PROGNOSTICS FOR OPTIMAL MAINTENANCE: MAINTENANCE COST VERSUS PRODUCT QUALITY OPTIMIZATION FOR INDUSTRIAL CASES

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Correlation between the quality degradation of a product and maintenance of a machine is often established by the production engineers. To asses this correlation, some assumptions are made. In most cases it is assumed that the quality of the product degrades after a fixed number of operation cycles of the production machine. Therefore maintenance of the production machine is only performed after this number of cycles is accomplished. This kind of assumptions is often not valid in modern industry since high variability of products, tolerances of machines / components, reliability variations of these components, extensive / smooth usage, etc. make this degradation quite dynamic in time. As a result, the quality of the product could get degraded in a fast way if this variability is high or in a slow way if this variability is low. Both cases will lead to low benefit because of lost production in the former case or redundant maintenance in the latter one. In this paper we propose a solution to this problem by maximizing the benefit using online monitoring of product's quality degradation and maintenance cost evolution. A Condition Based Maintenance framework for industry developed in Prognostics for Optimal Maintenance (POM) project [1] and described in [2] is applied to two industrial use cases in order to deploy and validate the proposed technique.

Key Words: Condition-based maintenance, Predictive maintenance, Data mining, Prognostics, Maintenance optimization

1 INTRODUCTION

Many models for Condition Based (CBM) or Predictive (PdM) Maintenance optimization exist in literature [3,4,5,6]. These models make clear that maintenance decision making based on real time information from the components and systems has a substantial benefit regarding maintenance cost, prevention of unexpected failures and reduction of downtime. However, for some systems it is not due to the state of the system itself that maintenance is needed but due to the quality degradation of the products the system is producing. The objective of this paper is to determine the benefit of CBM with regard to quality degradation of the product using a condition monitoring system. By this mean, the optimal time to perform maintenance is determined by considering the trade-off between maintenance cost and cost of quality degradation of the products. Predictive maintenance optimization in literature is mostly restricted to theoretical modelling of the degradation process, for example stochastic processes, and subsequently finding an optimal maintenance policy for this degradation process [7,8]. This results on putting many assumptions about the failure behaviour of components. However, these assumptions are only valid under certain circumstances. Operation and environmental conditions are assumed to be known and cannot change significantly. In general, however, this is not true for all machines because usage rates and environmental conditions are changing over time. These variations are unfortunately often not taken into account for the case studies covered in literature. This creates a gap between theory and practice [3,9]. Moreover decision making based on real time information from monitoring systems and components is still an under explored area in maintenance optimization [10]. The integration of predictive information into decision support systems is a very important step that needs further research. To overcome these flaws, two case studies are presented in this paper where real time predictive information coming from the industrial machines is directly used to support maintenance decision. This support is given by updating a cost function recursively when new information about the system performance becomes available. Based on this information, maintenance is scheduled in an optimal way. The activities of maintenance optimization by using condition-based maintenance are performed within the Prognostics for Optimal Maintenance (POM)

project [1]. The POM CBM framework is used as a tool for maintenance optimization by using a CBM policy [2]. This framework is based on the ISO-13374 standard for condition monitoring and diagnostics of machines [11].
The originality and contribution to the field of maintenance of this paper lies at different levels:

- A maintenance cost versus product quality degradation CBM optimization is performed, which has, according to the knowledge of the authors, never been published before. Although this should certainly be considered in many industrial production machines in order to be able to perform optimal maintenance.
- Degradation is not only caused by wear out, but mainly by usage rates and environmental conditions, which is accounted for in the condition monitoring approach taken in this paper.
- An integrating approach is taken by developing a decision support system based on condition monitoring information directly coming from the machine without any assumptions on the degradation process. The integration of condition monitoring that results in predictive information on equipment performance and decision making based on this predictive information is perceived as one of the biggest challenges in maintenance [10].
- Few case studies have been reported on maintenance optimization models for condition-based maintenance [9]. In this paper the developed CBM optimization model is applied to two different case studies to show the applicability of the developed methodology on real life industrial cases.

This paper is organized as follows. Section 2 describes the two different case studies considered for optimizing the condition-based maintenance policy. The POM CBM framework is described briefly in Section 3 and Section 4 presents the maintenance optimization model based on the predictive information. Finally, conclusions and future research are stated in Section 5.

