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Optimal scheduling in a Collaborative robot environment and evaluating workforce dynamic performance

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Abstract: After the emergence of industry 4.0 and the continuous technological development, it became vital for industries to transfer mass production expertise into personalized products in small batches. Clients became more aware of their needs and start basing their decision on specific quality requirements, lower cost, and the shortest delivery date. This is where collaborative robots intervene, these structures can work hand in hand with operators and take charge of hard, long, or repetitive tasks in a fast, precise, and robust manner. Although these structures have great potential, they lack flexibility and adaptability, these aspects can only be found in humans. The workforce competencies and performance are the ultimate precursors to any proper industrial evolution. Performances and competencies workforce must go further than the standard definitions attributed to them. This paper addresses the scheduling problem, our proposition relies on the assumption that the final programs attributed to collaborative robots can be divided into standard sub-programs. Based on the similarities between sub-programs can help propose a schedule that reduces significantly wasted time developing new programs or going from one program to another. This paper will also address the dissociation between human and robots' performances in a context where humans and robots work in very dependent proximity. Finally, we will also propose a new definition of workload performance while highlighting its dynamic aspect in terms of fatigue, motivation, and the correlation between repetition and the learning process.

Keywords: Industry 4.0, collaborative robots, workload performance, learning curve, forgetting curve, scheduling.

1 Introduction

Industry 4.0 brought technological, structural, and informational solutions for industrial organizations to prevail in an everchanging context where clients become more precise in the expression of their needs. The key to their success or -with lower expectation-survivor is to provide a large variety of products with high quality at the lowest prices and of course with the closest delivery date possible. These requirements imply that industrial organizations operate at a new level of flexibility and adaptability to produce highly personalized products with the hope to reach mass production performances.

Along came collaborative robots! These new technologies have the particularity of working alongside humans with no barriers and providing a large variety of products [1].
Collaborative robots (cobots) address the issue a standard robotic integration lacks: flexibility. While robotic structures present high performances, they can be a huge setback when it comes to satisfying dynamic personalized demands with different constraints of size and characteristics [2]. Figure 1 aims to compare the characteristics of collaborative robots to traditional industrial robots.

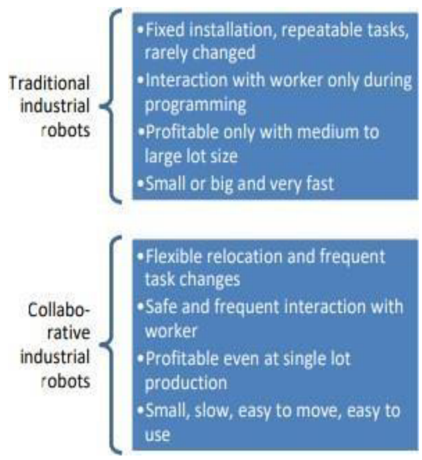

Fig 1: Comparison of collaborative robots and traditional industrial robots El Zataari et al. (2019)

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A structure prone to Human-Robot Interaction can benefit from the advantages of both collaborative robotics systems and human competencies: in other words, the flexibility and adaptability of operators are keys to orienting collaborative robots into the right course of action. Once it is done, optimal performances can be reached due to the precision of the Cobot. Structure[3]. It becomes abundantly clear that the definition of an operator's performance improves drastically from a very standard comprehension into a larger scope of skills. This will imply that scheduling becomes a highly complex issue since operator's performances can vary from one operator to another and products are highly variable as well.

This paper is organized into three main sections. The first one will assess the context of the study we will review the current state of the art and emphasize the issues of scheduling in a collaborative robot's environment. The next sections address three issues: the scheduling issue, the dissociation between human and robots' performances, and finally the operator's performance formulation. Finally, we will discuss this proposition and conclude.

2 Context of the study

In a job shop manufacturing system, a collaborative environment, real-time data utilization, and adaptative structures are the future of smart manufacturing. The robotic structure must gain more agility and flexibility to keep up with the highly changing and personalized demand, this can only be accomplished with collaborative robots working in high proximity and alliance with skilled operators [4]. The job shop floor becomes an ecosystem of human and collaborative robots exhibiting a highly dynamic, flexible, and adaptative behavior to meet the customers' needs in the shortest deadline at the lowest price possible [5].

