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Toward a Collaborative Sensor Network Integration for SMEs' Zero-defect Manufacturing

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Abstract. The increasing challenges in industry paved the way towards the next generation factory model or namely "Industry 4.0" through the availability and development of recent technologies in ICT such as industrial internet of things (IIoT) and cyber-physical production systems (CPPS). One of the main pillars of this paradigm is Zero defect manufacturing (ZDM), which aims to get work-pieces "right the first time". However, this technological uplift can prove itself to be very challenging in an industrial environment especially when it comes to the choice of available sensors, the motivation behind that choice, and the insurance that they comply with different guidelines for further exploitation in decision support. This is even more relevant when addressing low-volume high-variety industrial entities such as make-to-order (MTO) SMEs, inherently characterized by limited resources and highly variable business processes collaborating to respond to the demands of an increasingly cutting-edged market. This paper presents a collaborative approach to devise a suitable sensor network in an industrial machining environment generally and in an MTO SME context specifically, based on a joint analysis of all business process data related to quality control issues. Furthermore, the paper showcases the benefits of the approach in a real-world case study involving a 3-axis universal machining center as early validation.

Keywords: Sensor network, IIoT, machining process, industry 4.0, zero-defect manufacturing, collective manufacturing.

1 Introduction

The cost of poor quality, including the tolls of repair, rework, scrap, service calls, and so on, is estimated to range between 5 and 30% of a manufacturing company's total income with most of them ranging in the 10-20% area [14].

Industry 4.0, first introduced in Germany [7], has managed to make a breakthrough in manufacturing quality control (QC) through concepts such as Industrial Internet of Things (IIoT) and Cyber-Physical Systems (CPS) through data-based defect detection.

ZDM is generally defined as a strategy to get rid of defects in production. As such, it has always been considered the next level of quality control and consequently was seen from a "quality" lens mainly through quality management strategies. The framework (Fig.1) depicts this tendency from a high-level schematic perspective by only pointing sensors toward products on the CNC machine. Nevertheless, this approach has been increasingly questioned and deemed limited in literature as per recent reviews [12] asking for a more holistic approach by taking into consideration other production-related aspects.

Most SMEs trying to undergo an early lift towards an industry 4.0 approach face the hurdle of a high initial expenditure with no result certainties [9]. While bigger companies can afford certain strategies such as extensively equipping the shop floor with the necessary technologies to implement a smart-factory approach [2], small manufacturing factories can find it difficult to strategically statue between the early acquisition and development cost and the inaction toll on their business and hence justify a similar approach. This situation begs the question of how to ensure that the required expenditure is in sync with the company's needs and typology of issues.

Contrary to the widespread data-driven approach which starts from gathering data as much as possible through shop-floor sensor coverage, uncorrelated to the business processes and quality issues, and then diagnoses what problems can arise and how to treat them, our work strives for a more end-to-end and holistic and collaborative approach by analyzing business processes and linking them to non-compliance (NC) history to determine the problems which can typically arise in the shop-floor to negatively impact the end-product. Starting from this all-processes collaborative NC analysis, we determine the needs in terms of data coverage, and hence the typology and characteristics of the sensors to be used to bridge the data-flow gap based upon a grid of attributes, leading to an SN minimizing the needed sensing resources while maximizing detection to provide the necessary informative capacity for sensing the defects, which is the necessary first foothold for a ZDM initiative. This paper presents an answer to "how to appropriately design a sensor network for zero defect manufacturing in a high-variety manufacturing environment" by taking into account SMEs' characteristics when aiming toward I4.0.

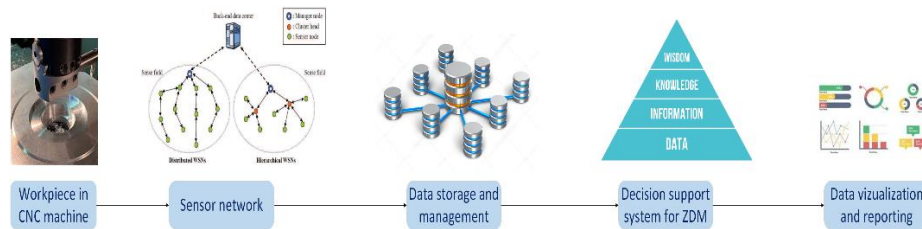


Fig. 1. ZDM overview in industry 4.0

While the approach is thought to be global and can be applied to any type of industry where raw material transformation is at stake to conceive the final product, our paper scope will focus on subtractive manufacturing with the case study being implemented in a metallurgical industry machining SME which production is heavily oriented towards an MTO business model.