2 USE CASES DESCRIPTION

2.1 Seal quality monitoring in a packing machine

The first industrial use case consists on a Vertical Form Fill and Seal (VFFS) packing machine. The machine produces bags of different products (chips, cheese, sugar, etc.) in food industry. A plastic film roll is supplied as a packaging material. After forming flaps that wrap around a main conical tube as depicted in figure 1, the film is pulled downward around the outside of the tube and a vertical heat-sealing jaws clamp onto the edges of the film bonding the film by melting the seam edges together. After the bonding, a knife cuts the film forming thus a produced bag.

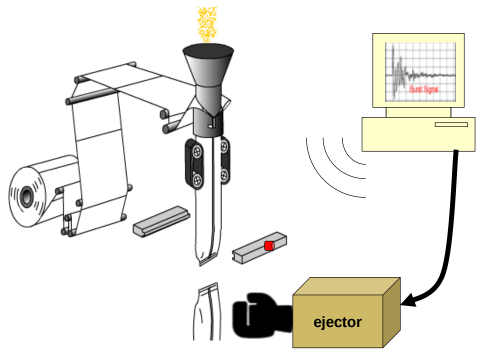

Figure 1. Seal quality monitoring in a packing machine

One of the main rejects in the field is the seal quality of the produced bags. The seal quality degradation is caused by accumulation of dirt and dust from the production environment and by leakage of the products during the cutting process on the sealing jaws and reducing their sealing performance. In order to monitor this degradation, a condition monitoring system called SealScope [12] is used. This system measures vibration signatures due to the impacts of sealing jaws during the bonding process and applies advanced multivariate quality control charts technique [13] to calculate prognosis features correlated to the studied degradation.

2.2 Print quality monitoring in copiers

The second use case consists on monitoring the quality of the copy papers from a fleet of copiers. This case study was carried out in a previous project called IRIS (Intelligent Remote Industrial Services) [14,15] where industrial services (machine's health management, remote configuration, etc.) are provided to the customers of machines builders. An illustration is shown in figure 2. Considering the machine's health management, the main purpose in that project was to identify features which are correlated to the degradation of different components in the copiers and perform predictive maintenance using these predictive features. In this work, the predictive maintenance action will not only be optimized based on degradation of components but also taking into account degradation of produced papers.

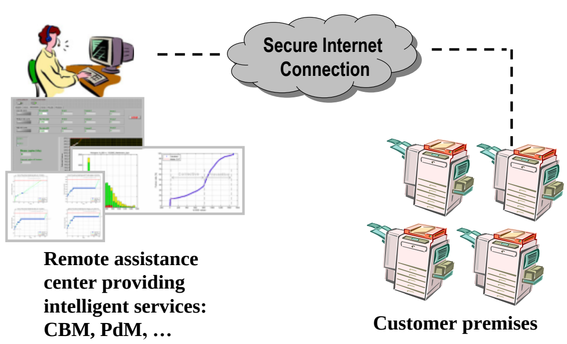

Figure 2. Print quality monitoring in copiers

3 POM CBM FRAMEWORK FOR CONDITION BASED MAINTENANCE IN INDUSTRY

In order to facilitate the design and the deployment of a Condition Based Maintenance policy in industry, more precisely machine manufacturer and production machinery, the POM CBM framework has been developed in the frame of POM project [1]. An illustration of the architecture of this framework is depicted in figure 3.

