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A cyber-physical system approach to zero-defect manufacturing in light-gauge steel frame assemblies

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Abstract

Recent advances in manufacturing research have set the stage for the industrial integration of zero-defect manufacturing strategies, aiming towards a more sustainable production paradigm. A systematically deployment guideline to implement zero-defect manufacturing is needed to transform the future cyber-physical factory floor. This paper describes a novel framework based on a well-known cyber-physical architecture that provides advanced information analytics, robust information flows, and data acquisition systems that support defect detection and prediction introduces repair technologies and sets up procedures for preventive maintenance. Through continuous inspection of product and equipment status during the manufacturing process, raw quality and tool health data from different sources is used to obtain key performance indicators. Statistical tools such as cross-correlation are then applied to quantify underlying relationships between product quality specifications and equipment health. The resulting correlations are then used to reduce non-conformance of products manufactured by implementation of preventive maintenance. A unified implementation for zero-defect manufacturing cyber-physical processes eases their integration in future Industry 4.0 facilities and validated in the context of offsite construction manufacturing of steel frame assemblies.

Keywords: zero-defect manufacturing; cyber-physical systems; industry 4.0; manufacturing processes; preventive maintenance; inspection systems.

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1. Introduction

Current manufacturing processes are being disrupted and transformed by the novel technologies introduced by the Industry 4.0 era. Long-standing production strategies, e.g., mass production, have not been successful in dealing with increased product customization and low-volume productions. To circumvent those limitations most manufacturing environments have shifted towards lean methodologies and customers' demand [1,2]. With recent advancements in communication, data acquisition systems and networks are pushing the industrial sector towards the implementation of state-of-the-art technologies, such as cyber-physical systems (CPS). A CPS refers to an integrated physical system with its computational capabilities that can interact with humans through novel cognitive methods and are characterized as a multidisciplinary methodology [3]. CPS goals can be listed: 1) close integration between physical and computational systems; 2) cyber capability in every physical component despite constraints in computational resources; 3) network at multiple scales; 4) adaptability and dynamical configurations; 5) high degree of automation; and 6) dependable and reliable operations [4]. The key to achieving CPS goals is the interaction between the physical and cyber elements, as well as the monitoring systems that control the digitization and actuation in closed control loops.

The purpose of CPS in manufacturing processes is manifold, offering increased potential in connectivity and computational power that can be exploited, for example, to support efficient production quality. Production quality combines quality, production logistics, and maintenance methods and tools that support the continuous improvement of its levels of quality while optimizing resources [5]. In recent years, several successful use cases for CPS have been developed and implemented for various production purposes. In most cases, the resulting cyber-physical production system (CPPS) provides active decision support for the human operators on the line and eases the human-machine interaction. The architecture of CPPS is also a recurrent theme of research and an evolution can be observed from initial guidelines for the development and construction of a CPS in smart factories by Lee et al. [6] to more recent studies on a unified framework for integrating CPS in manufacturing [7]. Overall, CPPS architectures are constantly evolving to match capabilities and desired outputs from manufacturing systems, including defect mitigation, quality prediction, and controlled production management [8].

Indeed, with a new paradigm in production lines, one of the most promising strategies to support mitigation of manufacturing failures and elimination of product defects is called zero-defect manufacturing (ZDM) [9]. ZDM's ultimate objective is to 'do things right in the first time' and aims to reshape the manufacturing ideology towards a more sustainable and profitable quality-centric scene. Although the concept of zero-defect was introduced in the early 60's, the following decades saw different manufacturing sectors trying to improve quality and reduce cost by focusing on reducing the number of defective products to zero. However, operation without failures did not translate into zero imperfections or non-conforming products as manufacturing systems could not adapt to changing situations [10]. Emerging technologies are providing new opportunities for the integration of ZDM in manufacturing environments, mostly derived from improvements in computational technologies and, more recently, knowledge discovery in databases (KDD) techniques [11].