The paper will be structured as follows: section 2 will discuss literature work related to the topic at hand, section 3 will present the proposed framework of our approach, section 4 will be dedicated to its implementation steps, and section 5 will describe a real-world case study based on the implementation while section 6 will conclude this paper and introduce future research perspectives.

2 Related Works

Many papers regarding the use of SN, in the manufacturing industry in general and in QC in particular, provide solutions for a specific industry and type of machines or the application of a specific solution. As such, Zheng et al [15] give a conceptual framework for smart manufacturing and some implementation showcases for industry 4.0 but don't delve into the devising of the sensing strategy if not being globally depending on the typology of considered machines.

Kulinska et al [6] present a study to reduce non-conformity and improve quality control through a Poka-Yoke sensor-enabled approach. And while the study considers NCs as an input it offers no link between the choice of the solution and the problems at hand and is rather specific to the hydraulic industry. A generic situation stated by the study of Silva et al [13] regarding the lack of general methodology for AI and machine vision systems in industrial QC.

Additionally, Marques et al [8], while dealing with IoT-based automatic NC detection in the scope of a metalworking SME use case similar to our work, focuses on architecture and interoperability of the data collection and communication, not covering the initial part regarding the choice of sensors and its link with business-oriented data or NC history.

Govindarajan et al [4] present an approach to dealing with legacy systems in the manufacturing industry, but the scope of the paper encases the data acquisition phase and how to integrate it into a particular architecture and project. Preuveneers et al [10] in its overview of I4.0 and the smart factory confirm the lack of context-aware decision making and how it can influence the cost of automation in general and sensors in particular as one of the main pillars of data acquisition. Psarommatis et al [11] propose a generic methodology to provide a tool for designing a manufacturing system that can enable a ZDM approach using digital twin models that were based on simulations.

Eleftheriadis et al [1] emphasized the difficulty of implementing ZDM when the manufacturing processes involve complex operations or a large number of components, such products often have a high probability of defective output and hence documentation of best practices has been gathered on the process management side.

On a wider scope, Psarommatis et al [12] presented a literature review on zero defect manufacturing summarizing the state-of-the-art, highlighting shortcomings and further

directions in research regarding ZDM in which they concluded that cost-benefit comparative analysis is not evident when it came to implementing it, especially for the early technological expenditure. The paper also stated that certain industries are under-researched in the literature, among which we find the metal industry and complex 3D parts since collecting defect data and training algorithms on well-defined NCs can be challenging.

Similarly, Galetto et al [3] show the difficulty of predicting defects and costs for quality inspection in low-volume productions due to multi-level uncertainty and developed an approach targeting the inspection level to accurately analyze and compare different inspection strategies.

Compared to the cited papers, our work suggests an approach in which we aim to address the choice of a sensor network for ZDM by starting from shopfloor NCs, paving the way for a cost-effective and reliable early industry 4.0 uplift regarding the IoT-based monitoring choice.

3 Proposed Framework

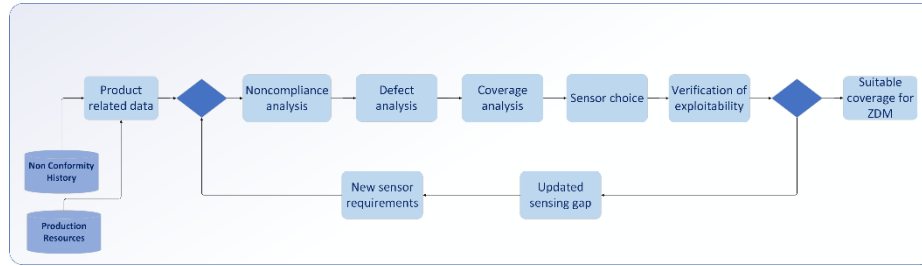


Fig. 2. The approach's general framework

3.1 Overview

An overview of our approach can be seen in (Fig.2) as a framework in which the input will be all the data related to defects. From in-process product control by machine operators on the shopfloor to process monitoring by the quality inspector through final control checks reports with laser precision machines. The expected output will be an accurately designed sensor network to help optimize machine behavior, ultimately leading to iterative reduction of defects towards a zero-defect manufacturing policy. This overview can be decomposed into several building blocks as follows:

3.2 Non-compliances

A non-compliance [5] is the absence or the inability to meet a planned requirement. It encompasses all the breaches in specifications for a manufactured product. Requirements which can be fixed either by the client or by internal standards such as customer

requirements, quality requirements, quality management requirements, Regulatory requirements ...

