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# Unsupervised co-training of Bayesian networks for the diagnosis of machining spindle

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The objective of Smart Manufacturing is to improve productivity and competitiveness in industry, based on in-process data. Indeed, failures can stop the production for a couple of days and generate costs of non-quality. Failures in industry can either damage the machine or the product being produced. In both cases, the earlier the failure is detected, the lower the impact on production. Thus, monitoring both the process and the machine condition is interesting, due to their potential interactions. Besides, the diagnosis of the nature of the incident is also important, in order to react adequately as fast as possible.

It requires reliable, explainable and understandable models such as Bayesian networks for performing tasks like condition prediction. Bayesian networks can be learned with incomplete data and in a supervised or unsupervised way, which is very useful because the collect of labelled data is costly and sometimes impossible, especially in industry where problems are, moreover, very rare.

In this paper, we propose a generic architecture based on two Bayesian networks and a collaborative learning strategy that improves the condition monitoring of rotating machines in unsupervised context by using information gathered from process monitoring.

*Keywords:* Industry 4.0, condition-based maintenance, process monitoring manufacturing, machining, tool breakage, Bayesian networks, unsupervised learning, co-training.

## 1. Introduction

Smart manufacturing is a promising research area for the improvement of productivity and competitiveness in industry, by exploiting the manufacturing digital data (Tao et al., 2018).

Rotating machines are widely used in many industries. This paper focuses on machine-tools and especially on the spindle, which is a very efficient and critical rotating machine. The spindle is the machine component that holds the cutting tool (in the same ways that a drill holds a drill bit). Ball bearings are used for the rotational guidance of the spindle shaft.

*Condition-based maintenance* of rotating machines is usually based on periodic measurements of vibration (Ebersbach and Peng, 2008; Mathew, 1984). Oil analysis (Craig

et al., 2009) and thermal measures can also be performed. Practically, the analysis of vibration signal of rotating machines can be performed through global criteria that evaluates the vibration level, such as the root mean square velocity ( $V_{rms}$ ). It is defined in the ISO standard 10816-3 (ISO, 2009) and widely used for condition-based maintenance. ISO standard 17243-1 (ISO, 2014) recommend the use of both velocity  $V_{rms}$  and acceleration  $A_{rms}$  for the monitoring of spindle condition. For more accurate monitoring, the frequency spectrum of vibration can be analyzed. Particularly, *BPFO* and *BPFI* reveal local defect on the outer race or the inner race of a bearing respectively. Besides, distributed defect can also be monitored, such as race waviness (Vafaei et al.,

2002) or worsening of surface roughness de Castelbajac et al. (2014). Randall and Antoni (2011) present the state of the art for the diagnostic of rolling bearing by analysis of vibration signal. Jimenez-Cortadi et al. (2020) review articles from the past ten years treating about predictive maintenance. The goal is to predict the remaining useful lifetime, which is very challenging. However, this paper focuses on condition-based maintenance, since machine-tool is complex use-case. Notably, spindle condition monitoring should be performed during idle rotation of the spindle, to avoid misinterpretation from vibration data collected during cutting.

*Process monitoring* consists in analyzing the machining in-process signals, in order to detect tool breakage, or predict the surface quality of the machined workpiece. Most of researches about condition monitoring in machining focus on tool wear monitoring (Teti et al., 2010). Other papers consider the impact of chatter on the surface quality of the machined surface (Peigne et al., 2004). Literature deals with the prediction and monitoring of such unstable vibration, by vibration or force signals (Munoa et al., 2016; Kuljanic et al., 2009). Tool condition monitoring can rely on machine learning; generally in a supervised way, to build a predictive model (Kim et al., 2018). For example, a Probabilistic Neural Network can classify broken tools and good ones (Huang et al., 2015).

In a more general framework, Bayesian networks (BNs) are probabilistic graphical models that are suitable for maintenance or in-process monitoring in the manufacturing industry (Weber et al., 2012). Indeed, their ability to model complex systems under uncertainty, to learn these models with unlabelled, incomplete, unbalanced or small datasets (Benferhat et al., 2020) is well known. Tidiri et al. (2016) review the main data-driven and model-based approaches for process fault diagnosis and compare their respective advantages and their drawbacks. Bayesian networks offer a great reliability to manage uncertainty. For example, Atoui

et al. (2019) propose to use BNs with a Gaussian mixture model for supervised data-driven process monitoring. Supervised approaches are often proposed, whereas the collection of labelled in-process data is generally impossible in industry. Moreover, the potential interaction between the machine condition and the process condition is not studied in literature, and even less with uncertainties consideration.