Myklebust proposed a ZDM concept, IFaCOM, which objective was to reach a level of excellence for a manufacturing process of near zero-defects output through improved process control and long-range stability using intelligent quality control systems [12]. Although it presented an evolution from the traditional "six-sigma" methods based on standard data analysis, this approach presented limitations in adapting to complex scenarios where best practices that minimize defects vary. Similarly, another ZDM concept, IFDAPS, was developed by NTNU that would support intelligent fault diagnosis and prognosis so that, according to the data acquired, possible faults could be predicted, and operations planned to minimize defects [11]. Finally, CPS has been identified as the key element to bring ZDM principles to the shop floor and support the implementation of systematic ZDM solutions at the machine level, i.e., work unit, and at the production line. CPS can proactively monitor and configure the manufacturing setup (namely workpiece, tools, machine logic, and product flow) to support ZDM goals and optimize production, as well as provide feedback to operators/stakeholders regarding quality in their processes [13,14]. All in all, the shift to ZDM setups implies a highly connected production environment that requires detailed recording and analysis of the data obtained. From that data, selected key performance indicators (KPIs) can show organizations the necessary performance indicators that support data-driven decision-making for quality control continuous improvement [15].

Regarding quality and defect mitigation, several CPPS have been presented that relied on sensing data to perform either product inspection or predictive maintenance, but none target ZDM principles. For example, Morgan and O'Donnell applied a CPS architecture to a CNC turning process to monitor the measurement of process conditions by using sensors in real-time however its reach to mitigate defects generated is limited [16]. Later, a CPS framework for predictive maintenance systems applied in ball-screw prognostics was later developed to minimize machine downtime through predictive analytics [17]. This study presented clear methods of how to analyze data acquired but the implementation was limited to the process. On the other hand, a CPPS framework for quality prediction and operation control in metal casting manufacturing was presented based on IoT, machine learning, and simulation technologies. This framework described the collaboration between the different elements that affect casting quality to improve current execution systems, as well as planning and scheduling systems [8]. However, the complexity of the data schema proposed constraints its analysis as massive data is acquired during production. To adapt the proposed CPPS to a more simpler data distribution and storage would facilitate data analysis and how decisions impacting quality would be managed.

Since ZDM is still a complex methodology to integrate within a manufacturing system, it is essential to clearly provide guidelines to ease its implementation in the industry. This study explores adapting this CPPS architecture to facilitate data management and expand data analysis towards ZDM goals. Also, when considering current ZDM researched architectures, such as GOoD MAN [18] or ForZDM [19], industrial integration is considered at a higher level (production level). ZDM benefits from a systems approach to support continuous improvement processes at a lower level. In this study, the proposed approach is applied to the automated screw-fastening process of steel frame assemblies, in the context of offsite construction manufacturing.

2. Dual ZDM-CPPS framework

The proposed ZDM-CPPS framework is based on the ZDM concept as proposed by Psarommatis et al. [9] and the generic CPPS architecture proposed by Lee et al. [8]. This framework builds upon a well-known CPPS architecture and addresses ZDM goals separating process and product inspections while maintaining a common continuous improvement process cycle. ZDM is implemented following two intertwined approaches: a product-oriented CPPS that identifies, analyzes, and eliminates defects in actual parts based on quality conformity evaluations; and a process-oriented CPPS that monitors the machine environment (tools, actuators, etc.) to identify setups that cause manufacturing failures and mitigate their impact through preventive maintenance. As illustrated in Fig. 1, the detailed ZDM-CPPS hybrid framework is outlined, differentiating between the machine-oriented ZDM-CPPS (which targets preventive maintenance as its ZDM goal) and the product-oriented ZDM-CPPS (which targets reprocessing, rework, or remanufacturing as its ZDM goal) based on the ZDM concept.

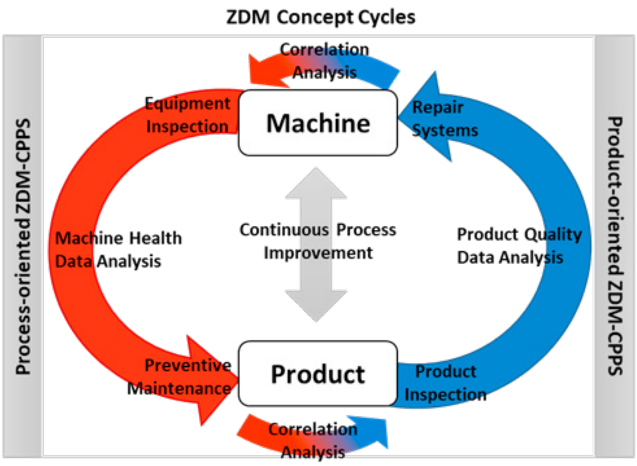

Fig. 1. ZDM Concept after [9] with the proposed CPPS integration.

