Data analysis of automated tasks in the manufacturing industry: preliminary report

Andres Alonso Perez, Hector Diego Estrada-Lugo, Maria Chiara Leva

Department, University/Organization, Country. E-mail: firstauthor_id@domain_name.org

Second Author

Department, University/Organization, Country. E-mail: secondauthor_id@domain_name.com

To deal with the rising complexity of the environment in which their employees work, organisations are increasingly resorting to team-based structures. The fast development of the new technologies for artificial intelligence, for example, the machine learning is allowing to improve productivity, reduce machine downtime as well as operational costs. However, the design of the teaming environments must not be only focused in the automation of the tasks but to include the human tasks whenever possible. In other words, special attention must be paid to the role of the human to increase the flexibility of the systems in the Industry 4.0.

This work consists on a preliminary report of the process status of a manufacturing system. The report consists on the description of the general milling process of metal components of a wind turbine at a manufacturing facility. To complement this description, a data analysis of the manufacturing process status is provided. The analysed data sets contain general information of relevant parameters of the manufacturing system as well as inputs from the operator and are subsequently displayed in a graphical manner. The purpose of this report is to establish the basis on which a thorough operational description of the manual tasks is defined. The operational description of the tasks can serve a number of purposes. For example, enhance the human performance of the operators by increasing their situational awareness in the shop floor. Moreover, to support scheduling of manual activities for the operator to perform while the automated task do not need direct supervision.

Keywords: Mutual performance monitoring, Collaborative Intelligence, Teamwork, Task analysis, Data analysis, Requirement specification

1. Introduction

The current developments in the well-known Industry 4.0 are being benefited from the new technologies in Artificial Intelligence (AI). For example, AI systems may do basic analysis, such as absorbing data, classifying, and prioritising information, relieving trained operators of a time-consuming duty Buchmeister et al. (2019). In the last decade, there has been a large growth of AI systems applied in the manufacturing industry Li et al. (2017, 2014). The vast availability of data, ongoing advancements in learning algorithms, and a growing acceptance of machine learning by industries are driving this growth Pan (2016). However, in order for manufacturing to fully exploit these new opportunities, a human-centered strategy is essential, which involves encouraging excellent interaction between operators and AI on the shop floor.

In industries such as manufacturing, some organisations are turning into team-based structures where their employees are supported by a different systems to cope with the growing complexity of the environments Katzenbach and Smith (2015). For a good team-based environment the *"Big Five"* concept has been proposed by Salas et al. (2005). This concept explains that team leadership, mutual performance monitoring, backup behaviour, adaptability, and team orientation are the core components that should be included for a practical teamwork. In this work, we will be focusing in the mutual performance monitoring. This component refers to the monitoring of the fellow team members to maintain an effective awareness to detect slips, mistakes, or lapses prior or shortly after occurrence McIntyre and Salas (1995).

This paper presents an example of a use case where the basic key elements for this type of teaming have to be set in motion and the methodology

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used to achieve them Mocan et al. (2022). This work consists on the following tasks:

- Identification of operator tasks that are currently not mapped into the automation
- Manufacturing process status data analysis
- Identification and collection of data regarding recurring causes of process deviations and downtime in operations
- Requirements specification for data to be collected and analysed to support a better automation-human collaboration on the case study

1.1. *Use case description*

For this study we are focusing in the case of GOIMEK which is a manufacturing company that produces high-precision machining of large-sized parts by either milling or grinding on the basis of cast materials or machine-welded structures. The operators at GOIMEK have to manipulate and manually clamp the milling parts before they are machined with the high precision manufacturing machines. This process takes an important part of the total cycle time of a working order and workers are exposed to occupational risks.

The machine of interest for this case study is an industrial milling machine for large parts such as **wind turbine torque arms reaction, and bearing house**. This is mounted on a mobile line that allows to transversely move between the two machining tables where the parts to be manufactured are clamped. The so-called machining tables are structures where special supports can be adapted to create the appropriate mooring areas to clamp the metal parts. Each table can move in a two-dimensional plane, allowing it to accommodate parts of different sizes (i.e., place them closer or further from the milling machine).

1.2. *Standard process description*

The standard milling process of a part consists on the steps described in this section. Note that some steps can vary depending on the type of part to be machined.

