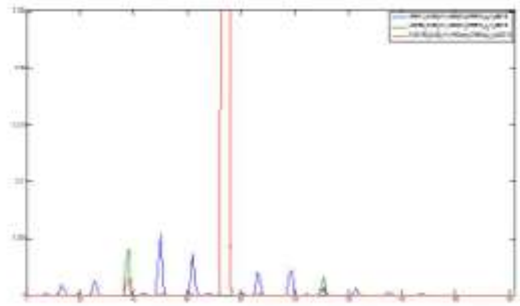

Figure 4. Frequency analysis of current signal in spindles. Y axis in Amps (external sensor) and X axis in Hz

If we compare the different features of one spindle before and after being repaired, it is promising to see the possibility to obtain an algorithm to assess the health of the spindle using current signal.

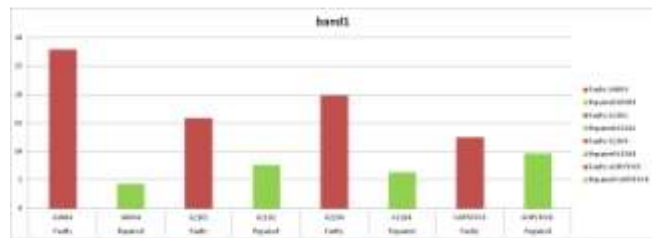

Figure 5. Spindle fingerprint feature comparison in test bench

3.3.3. New machines for delivery at Goratu

Fingerprint tests were done in machines that were sold during the project duration and were ready to deliver. In this way, the repeatability of the signal was studied and how the different machine configuration could vary the captured signals.

The fingerprint tests of machines, which were prepared for delivery at Goratu facilities, showed that the machines with similar configuration (design) have nearly the same behavior. Although there was some variation between the different spindles, it was clearer between spindles with a different design. It is also important to compare machines with the same characteristics. Having the same spindle does not make comparable signals, because the motor or other elements could be different.

3.3.4. Machines in production at Goratu

The last analysis was carried out on two production machines from facilities of Goratu, where the fingerprint test set was collected during the project, with the intention of comparing them throughout the time and seeing if there was any evolution of the signals. Initially a full range of tests was done, but with the intention of reducing them as we detected which were the most relevant ones.

Figure 6. General view of GORATU's production machine.

As explained, due to potentially varying load and speed conditions during machine usage time, a calibration in pre-defined conditions will be used in order to extract the features comprising the reference baseline that is characteristic of each machine. This approach, known as fingerprint, is repeated during the life of the machine. The obtained data on these movements is then analysed to monitor the health of the elements of the machine.

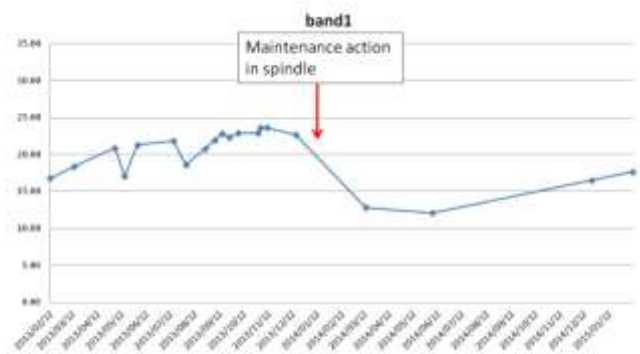

Figure 7. Feature evolution in Goratu's production machine tool. Y asis in Amps.

As the period of time to see any fault was not enough, in order to make a health assessment of the spindle, there is a threshold level on the deviation of features from the reference baseline.

The first version for the health assessment of the components will be quite conservative. The idea at the beginning will be to offer a system with few false positives. A false positive is when a test result indicates that a condition is present (the result is positive), but it is not in fact present (the result is false), while a false negative is when a test result indicates that a condition is not present (the result is negative), but it is in fact present (the result is false).

So, for our algorithm, it is not most important to detect a failure, but to continuously give a bad health status, because having too many alarms could lead to a lack of trust in the system. The system is also in a very initial state, where all the different machines and ways of working have not been tested.

The position and capacity of the algorithm will be improved as fleet dimension information aggregate value.

3.4. Improvement of the algorithms and Fleet dimension

One of the key points to provide added-value, according to the remote level, relies on the fleet dimension. Indeed, dealing with the fleet level can provide knowledge and data to improve expertise, diagnostics and prognostic models for supporting optimization (Rizzolo et al 2011, Medina-Oliva et al 2012). The fleet dimension brings more structured data, information and knowledge about the behaviour of the different units of the fleet and facilitates situation comparison.

The way the local algorithm will work and will be improved is based on three stages:

3.4.1. Fingerprint calibration

A calibration in pre-defined conditions will be used in order to extract the features comprising the reference baseline that is characteristic of each machine. Through the calculation of the reference baseline, the procedure will calculate the uncertainty of the data, for example the standard deviation of the features. Subsequent data recording for assessment purposes will be periodically performed in the same pre-defined conditions as well.