The used CPPS architecture provides a clear guideline for developing and deploying CPPS for manufacturing applications: by identifying its core components and the main information flows, the construction of CPPS from the initial data acquisition to analytics and final value creation is achieved. Following the same goal of reducing the number of defects in manufacturing applications, the CPPS architecture can be used to establish a clear definition of ZDM strategies implementation.

Fig. 2 presents the dual CPPS architecture that enables machine and product inspection, subsequent data analysis, and finally supports the implementation of ZDM strategies through human intervention; all within a continuous improvement cycle. Both CPPS make use of the standard architecture reported by Lee et al. [8], slightly modified to combine the outputs of the predictors and KPIs builders to a common decision-support system. Compared to previous ZDM architectures, this approach simplifies data synchronization and acquisition, as well as a more structured flow on information.

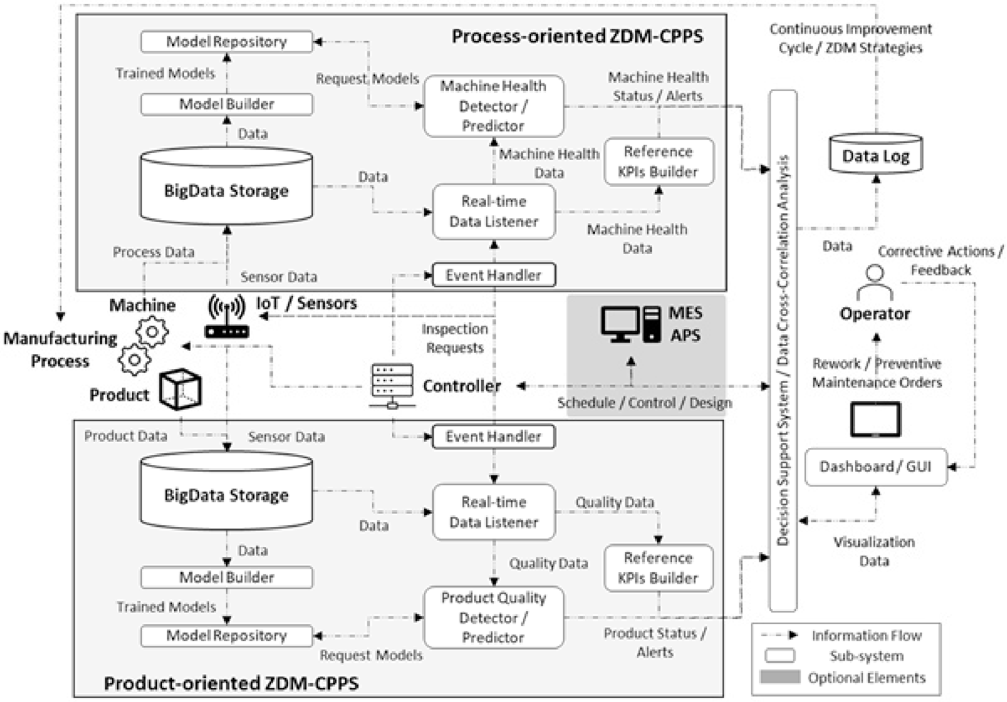

Fig. 2. Dual ZDM-CPPS architecture.

3. Case study: steel frame assemblies manufacturing

The presented case study serves as a manufacturing environment for validation of the framework proposed. The following subsections focus on the blocks of the dual ZDM-CPPS architecture that are unique to this study and the ones that have not been validated in previous works, namely the manufacturing process, the quality and machine health data schema, the decision-support system, and the visualization tools. In other words, this study considers that the CPPS architecture used for each individual ZDM-CPPS system has already proven to be valid [8].

3.1. Manufacturing process

Responding to the offsite construction industry's need for prefabricated light-gauge steel (LGS) panels, a unique steel framing machine was designed and prototyped at the University of Alberta. It consists of a semi-automated machine to safely manufacture LGS panels by sequentially performing automated screw-fastening operations. This prototype represents the capacities of the Industry 3.0 paradigm in terms of automation in the offsite construction sector: a manual assembly process is replaced by servo-actuated screw manipulators driven by a programmable logic controller. To manufacture a LGS panel, a sequence of operations is performed: first, a manual assembly of the LGS members (studs and tracks) is done to place each member at its correct location, also securing the positioning between members with electromagnets; then, automated screw manipulators fasten the members together, one by one, until the assembly process is finalized.

