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Human-Centric CBM Solution for Machine Tools: From Development to Deployment ⋆

Mohan Rajashekarappa * **Ebru Turanoglu Bekar** * **Alexander Karlsson** ** **Adalberto Polenghi** *** **Anders Skoogh** *

* *Department of Industrial and Materials Science, Chalmers University of Technology, Gothenburg, Sweden (e-mails: rmohan@chalmers.se, ebrut@chalmers.se, anders.skoogh@chalmers.se)*
** *School of Informatics, University of Skövde, Skövde, Sweden (e-mail: alexander.karlsson@his.se)*
*** *Department of Management, Economics and Industrial Engineering, Politecnico di Milano, P.za Leonardo da Vinci 32, 20133 Milan, Italy (e-mail: adalberto.polenghi@polimi.it)*

Abstract: Machine tools are essential to manufacturing for precise and efficient component production. With Industry 4.0, abundant machine condition data enables data-driven maintenance decisions. However, deploying condition-based maintenance solutions is challenging due to the diverse configurations of equipment, complex failure modes, and compatibility issues with the digital infrastructure. While machine tool health monitoring relies on detailed tests like Ballbar measurements, they consume valuable production time. To address these challenges, this article presents a human-centric development and deployment of a condition-based data-driven maintenance dashboard. The solution uses data from the controller system to improve machine tool testing in a Swedish heavy-duty vehicle powertrain facility.

Keywords: Condition-based maintenance, circularity test, human-centric solutions, machine tools, deployment, data-driven decision making

1. INTRODUCTION

Machine tools are the apparatus used to shape or machine metal materials or other hard materials by processes like cutting, boring, grinding or shearing (Liang et al., 2023). They play a key role in manufacturing parts with precise accuracy which is crucial for modern industrial manufacturing (Son et al., 2023). Machine tools are important for achieving high productivity and efficiency in manufacturing, boosting the company's competitiveness in the marketplace (Aghdaie et al., 2013). In the context of gear axis shaft manufacturing for heavy-duty vehicles, Computer Numerical Control (CNC) machines, whirling machines, hobbing and shaping machines, broaching and profile milling, grinding machines along with heat treatment equipment and measuring/inspection tools are the common machine tools used in a production line. These machines tools are expected to perform with high accuracy and precision ensuring reliability and efficiency in manufacturing processes. Various tests and methods are commonly used to assess the anticipated performance of machine tools as any part manufactured slightly out of dimension could lead to expensive scrap. Examples of some of the widely used tests include linear positioning accuracy test using laser interferometers, Ballbar test (circularity test), static accuracy test and cutting test (Usop et al., 2015).

A circularity test on machine tools assesses the contouring accuracy and identifies geometric errors by measuring deviations from a perfect circular path. This test is essential for validating the precision and performance of machine tools, identify any setup errors, geometric errors or servo mismatches especially in CNC systems. However, the time taken to set up and perform this test and analyse the data is high. Especially in a scenario of high-volume production of gear axis shafts where the number of working machine tools are high in number and performing these tests on hundreds of machine tools can be a bottleneck. This article, in an attempt to address the above stated challenge, leverages data from advanced CNC systems to develop a conditioned-based maintenance (CBM) dashboard. The contribution of this paper is the utilization of human-centric methodology for building and deployment of a dynamic, interactive CBM dashboard for the circularity test. This approach was validated using real-world production of gear axis shafts and powertrain parts for heavy-duty vehicles.

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This paper is structured as follows: Section 2 sets the theoretical and practical context. Section 3 outlines the research procedures and techniques. Section 4 presents the findings. Section 5 interprets the results and addresses their implications, significance, and limitations. Section 6 summarizes the study's contributions.

2. FRAME OF REFERENCE

CNC machine tools are sophisticated manufacturing systems that automate machining processes through computer programming. These tools are important for producing highly precise components and are widely utilized across industries for their efficiency with precision. They are integral to intelligent manufacturing systems, enabling data acquisition and monitoring to improve production efficiency and eliminate information silos (Guo et al., 2020). Though CNC machines are evolving to meet the demands of Industry 4.0 by incorporating features like fog computing and cyber-physical systems (Zhou et al., 2018), it is yet to be widely practically achieved. The data acquired by these sophisticated CNC machines can be used to perform CBM.