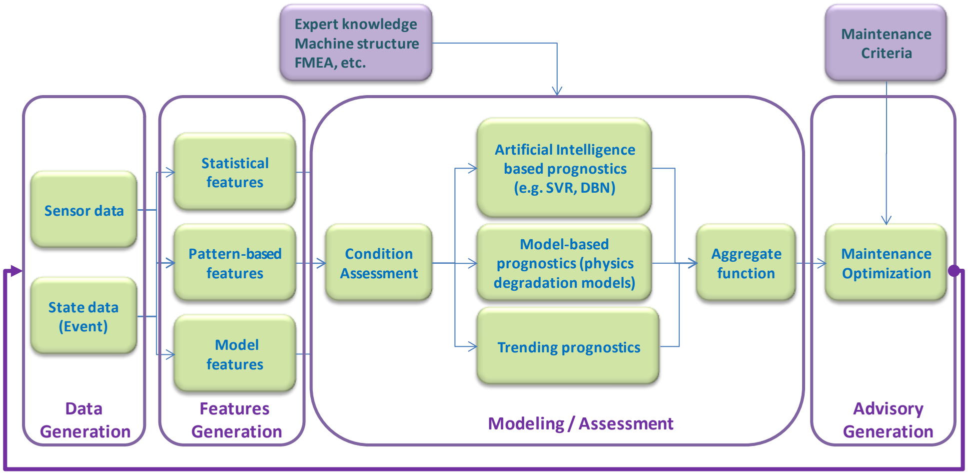

Figure 3. Overall architecture of POM CBM framework

A detailed description of this framework is given in [2]. The framework has been developed following the available standards like ISO 13374 for condition monitoring and diagnostics and OSA-CBM (Open Systems Architecture for Condition Based Maintenance) [11].

The different modules of the framework consist on (i) data generation, (ii) features generation, (iii) modelling and assessment and (iv) advisory generation. Every module is considered as independent from the others and could be customized accordingly to the studied application. This is afforded by a proper choice of inputs/outputs interfacing every module and allowing thus flexibility and interoperability. A module could also be divided to sub-modules where some external interactions could be set, like including information from experts in the field if available to make an assessment model more robust. Since the framework is supposed to work online for maintenance optimization, feed-backs between different modules are foreseen to fortify in an iterative way the prognostics against variability and environmental changes in the studied process.

In next sections, only the last module, Advisory Generation, will be described for the two studied use cases. The details about the predictive features used for the prognostics part are available respectively in [13] and [15] for the two use cases.

4 COST MODEL FOR OPTIMAL MAINTENANCE PLANNING

4.1 Maintenance Cost versus Product Quality Degradation

For both case studies a cost model considering the trade-off between the cost of maintenance actions and the cost of quality degradation is built. The cost function is continuously updated as new information about the condition and performance of the equipment becomes available from the monitoring system. This maintenance cost information enables optimal maintenance planning based on the real performance and degradation of the considered components or systems.

Figure 4 illustrates the advantage of using predictive information to schedule preventive maintenance actions compared to time-based preventive maintenance scheduling. The predictive information takes into account the changing usage rates and environmental conditions which influence the degradation process, while the time-based maintenance actions assume a fixed degradation over time. The timing of preventive maintenance actions are plotted on the x-axis, where t_M is the time of maintenance based on monitoring information and t_P is the time of the time-based preventive maintenance action. On the y-axis is the decision rule based on the monitored feature (β). This decision rule can have different implementations like, for example, a fixed threshold on a condition monitored parameter. For the first case study in this paper a decision rule based on the maximal profit is implemented, this will be discussed in section 4.2. The predictive maintenance policy prevents, for the first maintenance action, the loss due to quality degradation of the product by performing maintenance earlier compared to the time-based policy as depicted in figure 4. For the second maintenance action the quality degradation is less than anticipated by the time-based policy, a loss due to too much maintenance is incurred here compared to a predictive policy. This shows that a trade-off between the cost of quality degradation and the cost of maintenance should be used in an optimization process to come to an optimal maintenance policy. This is illustrated, together with the ability of the predictive maintenance policy to incorporate the changing quality degradation by changing usage rates and environmental conditions, in the next sections of this paper.