The objective of this paper is to propose a generic architecture to improve the condition-based maintenance of rotating machines in unsupervised contexts by exploiting information from in-process monitoring. In this way, the aim is to detect machine failures caused by the manufacturing process; and to explain and understand which type and intensity of incident damage the spindle, and which evolution of spindle condition monitoring criterion reveals those damages.

Our two main contributions are: (1) The proposal of a generic architecture based on BNs that models each monitoring task independently and allows to define strongly critical values for the continuous monitoring criteria provided as inputs of our architecture. (2) Each of our models is composed of a two-level structure that is able to take into account the different possible values of the criticality threshold used in the definition of these monitoring criteria.

The next section details the monitoring criteria used, as well as the data preprocessing step. Section 3 describes the model architecture and its different components, such as the learning strategy. In section 4, experiments are performed to validate the proposed architecture. Finally, section 5 draws the conclusions and perspectives of this work.

## 2. Monitoring criteria and data preprocessing

The choice of vibration sensor, of the signal preprocessing and of the monitoring criteria was performed in previous works by Godreau et al. (2019).

The raw in-process monitoring criteria are  $A_{rms}(t)$ ,  $V_{rms}(t)$ ,  $Nh(t)$  and  $Ub(t)$ .  $V_{rms}(t)$  and  $A_{rms}(t)$  are respectively the root mean square of the vibration velocity and acceleration, revealing the current vibration level.  $Nh(t)$  enables chatter detection, through the asynchronous vibration level, obtained by order tracking in the vibration spectrum. Lastly  $Ub(t)$  detects tool breakage, by the amplitude of the contribution at the spindle frequency that estimates the tool balancing.

These raw criteria are obtained by real-time signal processing (from 25kHz vibration signals) and collected at a frequency of 10 Hz (864000 values per day). To be compared with daily evaluation of spindle condition, the in-process monitoring criteria must be daily aggregated. Since incidents occurring during machining can be very brief, they cannot be detected by averaging over all the monitoring values measured during a day. Besides, only severe vibrations, exceeding a certain threshold, can damage the spindle. Therefore Godreau et al. (2019) proposed to aggregate these raw in-process criteria as described in equation 1 where  $\tau$  is the criticality threshold associated to a generic criterion  $X(t)$ . High  $\tau$  values reveal short and violent events, when small values highlight long and moderate events.

$$X^\tau = \sum_{t=1}^{t=864000} \max(X(t) - \tau, 0) \quad (1)$$

In this way, in-process critical events are daily monitored, by computing the advanced criteria  $A_{rms}^\tau$ ,  $V_{rms}^\tau$ ,  $Nh^\tau$ ,  $Ub^\tau$ . (Godreau et al., 2019) proposed values for the criticality threshold of these criteria.

Regarding the spindle condition monitoring: a vibration signature is performed once a day during idle rotation of the spindle, to evaluate its condition. Faulty bearing induced vibrations are evaluated in the frequency spectrum: the amplitudes at the fundamental train frequency  $FTF$ , at the Ball Pass Frequency on respectively the Outer and

Inner rings  $BPFO$  and  $BPFI$  criteria; as well as the shaft balancing (by the vibration amplitude at the spindle rotation frequency), noted  $1X$ .

### 3. Model

Our architecture, depicted in Figure 1, proposes to model independently the spindle condition and the in-process monitoring with two Bayesian networks. The aim is to predict the state of the system from the observation of the advanced monitoring criteria defined in the previous section.

As a preamble, all the advanced monitoring criteria are discretized in a three-level scale  $\{OK, degraded, KO\}$  (section 3.1).

As seen in the previous section, critical thresholds  $\tau$  can be defined for these monitoring criteria. We then propose to structure the in-process monitoring in a two steps procedure. The first step is a local aggregation with several critical thresholds  $\tau$  for each criterion, in order to provide a local decision based on each criterion (section 3.2). The second step is a global aggregation that takes into account all the local decisions in order to predict the state of the system (section 3.3). Finally, we propose collaborative strategies to jointly learn the two models that are respectively dedicated to the spindle condition and to the in-process monitoring (section 3.4).