A handful of literature is available where CBM is applied on CNC machine tools for circularity tests which demonstrates its effectiveness in maintaining machine accuracy and reducing downtime. (Harja et al., 2024) measured circular geometric errors on CNC lathes using Ballbar tests for assessing machine condition and recommending maintenance activities. In another research developed by (Werner et al., 2011), the authors concentrate on signal acquisition, data processing, and network communication for effective machine health monitoring. By integrating both internal and external sensors they introduce a framework that improves machine tool monitoring through real-time data acquisition of spindle vibrations and coolant temperatures. (Rangga et al., 2020) adopt an approach in their study to optimize the CNC machine settings using Ballbar and coordinate measuring machine (CMM) measurements to diagnose and adjust circularity errors.

The literature outlines two key approaches for implementing CBM in CNC machine tools. One involves integrating sensors to monitor and predict failures, while the other focuses on conducting tests, such as the Ballbar test, for example, to measure geometric errors. However, in a typical mass manufacturing environment, installing sensors on many CNC machine tools might not be the solution that provides operational efficiency due to increased system complexity and data management challenges, while performing traditional tests is often time-consuming. This work finds its motivation from this challenge and aims to bridge the gap between traditional manufacturing processes and modern digital infrastructure by developing a human- centric methodology. The focus is on creating practical solutions that can be readily deployed on the shop floor, making advanced maintenance strategies accessible to manufacturers regardless of their scale of operations.

Academic literature consistently shows that human-centric methodologies in data analytics solution development led to improved usability, better decision-making capabilities, and enhanced overall tool effectiveness. (Astudillo et al., 2020) in their work highlight that data analytics methodologies become more adaptable, efficient, and collaborative when users are actively engaged in the design process, as this human-centric approach ensures solutions are aligned with genuine user requirements and preferences. (Tong et al., 2019) discuss in their article that interactive and engaging features are common elements of human-centric tool design, enabling users to thoroughly explore data and identify patterns more effectively. Adding on, (Sharma and Osei-Bryson, 2009) emphasize that human expertise is vital for understanding business context and objectives in data mining, as this crucial phase cannot be automated and requires alignment with organizational goals.

Despite their automated nature, CNC machines require extensive human input during the initial process design and subsequent optimization of manufacturing parameters (Samsonov et al., 2023). Similarly, maintenance operations demand skilled personnel to conduct and interpret sophisticated tests and determine appropriate corrective actions for CNC lathe machine tools. The practical knowledge and insights gained through years of hands-on experience with machine tools are irreplaceable. Recognizing this valuable domain expertise, maintaining human-in-the-loop is crucial while designing, developing, deploying, and operationalizing any CBM solution. Inspired by the current literature, this research adopts human-centered methodology and emphasizes the importance of domain knowledge by actively engaging maintenance engineers and maintenance technicians from the beginning, ensuring their expertise is incorporated while building trust with the end users.

3. METHODOLOGY

This section provides a comprehensive description of the procedure used to develop the human-centric methodology illustrated in Figure 1.