In previous works, automated inspection systems were developed to assess the quality of the assembly and manufacturing operations within the machine. These vision-based systems provided real-time information regarding deviations during the manual assembly of the LGS frame [20] and defects occurring during the screw-fastening operations [21]. This gives LGS manufacturers continuous data about the quality of their processes and the capacity to adjust their best practices accordingly. An overview of the current LGS framing machine and additional information regarding the inspection systems is illustrated in Fig. 3.

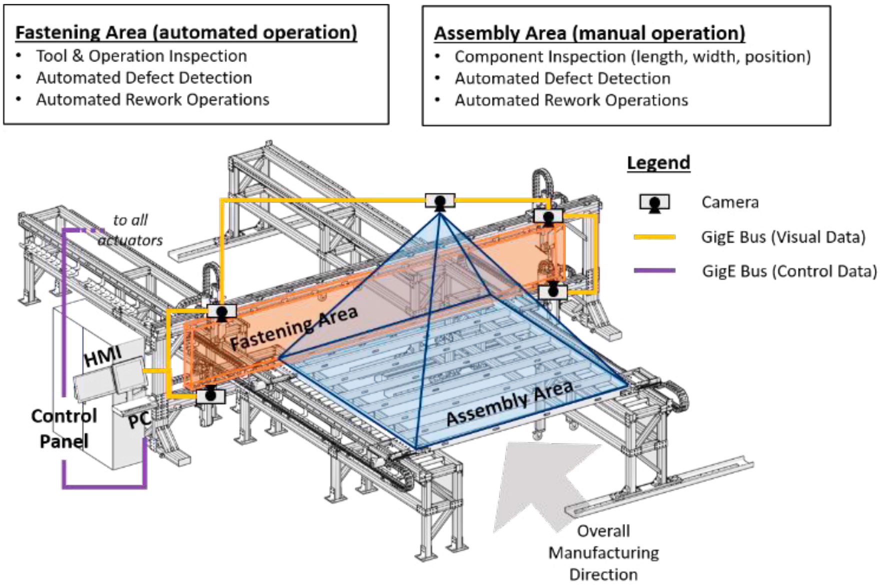

Fig. 3. LGS framing machine overview with current inspection systems.

3.2. Experimental setup

For this study, the relationship between product and machine health is to be analyzed, hence the focus of the presented experiments delves around the automated screw-fastening operations (where tool and product interact). A total of 7585 screw-fastening operations (over 9 hours of manufacturing) are monitored and the obtained data is stored for further analysis. Every screw-fastening operation lasts for about 7 seconds on average, the machine performs four operations simultaneously, and each screw-fastening operation is triggered every 20 seconds on average. For each operation, Table 1 presents a list of the data acquired and stored during the experimental monitored manufacturing process.

Table 1. List of inspected parameters and computed key performance indicators (KPIs).

Parameters & KPIs	**Source**	**Description**
System Time	System Data	Displays the time elapsed between operations
Processed Quantity	Process Data	Counts the number of screw-fastening operations performed
Defective Screw Fastening Operations (DFSO)	Sensor Data	Counts the total number of detected defective screw-fastening operations
Reworked Quantity	Process Data	Counts the number of reworked screw-fastening operations
Rework Time	Process Data	Time spent performing rework operations
Connection Angle (CA)	Sensor Data	Measures the angle of the steel connection after the screw-fastening operation occurs
Tool Life (TL)	Sensor Data	Shows the amount of time each tool has been in use.
Rework Ratio per Tool (RRT)	KPI	Rework ratio per tool – resets after a tool change has been reported
Total Rework Ratio (TRR)	KPI	Total rework ratio

The key performance indicators are calculated from the sensor and process data based on the needs of reducing the defective screw-fastening operations (as per the ZDM goals), subsequently focusing on the direct and measurable impact of defects on the production line (rework). Equations 1 and 2 present the relationship between them.

$$RRT = \Delta RQ / \Delta PQ \tag{1}$$
$$TRR = RQ / PQ \tag{2}$$

where the rework ratio per tool (RRT) is the quotient of the variation of reworked quantity units (ΔRQ) by the variation of total produced quantity units (ΔPQ), set from the start of each tool change to the current time, and the total rework ratio (TRR) is the cumulative reworked units over the manufacturing time. As per ZDM goals, the priority in this case study is to minimize both KPIs.

