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NON-QUALITY RISK EVALUATION FROM TOOL WEAR ASSESSMENT

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Abstract
The development of part quality virtual sensors requires knowledge and observability of cutting conditions and in particular tool wear as tool are consumables. This paper presents an unsupervised anomalies detection approach to assess tool wear from standard machine load sensors in order to evaluate a non-quality risk metric. The developed methodology combines physics and business rules with density estimators to analyse the behaviour of axes and spindle loads. Industrial data from an automotive production line are used to illustrate the methodology application.
Keywords:
Virtual Sensor, Quality, Behaviour Modelling, Tool Wear, Machine Leaning

1 INTRODUCTION

Zero-Defect Manufacturing (ZDM) is one of the challenges of Industry 4.0 dealing with both quality improvement and waste reduction. The industry is facing an unprecedented rise in costs, forcing a revolution throughout the manufacturing process to be as flexible as possible while maintaining competitive prices [Powell 2022]. Particularly in automotive production, where the emergence of electric vehicles is calling for a reallocation of machining lines. Indeed, some studies report that an electric vehicle reduces machining line requirements by 30-50%. Predictive quality is one of the levers for improving production line performance and moving towards ZDM.

Predictive quality analytics can be defined as an automated analysis of process, i.e., machining, incoming data in order to identify any parameter's drift as early as possible and thus to minimize or even to avoid losses. The work presented in this paper deals with an unsupervised business approach to evaluate the risk, i.e., a probability, that the machined part will present non-quality after a specific operation with an application to an automotive production line.

2 PREDICTIVE QUALITY

From business point of view, predictive quality means to find a link between process measurement during machining and geometrical characteristic of the part. For instance, in the case of a simple hole, find a link between spindle or axes speed, load, vibration and hole metric such as diameter or eccentricity. From data analysis point of view, the objective is to find a correlation model between the dynamic of the process collected time series and its geometrical characteristics. The development of this model can be viewed as supervised or unsupervised learning problem.

In the supervised case, very often, a regression model is fit to predict the value of the characteristics using features extracted from process time series. Then, at the end of production of each part the model is applied on the process measurements to estimate geometrical characteristics and thus to evaluate if the quality of the part is correct. This approach assumes that quality data is available and perfectly synchronized with process data. Also, this approach needs to have a representative training dataset, i.e., a dataset covering a large operational machining condition and particularly tool wear, especially when the control of the parts is done by sampling.

In the unsupervised case, quality data is not necessary to create the model. Indeed, first phase of this kind of approach consists in detecting anomalies in time series dynamics. A dataset, only composed of process data, is used to train a model able to learn correlation between extracted features, such as density estimator models as in [Hasilovà 2019]. If most of dataset content correspond to good quality part, the model learns the dynamic corresponding and thus the good part production pattern.

Automotive case is considered as an unsupervised case. Indeed, the machine can produce around 500 parts per day and only 3 parts are geometrically controlled per day. Under these conditions it is thus difficult to have a representative and consistent dataset for supervised approaches.

Developed methodology is based on cutting conditions' impact analysis assuming that these impacts should always be the same as far as machined part remains the same. To estimate cutting conditions' impact it is first necessary to recognize in the time series the process where tools cut the raw part. Then, impacts can be computed and modelized to finally use anomaly detection techniques.

Whatever the applied machine learning approach, features used as model inputs are key elements for the success of the methodology. Regardless of the machine learning approach employed, the chosen features play a critical role in the success of the methodology. Ideally, these features should represent causal or consequential phenomena of part quality metrics, leading to faster algorithm training and reduced data requirements.

Previous works [Armendia 2019, Peysson 2019a] have shown that using both business and physics concepts to preprocess data and create a first level of features called “Behaviours Indicators” allow to link process extracted feature drift with event on the production such as observation of streak in machined hole or tool breakage.