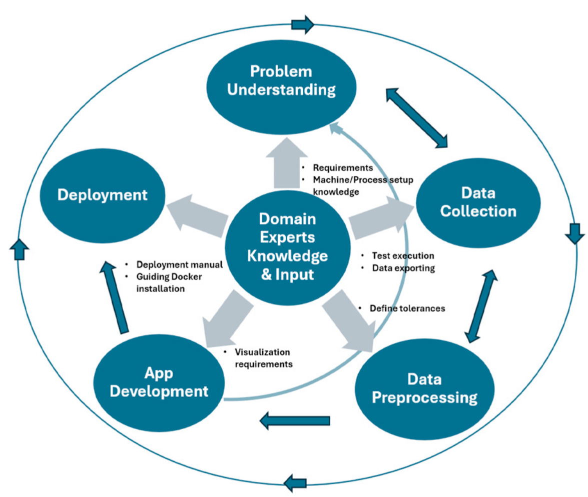

Fig. 1. Human-centric methodology

3.1 Problem understanding:

The methodology is tested on a gear axis shaft production line in one of the leading heavy-duty vehicle power train components manufacturing companies in Sweden, and the volume of production is high. The line includes soft turning with Lathe Machine 1 (outer surface) and Lathe Machine 2 (internal surface), with dimensional accuracy checks and adjustments to the CNC program between operations. The parts then undergo gear hobbing, drilling, chamfering, and washing before heat treatment and final hard turning for assembly. The CBM dashboard development initially focused on Lathe Machine 1 before expanding to other machines in the line. Built-in circularity test was scheduled weekly to check the machine's health before full-scale manufacturing could proceed. However, as noted earlier, this built-in test did not provide a comprehensive assessment of the machine's mechanical health. At the same time, the recommended Ballbar test was considered too time consuming for each machine tool and there were large number of machine tools in operation. The maintenance team needed an interactive, dynamic, and data-driven solution that could help them decide when to initiate a work order for the Ballbar test. Discussions were held regarding software solutions that were security-approved within the company's infrastructure. The ability to successfully deploy the solution was established as a key objective from the beginning.

3.2 Data Collection:

To collect data, the built-in circularity test was run on the system. A new program was created with basic settings including radius, feed-rate, plane selection, rotation direction, starting angle, and number of revolutions, along with other general settings. After the tests were performed on the revolvers shown in Figure 2, the data was exported for analysis. Domain experts handled the testing, data export, and data collection processes.

Fig. 2. "Lathe Machine 1" with two revolvers (Left: Revolver-1, right: Revolver-2

3.3 Data preprocessing:

The collected data files were processed by organizing and extracting relevant information based on key measurement categories. Data parameters were standardized to numerical values to ensure consistency in the analysis. Calculated column for deviation from the mean radius was added to capture dimensional variation. Data was transformed by calculating statistical metrics based on user-defined tolerance (the acceptable range of deviation from the specified radius) and threshold (the maximum allowed percentage of data points falling outside the tolerance range). This included measuring deviation, percentage of points outside specified tolerance levels, and categorizing each dataset as pass or fail according to these customizable parameters. Finally, processed data from individual files were concatenated into a structured dataset ready for further analysis.

3.4 CBM App Building Using Flask:

To construct a data visualization application for condition monitoring, an iterative approach was taken, focusing on interactivity and modularity to support real-time user interaction with circularity test data. Flask, a lightweight, open-source Python web framework, was chosen for its simplicity and flexibility in building web applications and visualization interface. Discussions were held iteratively with the domain experts regarding:

- What kind of visualization/information display would be adding value for decision making?
- What design keeps the insights explainable?
- What should be the scope and granularity of the monitoring system? individual machine, production line, or overall process?
- User friendly design and what parameters to be chosen for user input/drop-down selection/push buttons?
- Optimum Scaling factor values to amplify and visualize the small micron level deviations clearly.
- Preconditions for pass/fail of a test.
- Finally, does the developed app address the defined problem?

The application's interactive design allows user-defined parameters, such as tolerance and threshold, to be adjusted through the user interface, ensuring adaptability for diverse contexts. Additionally, a second visualization is embedded in the Flask application, which gives the trend of change in the percentage of deviations outside the defined tolerance over time for predictive maintenance in the long run. Interactive features, such as data cursors, allow users to hover over individual points to examine specific deviation values, adding precision to the analysis.

3.5 CBM App Deployment Using Docker:

To deploy the CBM application in a consistent and scalable manner, Docker was utilized to package and manage the application environment. The deployment architecture, as illustrated in Figure 3, includes essential project files like app.py (Flask application), docker-compose.yml, Data-preprocessing.py, and requirements.txt, Data folder to drop in test files, template folder which has the HTML file for the front-end app development. This structure ensures that application logic, dependencies, and configurations are well-defined and isolated within a single directory. Docker Compose was employed to streamline deployment by defining a reproducible application environment. Key configurations in docker-compose.yml included specifying Python 3.9-slim as a lightweight base image and mapping the local data directory to the container (./data:/app/data) for direct access to essential data files. Additionally, the configuration exposed port 5000 to allow external access to the application, while environment variables, such as FLASK-APP and FLASK-RUN-HOST, ensured the application runs correctly within the Docker environment.