#### 3.1. Discretization

The advanced monitoring criteria defined in section 2 characterize critical vibrations that could damaged the spindle. They can be classified as weakly critical (values near 0), moderately critical (medium values) or strongly critical (higher values). We thus propose to discretize in a three-level scale  $\{OK, degraded, KO\}$  each continuous criterion  $X^\tau$  (noting its discretized counterpart  $X_d^\tau$ ).

Considering the discretization step in the model itself is a usual practice when dealing with probabilistic graphical model (see for instance (Mabrouk et al., 2015)). We

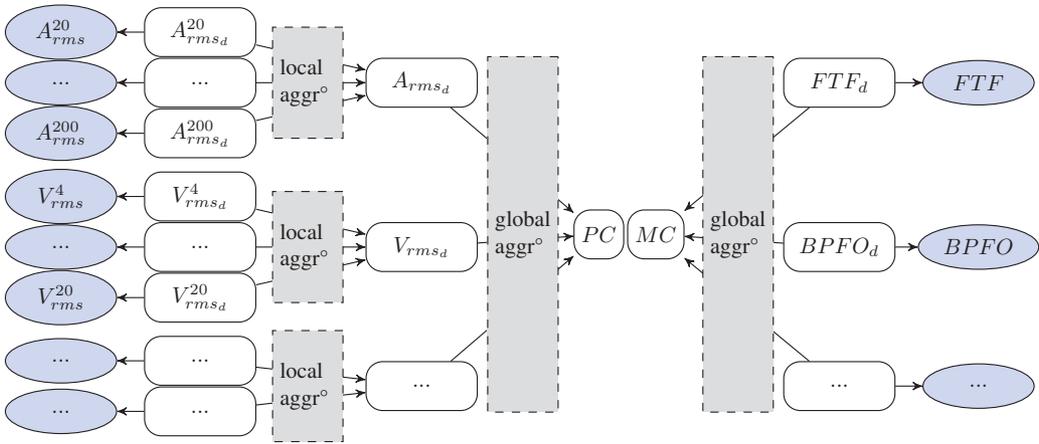


Fig. 1. Our generic architecture based on two Bayesian networks that models the spindle condition monitoring task (right) and the in-process monitoring one (left) independently, including a discretization step for the daily-aggregated monitoring criteria (blue nodes). Circles denote continuous random variables and (rounded) squares discrete ones. PC and MC stand respectively for Process Condition and Machine Condition.

then propose in a similar way to deal with this discretization step in the form of a Gaussian mixture model where the parameters are learnt in an unsupervised way by Expectation-Maximization (EM) algorithm (Dempster et al., 1977).

### 3.2. Local aggregation

Each in-process monitoring criterion  $X$  provides us a set of (continuous) advanced monitoring criteria  $X^T$  and their discretized counterparts  $X_d^T$ . The objective of this step is to provide a local decision  $X_d$  for each criterion, considering several critical thresholds  $X_d^T$  simultaneously.

We propose in this work to perform this aggregation in two different ways. The first one is the very naive *Max* operator that describes the fact that the local decision is the worst one returned by this criterion with all its possible thresholds. The second one is more evolved and consists in using a probabilistic aggregation such as the *NoisyMax* model (Srinivas, 1993). With this kind of aggregation, the dependency between the decision and the inputs is no more deterministic, and the influence of each input on the output is no more constant.

### 3.3. Global aggregation

The objective of the global aggregation is to provide a global decision for one sub-model based on the local decision provided by the different advanced monitoring criteria (e.g.  $A_{rms_d}, V_{rms_d}, Nh_d$  and  $Ub_d$  for the in-process monitoring sub-model).

As for local decision, we propose to deal with this aggregation with a deterministic *Max* or a probabilistic *NoisyMax* function.

This global aggregation is then simplified from the initial three-level scale  $\{OK, degraded, KO\}$  to a binary decision  $\{NOC, KO\}$  for the in-process condition or the spindle condition, where *NOC* stands for Nominal Operating Condition  $\{OK, degraded\}$ .

### 3.4. Learning strategy

A classical approach of this condition-based maintenance issue would be to learn the spindle condition model in a supervised way, with the ground truth of daily degradation of the studied machine part. In our industrial application, the collect of labelled data is impossible, but we can access to the data collected during the in-process monitoring task.