NCs can be classified by tiers from minor to critical depending on many criteria such as occurrence or impact. Each NC is reported with many other attributes such as the problem, the detection time, the impacted product, details on why/how it happened, in which machine, the cost, and the decision (salvaged/scrapped ...), and so on.

In industry, and especially for manufacturing actors which are bound by demanding and challenging norms such as ISO-9001 and EN-9001 (aerospace and armament sectors), these non-compliances or nonconformities are to be closely monitored from the beginning of the process (client's request for quotation) until the products end of manufacturing life (EOML).

3.3 Defects Analysis

As stated by ISO-9001 [5], a defect is a type of NC where a product (for the manufacturing scope) will fail to meet intended use requirements. This specific type of nonconformity needs to be filtered out from the different quality data sources (ERP, quality reports, quality reviews). This will on one hand ensure that the SN will be able to "sense" the defect through physical measurements and on another hand will be the input specifying the type and specifications of these measurements, which will be the stepping stone for the sensor network choice.

The defect analysis can be tricky to perform and even trickier to link to specific processes or operations in an MTO industrial environment. Notably, the high variety tag implies that there are multiple types of products, specifications, clients, and so on. Each workpiece can be conceptually considered to be virtually a new one, which will introduce several complexity layers in the root-cause analysis.

Another difficulty comes from the low-volume aspect which gives little to no historical data to extract knowledge from in order to build the defect classification.

3.4 Sensor Choice

For the main manufacturing-related data sources that can be monitored in-process, we find the following when thinking of suitable industrial monitoring for SMEs:

- Temperature: can be used to detect surface condition issues, tool-wear, tool chatter, and also inappropriate machining parameters such as speed or advance for cutting (milling, drilling, turning ...). Thermocouples are inserted into cutting material through holes or welding and are unsuited for out-of-lab research since tools are changed hundreds of times a day in the industry, making the monitoring unpractical and costly as well as dangerous for the tool integrity (compliance with ISO/client norms). Contact-less pyrometers with suitable metal wavelengths compatibility and measuring range (150 to 1000°C) should be privileged, as close as possible to the cutting field.
- Force: it can be used to detect excessive clamping, plastic deformations, collisions, spindle head condition, coaxial misalignment, and tool wear. Laboratory

dynamometric table dimensions aren't suited for industrial purposes due to dimension and measuring range, and customized spindle-head force/torque acquirers are costly and raise the same issue of interchangeability and tool integrity as the one raised by embedded thermocouples. If necessary, can be indirectly measured through spindle electric current.

- Acoustic emissions: can detect surface condition issues, tool chatter, and elastic stress. The sensor placement can however be tricky since it needs to be close to the machining field while also keeping a distance in order to not be flooded by ambient noise and the clogged environment. They can add another layer of redundancy and variability with the vibration sensors since they both convey energy-related data from the material (tool and/or workpiece).
- Vibration: industrial metal-removal machining involves operations (milling, drilling, turning ...) where a lot of rotation movements are entangled, from the engine to the bearings to the spindle until the cutting tool, vibration is one of the most important data sources for process and machine monitoring and can detect surface condition issues, poor clamping, bearings condition, imbalances, and tool chatter. Since the physical phenomenon is related to the rotation oscillations, the sensor needs to be positioned as close as possible to the operation field to capture a high ratio of signal to noise.

For vibration, one of the main choice criteria is the measuring range. The sensor's frequency needs to be adapted to the transformation operation speed. At the very least, to be able to capture the fundamental frequency of the operation the sensor has to have a maximum frequency range of:

$$f_{sensor} = \frac{R_{spindle} * n_{teeth}}{60}$$

With f_{sensor} being the maximum frequency the sensor can acquire in Hz, $R_{spindle}$ the maximum spindle rotation speed in rpm, and n_{teeth} being the maximum number of teeth of the machining used tools (1 for drills, generally 3-4 for mills but can go as far as 12 or more).

In general, one preferably needs to have at least 3 or 4 times the maximum calculated frequency in order to be able to also capture the frequency spectrum harmonics which also conveys crucial information about vibratory energy.

