Prognostics for optimal maintenance: industrial production capacity optimization using temperature condition monitoring

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Prognostic Health Management (PHM), Condition Monitoring (CM), Condition Based Maintenance (CBM), Maintenance Optimization

Abstract

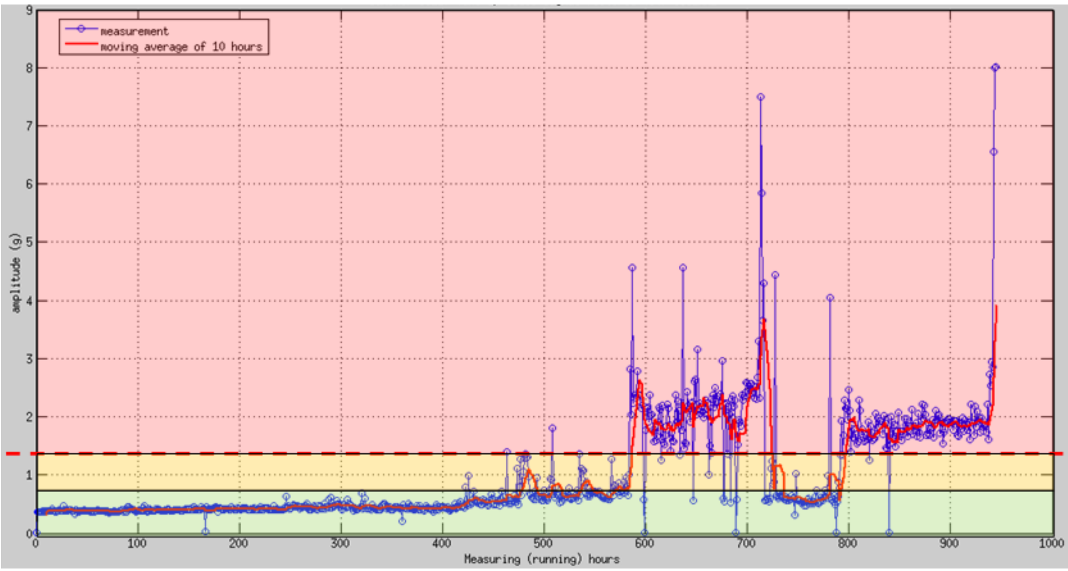
Using condition monitoring to track machine health and trigger maintenance actions is a proven best practice. By monitoring machinery health, costly failures are avoided and downtime due to outages is reduced, which finally results in an increase of operational efficiency and productivity of the equipment. Many papers discuss the implementation of condition monitoring to prevent failures and optimize maintenance actions. However, much less attention is paid to the use of condition monitoring information in order to optimize production capacity of a machine or a plant. Therefore, the objective of this paper is to establish the link between condition monitoring information and production capacity optimization by continuously adjusting production parameters (e.g. production speed) according to the measured condition monitoring information. In this paper condition monitoring of steel production machines using cost-effective temperature sensors is applied to monitor possible overheating of the machine and used to optimize the machine's speed. Without optimization, the machine is simply stopped when overheating is detected. This results on lost production capacity. Therefore, the condition monitoring information is used as an input to the machine's controller in order to optimize the production speed. The speed of the production machine is namely directly related to the corresponding temperature increase or decrease. Optimization of the production speed results in maximal production capacity and minimal machine downtime by prevention of overheating. The paper clearly illustrates how temperature condition monitoring information can be used to maximize industrial production capacity. This approach extends the use of condition monitoring information from purely avoiding unexpected failures to productivity optimization of an entire system.