3.3. Quality and machine health data analysis

The results obtained are 7585 instances for all the parameters and KPIs presented in Table 1. These instances quantify the quality and machine health during the experimental setup. In this subsection, the obtained data will be analyzed and tested to move towards ZDM goals. Aiming at modeling the impact of the inspected product (quality) and process (machine health) variables regarding the studied KPIs and exploring linear relationships between variables in this study, a Pearson correlation analysis is performed. This correlation analysis measures the strength of a linear association between two selected variables. The results of this analysis can be found in Table 2 with a significance level of 5% (p-value < 0.005 to confirm correlation).

Table 2. Results of the Pearson correlation analysis based on the experimental data (cell content: **Pearson correlation coefficient** / p-value).

	RRT	TRR	TL	CA	DSFO
RRT	1	-	-	-	-
TRR	**-0.14917** 0.0451	1	-	-	-
TL	**0.98131** 0.0002	**-0.10565** 0.0632	1	-	-
CA	**0.54563** 0.0022	**-0.24531** 0.0547	**0.23745** 0.0017	1	-
DSFO	**0.87412** 0.0005	**0.16742** 0.0156	**0.97423** 0.0008	**0.70213** 0.0214	1

As noted, both studied KPIs, (RRT) and (TRR), have little correlation (-0.14917) supporting the need to monitor both. For the rework ratio per tool (RRT), a strong positive correlation is obtained with current tool life (TL – 0.98131) and resulting non-conforming screw-fastening operations ($DFSO$ – 0.87412) and a moderate relationship with the inspected connection angle (CA – 0.54563). In other words, a rework ratio increase is strictly correlated to the status of the tool under normal deterioration (tool life), as well as the number of detected defects during operations in both the manual assembly (connection angle) and the fastening operations. However, the Pearson correlation analysis does not provide any significant relationship between the studied quality and machine health data with the total rework ratio (TRR). A negligeable negative correlation can be found with the tool life (TL – -0.10565) and the inspected connection angle (CA – -0.24531) and a negligeable positive correlation is found with defective fastening operations ($DFSO$ – 0.16742). In between inspected quality and machine health parameters, tool life and connection angle (manual assembly) have a small positive correlation (0.23745) however those two parameters show strong positive correlation with the number of defective screw-fastening operations occurring (TL – 0.97423 and CA – 0.70213).

From this analysis, the complexity of multivariate relationships between product design and process equipment regarding quality is showcased. From all the measurable product and machine health parameters, the quantification of the impact of each variable on a certain target is achieved. By quantifying the linear relationships between different quality and machine health parameters and relevant KPIs, low and negligeable correlations can be ignored in favor of considering them as independent variables. Assuming linearity between variables, the order of magnitude of the problem can be reduced, or in other words, the number of variables to explore when tracing the sources of rework operations or defects can be reduced. Also, it can be used to analyze the usage of the measured data to perform any kind of data-driven modeling, i.e., deep learning. For example, current measurements would not be able to provide a linear model to explain the total rework ratio (TRR) of the presented operations. Either different data is required, or the relationship needs to consider non-linearities. These questions will be researched in the near future.

Over the experimental setup manufacturing activities, Fig. 4 illustrates an example between highly correlated and uncorrelated variables. In this case, it presents the relationship between the resulting KPIs (TRR and RRT) and the tool life (TL). In current experimental conditions, a 7% is set as the maximum acceptable rework ratio based on expected machine performance and similar industrial performance, hence a change in tool would be performed when that level is reached. During the experimental setup, two tool changes were performed when (RRT) reached 7%. The experiment stopped a few operations before the third tool change would be required. It can be easily observed that as tool life increases, the rework ratio per tool increases too whereas the total rework ratio has a more complex (quadratic) relationship, confirming the results obtained during the correlation analysis.