The difficult part of implementing collaborative robots is the modulization of human-robot interaction. When robots and humans are highly dependent, the notion of performance can only be attributed to both of them [1]. The teaching or programming part of the robots can be very long or tiring and moving from one program to another can be frustrating [6]. Therefore, the scheduling problem becomes more difficult to resolve.

2.1 Scheduling issues

In a job shop standard environment, the versatility of operators offers the possibility of conducting a large variety of products, the scheduling problem can be resolved while using software equipped to propose the planning that will respect all deadlines and ensure an optimal resources utilization.

In the context of industry 4.0, the variety of products is not only more pronounced, but the deadline becomes shorter and the batch sizes are extremely variable. The expectations of clients are rising since they are aware of the technological evolution.

The scheduling problem becomes more and more difficult to solve in a collaborative environment context for three reasons:

- The first one can relay the time needed to transfer from one product to another, changing completely the setting, the program configuration, the program itself, or in some cases readjusting the manufacturing system in additive manufacturing.
- The second one is in high correlation with the operator's performance: the collaborative robot is based on the ability of a machine and skilled operators to work hand in hand with no interruption, although the machine performance can be calculated, the task that requires both human and machine synergy cannot be guaranteed.
- The high variety of products increases significantly the number of maneuvers the operators must learn to be qualified as versatile.

AI solutions such as deep reinforcement learning and fuzzy logic Genetic algorithm for Cobots assignment have been considered also to solve the scheduling problem in an assembly job shop structure with collaborative robots [7] [8].
Many studies have been conducted to resolve such a complicated problem, based on CPS technologies, the focus can be on real-time data to figure out the shop floor status and ensure a common cloud platform to get access to real information to make informed decisions, although this proposition can be promising, it assumes a specific sensors and actuators, powerful processing system and highly efficient security system since any breach can be fatal to the whole structure [5]. In [3], the role of humans as supervisors and co-workers combine with learning by demonstration can lead to a proactive planning system based on Digital Human Modelling (DHMs), this proposition represents the disadvantage that operators might feel irritated while demonstrating a task to robots, it also addresses the issue of tasks and not scheduling several tasks simultaneously, where supervisor must divide their attention to several robotic structures, it lacks also a proper distinction between tasks that are to be made by human and task to allocate to robots. A programming supporting system can be of use to assist humans in their task execution [9].

2.1.1 Workload performances in the industry 4.0

A review treating the subject of Industry 4.0 evolution stresses the existence of an obvious gap regarding Human Resources Management. A big variety of subjects field lacks innovation and research: the definition of skilled workload has extended to managerial skills, such as decision, programming skills, and technological expertise [10].

Although programming might not be for everyone, however a well-configurated interface with real-time data combined with proper training and the accurate presentation of its advantages can highly motivate operators to incorporate the changes in the structure without fear of losing their position [11] [12].
As an efficient training program is a key to performance enhancement, many studies propose a framework for growing the workload competencies, learning factories emerge [13], reward augmentation, and a repair explanation framework proposes a reinforcement learning to access the right degree of performance [6], cross-training can enhance significantly human performances while strengthening the operator's trust in the robots [14]. Knowledge management is also a subject of study since the new competencies required of Industry 4.0 deepen the presence of tacit data and personalized skills, the proper training must address also the proper way to pass the proper knowledge to the proper operators in the best and fastest way possible.
To sum up, there are four categories of competencies operators 4.0 must acquire:

- Technical competencies such as media skills, IT and security skills, and coding skills.
- Methodological competencies such as decision and research skills problem solving, entrepreneurial thinking, conflict-solving, and creativity
- Social competencies such as language, communication, and networking skills; leadership skills, teamwork, and transfer of knowledge
- Personal competencies like flexibility, compliance, ambiguity tolerance, and the ability to work under pressure. [15]

2.1.2 The dynamic aspect of performance in the industry 4.0

In a standard job shop structure, operators are required to master, to a satisfying level several tasks. Performances can relate to three main aspects:

- Work performance: this means respecting the standard time of execution
- Execution quality: which aims to meet the customer's precise quality needs
- Consumption ratio: which means to have a minimum waste in terms of raw material used for production.

When we face a scheduling issue, we must propose a human resource allocation that will reduce the cost of execution [16].
The notion of performances is highly linked to a time-related notion, the dynamic aspect of performances depends on the repetitiveness of the task, as precisely presented by Wright's learning curve equation below [17]:

$$Yx = Y1.x\text{-}b \quad (1)$$

Where:
- Yx is the average duration time to produce the x^{th} unit,
- $Y1$ is the average duration time to produce the first unit,
- b is the learning exponent, which is computed with LR being the learning rate [18].