1. Introduction

Maintenance optimization has been subject of different papers in the last two decade (Blair, et al 2001; Mobley, 1990; Goh, et al 2006; Sholom, et al. 1998). From this literature, it is often found that this optimization is associated to Predictive Maintenance (PdM) where the health of the machine is continuously monitored via a Condition Monitoring (CM) system and the optimal maintenance is scheduled when a specific threshold is crossed. This simplified version of maintenance optimization is valid when enough history data is available both with sensors recording the state of the machine and the maintenance logs which teach us the behaviour of the machines after a maintenance action is done. In line with this version, examples where PdM policy has been successfully applied to industrial cases were published in (Bey-Temsamani, et al 2009). In this work, data mining techniques following CRISP-DM standard (Shearer, et al 2000) were combined with a prediction algorithm based on weighted mean slopes to develop a PdM policy for copiers / printers industry with an estimated benefit of €4.8 million per year worldwide. Such a clear benefit was only possible to estimate thanks to the available sensors and maintenance databases which are necessary required to develop the PdM solutions. However, in most industries it has been observed that often sensors data are available but not the maintenance logs history. This may be explained by the large efforts needed to collect such data. Furthermore, the quality of the sensors data is not always high. A customized solution is then needed to develop an optimized maintenance policy based on the available data in the industry of interest. Therefore, the POM-CBM framework has been developed in conformity with ISO-13374 CBM standard (Sheppard, et al 2008). This framework is composed of modular blocks that are selected depending on the final goal of maintenance optimization analysis. This framework is introduced and explained in (Bey-Temsamani, et al 2011). In the POM-CBM framework, maintenance optimization is more largely described than through Predictive Maintenance (PdM) policy. Actually, after interviews with different machine builders in Belgium for maintenance optimization requirements capturing, it has been clearly concluded that maintenance optimization should not only take into account the health of the machines but should also include final product quality and production capacity as optimization parameters. Results of analyses related to maintenance cost versus product quality optimization were published in (Van Horenbeek, et al 2011). While industrial production capacity optimization is the topic we want to discuss in the current publication. This publication fits in the framework of Prognostics for Optimal Maintenance (POM2) project (POM2 website, 2011).The overall goal of the project is to develop integrated methodology for implementing predictive maintenance on industrial machines and software tools / algorithms to support the assessment of cost / benefits ratio of the predictive maintenance. This paper is structured as following. In Section 2, advantages of online condition monitoring for machines is illustrated. In Section 3, the approach followed to optimize production capacity is explained. In Section 4, validation on an industrial use case is given. Conclusions and next steps are summarized in Section 6.

2. *Online condition monitoring*

With the continuous decline of sensors prices, thanks mainly to the automotive industry, online Condition Monitoring (CM) programs are becoming possible in machine manufacturing industry. These programs consist on monitoring the condition of machines in order to assess their performance and take necessary actions when needed. As a consequence, the way companies manage maintenance has drastically changed thanks to such programs. Therefore, Condition Based Maintenance (CBM) and Predictive Maintenance (PdM) policies became practically possible once a Condition Monitoring program is adopted. A typical use case to show these advantages is a catastrophic failure of a steel wire production machine due to bearings failures (Techniline article, 2011). The most common bearing rating factors are speed and load. Of the two, load has by far the greater effect on bearing life. For example, speed and life are inversely proportional. Doubling the speed of a ball bearing halves its life, while, reducing speed by one-half doubles its life. However, doubling the load on a ball bearing reduces its life by a factor of 8 to 10. The detrimental effects of load on life are even more dramatic with roller bearings. One of the consequences of excessive speed is broken cages and retainers. High speeds increase inertial forces within the bearing. These forces, combined with inadequate lubrication and sudden stopping or starting, can produce high forces between rolling elements and the retainer. Repeated forces skew and eventually crack the cage or retainer. The catastrophic failure can be very sudden and impossible to predict using an intermittent condition monitoring system. Another problem hampering such a prediction could be due to the stochastic nature of vibration signals in production process, due to other vibration sources, and which make the optimal choice of the time to measure with an intermittent CM system very crucial. A continuous monitoring system, however, allows a continuous tracking of bearings conditions and is able, with the right features in place, to anticipate such failures in advance allowing thus the service people to take actions on the right time and optimize availability of the machines. The feature monitoring the condition of the bearing is shown in graph 1 using raw data (circles) and smoothed data using a moving average of 10 hours (solid line). Initially the vibration level was quite low and considered as a good state of the bearing. Incipient degradation start evolving slowly afterwards till around 600 hours after measurement start, where an abrupt change was recorded. Recording this change with an intermittent CM system would depend on the time you choose for measuring. If unluckily this measurement took place when the raw data amplitude is low, this abrupt change will not be recorded. The continuous monitoring system helps also to observe the behaviour of the machine, allowing thus some insight to understand it. For instance, after this abrupt increase in vibration, a decrease of amplitude was also recorded right after 700 hours followed by a second increase around 800 hours and then a catastrophic failure around 950 hours. These sequences records are certainly good inputs for machine builders to better understand the behaviour of their machines and use this information to discuss improvement with their suppliers. Another even cheaper condition monitoring system to track some bearing failures is based on temperature sensors. Initial results showed clearly the feasibility of such a monitoring. The results of this study will be published later. These results showed that the cage failure illustrated in graph 1 could also be predicted using cheap temperature sensors a couple of weeks in advance. Therefore temperature condition monitoring is a cheap and a robust condition monitoring system for industry with much more advantages compared to accelerometers, for instance, the easy way to get the data directly via machine's controllers.