Part set up and clamping: Once in the facilities, the metal parts are placed on the machining tables using a ceiling-mounted crane system with the capacity to carry pieces of several tons of weight. The parts are secured with a system consisting of chains, slings, closures, and moorings. Moving the parts to the table represents a high risk for the operators as pieces moved at an overhead level. Operators must ensure the good conditions of the systems, i.e., the wear of the slings, moorings, and chains are in good conditions. Depending on the shape of the metal part, a specific support stand is chosen to clamp the part for machining. The support stands can go from horizontal short stands, *as shown in Figure 1*, to vertical walls also known by the operators as carpenter's squares, *see Figure 2 left*. The manipulation of the tools for securing the part to the base of the machining table is currently facilitated by the use of an overhead crane above the turning tables that are controlled by the operators so as to minimum ergonomic risks related to manual handling. However, there is still room for improvement as the tasks related to setting up the support to secure the parts to be machined to the turning table required meaningful manual intervention and handling of parts (clamps and tools) that have a non-negligible weight and require considerable forces.

Computer Numerical Control (CNC) program execution: When the part is correctly clamped to the base on the table, the operator should choose the correct operation package on the CNC program. This task is done manually by the machine operator. The timing of this task is not currently recorded anywhere and represents a source of variability in the overall machining of the product. For instance, the overall estimated machining time associated with the bearing house part is around 4.1 hours but the manual set up of the turning table may require from 1.5 to 3 hours depending on the set up of the previous product.

Previous to the execution of the CNC program, the operator must ensure that the correct tools are installed in the machine their automatic use. The conditions or the tools are the following:

- The machine magazine can store up to 80 different tools.
- Manual and automatic tools are labelled

with a different series of numbers.

- The probe heading is always placed manually to avoid damage due to its sensitivity.
- The tasks for the milling machine are defined. But not the details in the process (this information is not contained in the working order)

Part machining: When the correct CNC program has been started, the milling machine automatically begins the machining of the part. However, this automatic process needs sporadic operator intervention. The description of the general machining steps are as follows:

- Probing:
  - The machine uses a touch probe, to automatically test how much the extra-material the piece contains.
  - The probe is calibrated using a circumference of a known diameter, previous to starting probing. If there is any problem with the touch probe, the machine will raise an alarm.
  - The machine also tests if the piece is well located by touching key points in the piece.
  - If the piece is not properly placed, operator has to correct its position.
  - If the dimensions of the piece are out of tolerance (e.g., because of a defective casting), the machine will raise an alarm. However, the operator takes measures of the piece when clamping it, to asses if they are correct, in order to save time in case it is defective.
- Deburring:
  - The operator re-activates activity block (resumes the program in execution) so the machine starts the milling. This is done after the probing has been successfully finished.
  - The machine starts milling to deburr the extra material from the piece, this is an automatic task.
  - When the machine has the finished the milling (i.e., executed all the block lines) it emits a Finished-process alarm.
  - Operators then need to dismount the milled piece and get the machine ready for the new piece.

Note that these steps might change depending on the part to be machined. The change rate of parts is variable.

To visualise the progress of the machine GOIMEK uses a graphic interface accessible from its intranet. This interface shows information regarding the working order, article id, working order, cycle time and execution state. Note that when the machine is showed to be stopped in the Cycle Time and Execution State, the reasons for the stop are not specified. This represents an opportunity for improvement as discussed later in this document.

Fine milling: Once the piece has been milled, the next step is to refine it in order to adjust the piece to the adequate tolerance values. If, for some reason, the milled piece is not adjusted to the right tolerance values, the operator will have to mill the piece with a special boring head, measure it again, and repeat this sequence until the tolerance value has been reached.

Part dismount: Once the CNC program has finished the machined part should be ready for dismounting. Ideally, when one part is finished the milling machine moves to the other table to continue the milling of another part. This leaves room to the operators to disassemble and unload the piece following safety protocols. This involves the use of manual tools and cranes as described before. This task involves some work hazards such as the position of the operator while managing the handling of load through the overhead cranes that sometimes requires the operator to get within the zone of possible dropped object risk. In addition to this, due to fine-tuning of the position of the product on the turning table clamping and bases required.

1.3. *Manufacturing process status data analysis*

Data sources and objectives: As a part of the manufacturing system, information about the positions, temperatures and other multiple sensors from the machine is stored and combined with inputs from the operator, such as working order and article Id, and are subsequently displayed in a graphic interface as described in Section 1.1. The sampling frequency of the data is of approximately 1 second.

The manufacturer provided two datasets from each source of data, the fist one including the operator and reduced machine data between 2022-01-23 00:00 and 2022-01-29 23:58, and the second one including the data between 2022-02-18 00:00 and 2022-03-11 23:58.