The deployment process required a single command: docker-compose up. This command automatically builds the Docker image by encapsulating the application code and dependencies defined in requirements.txt and launches the container, mapping it to port 5000 on the host machine. A comprehensive, user-friendly CBM manual was created, guiding domain experts from Docker installation to interpreting test results using the dashboard.

Fig. 3. Deployment Architecture

The methodology is referred by the authors as human-centric as it integrates domain expert's input (Figure 1) at every stage. User-centered design prioritizes user needs, the structure in Figure 3 grants control over data management. Continuous feedback loops enable iterative improvements, while early planning and emphasis on deployment and scalability ensures adaptability for future needs. These factors improve usability and build user trust, reinforcing the human-centric approach.

4. RESULTS

The CBM dashboard was iteratively built based on the received input from the discussions and the above stated human-centric methodology and deployed on the shop floor. Figure 4 shows the dashboard's user interface, where users can select between 4-axis lathe machines, 2-axis lathe machines, and training machines. The dashboard also enables analysis of circularity test data for Revolver 1 and Revolver 2 of the 4-axis lathe machine. Additionally, users can set a threshold percentage to determine test pass/fail criteria and specify tolerance levels in microns. It was decided with the maintenance engineer that the inbuilt circularity test will be conducted once a week and the data will extracted for the respective machine tool and stored in the "Data" folder(Figure 3). The naming of filenames for each week provided information regarding the week number and which particular machine tool/revolver the test belongs to for performing the trend analysis. The operator could also set the overall threshold percentage to decide the test results and display it. The circle test in Figure 5 represents a passed test results within the set tolerance of +5 to -5 microns.

The predictive maintenance trend displayed in the dashboard (Figure 5) reveals that Revolver 1 of the 4-axis lathe machine consistently shows a higher frequency of deviations exceeding the 5-percentage threshold compared to Revolver 2 (Figure 6). This discrepancy prompts the