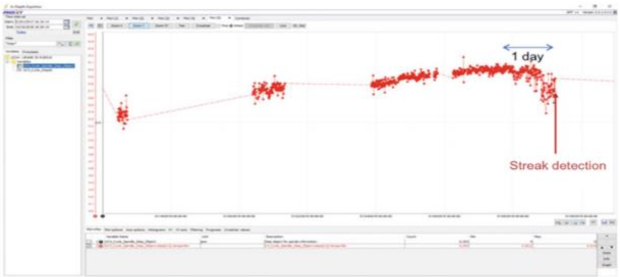

Fig. 1: Feature trend before streak detection in Automotive

Observation of drifts means that these phenomena could be at least early detected and anticipated and under some conditions predicted in the future. Figure 1 depicts the trend of a torque-based feature trend. Change on trend is clearly recognizable one day before the streak detection, meaning that the risk of non-quality has increased.

The common thread of most of part quality prediction approach is the monitoring of cutting conditions resulting from the contact of the tool and the part. Empirical surface quality prediction models have been investigated in further research [Moreira 2019] and remind that this complex phenomenon depends on a large set of parameters such as tool wear [Kolar 2022], tool mechanical characteristics, lubrification, raw material characteristics of the part, etc. During machining, cutting conditions must be supported by various machine components as spindle and axes. These actuators must therefore compensate the cutting conditions to precisely respect the orders of the Numerical Control (NC).

3 AUTOMOTIVE USE CASE

The case study is focused on the combustion chamber within the cylinder head. This is a high productivity case study with a high number of parts produced per year. Produced part, shown in figure 2, correspond to a 4-cylinder engine with two lines of 8 valves: admission line (in purple) and exhaust line (in green). Machining of a valve seat is a complex process due to its concave shape and uses specific tools. Two versions of the part are produced on the production line.

Production cycle time is around 156 seconds for the version and 170 seconds for the other one. Machine operates 24 hours per day, 7 days per week.

Data collection is based on S7COMM protocol from Siemens. The numerical command - 840D Solution Line of the machine is connected to the factory network using NC port X130. As depicted on Figure 3, “CASIP® software suite” is installed on a computer which is also connected to the factory network and can collect variables from NC and Programmable logic controller (PLC) of the machine.

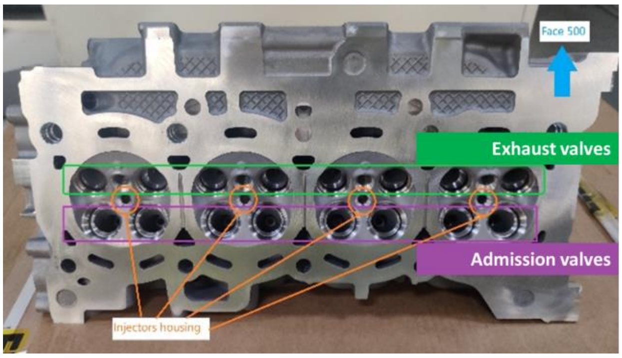

Fig. 2: Produced part details

Around 180 times series are collected with a sample rate between 100Hz and 10Hz. 70 time series are “Analogic” time series meaning that they contain measurements like axis’ torque or position. Other time series are “Boolean” and contain status information like “machine in automatic mode”, alarms. Collected process are daily transferred to a cloud platform hosting KASEM® application.

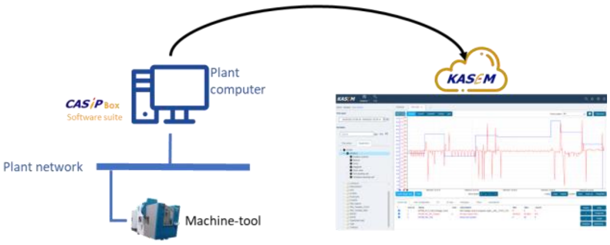

Fig. 3: Data collection architecture.

Whereas many data are collected, the methodology only requires axis speed and load data. Hence it is possible to extend this use case to all the NC (Fanuc, Heidenhain, etc.) that have the ability to deliver such information at an equivalent sample rate.

In this paper, the analyses are conducted utilizing the PREDICT software suite as a foundation. Nonetheless, it is imperative to acknowledge that the proposed methodology remains entirely autonomous from these particular tools.