We propose to apply a collaborative strat-

egy in order to learn jointly, and in an unsupervised way, the two models respectively dedicated to the spindle condition and to the process monitoring.

In the following scenarios, the learning of the Bayesian networks is limited to the parameter learning in presence of incomplete data by using the EM algorithm.

We consider two different collaborative strategies for this learning task. The simplest *naive strategy* consists in learning simultaneously both models, by adding an equality constraint between the global decisions of the two models.

The second strategy is the application of the *recursive unsupervised co-training strategy*, proposed by Monvoisin et al. (2021). It is an interesting solution to jointly learn two models in an unsupervised way. The idea is to firstly learn one model in an unsupervised way (for instance the model dedicated to spindle condition monitoring) and then to learn the second one (process monitoring) enriched with the results of the first one, obtained by probabilistic inference. In the recursive strategy, this step is repeated several times until convergence.

## 4. Experiments

### 4.1. Experimental context

Those experiments are realized on real industrial data that contains 436 days of aggregated and unlabelled data, collected over three spindle lifetimes (a year and a half).

The results obtained by Godreau et al. (2019) which were afterwards confirmed by an expert are considered as the ground truth. The optimal thresholds identified in that study for each criterion (by genetic algorithm) are also used in some experiments where we will short-circuit the local aggregation step.

Incidents are rare in machining: from respectively the in-process monitoring and the spindle condition monitoring datasets only 7 (1.6%) and 5 (1.1%) events were found in that study as events that should have seriously

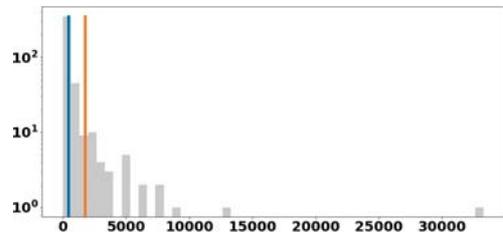


Fig. 2. Distribution (on a logarithm scale) of the values of the continuous criterion  $V_{rms}^{120}$  and cut-points estimated after the discretization step.

damaged the spindle.

Another issue in this real application is the fact that the two diagnosis do not coincide perfectly: only 3 of the 5 spindle damages are explained by the 7 events detected during the in-process monitoring.

The implementation of the models and strategies described in section 3 has been performed with our library dedicated to Probabilistic Graphical Models (PILGRIM) with the help of ProBT<sup>a</sup> library. Parameters used during learning were a stopping criterion equals to  $10^{-4}$  for the EM algorithm and  $n_{step} = 30$  for the recursive strategy.

The performances of the spindle condition monitoring model (balanced accuracy, specificity, sensitivity) are estimated with five separate iterations of two-fold cross-validation as proposed in (Dietterich, 1998). Some preliminary experiments were realized in order to take into account the very high imbalance ratio by applying an over-sampling strategy. It did not improve the performance. So we do not use over-sampling in the following experiments.

### 4.2. Discretization

Fig. 2 shows an example of the discretization process proposed in section 3.1. The grey area is the histogram of the  $V_{rms}^{120}$  values. The blue and orange lines are the cut points between the three states *OK*, *degraded* and *KO*,

<sup>a</sup><https://www.probayes.com/>

determined as proposed by Mabrouk et al. (2015). Weakly critical vibrations are considered for this variable when  $V_{rms}^{120} < 429$ , or strongly critical when  $V_{rms}^{120} > 1735$ .

#### 4.3. Learning strategies

The first element we want to study is the learning strategy. As defined in section 3.4, we here compare the *Naïve* strategy (where both models are jointly learnt with an equality constraint) with the *Recursive* strategy.

In this experiment, the local aggregation step is bypassed by only using the *optimal* critical threshold identified by Godreau et al. (2019) for each criterion. The global aggregation is performed by *Max* aggregation.

Table 1 shows the performances of both learning strategies (line (1) for the naive learning and (2) for the recursive co-training strategy). As seen in this table, the recursive co-training strategy slightly improves the balanced accuracy, with a perfect sensitivity (i.e. the proportion of *KO* correctly detected among the real *KO*), but a smaller specificity (i.e. the proportion of *NOC* correctly detected among the real *NOC*).