4 Implementation

4.1 Overview

The proposed approach in this paper was implemented in Tardy SAS, a subtractive metallurgy industry SME that offers a wide range of services from conceiving to realizing metal workpieces and special purpose machines. As an MTO rank 1 subcontractor for different critical sectors such as armament and aerospace, Tardy is faced with growing demand over technically challenging low-volume/high-variety requests. As such,

implementing an approach toward zero-defect strategies is of the utmost importance to keep client satisfaction and company reputation in an increasingly competitive market.

In order to do so Tardy needs an efficient uplift towards this I4.0 concept to enhance the reactivity, security, and control over the highly variable production processes while keeping in mind the inherent conditions and resources (old legacy machine, technological investments limitations ...).

4.2 Defect Classification

A thorough analysis was conducted to come up with a classification of the main manufacturing deviation causes, both on a quantitative level with QC data, NCs reports, business process bottlenecks, cost prices, and customers feedback as on a qualitative level with field surveys of different process stakeholders. As a result, we achieved the following classification:

- Tool issues: Accounted for roughly 49% of the critical deviations. Using the right tool for the right operation can be very challenging for make-to-order production in which every workpiece is unique in terms of specifications, machining parameters used materials, and so on. This results in a lack of visibility and control of tools functioning and lifetime management, leading to cutting tool issues such as wear, breakage, heating, and deviation.
- Material deformation: Accounted for 27% of the critical deviations. Since The transformation process involves material removal from raw parts, depending on the drawings, production process, and operations sequence, the raw will need to be locked down at different angles/positions/intensity.

If the clamping is too tight a raw deformation can occur during the cutting with risks of tool breakage or making the produced piece outside of tolerance limits, which can be very precise (up to 2×10^{-5} m). If the clamping is not tight enough slight movements or vibrations throughout the removal process can occur, leading to bad surface quality such as roughness or altered material coating and deviation in the tool path.

The make-to-order nature results in a lack of control over the clamping dispositions, which not only can cause tool issues but is also related to machine safety in terms of spindle, clamping table, and claws.

4.3 Target Data Sources

From the critical deviations classification stated above as well, it was decided to deploy a sensor network that will be able to monitor vibration in order to tend to the deviations.

The SN must also be able to differentiate between different sets of machine-cutting parameters, i.e. {tool feed rate, cutting depth, rotation speed} in addition to differentiating between other parameters such as tool type (shape, material, geometry), angle, and so on. While there are general guidelines for those parameters such as tool feed rate cutting advance and rotation speed depending on the material couple workpiece/tool suggested by raw/tool suppliers, precisely and accurately defining them remains a

difficult task in an MTO paradigm considering the variety and complexity of the processes. It is often decided by rule of thumb and left for the machine operator to customize on the go depending on how the machining unfolds.

This lack of fine-tuning leads to many issues by reducing cutting efficiency, the quality of the final product (finish, roughness ...) and its compliance with requirements, the safety of the machine (especially the spindle head), the consumption rate of new cutting tools and so on. Optimizing it can lead to greater customer satisfaction, machine up-time, and fabrication costs.

5 Experimentation

5.1 Overview

From the implementation of the approach that was devised above and the deviations classification that collaboratively resulted from it, an initial SN was deployed and real-world experimental steps were devised to validate it.

5.2 Setup



Fig. 3. CNC machine



Fig. 4. ICP 603C01



Fig. 5. KRYPTON DAQ

The used machine was a 3-axis portal-type universal machining CINCINNATI Dart 500 (Fig.3), with a maximum rotation speed of 6000rpm.

The global setup of the SN was comprised of 2 piezoelectric ICP 603C01 industrial stainless-steel accelerometers (Fig.4) with a measurement range of 0-10000 Hz, a sensitivity of 100 mV/g, a temperature working range of -54 to +124 °C and an IP protection index: IP68. The sensors were linked through 2×3m Heavily reinforced waterproof data cables to an industrial data acquisition module (DAQ).

The data source, i.e., vibration, was chosen for its compatibility with the monitoring of material deformation and tool issues. The sensors were chosen for their cost-effectiveness and characteristics (measuring range, sensitivity, working temperature, and waterproofing).

The DAQ is an industrial Dewesoft KRYPTON with a certified robustness an IP68 index, and a maximum sampling rate of 250 kHz.

In terms of placement, the first sensor was fixed as close to the spindle head as possible (left in Fig.6) while the second was placed on the table clamping claw (right in Fig.6). Both positions were secured using a magnetic mounting base and accurately

placed to not hinder machining operations while also having minimal distance from the cutting operation area.