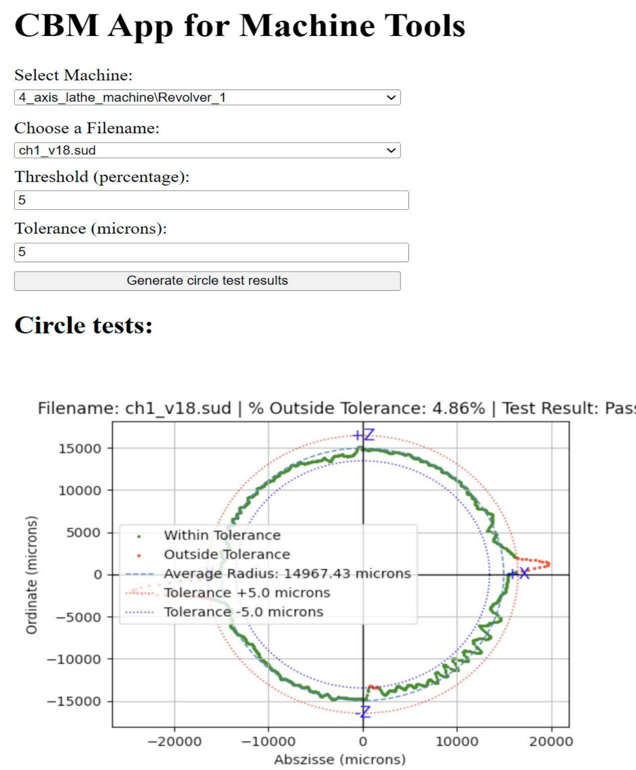

Fig. 4. CBM Dashboard

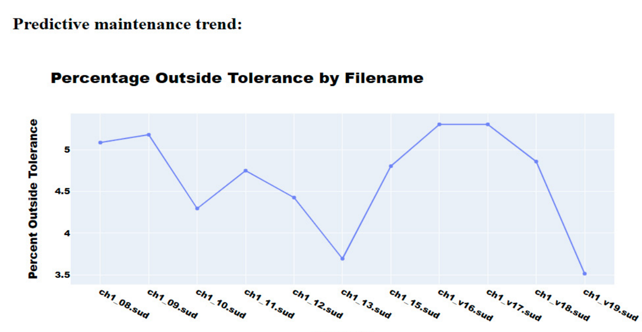

Fig. 5. Revolver 1 trend

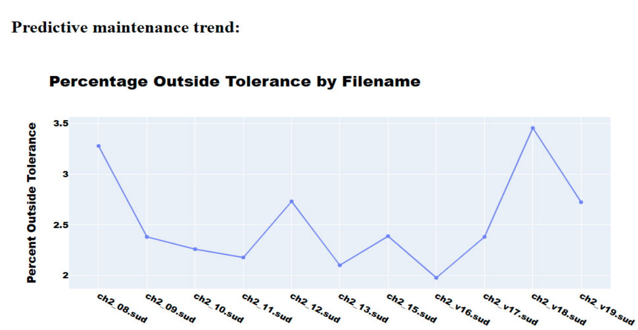

Fig. 6. Revolver 2 trend

creation of a maintenance work order to perform a Ballbar test on Revolver 1. Adding on, it was confirmed by the maintenance engineer that Revolver 1 had history of under performance and crashes which adds more trust. The dashboard also displays historical data of instances where the threshold was marginally exceeded. While individual minor breaches are overlooked, repeated occurrences of such deviations lead to the initiation of maintenance work orders, as demonstrated in this case.

Circle tests:

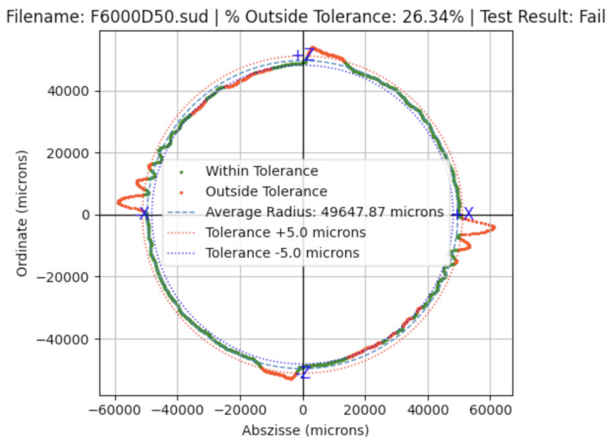

Fig. 7. Failed test due to high percentage of deviations and presence of vibrations close to the horizontal axis that represents change of direction of axes .

Figure 7 illustrates a failed circularity test in a soft turning process on a 2-axis lathe machine. This failure may be attributed to various mechanical issues, such as misalignment, tool wear, instability, backlash in the gears, or uneven wear in the bearings and guides. To confirm the root cause, a detailed Ballbar test is required. In this case, a maintenance work order was issued to conduct a Ballbar test, aiming to thoroughly assess the machine, identify the cause of the degradation, and implement corrective actions.

The Ballbar test can identify various machine tool errors, including backlash, reversal spikes, and stick/slip effects (Renishaw plc, 2017) in the company's production environment, we primarily detected reversal spikes and stick/slip errors. From Figure 4, the measurements showed noticeable deviations along the X and Z axes. Reversal spikes typically emerge when an axis changes direction, as the machine's moving parts experience momentum and inertia effects. This is particularly evident in the X-axis of horizontal setups. The stick/slip error shows up as irregular motion patterns, usually stemming from uneven friction, poor lubrication, or bearing clearance issues. While these measurement deviations point to potential mechanical problems, a full Ballbar test is needed for definitive confirmation. The dashboard's monitoring system helps track these deviations over time, with special attention to the horizontal axis – where growing deviations might indicate wearing components. The vibrations we observed during direction changes (Figure 7) suggested possible backlash issues. Based on the dashboard's data, particularly the high deviation readings and direction-change vibrations, the maintenance engineer determined a Ballbar test was necessary. Though we have only gathered 10 weeks of data so far, we are working towards implementing predictive maintenance capabilities to anticipate deviations before they become critical.