The datasets come divided in different csv format files to make them more portable, and are concatenated to make the analysis. Even if the two datasets do not correspond to consecutive intervals of time, they can be combined, since there is no significant difference in the manufacturing process or in the features presented.

This analysis will study the first data source consisting of operator inputs joined with some of the machine data. The complete machine data, which has over 100 features, would be of great use if the quantity of data was greater, and Statistical or Artificial Intelligence models could be used to extract information. However, since each manufacturing process for one piece takes between 5 and 8 hours, the data does not contain a significant amount of complete cycles, and the models could easily be overfitted. The analysis will rather be a graphical analysis with the potential to disclose useful information for the manufacturer, that can help to make some improvements in some parts of the processes, and to set the base to a future resolution of the scheduling problem.

Also, the analysis will only focus in two of the articles, which are the most produced by the manufacturer at the moment of data collection and, therefore, the ones that would have a greater impact if improvements were made.

The relevant features in the analysed dataset are:

- *Date* of the event, with precision of milliseconds
- *OperationMode*: Operation mode of the program. Categorical variable with three possibilities: MAN (Manual), MDI (Manual Data Input) and AUTO (Automatic)
- *ExecutionState*: Execution State of the program in the machine. Categorical variable with four possibilities: 0 (Ready), 1 (Paused), 2 (Stopped) and 3 (Working).
- *ArticleID*: The type of article that is being manufactured or, if the machine is not working, the task that is being made (such as maintenance, meetings, etc.). Categorical data that is input by the user.
- *WorkingOrder*: The identifier (number) of the piece that is being manufactured. It is used to keep the track of different pieces, even if they are of the same type. If its value is 0, it would mean that no piece is being worked one at the time. It is also information provided by the workers.
- *ProgramName*: The programs that are being used for the machine. There are specific programs defined for each type of piece, along with other programs to change the head of the machine or change the working surface. In this case, they are named *Art1_Prog1* and *Art1_Prog2* for the first article, and *Art2_Prog1* for the second article.
- *ToolNumber*: The number of the tool head that is being used by the machine. If the tool head is changed manually, the number will be above 200. Some tool heads are shared for both pieces, and some others are specific for some types of articles and programs.

2. Methodology

2.1. *Operational task description*

An operational task description are agreed-upon safe procedures. They generally contain instructions and other relevant information to assist in the safe completion of jobs. Step-by-step instructions, checklists, decision aids, diagrams, flowcharts, and other job aids are examples of procedures. This information can then be used in the design of a interface that allows a communication between the human and the machine to decrease the dead-times while the machine is waiting for the operator's input. As stated in OHara et al. (1994), the most important aspect of designing this type of evaluation is knowing what functions are assigned to plant personnel and the tasks they must perform.

The Health and Safety Executive recommends that some of the keys in designing an operational task description we have to determine which activities require procedures and how they are produced, implemented, and reviewed/updated [a]. For this purpose, different methods/tools can be implemented to inform procedure content. For instance, the talk-aloud protocol where the operator is walking and talking through the task with users. Such a protocol can be benefited by recording the description with simple audio recorders or eye-tracker devices.

The methodology used to map out the activities carried out by the operators in the shop floor consist on the following:

Talk Aloud Protocol (TAP). This is a data collection approach in which participants are requested to speak aloud while performing a certain task, describing what they are thinking as they complete the exercise. The subject is instructed to speak aloud whatever thoughts come to mind, offering a simultaneous account of thoughts while avoiding interpretation or explanation of what is being done. The TAP uses verbal reporting and raises thoughts into consciousness to collect information about an individual's cognitive processes Ericsson and Simon (1984). Think aloud verbal protocols provide detailed information about reasoning during a problem-solving or decision-making job. This technique has been applied in a broad range of situation, e.g. training purposes Vie and Arntzen (2017).

Eye-tracker. In short, an eye-tracker device consists on a video recording instrument focused in the eye movements of the wearer (observer). The observer's gaze pattern gives useful information based on where and what the observer is looking at when studying eye movements Duchowski and Duchowski (2017). The information collected with such a device can range from attention, fatigue level, perception, consciousness, and cognitive processes Yarbus (2013). Most studies have employed objective approaches to study the relationship between oculomotor behaviour and cognitive processes throughout diverse visual tasks. The popularity of the eye-tracker studies has grown with the improvement of their technology. Mobile eye-trackers provide freedom of head movement as well as commuting in the work area and other properties of natural vision, which results in a superior approach for researching visual attention and perception in a real-world setting Kiefer et al. (2012). Even some models offer the possibility of recording audio and video at the same time. This feature becomes handy when combining it with the TAP.