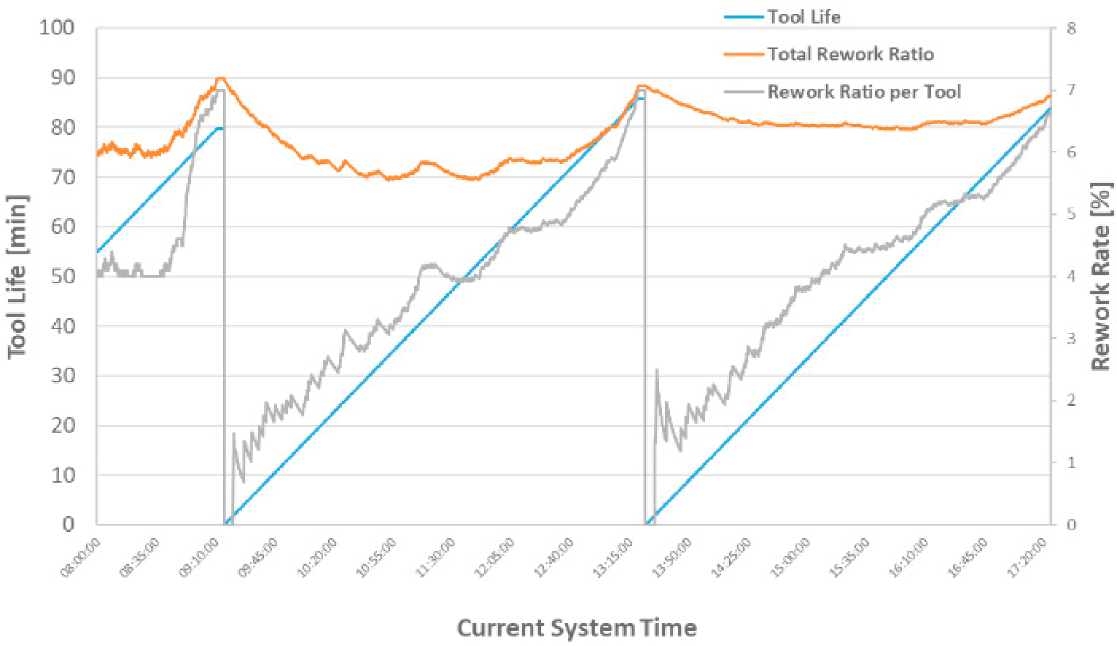

Fig. 4. Results for the tool life, total rework ratio (TRR), and rework ratio per tool (RRT) during the monitored manufacturing operations.

Considering the correlated variables, modeling approaches can be used to provide interesting management tools that support ZDM goals. For example, forecasts can be performed to predict maintenance orders to replace the tool based on current and past rework ratios. Fig. 5 shows an exponential triple smoothing prediction of the rework ratio by the last tool in use at the end of the experimentation shown in Fig. 6. This forecasting approach can be used to minimize the peak generation of defects that occurs at the end life of the tool. For the machine presented, rework and defect generation are reduced between 2-3% by introducing preventive maintenance operations based on forecasting, while only sacrificing on average 16 additional manufacturing operations per tool (2.4% of total tool life). Forecasting is key as the probability of obtaining a DFSO at the end of the tool life increases considerably after the 70-minute mark. Regarding its industrial implementation, the cost efficiency of such changes however remains to be analyzed.