4 METHODOLOGY

In numerical machining business, tasks are controlled with a program run on a computer and most of the time these tasks are repetitive. Thus, a machining program can be seen as a pattern that is repeated for each part. This pattern being composed of sub-patterns like M06 function that represents tool change, acceleration or deceleration phase of the spindle. All these patterns / sub-patterns are interesting time periods to evaluate and analyse machine dynamics. Indeed, analysing system behaviours are always in the same machine conditions, i.e., patterns or sub-patterns, allow to have a robust and reliable analysis because of the known machine conditions.

Different operating conditions can be collected directly from the machine numerical command. If it is not the case, they should be inferred from the raw sensor’s measurements such as the axes positions. First solution requires a knowledge of the location of the information in the machine, but many of them that are needed to create machine condition are not still normalized in G-Code primary or auxiliary functions. Frequently, manufacturers tend to modify memory addresses for each machine version they produce, requiring documentation and PLC program analysis to find operating conditions. In addition, this type of information is not always shared in the connected "4.0 machines" of the future. Work necessary to collect these information's cannot be done and maintained for a large-scale deployment. For these aforementioned reasons, a second solution consisting in inferring operating conditions from machine sensors' data like axes position and spindle speed is required.

Due to the highly repetitive operations in numerical machining business, analysing system behaviours in the same machine conditions, i.e., patterns or sub-patterns, allow to have a robust and reliable analysis. Hence machine conditions must be inferred from the raw sensors' measurements. The operating condition computation problem then relies on a pattern extraction and labelling problem as described in figure 4. The figure 4 upper section specifies the use of business knowledge in the selection and annotation of training references, i.e. specific machining phases. The lower section delineates the process of real-time tool behaviour through the trained contextual pipeline. Finally, the assessment of non-quality risk is manifested through the residue between live pipeline result and the expectations of the contextual model.

Using business knowledge to drive model and pipeline building ensure a "quick" learning time that is more compliant with industrial activities.

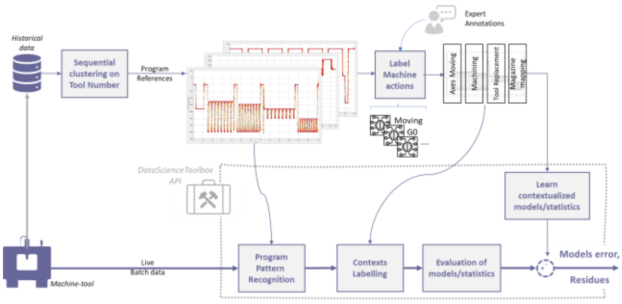

Fig. 4: Business approach for non-quality risk evaluation.

4.1 Contextualization

Given our objective of identifying business-defined patterns, our attention is directed towards the field of pattern recognition.. A pattern is a timeseries of interest, potentially multi-dimensional. Given a query and a reference timeseries, our goal is to find all the occurrences of the reference (pattern) in the query. To find the most appropriate algorithm, the following elements must be considered:

- The number of observations needed to train the algorithm must be as low as possible given that data labelling is a highly time-consuming task.
- A query may contain from one to several times the pattern of interest or no pattern at all. If present, beginning and end of each found pattern have to be returned.
- The size of the query can be significantly larger than the size of the reference pattern being searched.

The timeseries classification (TSC) field provided many competitive algorithms these recent years but many, if not all, of the previous requirements are missing mainly due to: a fixed and limited timeseries' window size, the presence of a single pattern in the query, and the need of dozens or hundreds of samples for training [Bagnall 2016, Ruiz 2021]. In addition to this, a crucial assumption is that the pattern has already been found, which, however, poses a challenging and frequent problem in the industry. To address this, a solution based on the Dynamic Time Warping have been developed. The next two paragraphs will address the algorithm technical details and its application for our use case.

Dynamic Time Warping

Dynamic Time Warping (DTW) is an algorithm that measures the similarity between two timeseries which may vary in timing [Sakoe 1978]. It creates a matrix of the size of the reference by the query where every possible warping between the two timeseries is a path through the matrix (cf. *Fig. 5* 5). The path that minimizes the total distance in the matrix is the final distance returned by the algorithm. By releasing the constraints that assign the begin and end of the reference with the begin and end of the query, it is possible to locate the start and end timestamps of the searched pattern in the query. Hence the base DTW with released constrains act as a search pattern algorithm and has the advantage to perform with a unique labelled reference. Its popularity leads to more optimized implementations to fit large scale and real-time problems [Rakthanmanon 2012] so it can find the best match given a large query.