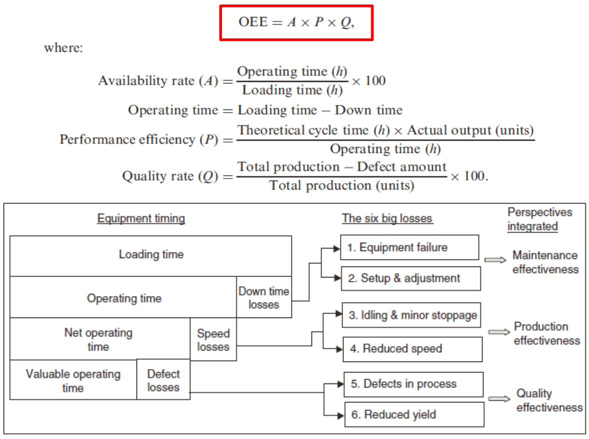
Graph 1 online condition monitoring example for a bearing in an industrial machine

3. *Production capacity optimization approach*

Different measures of productivity exist in the available literature. The overall equipment effectiveness (OEE) concept has been widely used as a quantitative tool essential for measurement of productivity (Muchiri, et al 2008). The OEE measurement tool evolved from the total productive maintenance (TPM) concept introduced by (Nakajima, 1988) and is defined as a measure of total equipment performance, that is, the degree to which the equipment is doing what it is supposed to do (Muchiri, et al 2008). It is a three part analysis tool in order to determine equipment performance based on its availability, performance and quality rate of the output. It is used to identify the related equipment losses for the purpose of improving and optimizing the total productivity and performance of the considered system. Six major categories of losses are identified within the OEE concept; these are depicted in Graph 2 and can be summarized as follows (Muchiri, et al 2008):

- *Breakdown losses* categorized as time losses and quantity losses caused by equipment failure or breakdown.
- *Set-up losses* occur when production is changing over from one item to another.
- *Idling and minor stoppage losses* occur when production is interrupted by temporary malfunction or when a machine is idling.
- *Reduced speed losses* refer to the difference between equipment design speed and actual operating speed.
- *Quality defects and rework* are losses in quality caused by malfunctioning production equipment.
- *Reduced yield during start-up* are yield losses due to machine start-up.

By considering the six major losses defined in OEE an optimal performance of the process can be achieved by monitoring and corresponding optimization of process and system parameters. This can be done by defining an efficient maintenance schedule, a good output (product) quality and an optimal production speed. Many papers on optimal maintenance scheduling exist in literature (Van Horenbeek, et al 2010). Furthermore, previous research has been done on optimizing maintenance with regard to output quality (Van Horenbeek, et al 2011). Therefore, in the remainder of this paper we will focus on production speed optimization (i.e. in order to maximize production capacity) through process monitoring.