Fig. 6. Sensors placement

5.3 Experiment Protocol

An experimental protocol was devised to validate the sensor characteristics as well as their exploitability. The protocol consisted of different variations of milling and drilling. The varying parameters were feed rate, rotation speed, usage of lubricant or not, and used material.

Milling. The milling operations used two mills. A 16mm 2-teeth carbide inserts mill (nominal feed of 800mm/min and a nominal rotation of 3200rpm). A second 63mm 3-teeth carbide inserts mill (nominal feed of 390mm/min and a nominal rotation speed of 1200rpm).

The chosen variations were combinations of feed rate (140%, 120%, 100%, 75%, 50%), rotation (120%, 100%, 75%, 50%), lubricant (with/without), and material (mild steel/aluminum).

The milling was done on 120×90×41mm (X-Y-Z axis) cuboids in two sequences for each raw. The first sequence using the first mill milled 2 grooves in X-axis in respectively 18 and 9 runs of 0.5 and 1mm depth each until -9mm, then 3 grooves in Y-axis in respectively 18-9-6 runs each with 0.5-1-1.5mm depth until -9mm. The second sequence used the second mill for a first surfacing until -4.5mm depth in two runs and a second until -9mm in two runs also.

Drilling. The drilling was made in two sequences using two drills. An 8mm steel point drill with a nominal feed rate of 150mm/min and a nominal rotation speed of 1000rpm. A second 8mm steel drill with a nominal feed rate of 150mm/min and a nominal rotation speed of 1250rpm with the same variations in parameters.

The drilling was made on the milled raws in two sequences. A first sequence of 6×4 holes of -1.5mm each for guiding. Then a second sequence of 6×4 holes, each drilled

in 10 runs with a logarithmically decreasing depth until reaching the maximum depth of -15mm.

5.4 Data Pipeline

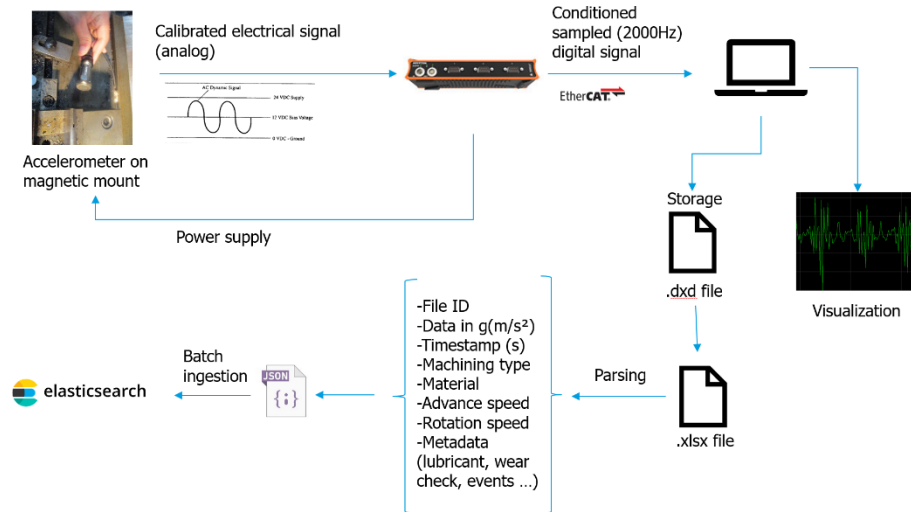


Fig. 7. Data pipeline

As per Fig.7, the DAQ powers the accelerometers. It receives analog signals, and calibrates and converts them (2 kHz sample rate) to a numerical signal. The signal can be visualized on *Dewesoft X* and stored in compressed files in near real-time. After conversion into regular data files (text, CSV, HDF5, JSON, S3 ...), parsing will extract suitable data/metadata which is then sent to Elasticsearch (ES) for batch ingestion. Each data point is stored as a JSON document (Fig.8) in a 3 nodes distributed (1 master, 2 slaves) ES cluster for a total load of 30 Gb storage representing around 220 million ES documents.

```

1- {
2-   "_index": "poc3",
3-   "_type": "_doc",
4-   "_id": "70H6Dn88FVtNmcp0c_-I",
5-   "_version": 1,
6-   "_seq_no": 238113,
7-   "_primary_term": 1,
8-   "found": true,
9-   "_source": {
10-    "Sensor": {
11-      "name": "acc_table",
12-      "unit": "g"
13-    },
14-    "Date": "2022-02-20T14:15:37.548000",
15-    "Data": -0.09936405,
16-    "seq": 119057,
17-    "meta": {
18-      "number": "13",
19-      "filename": "C:\\Users\\Badreddine\\Desktop\\POC\\Expérimentations\\Fraisage\\Acler\\Avec lubrifiant\\13_2022_01_10_135525_1",
20-      "start": 0,
21-      "end": 882.8875,
22-      "date": "2022-01-10T13:55:25",
23-      "rate": "2000",
24-      "usage": "fraisage",
25-      "matiere": "acler",
26-      "lubrifiant": "avec lubrifiant",
27-      "avance": "120%",
28-      "rotation": "100%",
29-      "control d'usure": "non"
30-    }
31-  }
32- }