2.2. *Data processing method*

The method to process the data, performed in the *Python* programming language, is the following:

(1) Concatenation of the different files in format *.csv* to reconstruct the combined dataset. The first dataset has 604857 instances ordered by their date, while the second dataset has 1901303 instances.
(2) Substitution and removal of *null* values: in some of the columns, there is a relatively high number of *null* values. For the instances of *ProgramName* and *ArticleId* that are missing a value, they are replaced with "unknown". For the instances of *OperationMode*, *ExecutionState* and *WorkingOrder*, the values are

[a] `https://www.hse.gov.uk/humanfactors/topics/procedures.htm`

replaced with 0, 2, and 0 respectively. The remaining *null* values present in some of the rows are less than ($< 1\%$), so the whole rows are removed in those cases.

(3) Conversion of the types of the columns. For example, the *Date* column is changed to Datetime format in the timezone of the manufacturer (Europe/Madrid), the numeric values in the categorical variables like *ExecutionState* are changed to the proper names already described, and *WorkingId* is set to a *string* variable type.

(4) Column addition. There are some columns derived from the data that could be of great use to describe the possible causes of the machine stop time. The Week Day is added as a column, and also the *ToolChange* variable, that describes whether the tool change is done manually or automatically by the machine.

(5) Data anonymization. This is a necessary step to protect industrial information. The original article names are changed to Article 1 and Article 2 as described previously, and the original names of the programs are also changed. In this step, Article Id and Program Names that do not involve the pieces manufactured or are not unknown, are all classified as *others*.

(6) Data filter. This involves the removal of the data out of working hours, that does not contain useful information. In this case, only data from Sunday at 10 p.m. until Friday at 10 p.m..

(7) Time series visualisation. It involves the creation of graphs of the process. It allows to examine the features different events prior to a further analysis.

(8) Feature exploration. An averaging of the is done for the piece processes times, differentiating between the Execution States, so the events in which the machine is stopped can be identified and addressed. This can also lead to an identification of possible improvements of the data. For the features other than Article Id, specific pieces are selected, since the execution times are different for each of them, and the other Article Id, that represent other tasks or meetings in which the machine is not working, or other less common pieces manufactured, are not addressed.

3. Results

3.1. *Operational task sequence: the missing ingredient*

As an example of the level of detail needed to describe the operational sequence of the tasks that the operator carries out during *the ending* process, the following task sequence is provided.

(1) Coupling the boring head to the milling machine (manual mode).
    (a) Setting the milling machine to manual mode.
    (b) Grabbing the milling machine remote control and coupling it into the left side of the milling arm.
    (c) Grabbing the crane remote control.
    (d) Hooking the crane to the boring head.
    (e) Approaching the boring head to the milling machine by using the crane with the remote control.
    (f) Cleaning the coupling contact surfaces of the boring head and the milling arm.
    (g) Coupling the boring head to the milling machine.
    (h) Unhooking the crane from the boring head.
    (i) Release the crane remote control.
    (j) Grab the milling machine remote control.
    (k) Release the milling machine remote control in the main control panel.
    (l) Release the crane remote control.

(2) Setting the boring head tool manually to the right value for milling the excess material from the piece.
    (a) Grabbing the proper screwdriver.
    (b) Manually adjusting the boring head with the screwdriver to the proper setting for milling the excess material from the piece.
    (c) Release the screwdriver.

(3) Starting the milling process.
    (a) Isolating the milling machine cabin by closing both doors (internal and external doors).

   (b) Adjusting the proper settings in the milling control panel machine.

(4) Checking the tolerance value of the piece (redsteps to be defined).
(5) Repeat steps 3-4 until the tolerance value is in proper range.
(6) Decoupling the boring head from the milling machine (redsteps to be defined).

3.2. *Eye-tracking analysis*

As described in Section 2.1, an eye-tracker system can provide useful information on what the observer is looking at when studying eye movements. This information can be analysed to generate an operational description of the tasks.

In Section 3.1, the first task listed in the sequence is *Coupling the boring head to the milling machine (manual process).* The event starts when the operator takes the crane remote control (in this particular case task sequence (a), (b), and (d) were already done before the start of the recording. Therefore, we have considered the action "Grabbing the cranes remote control" as the starting time for the event) and ends when the employee release the crane remote control inside of the milling machine cabin. During this event, the employer attaches the boring head to the milling machine in order to start with the so-called "ending task".