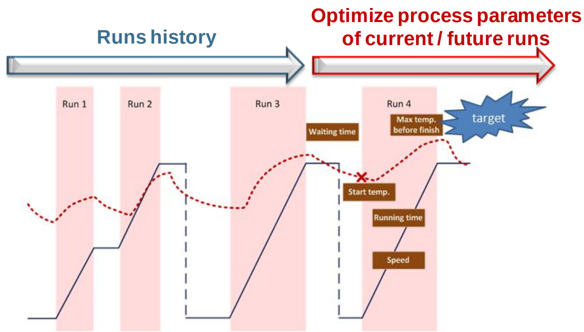
Graph 2 OEE concept for performance measurement

4. Validation on an industrial case study

The case study analysed in this paper corresponds to wire processing industry. The ultimate goal would be to clearly illustrate how temperature condition monitoring information can be used to maximize industrial production capacity. This approach extends the use of condition monitoring information from purely avoiding unexpected failures to productivity optimization of an entire system.

4.1 Problem formulation

In the wire processing industry, production cycles are repeated in order to produce a product. During these cycles the temperature and the speed of the machines are recorded. The temperature sensors are monitoring possible overheating of the machine and will be used in this paper to optimize the machine's speed. Without optimization, the machine is simply stopped when overheating is detected. This results in lost production capacity. Therefore, we will illustrate how the condition monitoring information can be used as an input to the machine's controller in order to optimize the production speed. The speed of the production machine is namely directly related to the corresponding temperature increase or decrease. Optimization of the production speed results in maximal production capacity and minimal machine downtime by prevention of overheating. The problem is schematically depicted in graph 3.

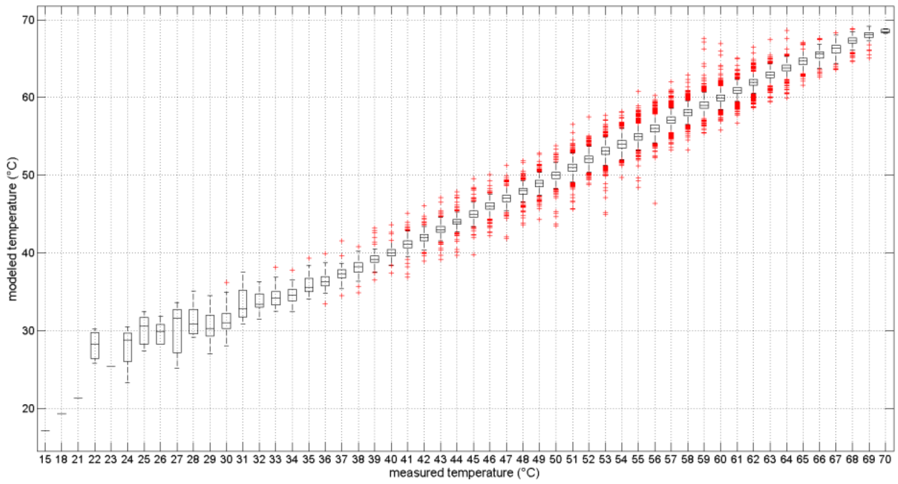


Graph 3 production speed optimization by avoiding machine's overheating

The information about speed and temperature gathered in previous runs would be used to propose an optimal production speed for current and potentially future runs. The machine health is supposed in this scenario to be within the safe band as the temperature should not exceed a fixed value or threshold corresponding to machines overheating. However, the technique could be extended to take into account the dynamic change of machine's health by simply changing the fixed threshold to a varying function versus time which describes the health degradation if this is known. In order to solve the problem described in this section, a model of the temperature versus the production speed is needed. This is explained in section 4.2.

4.2 Temperature – speed model

After an extensive data cleansing and preparation by removing all kind of outliers and dividing properly the data into subsets corresponding to different runs, a physics-based parametric model has been developed to model the machine's temperature versus the production speed. It was estimated under the nonlinear mixed effects framework that allowed describing the run-to-run variability in the data (Davidian and Giltinan, 1995). Parameters were estimated using Restricted Maximum Likelihood (REML). The results showing the modelled temperature versus the measured ones are shown in graph 4.