Considerations on usage include:

- The calibration procedure is used for the reference baseline and shall reflect normal operation of a healthy machine. In this regard, it is best performed after the running-in period, and the machine pre-calibrated after significant replacements, repairs and refurbishment as the fingerprint of the machine may vary.
- Features can be added, removed or modified via (remote) software update.

3.4.2. Envelope

This is a threshold level on the deviation of features from the reference baseline. This level can be set from data and from expert evaluation. In the former case, and as a first step in order to detect anomalies serving as a caution sign, a deviation of two or more standard deviations with respect to the reference baseline can be used as a criterion in order to provide an indication of potential anomalies.

Considerations on usage include:

- Should the system be re-calibrated, the envelope will be re-calculated internally.

- The proposed level is tentative and may be further refined with periodic information on the actual process/machine status.
- Operational usage conditions may be considered for setting threshold levels, along with client requirements. For example, a higher threshold can be suitable for heavy usage, while a lower one for lighter usage, and it depends on client requirements.
- Also, feedback from expert evaluation on the machine condition can be used to set threshold levels, such as warning and even failure.
- Thresholds are configuration parameters in the software and can be set or modified.

3.4.3. Assessment

As new data is recorded, the comparison with fingerprint and envelope will detect the anomalies. The availability of data and of expert evaluation of the machine condition can be exploited for further refining thresholds, along with operational usage information and client requirements.

This information is of particular importance for future analysis of trends and the remaining useful life (RUL) estimations. Besides this, intelligent techniques can be explored regarding the potential grouping of data from multiple machines in order to research improvements in the generalization capabilities of the algorithm, and so as to help with data scarcity issues that may arise.

As it might be difficult for certain machines/situations to establish thresholds on the data, the future application of more sophisticated algorithms has been envisaged. These algorithms are built on data, and based on expert assessment of the machine condition. This is to say, algorithm development builds on recorded data for which the actual health condition of the machine is known. The design and development of such an algorithm is performed by expert data mining engineers. Hence, the algorithm fed with new data will provide the health assessment for the machine. An additional advantage of this approach is the possibility to improve and to adapt the algorithm as new data is collected.

4. CONCLUSIONS AND FUTURE WORK

These days, new business models are emerging around production companies related to maintenance activities, to cover customers' necessities, to ensure the successful operation and to reduce production costs. In that way, companies should search new and complementary business solutions to the current ones. Condition Based Maintenance is the most cost-effectiveness maintenance strategy, but it can be improved throughout the use of smart sensing technologies so as to provide the Original Equipment Manufacturer (OEM) with new capabilities and added value services. The paper presents the methodology to be followed for the implementation of Condition Monitoring and Fleet Management strategies, but improved significantly due to the use of technologies and concepts from Industry 4.0 (the fourth industrial revolution).

As a future work, current algorithms still need to be improved. Now, they are based on the deviation from the reference baseline and it is necessary to monitor existing machines of the customers of Goratu to obtain new and additional data. As a new data about the failures of the machines becomes available from the machines, the threshold for this condition of failure will be assessed. And as long as this value will be significantly different from the healthy data, it will be used by the algorithm into the engineering process to improve its generalization, robustness and accuracy.

But to establish levels of degradation for the machines, it is essential to know the usage of the machines and the 'culture of maintenance' of the customer, and it is not an easy task. This means that probably we will have little information about the state of deterioration or degradation of the machines at the very beginning. And even though the algorithm will show some alarms, the component will be working until failure. In this way, the OEM or maintenance service provider will be able to establish some degrees of degradation (i.e., healthy/anomalous/failure). And finally, taking into account these levels of degradation, machine learning classifiers can be applied to learn and improve the algorithm. Moreover, more complex data driven studies and technologies can be applied in case of having more information of the machine. This procedure leads to improved versions of the algorithm that can be implemented as a local algorithm into the machine.

ACKNOWLEDGEMENT

The work presented in this paper is part of the research work done in the project Power-OM, funded under FP7 under grant agreement no. 314548, as part of the Factories of the Future initiative.

REFERENCES

Arellano-Padilla, J.; Sumner, M.; Gerada, C. & Jing, L (2009). *A novel approach to gearbox condition monitoring by using drive rectifier input currents.* 13th European Conference on Power Electronics and Applications, pp.1-10, 2009

Bonaldi, E.L.; Oliveira, L.E.L.; Borges da Silva, J.G.; Lambert-Torres, G and Borges da Silva, L.E. (2008). ―*Detecting Load Failures using the Induction Motor as a Transducer*‖, 10 th International Conference on Control, Automation, Robotics and Vision; Hanoi, Vietnam 2008 pp 196-199.

Jardine, A.K.S., Lin, D. and Banjevic, D. (2006) *A review on machinery diagnostics and prognostics implementing condition-based maintenance,* Mechanical Systems and Signal Processing, Vol. 20, Issue 7, pp. 1483-1510.