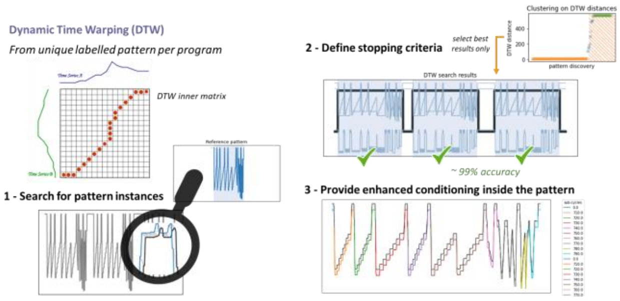

Fig. 5: DTW based approach for Program pattern recognition. The top-left figure represents the inner matrix and the warping path (in red) between a given reference and a query. The main three step of our DTW-based algorithm are then explained: iterative search, stopping criteria and sub-pattern labelling.

The developed methodology tunes and extends the base algorithm to find not only the best match but all the instances of the reference with an iterative process (e.g., first step in figure 5). The query search makes use of smart rules to ignore sections where the pattern cannot be present. To prevent false-positive match, a stopping criterion is defined by a clustering method (e.g., second step in figure 5) based on the returned DTW distance of each pattern occurrence found in the query. Thus, it enables to bypass the use of a threshold and hence to be generic.

Moreover, the method is able to assign to each returned pattern a sub-pattern without any added computational cost by making use of the inner matrix produced by the DTW algorithm (e.g., third step in figure 5). The sub-pattern previously defined on the reference is warped to each occurrence of the pattern in the query. Hence it is possible to define and look for multiple sub-patterns of a given reference by only running once the pattern recognition algorithm.

Application

Pattern recognition algorithm have been extended and used to identify cutting phases, i.e., phases where the tool is in contact with the part. This application required at first to manually label one occurrence of the two programs used in the production line. Figure 6 shows an example of labelling for a specific program and a specific tool.

Left part of the figure represents machine tool's X, Y, Z and A-axis positions during one occurrence of the program execution. Red and blue plots clearly show the admission and exhaust eight valves. Right part of the figure shows an example of labelling made for the first line of valves with tool 40. In this case, Z position have been used to characterize tool cutting condition.

In addition to the cutting phase recognition, it is also necessary to identify the tool replacements. A Tool replacement occurs when the current tool reaches its maximum number of machined parts. For this purpose, DTW-based recognition coupled to a smart algorithm able to reconstruct tool life cycle in tool magazine has been developed.

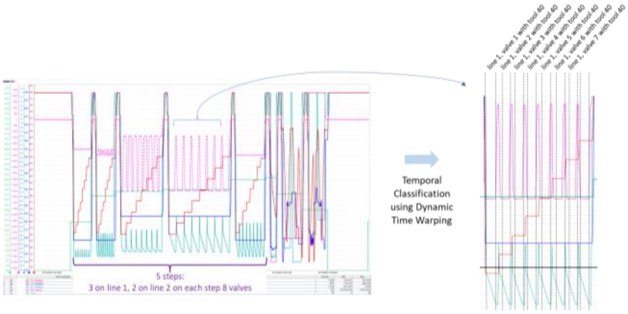

Fig. 6: Example of program cutting phase labelling.

The DTW-based model is used to find a tool replacement pattern based on a single predefined reference. To be more precise, our interest reside in a single specific sub-pattern of the tool replacement. The algorithm is evaluated to not only detect a pattern, but also to find at the same time another specific sub-pattern inside the pattern as shown in figure 7.

To validate its precision and robustness, our DTW-based model results is compared to our domain expert pattern recognition process. To that end a generic evaluation algorithm is develop to match each domain expert pattern, to the best matching predicted pattern and integrated it in our Data Science Toolbox API (figure 4).