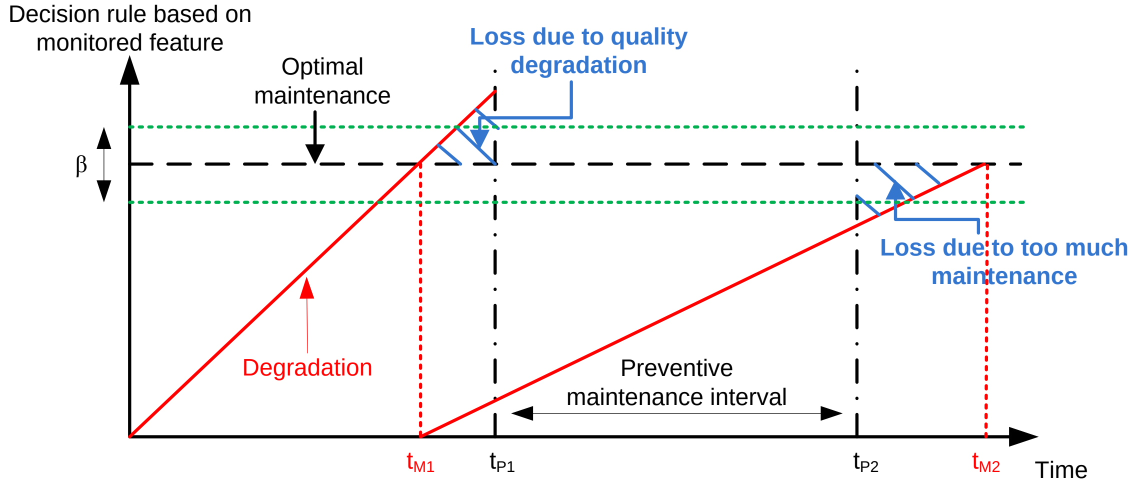

Figure 4. Advantage of a predictive maintenance policy over a time-based preventive maintenance policy considering a trade-off between the cost of maintenance actions and the cost of quality degradation for different deterioration rates.

4.2 1st Case study: Seal quality monitoring in a packing machine

For the first case study, the relevant feature, which is correlated with the performance of the machine, is the percentage of bad bags produced by the sealing machine. Zero padding technique is applied to this feature in order to avoid divergences due to bad seals in beginning of production. This feature is used to represent quality degradation of the produced bags in a cost function as follows:

$$P_t = (P \times (1-\alpha)) - (C \times \alpha) - (M/n) \tag{1}$$

Where:

t: time after previous maintenance action
P_t: profit per bag (€) until time t
P: profit for one good sealed bag (€)
C: cost for one bad sealed bag (€)
M: maintenance cost
n: number of produced bags until time t
α: percentage of bad sealed bags until time t

Based on this cost function it is possible to come up with a decision rule which determines when maintenance should be performed. For this specific case study maintenance is performed when:

$$P_t < P_{\max} \times (1-\beta) \tag{2}$$

Where:

t: time after previous maintenance action
P_t: profit per bag (€) until time t
P_{max}: maximal profit per bag (€) until time t
β: maintenance percentage

This means that at each time *t*, when a bag is produced, the profit per bag P_t is updated according to the new information on the percentage of bad sealed bags α. When P_t becomes smaller than a certain percentage, which is determined by parameter β, of the maximal profit per bag P_{max} until *t*, a preventive maintenance action should be performed. The reason why P_t is allowed to decrease compared to P_{max} is because the considered feature of percentage of bad sealed bags is not monotonically increasing and may fluctuate due to 'self cleaning' phenomenon. This phenomenon consists of disappearance of dirt during production process after it gets accumulated in the sealing jaws. The maintenance percentage β is the parameter in the decision rule which determines when maintenance should be performed in order to maximize the profit per bag P_t. The determination of the optimal value of β is performed based on data coming from experiments on the packaging machine itself. Simulations on this data were used to determine the value of β which optimizes P_t. Figure 5 shows the result of this optimization where $P = 10€$, $C = 10€$. The maintenance cost *M* for the specific case study performed in this paper is 200€, which according to the optimization means that a value of 0.02 for the maintenance percentage β is optimal. Of course it is possible to update the value of β continuously when more data becomes available.