Kar, C. & Mohanty, A. R (2006). *Monitoring gear vibrations through motor current signature analysis and wavelet transform.* Mechanical Systems and Signal Processing, vol. 20, pp. 158-187, 2006

Koch, V.; Kuge, S.; Geissbauer, R. & Schrauf, S (2014). *'Industry 4.0. Oportunities and challenges of the industrial Internet'* Report, 2014.

Martin, K. F. (1994) *A review by discussion of condition monitoring and fault diagnosis in machine tools.* International Journal of Machine Tools and Manufacture, 1994, vol. 34, no 4, p. 527-551.

Medina-Oliva G., Voisin A., Monnin M., Peysson F., Leger JB. (2012). *Prognostics Assessment Using Fleet-wide Ontology.* PHM Conference 2012, Minneapolis, Minnesota, USA.

NILSSON, Nils (1998) *J. Artificial intelligence: a new synthesis. Morgan Kaufmann, 1998.*

Power-OM Consortium (2012), *Power consumption driven Reliability, Operation and Maintenance optimisation,* www.power-om.eu

Rizzolo L., Abichou B., Voisin A., Kosayyer N. (2011), *Aggregation of Health Assessment Indicators of Industrial Systems.* In Proceedings of the 7th conference of the European Society for Fuzzy Logic and Technology, EUSFLAT-2011, Aix-Les-Bains, France.

Robert B. Randall (2004), *State of the Art in Monitoring Rotating Machinery – Part 1 & 2,* Sound and vibration, 2004

Saravanan, S., Yadava, G.S. and Rao, P.V. (2006) *Condition monitoring studies on spindle bearing of a lathe,* Advanced Manufacturing Technologies, pp. 993-1005.

Wang, Wilson Q., Fathy Ismail, and M. Farid Golnaraghi (2001). *"Assessment of gear damage monitoring techniques using vibration measurements."* Mechanical Systems and Signal Processing 15.5 (2001): 905-922.

BIOGRAPHIES

Susana Ferreiro got her degree in Computing science at the Technical School in the University of the Basque Country (Spain) in 2005. In 2012 she received her PhD (cum laude) in the area of “Probabilistic Models for Artificial Intelligence and Data Mining”. Since 2005 she has been working in IK4-Tekniker on national and European projects in the area of health assessment, diagnosis and prognosis applied to different industrial sectors such as manufacturing, aeronautics, chemistry, etc. She is an expert in several technologies related to data processing and analysis (such as artificial intelligence, data mining, machine learning, probabilistic models, etc) applied to diagnosis and prognosis for an intelligent and predictive maintenance support; and in the design and implementation of expert systems based on these techniques with friendly graphical user-interfaces (i.e., for the control of high precision laboratory equipment). Currently, she is working on aviation projects aimed at the development of health monitoring systems, on electromechanical actuation systems of A/C and UAVs, to detect and predict system failures. She has published more than 10 papers in conferences, 5 articles in journals with impact index (ISSI) and some book collaborations.

Egoitz Konde got his degree in Industrial Engineering in 2006 at University of Navarra in Spain. He worked in Spicer Ayra Cardan, a member company of Dana Holding Corporation, world leader in the supply of products for automotive industry. He implemented Lean Manufacturing projects in the maintenance area to improve the availability of machines and thereby optimize production. Nowadays, he works in the Maintenance and Reliability area of IK4-Tekniker on different projects related to dependability, predictive strategies and new technologies to obtain maintenance optimization. Using different techniques related to failure modes and event analysis (FMEA, FTA), reliability calculation tools and statistical analysis. He is part of the teachers in the Own Master in Industrial Maintenance of the Mondragon University, as an expert in Reliability Engineering, and he has collaborated in the edition of the 7th Maintenance Book of the Spanish Maintenance Association, as well as in different articles and conferences related to dependability and maintenance.

Santiago Fernandez received his B.Sc. in Physics from the University of Santiago de Compostela in 1996, and M.Sc. (equiv.) in 1997. In 2001 he received his Ph.D. degree for work in the area of speech perception and acoustic phonetics. From November 2001 till 2003, he held a part-time lecturer position in the Department of Applied Physics of the University of Santiago de Compostela. Between 2003-2005, he was a post-doctoral Marie Curie Fellow at University College London, where he studied the importance of the local segmental context in the recognition of phonemes in speech signals by humans and machines. Between 2005-2008 he was a post-doctoral researcher at the Dalle Molle Institute for Artificial Intelligence, Switzerland, focusing on artificial recurrent neural networks for sequence learning tasks and in particular in aspects of speech recognition. In 2008 he joined Tekniker, where he works on intelligent information systems. He has published more than 25 papers in conferences, and 7 journal articles.

Agustín Prado got his Engineering degree in 2005 in the Machine-Tool Institue (IMH) of Elgoibar. He has worked for Goratu Máquinas-Herramienta, S.A. for more than 20 years having different responsibilities. Mechanical designer, Application Engineer, Production Management. The last 6 years has been working as Project Manager in the R+D department in product development and maintenance improvement strategic development.