This is a mandatory step as multiple predictions could intersect the expert label or vice versa – multiple expert labels could intersect a prediction. In a sense, the algorithm is given an awareness of the surrounding expert and predicted label to make the best matches from the whole dataset perspective. The evaluation result is relatively close to a binary classification evaluation. Here the best matching pattern is marked as a True Positive (TP) and the other predictions intersecting the expert label are marked as False Positive (FP). If an expert label is unmatched, this is a False Negative (FN). The Jaccard Index can be defined as:

$$Jaccard\ Index = \frac{TP}{TP+FN+FP} \quad (1)$$

To measure the success of finding the correct pattern. Its ranges in [0,1] with one meaning all patterns were founds with no error. The score obtained is 0.913, with 5 false discoveries and 41 not discovered on a total of 531 patterns, which demonstrate the solid performance of the model. Most of the undiscovered patterns were extreme cases where the change of tool lasted several minutes instead of the expected few seconds.

On top of this “search” quality metric, the model should be able to finely detect the start and the end of each reference pattern. To that end the Jaccard Distance usually used in the field of object detection has been adapted to our timeseries pattern recognition use case, such as:

$$Jaccard\ Distance = \frac{Section\ of\ Time\ Overlap}{Section\ of\ Time\ Union} \quad (2)$$

By design its results ranges in [0,1] with one being a perfect match such that the beginning/ending of the reference and predicted pattern are the same. On average our DTW-based model score at 0.930 demonstrating an excellent ability to match the start and end of the searched pattern. As a conclusion, our DTW-based algorithm enables us to successfully define sub-patterns on the discovered patterns, thus bringing a higher conditioning and analysis capacity.

Fig. 7: KASEM® powered visualization of repeated change of tools - in black. The upper part represents the position of the X, Y and Z axes on the machine tool. The lower part represents the sub-pattern presence - in blue the expert label, in red our DTW-based model results.

Figure 8 depicts identified tool per program type associated to their respective magazine position. At each tool change during part machining, tool position in the magazine is saved to create a map of the magazine.

Map of the magazine and tool replacements recognition allows to identify which tool is replaced by operator, an essential information to study tool wear evolution and develop cutting behaviours indicators.

4.2 Anomaly detection

Kernel Density Estimator

Kernel Density Estimator (KDE) is a non-parametric method to estimate the underlying probability function of a dataset. When fitted, the KDE output a log-density that an observation belongs to the learned distribution. Two properties are to consider for the KDE configuration: the kernel choice, and the bandwidth. Although a large variety of kernels are available, the normal kernel, i.e., the standard normal density function, is the most convenient due to its mathematical properties. The bandwidth acts as a smoothing parameter, controlling the trade-off between bias and variance in the result. Best bandwidth value is here inferred with least-squared cross-validation as one of the methods suggested in [Chen 2017].

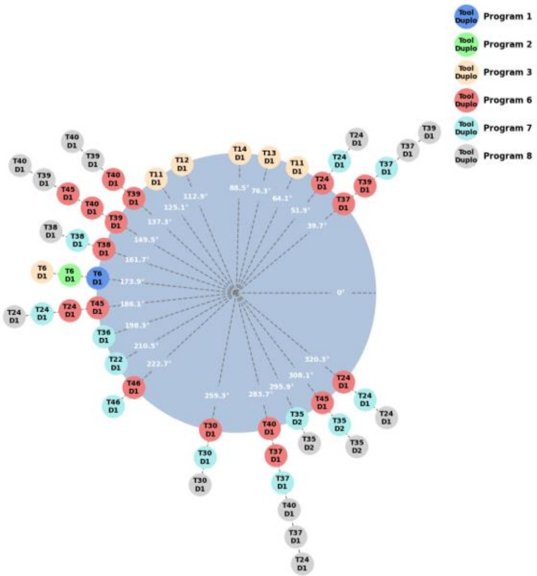

Fig. 8: Reconstruction of tool magazine life from process data.

Application

The goal of cutting behaviours indicators is to provide images of effort and vibrations during machining. These indicators are computed from load measurements of spindle and axes in previously identified cutting phase. Quality and representativeness of indicators are closely linked to data acquisition quality, identification of cutting phase and tool replacements, and computed features from load. Indeed, cutting condition and tool kind are key input to choose the right feature.