Fig. 1. Gaze plot of operator's point of view when installing boring head in milling machine.

The data in Table 1 give us information about the behaviour of the operator while the employee spend most of the time looking at the milling machine ($43719ms/12visits$), followed by the boring head ($6872ms/8visits$). The employer switches his attention mainly between the milling machine and the boring head. Some few times the crane remote control and the milling machine control require his attention.

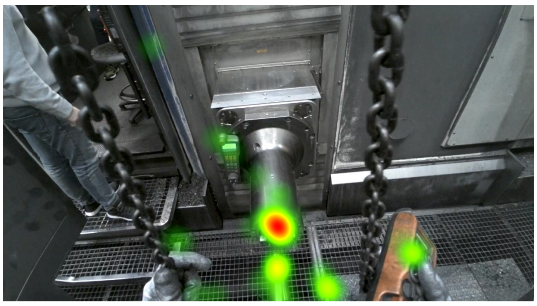

Fig. 2. Heat map reflecting more relevant areas for operator when installing boring head in milling machine.

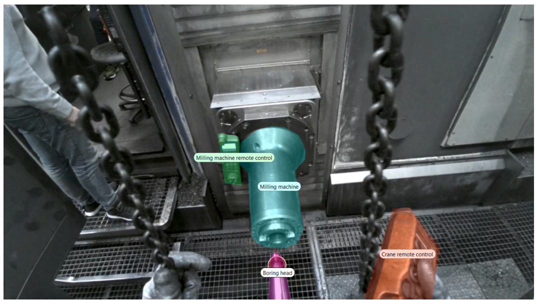

Fig. 3. Areas of interest when operator is installing boring head in milling machine.

Milling initiation. Once the operator has manually adjusted the boring head settings, he gets inside of the milling machine cabin (start of the event), introduces the proper values in it and starts the milling process (end of the event).

According to Table 2, the employee started the event using the control panel and then the main control screen for introducing the proper values for refining the milling of the piece. We can see how he spent most of the time switching his attention from the main control screen ($10038ms/4visits$) and the main control panel ($6492ms/10visits$), to the door window of the milling cabin ($13444ms/4visits$), in order to monitor the execution of the milling process.

Table 1. AOI data for operator when installing boring head.

AOI	Total duration of visit (msec)	Average duration of visit (msec)	Number of visits	Time to first visit (msec)	Average pupil size (mm)
Boring head	6872	859	8	1102	5.82509
Crane remote control	2304	461	5	7033	5.89727
Milling machine	43719	3643	12	220	6.01385
Milling machine remote control	4067	2034	2	55460	6.08495

Table 2. AOI data for operator initiating milling process.

AOI	Total duration of visit (msec)	Average duration of visit (msec)	Number of visits	Time to first visit (msec)	Average pupil size (mm)
Door window	13444	3361	4	10399	4.76855
Main control screen	10038	1115	9	1403	3.80863
Main control panel	6492	649	10	0	4.31454

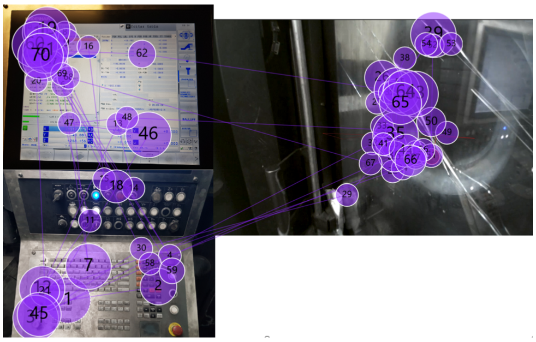

Fig. 4. Gaze plot of milling process initiation by operator.

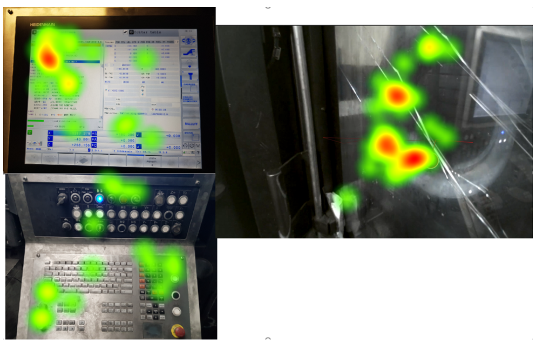

Fig. 5. Heat map showing relevant areas for operator when initiating milling process.