```

Fig. 8. JSON data-scheme

5.5 Exploitation

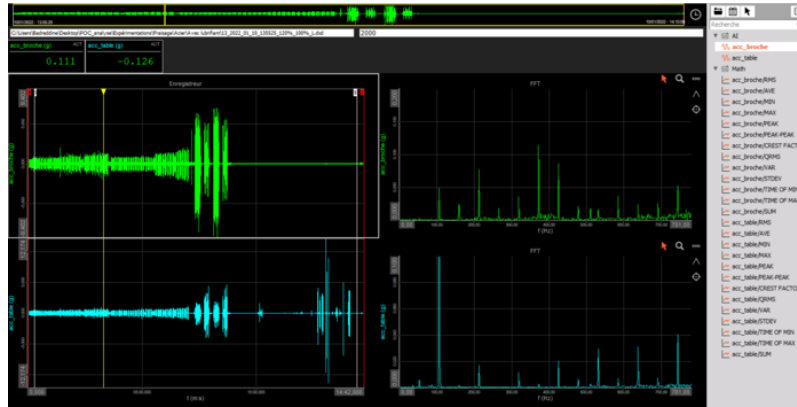


Fig. 9. Table/spindle milling time series

An analysis of the time series data indicates that the end-to-end proposed solution offers the ability to sense and monitor the machining operations in terms of precision (up to 10^{-6} g) and variability of data. The SN meets the different requirements in terms of targeted phenomenon by being able to finely represent the different machining sequences (Fig.9). It also accurately captures the variation in machine parameters (Fig.10), tool wear impact as well as tool breakage (Fig.11).

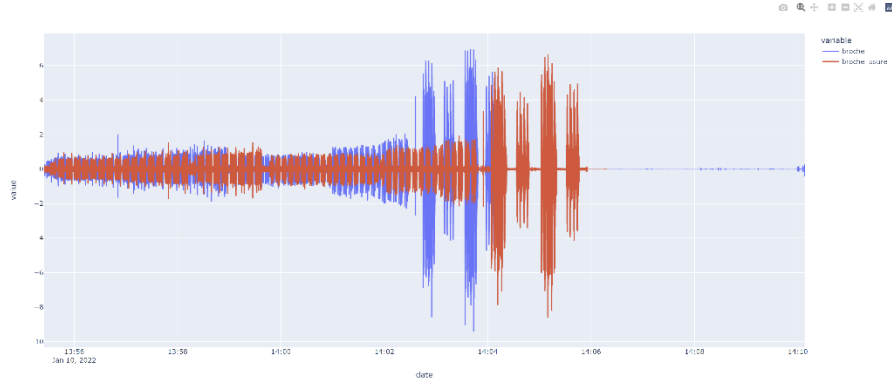


Fig. 10. Milling variations time series

The designed SN also offers good scalability perspectives since more sensors can be added to the DAQ (vertical) and DAQs can be synced to monitor several machines (horizontal). The data pipeline can also be turned from a batch-oriented strategy to a stream-oriented one for near real-time monitoring and reactivity.



Fig. 11. Second mill (left) insert breakage

6 Conclusion

Zero defect manufacturing as an I4.0 concept that aims to provide a holistic approach to reduce deviations presents a lot of challenges to adopting for industrial actors, all the more so for MTO SMEs with high-volume/low-variety aspects and limited resources. As such, our paper offers an approach to tackle this issue through the angle of sensor network design, an essential building block for the IIoT and CPPS systems aiming to be a stepping stone towards ZDM. The methodology presents a design of the SN through all business-related process collaboration to ensure the suitability and exploitability of the acquired data. The different steps of the approach were validated in a real-world case study from both architectural and data angles. For future work, we aim to

increase the scope of machines and sensor types to tackle more NC as well as integrate this work into a more holistic approach by including an AI-centered decision support system for ZDM.

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