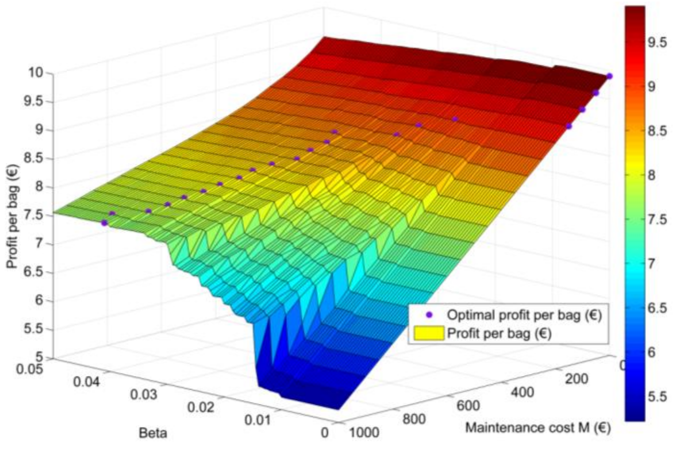

Figure 5. Determination of β which maximizes the profit per bag P_t

In order to quantify the added value of decision making based on real-time evaluation of the earlier introduced cost function and decision rule, a comparison is made between this policy and the maintenance actions that were performed in real life. The maintenance actions performed in real life are based on the experience of the operator. When the operator believes that the packaging machine produces too many bad sealed bags, a preventive maintenance action is performed. The results of the comparison are given in Figure 6, which shows the percentage of bad bags (α) and profit per bag P_t in function of the number of produced bags. Both a reference maintenance scenario, which shows the real life situation, as well as a predictive maintenance policy are presented.

The maintenance timing reference that is shown in Figure 6 is the timing of the maintenance actions performed based on the experience of the operator without making use of the monitored feature (α) for decision making. A total profit per bag $P_{TOT,REF}$, which is the profit of the reference scenario for the entire experiment, is also calculated in order to make comparison with the predictive maintenance policy possible. By using the monitored feature, percentage of bad bags (α), it is possible to implement the predictive maintenance policy to the real life data collected from the packaging machine. The continuously updated profit per bag P_t, which is used to schedule maintenance as described before, is presented in Figure 6. Based on the decision rule [Equation (2)] a preventive maintenance action is scheduled which takes into account the trade-off between the cost of quality degradation and the cost of maintenance. From this simulation it is clear that in general the operator waited too long to perform a preventive maintenance action, which results in a decrease in profit per bag due to quality degradation of the produced bags. A total profit per bag for the entire experiment is calculated for both the reference scenario ($P_{TOT,REF} = 8.3436€$) and the predictive maintenance scenario ($P_{TOT,PdM} = 8.9720€$). An increase of 7.01% in the total profit is possible by implementing a predictive maintenance policy. That incorporates the changing quality degradation due to different usage rates and environmental conditions. This predictive maintenance policy makes it possible to monitor the profit per bag in real-time, which assists the operator to perform maintenance at the optimal time.

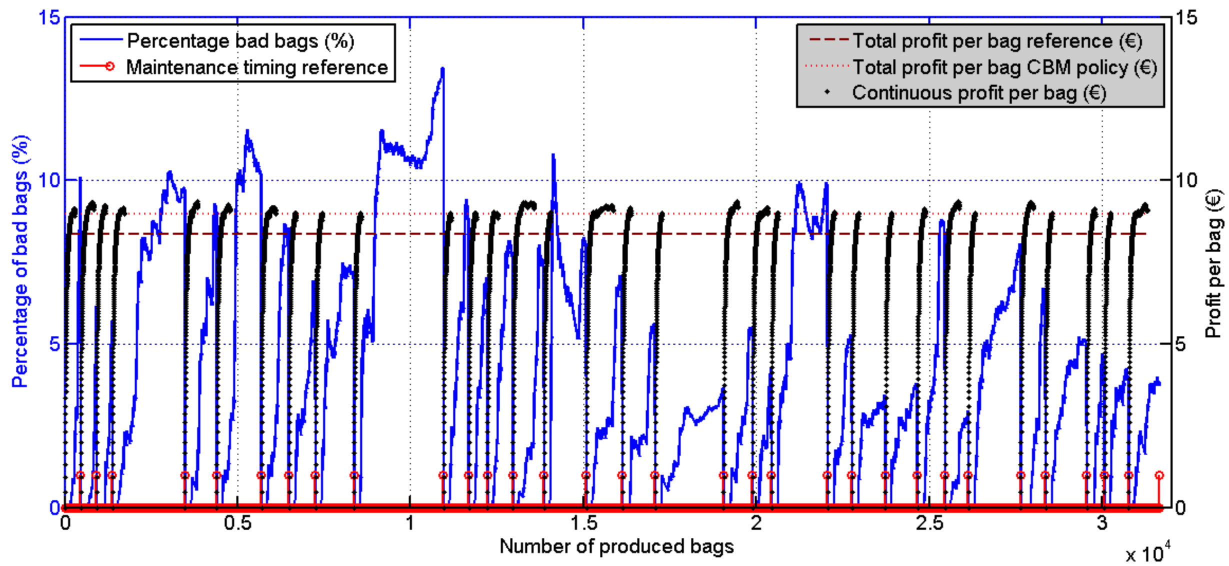

Figure 6. Comparison between reference maintenance policy and predictive maintenance policy