3.3. *Data process results*

The Figure 6 is the time series visualisation of the first dataset (from 2022-01-23 00:00 to 2022-01-29 23:58), once the non working hours have been removed, and places all the events and pieces on a timeline. This is the only visualisation that is not performed with the combined dataset, so that the events are visible.

The figure 7 shows the average duration of the processes for the different articles. *Article1* and *Article2* are the main articles manufactured by the company, and the main object of this studio.

The figure 8 shows the average duration of the processes for the different articles, if working order number 0 (the value assigned when the machine is not working on any article) is excluded from the average computation in this and the following data visualisations to exclude irrelevant data.

The figure 9 shows the average duration of the programs when *ArticleId* is Article 1. *Art1_Prog1* and *Art1_Prog2* are designed for this article.

The figure 10 shows the average duration of the programs when *ArticleId* is Article 2. *Art2_Prog1* is designed for this article.

The figure 11 shows the average duration of the usage of each tool number when *ArticleId* is

Fig. 6. Machine multivariate time series visualisation.

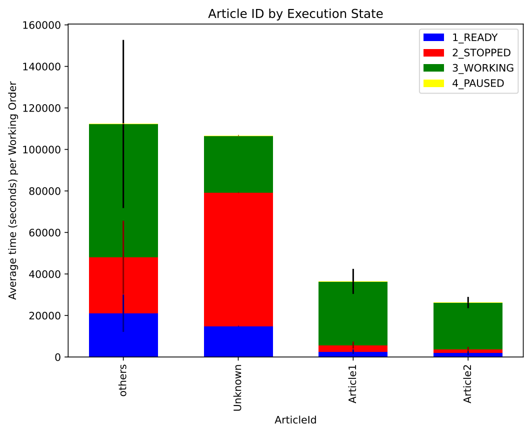

Fig. 7. Article ID by Execution State (including working orders equal to 0).

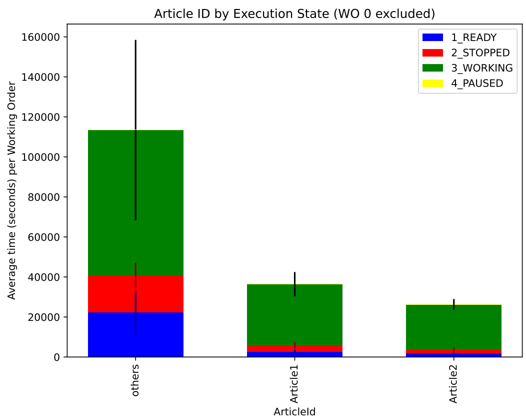

Fig. 8. Article ID by Execution State (excluding working orders equal to 0).

Article 1 and *ProgramName* is the first program for Article 1.

The figure 12 shows the average duration of the usage of each tool number when *ArticleId* is Article 1 and *ProgramName* is the second program for Article 1.

The figure 13 shows the average duration of the usage of each tool number when *ArticleId* is

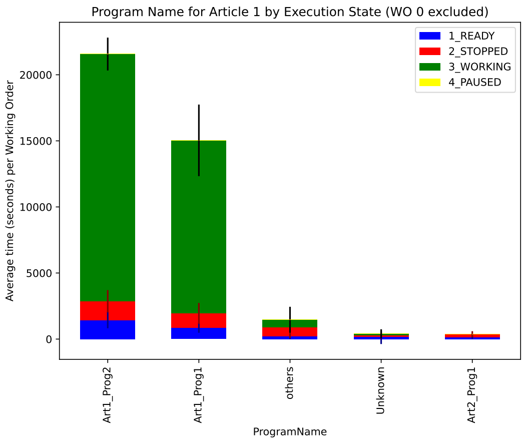

Fig. 9. Program Name for Article 1 by Execution State (excluding working orders equal to 0).

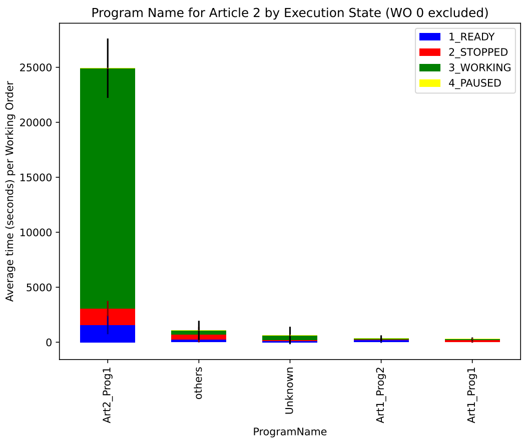

Fig. 10. Program Name for Article 2 by Execution State (excluding working orders equal to 0).