5. DISCUSSION

The CBM dashboard prioritized trustworthiness and explainability by involving maintenance operators and domain experts from the outset. This early engagement ensured the dashboard was seen as a reliable and tangible solution reflecting their expertise, leading to successful deployment. Designed as a decision support system, it avoided being perceived as a 'black box' by incorporating user requirements and providing clear documentation, thereby fostering trust and transparency.

Key contributions of this work include:

- Time and Resource Efficiency: The developed dashboard significantly reduces testing time for circularity assessment in machine tools. The built-in circularity test, which serves as the dashboard's data source, requires approximately 10 minutes for setup and reading acquisition. This represents a substantial time reduction compared to the detailed Ballbar test, which can take between 30 minutes and 4 hours depending on the machine tool. Furthermore, operator training for the built-in circularity test is estimated at 2 hours, whereas training for the Ballbar test exceeds a day and necessitates additional practice and skill development. Given the facility's 900 machine tools, the selective testing enabled by the dashboard addresses the inefficiency of performing time- and resource-intensive Ballbar tests on tools that do not require them. The estimated time and resource savings of the developed dashboard are currently based on end-user evaluations and experiences with the machine tools in the pilot production line, which may lack rigorous validation. To address this limitation, ongoing work within the project involves a comprehensive quantitative study aimed at affirmatively quantifying the potential efficiency improvements of the dashboard. This study will also expand the solution from the pilot production line to additional lines in a phased manner, ensuring a broader applicability and validation.
- Human-Centric Solution Design: The integration of domain expert's knowledge into the CBM dashboard highlights the benefits of combining human expertise with technological solutions, shifting from purely automated decision-making systems. However, this approach also introduces a limitation: the lack of explanations regarding the selection of user input tolerances and threshold values, which are critical for decision making. Future work aims to address this by capturing detailed data on the reasoning behind these selections from maintenance engineers and expert operators which are purely based on their experience and expertise. During the app development phase, unstructured usability tests and user experience feedback were collected using the iterative methodology presented. Future work will involve conducting more comprehensive and structured usability tests.
- Practical Industrial Application: The successful implementation of the dashboard in gear axis shaft production proves its practical viability in real manufacturing settings, particularly in the automotive sector, where high precision and efficiency are crucial.

The literature in Section 2 discusses that data analytics tools are more effective and better support decision-making when they prioritize user needs and adopt a human-centric approach. The current study provides additional evidence to this through a real-world case study involving the development and deployment of a CBM dashboard using a human-centric methodology.

6. CONCLUSION

This article presents a human-in-the-loop methodology for CBM dashboard development and deployment, specifically designed as a decision support system to guide maintenance engineers and operators to initiate work orders for Ballbar testing in machine tools. A detailed Ballbar test can take anywhere from 30 minutes to 4 hours (for a 2-axis lathe machine tool in this facility) and requires skilled personnel to perform the test accurately. This can lead to production delays and impact productivity. The developed dashboard provides maintenance operators with three essential insights to guide work order decisions: percentage deviation from user-defined tolerance circles, historical trend analysis of marginal deviations, and amplified visualizations of micron-level deviations. These features help to understand both the magnitude and nature of machine tool errors and initiate a work order for detailed testing only when needed. Reversal spikes, slip/slick and backlash were the errors identified by the experts using the dashboard and to confirm this, maintenance work order for Ballbar test was triggered in two instances during the study. The proposed CBM solution is developed and deployed using a human-centric methodology and aids the maintenance engineer and maintenance operators to take informed decisions thus optimizing production time and cost. Future work involves gathering more test data to perform predictive maintenance using machine learning and also to perform quantitative study to validate the advantages of using the solution when scaled to all the machine tools in the facility.

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