#### 4.4. Global aggregation

The second choice we want to study concerns the global aggregation, by comparing the deterministic *Max* and the probabilistic *NoisyMax* functions defined in section 3.3.

In this experiment, the local aggregation step is bypassed again. Based on the previous result, the learning strategy is the recursive one.

Table 1 shows that the performances when applying respectively the *Max* aggregation (line (2)) and the *NoisyMax* one (line (3)) are almost the same, with only a very small decrease of the specificity and a non prohibitive increase of the computation time due to the increase of the number of parameters in *NoisyMax* model. Using the *NoisyMax* global aggregation can help by weighting differently the inputs of this aggregation and providing

meaningful interpretation of the relevant inputs. But in this experimentation, it does not help in improving the balanced accuracy.

#### 4.5. Local aggregation

After dealing with the learning strategy and the global aggregation, we are interested here in the choice of the local aggregation for the process monitoring model.

As defined in section 3.2, we here compare the deterministic *Max* and the probabilistic *NoisyMax* functions for both local and global aggregation. The learning strategy is the recursive one, based on the previous experiments.

Table 1 shows the performances when applying respectively the *Max* function in the local and global aggregation steps (line (4)), the local *Max* and the global *NoisyMax* (line (5)), and the local *NoisyMax* and the global *Max* (line (6)).

Let us recall here that the previous results were bypassing this local aggregation step by using the optimal inputs identified for each criterion in a previous study. We can see here that working with the whole set of inputs provides us more and more complex models in these three experiments, with more and more parameters, which explains the increase of the computational time. We can also see that we are able to get a comparable balanced accuracy when we are no more bypassing the local aggregation step. This shows us that we can learn one full model without taking into account any previous knowledge.

## 5. Conclusion

In this paper, we were interested in the unsupervised co-training of Bayesian networks for the diagnosis of machining spindle by condition monitoring, with the help of data collected during in-process monitoring. We have proposed a generic architecture that models each monitoring task independently and applies a collaborative learning strategy that takes into account both tasks. Our architecture is also able to take into account the fact

Table 1. Performances (Balanced accuracy, Specificity and Sensitivity in %) and computational time (s) obtained in different experimental setup (choice for the three parts of our architecture: local aggregation, global aggregation and learning strategy, as proposed in section 3)

	Local agg.	Global agg.	Learn. strat.	Bal. acc.	Spec.	Sens.	Time
(1)	Optimal	Max	Naive	84.2	90.0	78.3	0.7
(2)	Optimal	Max	Recursive	85.6	71.5	100.0	0.6
(3)	Optimal	NoisyMax	Recursive	85.5	71.0	100.0	3
(4)	Max	Max	Recursive	85.2	70.4	100.0	2
(5)	Max	NoisyMax	Recursive	85.1	70.1	100.0	59.6
(6)	NoisyMax	Max	Recursive	83.9	68.3	100.0	1945

that several possible critical thresholds can be used in the daily computation of advanced monitoring criteria.

Our experiments, based on a real and imbalanced dataset, were able to identify the same degradations than Godreau et al. (2019). It led to surprising results where the simple aggregation schema (*Max*) in both local and global aggregation steps provided the best results, without considering any external knowledge (i.e. without using the *Optimal* local aggregation). Complexifying the aggregation with *NoisyMax* led to more complex models that are not useful with our limited number of data, which is conform with the principle of parsimony in Machine Learning. A paired t-test between the different models investigated, did not exhibit any significant difference between them. In another way, these more complex models could estimate which input or sensor are interesting. Based on this observation, one of our perspectives to improve this work is to add a feature selection procedure when using the *NoisyMax* aggregation in order to select the relevant monitoring criteria in the model, to decrease the number of parameters and to converge to similar results than the ones obtained with the *Optimal* models. Another perspective is related to the improvement of the unsupervised co-training procedure as described in Monvoisin et al. (2021).

One last perspective concerns the very specific dataset we have used for our experiments. This dataset was initially unlabelled

and the results obtained by Godreau et al. (2019), afterwards confirmed by an expert, were considered as the ground truth. This means that all the existing points labelled as *KO* have been confirmed as real ones in this dataset; but not that all data that are currently labelled as *NOC* are real ones. The sensitivity obtained by our system is 100%, which means that we are also able to detect the same *KO*. New and unknown *KO* could be discovered soon in the dataset by our improved co-training method.

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