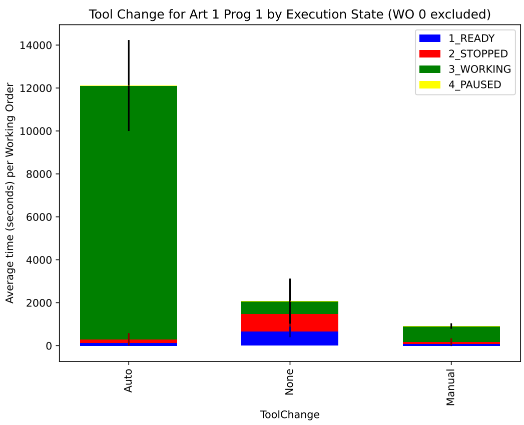

Fig. 11. Tool Change for Article 1 Program 1 by Execution State (excluding working orders equal to 0).

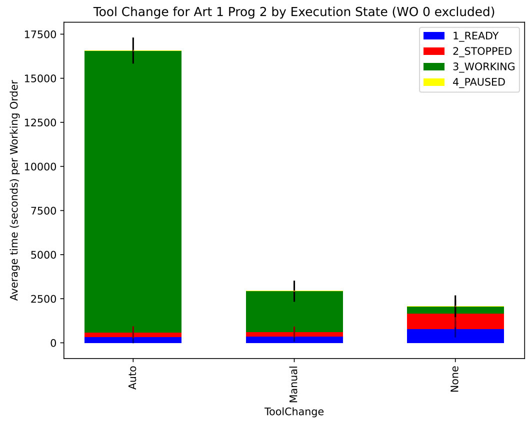

Fig. 12. Tool Change for Article 1 Program 2 by Execution State (excluding working orders equal to 0).

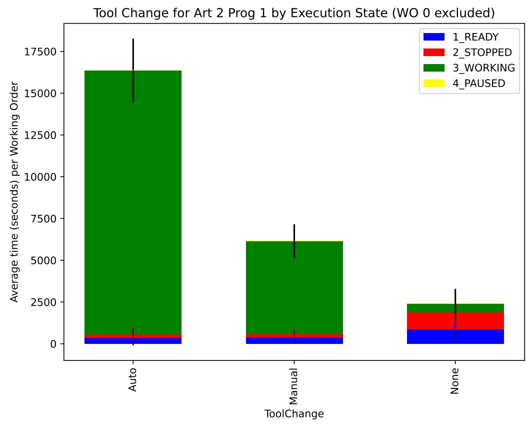

Fig. 13. Tool Change for Article 2 Program 1 by Execution State (excluding working orders equal to 0).

Article 2 and *ProgramName* is the first program for Article 2.

4. Discussions

Figure 6 shows how the articles are alternated and how they schedule the different pieces. It also reveals how important is to remove the working 0 orders: for example, between the 2022-01-25 and the 2022-01-26, there is some downtime that does not correspond to any article or activity, but that has a program and tool associated. It is an uncommon event registered by the workers. Erasing working 0 orders also allows to remove the downtime at the start at the end of the week, when the workers go out of working hours (e.g., on the last hours of the 2022-01-28, where the workers finish the last piece before time and do not initiate the process of another).

Comparing Figure 7 and Figure 8, the invariability of the *Unknown* Article Id can be explained: all *Unknown* Articles are labeled with a 0 in the Working Order. However, the proportion of *3_WORKING* in the *Unknown* Article Id suggest that the information about the Article Id, which is submitted by the worker, has a delay with respect to the information of the machine. This could means that the machine has already been working for some seconds before the worker inputs that information. Data correction could be used to address this delay.

On the other hand, the variability shown in the *others* article ID shows that the duration of these articles is very variable. They are associated to either other pieces less commonly produced by the manufacturer, or other activities performed by the workers, e.g., preventive maintenance.

Figures 9 and 10 also show the delay mentioned before: there are some programs showing that are not designed for the corresponding articles (e.g., *Art2_prog1* for Article 1). This shows that the delay also exists when the worker inputs the Article Id once the new programs are being executed. Again, this delay cannot be avoided, but could be corrected in the data.