Using both temporal clustering on process data allow to extract features from machine axes and spindle loads. These features “contain” both information of cutting effort and tool wear as shown in figure 9 for tool 45 from spindle point of view. The features analysis shows that similar trends are observed in machine axes behaviours.

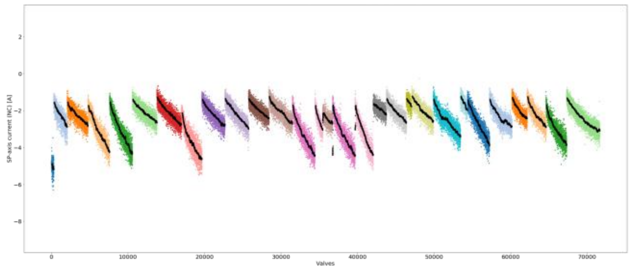

Fig. 9: Tool 45 wear with colorized replacements from Spindle point of view.

Y-axis represents the spindle load during valve machining. Colorized points correspond to the spindle load for each valve while a rolling (over 10 parts equivalent to 80 valves) median load is plotted in black. Plot has been colorized according to identified tool replacement, and x-axis represents the number of machined valves with the tool. Tool wear is thus clearly identified and each step in the trend can be linked to a tool replacement. Also, clusters of trends can be visualized with sometimes higher level of wear which increase both risks of tool breakage and part non-quality. Modelling of nominal tool wear to detect any anomaly behaviour in tool wear is thus possible and necessary.

Data modelling approaches have been applied to learn the median dynamics of tool wear, especially kernel density algorithms, with features extracted from spindle and axes value and that represent force and vibration images during cutting phases. Inputs of the data modelling algorithms are composed by these features for spindle load and Z-axis and their derivatives. Tool wear is thus considered by the discrete time equation system:

$$\begin{bmatrix} SP_{l_f} \\ SP_{l_v} \\ Z_{l_f} \\ Z_{l_v} \end{bmatrix}_{k+1} = \begin{bmatrix} SP_{l_f} \\ SP_{l_v} \\ Z_{l_f} \\ Z_{l_v} \end{bmatrix}_{k} + \begin{bmatrix} W_{SP_{l_f}} \\ W_{SP_{l_v}} \\ W_{Z_{l_f}} \\ W_{Z_{l_f}} \end{bmatrix}_{k} \qquad (3)$$

where l_f and l_v are respectively force and vibrations extracted from motor loads. W is the slope vector and k a sliding window of part to take into account measurement value and time uncertainities. Both instant k vectors defined the KDE inputs.

Log-likelihood is output of the kernel density algorithm: low values meaning that points do not fit with the learnt distribution. From the quality problem, this output is considered as a risk of non-quality. Figure 10 shows the behaviour of the developed non-quality risk according to simulated tool wear trajectory where dark points mean a high risk of non-quality. Fault on tool wear is introduced during part 40 then the top curve depicts the fault free case and the bottom curve the faulty case.

This metric clearly enables the detection of undesirable behaviour considering several features as input. In addition,it is robust to the “life” of the tool, i.e., the metric is robust when the tool installed on a machine is not new and without any knowledge of its past usage.

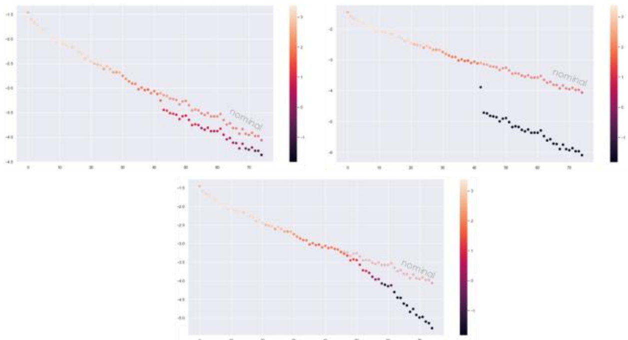

Fig. 10: Validation of data modelling with simulated tool wear.