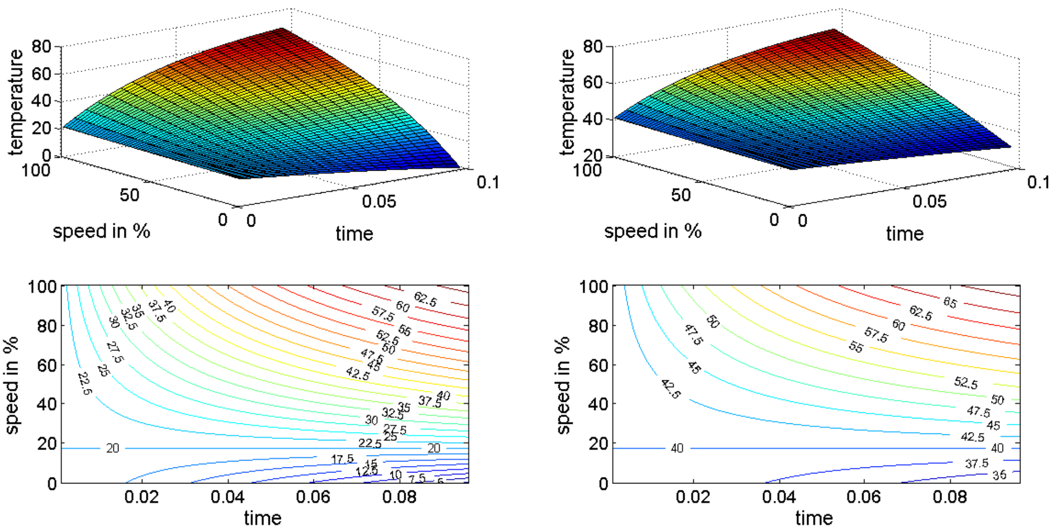


Graph 4 modelled versus measured temperature

The model describes quite accurately the temperature from the speed data with a coefficient of determination R^2=0.9815.