The graphs also show a noticeable variability of the program length for each article, which is considerably larger than the delay and is worth studying. Although the *working* part of the programs is supposed to be the same (once the machine is active, the programs usually have a fixed duration), part of that variability could be explained by the differences between the cast pieces (they have tolerances and sometimes more material is to be removed) or the override that the workers sometimes enforce in the machine to increase the productivity.

Regarding figures 11, 12 and 13, a high variability can be appreciated in Tool Change *None*, which is the value assigned when the machine has no tool. This tool shows, additionally, the highest proportion of *2_STOPPED* and *1_READY* Execution States, in which the machine is not working. This could be useful information for the manufacturer, since the study of the causes of this variability and downtime can lead to a reduction of the overall production time of the pieces.

Additionally, in all the programs of the two main Articles, the tool heads that are changed manually present a noticeably higher variability and proportion of unproductive time if compared with the tools changed automatically. This is also worth of study from the manufacturing company. Despite the fact that the change in manual tools will always be less efficient

There is space for a future study extension with the distribution times for each sub-process in the program.

5. Conclusions

This work presents the description of the general tasks of a manufacturing company in charge of machining metal parts. Such a description is part of the basis to understand the graphical data analysis of the tasks carried out on site. The analysis only focused in two of the articles, which are the most produced by the manufacturer at the moment of data collection and, therefore, the ones that would have a greater impact if improvements were made.

It must be noted that the data has been labelled to describe when the operator is needed, not when the operator is doing a manual task. A thorough operational description of the manual tasks, as the one provided in this report, would benefit the time calculation of such tasks. The authors envision a potential for AI collaboration. Supporting scheduling of other activities for the operator to perform while the automated task do not need direct supervision. for this to be achievable it requires mapping and data collection for the human tasks currently unaccounted for. This is also to satisfy the principle of good teamwork of communication loop and shared mental picture (the automation is missing this picture currently).Salas et al. (2005)

The data analysis shows that there is space for a future study extension with the distribution times for each sub-process in the program.

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Ethics Statement

All procedures performed in studies involving human participants were in accordance with General Data Protection Regulations or comparable ethical standards. Informed consent was obtained from all individual participants included in the study.

References

Buchmeister, B., I. Palcic, and R. Ojstersek (2019). Artificial intelligence in manufacturing companies and broader: An overview. *DAAAM International Scientific Book*.

Duchowski, A. T. and A. T. Duchowski (2017). *Eye tracking methodology: Theory and practice*. Springer.

Ericsson, K. A. and H. A. Simon (1984). *Protocol analysis: Verbal reports as data.* the MIT Press.

Katzenbach, J. R. and D. K. Smith (2015). *The wisdom of teams: Creating the high-performance organization*. Harvard Business Review Press.

Kiefer, P., F. Straub, and M. Raubal (2012). Towards location-aware mobile eye tracking. In *Proceedings of the Symposium on Eye Tracking Research and Applications*, pp. 313–316.

Li, B.-h., B.-c. Hou, W.-t. Yu, X.-b. Lu, and C.-w. Yang (2017). Applications of artificial intelligence in intelligent manufacturing: a review. *Frontiers of Information Technology & Electronic Engineering 18*(1), 86–96.

Li, B. H., L. Zhang, X. Chai, et al. (2014). Smart cloud manufacturing (cloud manufacturing 2.0)-a new paradigm and approach of smart manufacturing. In *ISPE CE*, pp. 26.

McIntyre, R. M. and E. Salas (1995). Measuring and managing for team performance: Emerging principles from complex environments. *Team effectiveness and decision making in organizations 16*, 9–45.

Mocan, A., A. Gaureanu, G. Szabó, and B. Mrugalska (2022). Arguments for emerging technologies applications to improve manufacturing warehouse ergonomics. In *Sustainability and Innovation in Manufacturing Enterprises*, pp. 115–164. Springer.

OHara, J. M., W. Brown, C. Baker, D. Welch, T. Granda, and P. Vingelis (1994). Advanced human-system interface design review guideline. evaluation procedures and guidelines for human factors engineering reviews. Technical report, Nuclear Regulatory Commission, Washington, DC (United States).

Pan, Y. (2016). Heading toward artificial intelligence 2.0. *Engineering 2*(4), 409–413.

Salas, E., D. E. Sims, and C. S. Burke (2005). Is there a "big five" in teamwork? *Small group research 36*(5), 555–599.

Vie, A. and E. Arntzen (2017). Talk-aloud protocols during conditional discrimination training and equivalence class formation. *The Analysis of Verbal Behavior 33*(1), 80–97.

Yarbus, A. L. (2013). *Eye movements and vision*. Springer.