4.3 2nd Case study: Print quality monitoring in copiers

For the second case study, the monitored feature is directly correlated to the quality degradation of the product [16]. For a photocopier, quality degradation can be seen as bad copied pages. The general overview of how the predictive information is used to optimally schedule maintenance actions based on a trade-off between maintenance costs and quality degradation costs is shown in Figure 7 and Figure 8. Figure 7 depicts the prediction of the evolution of the monitored featured and the corresponding degradation. A lower threshold (feature value of 800 (TH_1)) and an upper threshold (feature value of 1500 (TH_2)) are used to describe the quality degradation over time. Before reaching the lower threshold no bad copies are produced, which means the photocopier is in perfect working condition. When the degradation feature reaches the lower threshold, quality degradation of the produced copies starts and evolves through time according to a quality degradation function. This quality degradation function is assumed to be linear in this paper and is shown in Figure 8. The quality degradation function describes a linear relation between the monitored feature and the probability of producing bad copies. When the monitored feature reaches the upper threshold, the probability of producing bad copies equals 1, which means only bad copies are produced at this time and the photocopier is in a failed state. The time that the feature value reaches the lower threshold is defined as t_1 and the time of reaching the upper threshold is defined as t_2.

Based on the predicted deterioration and the corresponding quality degradation function it is possible to optimally schedule preventive maintenance actions by optimizing a cost function. Each time new monitoring information and a corresponding prediction about the state of the component becomes available, the cost function and preventive maintenance timing is updated. The cost function is defined as follows:

$$P(t_a) = \frac{(t_1 \times n_1 \times P) + ((1 - D(x)) \times n_\Delta \times P) - (D(x) \times n_\Delta \times C) - M}{n_1 + n_\Delta} \tag{3}$$

Where:

$P(t_a)$: profit per copy (€) when maintenance is performed at time t_a
t_1: time when lower threshold of monitored feature is reached
n_1: number of copies produced until reaching the lower threshold of the monitored feature
n_Δ: number of copies produced between t_1 and t_a
P: profit for one good copy (€)
C: cost for one bad copy (€)
M: maintenance cost (€)
D(x): percentage of bad copies between t_1 and t_a

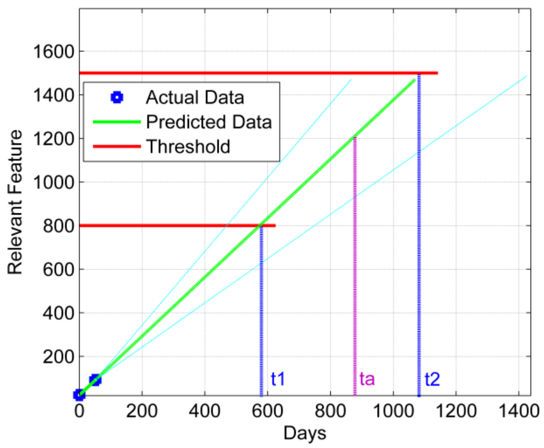

Figure 7. Prediction of deterioration

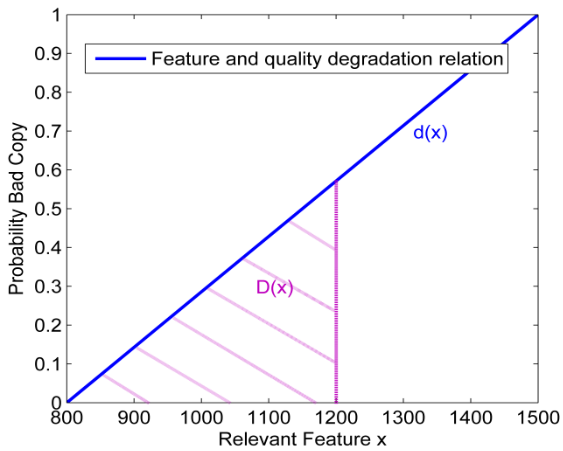

Figure 8. Quality degradation function

In this cost function the quality degradation is incorporated by the function D(x), the percentage of bad copies between t_1 and t_a, which reflects the quality degradation function as defined in Figure 8. The function D(x) is calculated as follows:

$$D(x) = \int_{x_{t1}}^{x_{ta}} d(x)dx \Big/ (TH2 - TH1) \tag{4}$$

Where:

D(x): percentage of bad copies between t_1 and t_a
x_{t1}: feature value at time t_1
x_{ta}: feature value at time t_a
d(x): quality degradation function
TH_1: feature threshold value where quality degradation starts
TH_2: feature threshold value where quality degradation is maximal

Based on the deterioration prediction (Figure 7) and the quality degradation function (Figure 8), it is possible to determine the optimal time to perform maintenance by evaluating the cost function defined in equation (3) for different timings of maintenance. The time where the profit curve is maximized is the optimal time to perform preventive maintenance. This is shown in Figure 9 and Figure 10, respectively versus relative days after lower threshold is reached and absolute days. This profit curve, together with the corresponding optimal time to perform preventive maintenance is updated each time new predictive information becomes available.

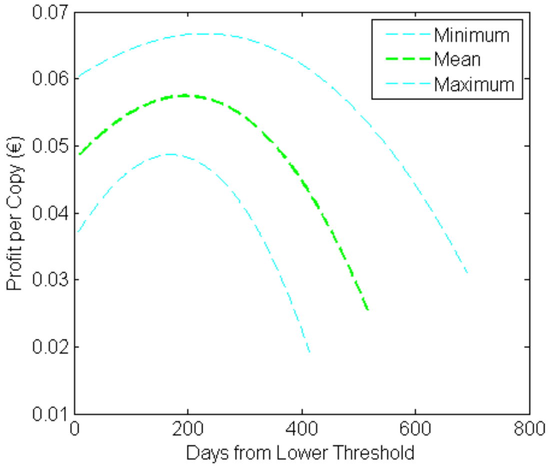

Figure 9. Profit curve for relative time unit since lowest threshold

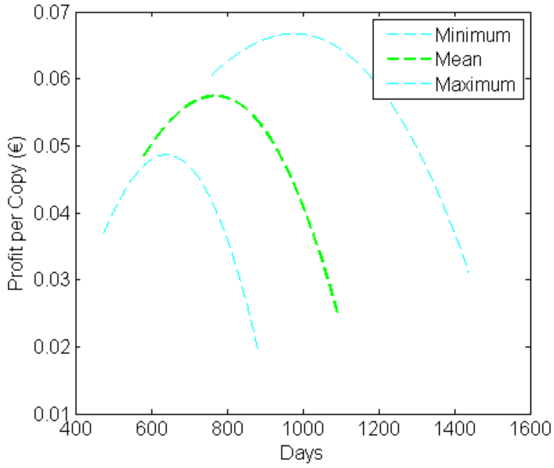

Figure 10. Profit curve for absolute time unit

5 CONCLUSIONS

Condition Based Maintenance (CBM) optimization with regards to maintenance cost and quality degradation has been theoretically described in this paper and experimentally validated on two industrial use cases.

This CBM optimization utility which fits in the POM CBM framework for designing and implementing CBM for industrial cases, proved to be able to deal with real data from studied use cases, where complexities in predictive features, like local minima, measurement noise and abrupt usage changes could take place.

Based on the developed profit maximization technique, it is possible to optimize robustly the maintenance in real time by monitoring online degradation of the product.

Regarding the trade-off between maintenance cost and quality degradation cost, the added value of predictive information in maintenance optimization is substantial.

In future research, we will cover complexities met in industrial cases, like 'self cleaning' phenomenon described earlier in this paper resulting on fluctuating predictive features, and automatic updating of optimization parameters (β in Figure 5). The robustness of the optimization utility will also be validated with more industrial cases and more online dataset.

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