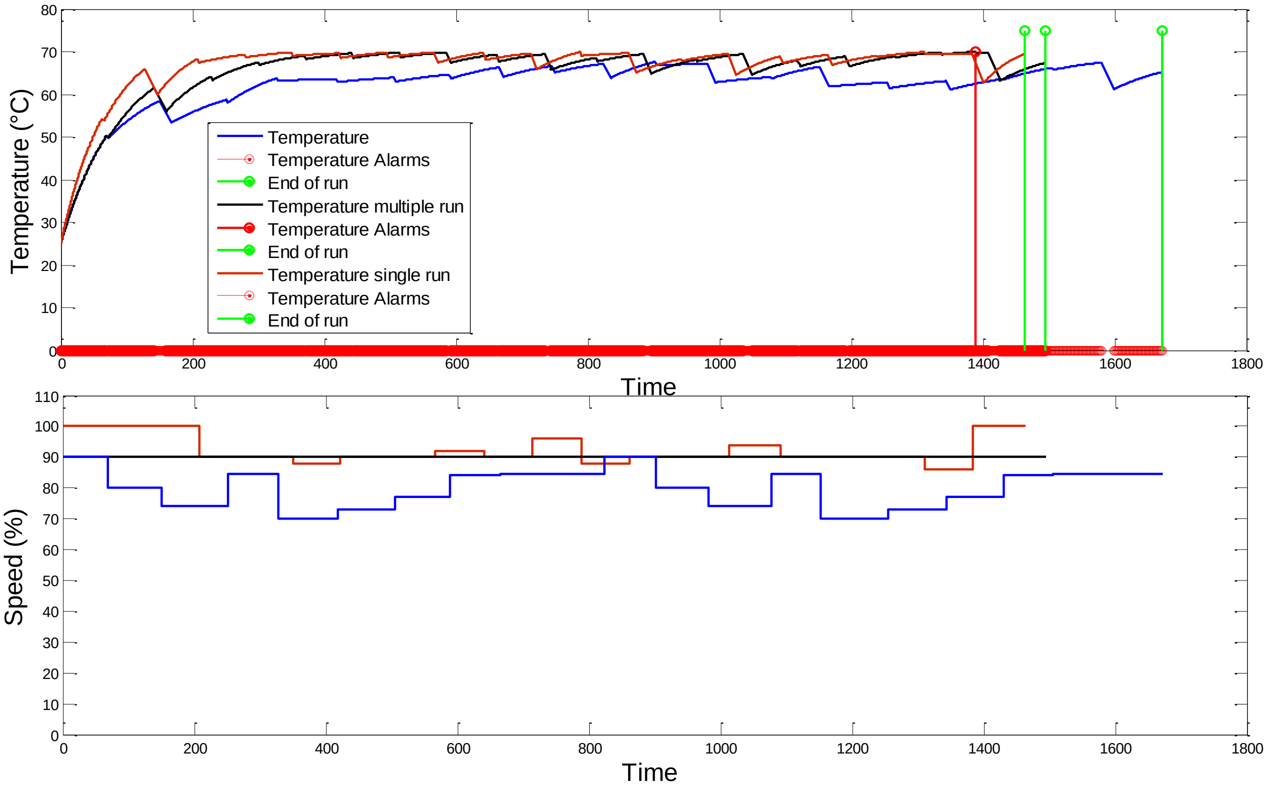
4.3 Production speed optimization

The production speed optimization consists of proposing a production speed where the machine will run the current and future cycles without the risk of overheating. If the temperature at the start of the cycle and the needed time to finish the current cycle are known, which is valid for the current case study, then the optimal speed can be derived and proposed to the machine's users / controller. Graph 5 is showing different possible speeds depending on temperature at the start of the cycle and the time to finish the cycle. For example, if the temperature at the start of the cycle is ~42°C and the needed time to finish the cycle is < 0.01 time unit, then the machine may almost run at the higher allowed speed.



Graph 5 possible speed values versus temperature at start of the cycle and the time to finish the production cycle

Simulation based optimization of the running speed based on recorded process data was done to illustrate the benefit of doing such an optimization with regards to the current way of working. The results are shown in graph 6. Here "Temperature" is defined as the measured temperature within the current way of working. Two major possibilities for optimization are considered, which are defined as single run and multiple runs optimization. In single run optimization, the optimal speed is defined for only the next run based on the current temperature at the start of the run. After each run the temperature and corresponding optimal speed is updated (this can also be seen in graph 6). In multiple runs optimization the optimal speed is determined for multiple runs at once (i.e. the speed remains constant throughout these runs). The results are shown in graph 6. The machine that uses an optimization of the speed would finish sooner the production compared to the machine that does not use the optimization technique (i.e. current way of operation). Possibility to optimize the machine's speed for more than one future run is possible with still some gain compared to a machine with no optimization. However, the gain from a single run optimization is bigger compared to multiple run optimization because of the continuous updating of the monitored temperature and the corresponding speed. This simulation shows a high potential of production maximization which needs to be validated in a real plant.



Graph 6 simulation of production with and without speed optimization technique

5. Acronyms

Predictive Maintenance (PdM)
Condition Monitoring (CM)
Condition-Based Maintenance (CBM)
CRoss Industry Standard Process for Data Mining (CRISP-DM)
Prognostics for Optimal Maintenance (POM)
Overall Equipment Effectiveness (OEE)

6. Conclusions

Industrial production capacity optimization using temperature monitoring was presented in this paper with application to wire process industry. The online condition monitoring benefit of industrial machines was illustrated. Online monitoring using temperature sensor has a high use potential in industry. The sensor itself is very cheap and data collection / processing might be done directly with the machine's controllers / PLCs. This collected temperature data could be deployed in an optimal way instead of the traditional way of using it by implementing basic temperature protections. An example of wire process industry was used to show how such an optimization approach can be practically applied. Simulations based on real process data showed the capacity benefit (here is the time to finish production of a machine with and without optimization technique). Next steps will be to validate these simulations in a real production plant. This approach could be adapted and applied to any production machine / process and allows thus an optimal way to run production without causing machines downtime.

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