5 RESULTS

5.1 KASEM®

KASEM® (Knowledge and Advanced Service for E-Maintenance) is a web platform with a service-oriented architecture (SOA), integrating collaborative e-maintenance, engineering, proactive maintenance, decision-making and expertise tools. KASEM® is developed, maintained, and improved by PREDICT [Peysson 2019b].

Functional and dysfunctional analyses are integrated and structured in KASEM® knowledge base to describe the machine. A systemic approach is being developed to build a description of the machine and its components by its functions, their consumed or produced flows and to anticipate how they could malfunction. The malfunction of the system is studied using the HazOp (Hazard and Operability) and FMECA (Failure Modes, Effects and Criticality Analysis) analyses.

In addition, the KASEM® platform integrates the following services:

- Data Visualization gathering all the tools and ways to communicate clear and efficient information to the users, making complex information more accessible, understandable, and usable.
- Event management gathering all the tools and ways to generate events relative to systems' status (fault detection, prognostics, health) and to manage these events (validation, cancellation).
- Analysis and Investigation gathering all the tools and ways to analyse and understand events, to explain what the causes are (diagnostic) and the consequences (prognostic).
- Knowledge sharing gathering all the ways to create and consult system's documentation and information.

The results of the developed pipeline have been implemented in KASEM®. In addition of presenting the non-quality risk metric, intermediate steps of the pipeline allow to build dashboards on production and tool management statistics.

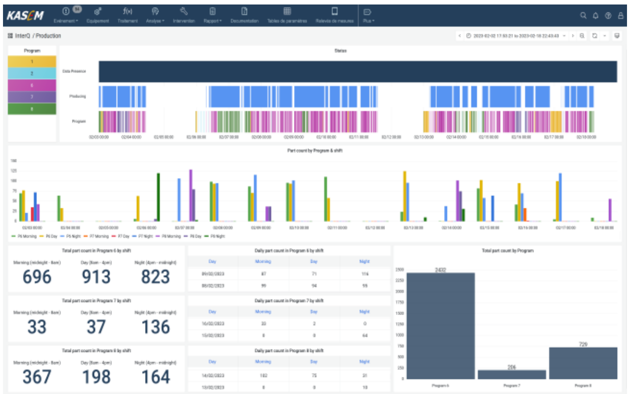

Fig. 11: KASEM® dashboard of production features.

5.2 Tools life monitoring

Producing periods are automatically detected and defined as spindle rotating with at least one axis moving and the machine is in automatic mode. During these periods of production, the type of program is identified thanks to tools sequences. Programs number 1, 2 and 3 correspond to heating programs, whereas programs 6, 7 and 8 are different types of produced parts. Figure 11 shows an example of dashboard presenting count of produced parts by shift and by type of part.

As seen above, tool replacements are identified inside KASEM® and allow the development of specific dashboards following tools life, without any additional calculation. The dashboard, depicted in figure 13, presents the count of replacements and the date of the last replacement for each tool. A histogram compares the count of replacements of every tool and helps to identify the most critical ones. Finally, the number of parts produced with the current tool can be compared to the mean count of parts produced before replacement and easily estimate the tool age.

5.3 Non-quality risk

Non-Quality risk dashboards present link of non-quality risk indicators with measurements of quality characteristics. For each tool, a list of characteristics influenced by the tool has been defined, i.e., the measurement of quality characteristic is done directly on a surface machined by the tool. The non-quality risk is computed from spindle force and vibration images which are calculated from spindle load. As can be seen on figure 12, the quality characteristic is above threshold on the period where non-quality risk is also drifting. The main goal here is to link quality measurements with non-quality risk based on tool degradation and spindle force and vibration images.

Fig. 12: KASEM® dashboard of non-quality risk.

Figure 14 shows two examples of the non-quality risk metric according to a quality characteristic over two distinct periods during years 2021 (top image) and 2022 (bottom image). Models used, more specifically for anomaly detection, have been trained on 2020 data. On the graph: black curve is the non-quality risk metric, the magenta one is a quality characteristic, red line represents the quality pre-alarm threshold defined by the production line manager. Quality characteristics are measured directly on machined surfaces such as valve seat circularity, location, tilt, flatness, valve guide diameter, etc. Note for interpreting that quality characteristic is plotted according to date of quality control which may be a few hours later than the production date, also Y-axis of both graphs are not the same.