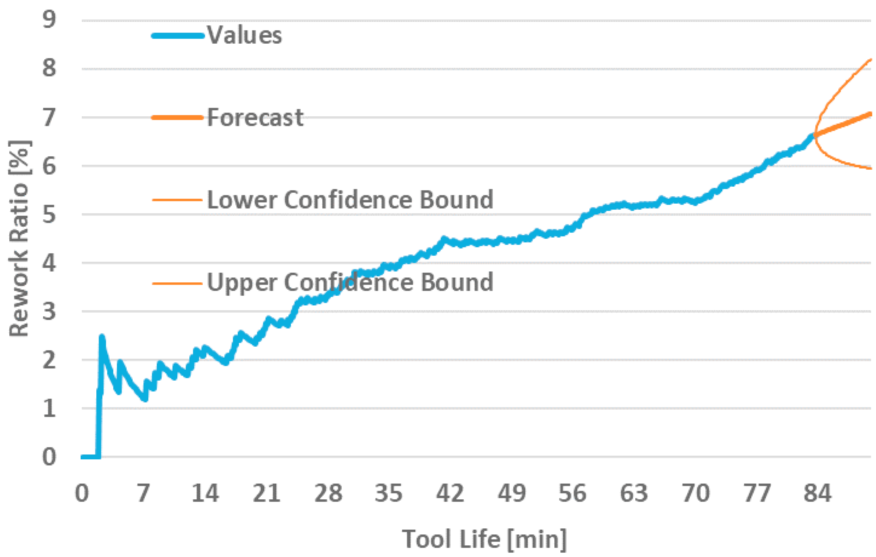

Fig. 5. Forecast model for tool life and rework ratio in the reported experimental conditions.

3.4. Visualization

To interact with the machine user and/or stakeholders, a user interface is created to relay information. This interface also enables human intervention on the inspection process and serves as the critical cognitive layer for the inspection results, either to ratify or deprecate them. The interface builds upon the data stored from the inspection results (process and sensor data), as well as the KPIs built during the manufacturing process. An overview of the CPPS interface is shown in Fig. 6.

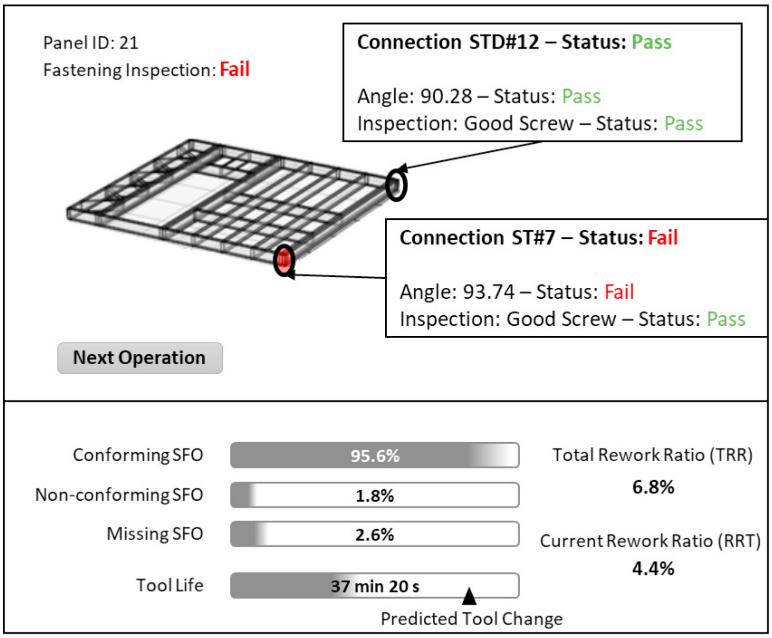

Fig. 6. CPPS graphical user interface main screen (dashboard).

As the production of a frame assembly progresses, the production status is continuously updated in the dashboard in real-time. It shows the existence of any defects in the product, and the overall historical inspection results for the duration of the current tool life. The current tool life is also showcased, providing a comparison to the average historical performance of the same tool type to indicate tool efficiency. A brief overview of the current state of selected KPIs is also given. Operators use the shown information to assess the quality of the current product and processes and determine whether to follow preventive maintenance and rework operations as suggested or continue with the next manufacturing step. The operator's decision is then communicated through the dashboard and stored within the system's data log.

4. Conclusions

Future manufacturing processes and smart factories will evolve into autonomous plants that will rely on real-time production monitoring, process optimization, and quality diagnosis and prediction. This paper proposes using well established cyber-physical architectures to enable zero-defect manufacturing strategies. By using already existing inspection methods, the manufacturing process is monitored focusing on product quality and machine health, while supporting operator decision making in terms of rework operations and preventive maintenance operations. Using light-gauge steel framing as a case study, the proposed framework enables modeling of relationships between inspected elements and the development of predictive models. A forecasting model between rework ratio and tool life is briefly discussed and preventive tool changes are shown to reduce between 2% and 3% the amount of rework required due to defective screw-fastening operations. Current data analysis is limited to linear relationships and future work will include further analysis into possible non-linearity relationships between variables and KPIs and study the cost effectiveness of zero-defect manufacturing approaches considering rework and preventive maintenance operations based on forecasting.

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