Non-quality risk metric clearly shows different trend through various tool replacements. Some tool "instance" have very low log-density which means that observed cutting responses are far from those learned.

In particular, the image above shows that a low log-density is followed by a pre-alarm during quality control. This is confirmed by the bottom image in 2022 which also shows that precise synchronization is required to enable correlation and validation.

As you can see on Figure 14, when non-quality risk indicator (in black) is dropping, quality measurements (in pink) are often over the threshold

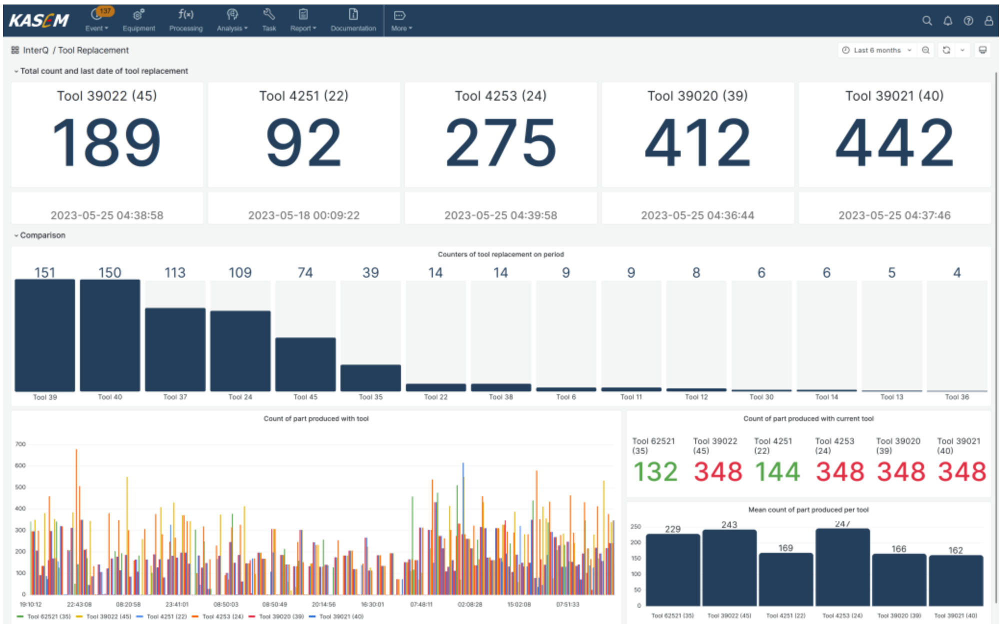

Fig. 13: KASEM® dashboard of tool life (replacements) monitoring without adding new machine or tool sensors.

6 CONCLUSION

The presented methodology enables to extract machining features, mainly from spindle and axes load, that reflect cutting conditions and allow to monitor tool wear and tool life. The use of an unsupervised AI, from quality data point of view, approach enables the detection of anomalies in the tool wear trajectory, thus anticipating quality problems on the one hand through data analysis and in-depth knowledge of cutting tools. These results are obtained without adding new sensors to the machine or tools. Initial results show a correlation between the non-quality risk indicator and quality control sampling. In order to improve the study of this correlation, sampling should be made dependent on this indicator in the future.

Current models only take into account a single machining operation, whereas generally there is at least one roughing and one finishing step, and the behaviour of the latter may depend on the behaviour of the former. To take this into account, machining data, quality data and traceability data need to be properly synchronized. In addition, cutting conditions may also depend on other factors such as the properties of the cutting fluid or the characteristics of the raw material. Both were regarded as invariant in this study and will be considered in future work.

7 ACKNOWLEDGMENTS

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Fig. 14: KASEM® powered visualization of non-quality risk linked with quality measurement - in black the non-quality risk, in pink the quality measurement (in this case the admissible valve seat oscillation 0,05/H1), in red and green quality measurement thresholds.