It can also be related to the forgetting curve which is the opposite effect of the learning curve previously presented [18]. These two notions can also be affected by fatigue [19] depending on the shift and the day [20]. We can also introduce another criterion to describe the human factor: preferences. These criteria can approach the current performances after a multi-period of working on several tasks and forming an appreciation over each in a dynamic environment.

3 Proposition

This paper aims to address the three aforementioned scheduling issues we previously presented in section 2.1. This article will focus on three aspects:

- Reduce transfer time from one program to another.
- Dissociate Cobot's performance from the operator's performances when in a highly dependent collaborative robots' environment.
- Formulate the dynamic aspect of the operator's performance.

This solution will rely on several hypotheses:
The first one is regarding the high range of tasks that can be performed on a machine, to address this issue we will reduce the actions of a collaborative we will refer to the genetic behaviors of Cobot's in a collaborative environment presented in [20]: cobots can be in one of those states:

- Move to a certain position, (Mp)
- Pick up product tool, (Pup)
- Place product or tool, (Pp)
- Wait to adjust parameters, (Wp)
- Wait for operators to finish intervention (Wf)
- Execute sub-routine. (SubT1, SubT2,., SubTn)

This will result in a large scope of similarities between several products, not in terms of parameters or batch sizes, but in the machine program utilization on each Cobot.

The second hypothesis is in a high correlation with the similarities between programs, operators must have the proper training to execute all the possible tasks, this doesn't mean that they have the same performances, it's supposed that they gain sufficient knowledge to adopt the right behavior. Based on programs similarities, we will assume that the learning continues to occur when an operators continue to execute a similar task, not only that repetitiveness of the same task can induce fatigue [19], the number of shifts, the days of the week, as well as motivations, can contribute to the dynamic aspect of operator's performance, This means that performance is adopting the proper behavior according to the environment [21].

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3.1 Reducing transfer time from one program to another.

The first step of our study aims to standardize the scheduling issue, assuming that the operator's preferences will not affect the choice of task orders. The scheduling must be proposed by the supervisor based on the product to execute in a shift.
In a scenario where more than one shift must be executed in a period, a classification of the tasks will help propose an order where the final execution time is largely reduced. This classification should be based on similarities between tasks as well as the order of passage from one machine to another.
Let's suppose we have three machines, and five products, Product 1 passes from machine 1: execute the program Pick up product 1 ($Pup1_1$) Move the product 1 to a precise position (Mp_1) then place it in its precise place ($Pp1_1$) than it moves to machine 2 where operator set up parameters ($Wp1_2$) while the machine waits, then it executes a subroutine ($SubT1_2$), wait for the operator ($WF1_2$) and move to product to the desired position, machine 3 waits for operator set up parameters ($Wp1_3$), then it executes a subroutine ($SubT2_1$), wait for the operator ($WF1_3$) to conduct quality control and move to product to a precise position for transfer.
This applies to the 4 other products. Table 1 illustrate the specification of each product in terms of orders of the machine as well as the task performed and their time. The mention (Ph) expresses the Phases of transformations: the first phase is 10, the second is 20, and so on.

Table 1: Tasks and machine orders for 5 products

	M1	M2	M3
P1	Ph=10	Ph=20	Ph=30
	$Pup1_1$, $Mp1_1$, $Pp1_1$	$Wp1_2$, $SubT1_2$, $Wf1_2$, $Mp1_2$'	$Wp1_3$, $SubT2_3$, $Wf1_3$
	3min	15min	10min
P2	Ph=20	Ph=10	
	$Wp2_1$, $SubT4_1$, $Wf2_1$	$Wp2_2$, $SubT2_2$, $Wf2_2$, $Mp2_2$	
	10min	10min	
P3		Ph=10	Ph=20
		$Wp3_2$, $SubT2_2$, $Wf3_2$	$Wp3_3$, $SubT2_3$, $Wf2_3$, $Mp3_3$
		12min	10min
P4	Ph=10	Ph=20	Ph=30
	$Pup4_1$, $Mp4_1$, $Pp4_1$	$Wp4_2$, $SubT1_2$, $Wf4_2$, $Mp4'_2$	$Wp4_3$, $SubT3_3$, $Wf4_3$
	5min	10min	15min
P5	Ph=30	Ph=20	Ph=10
	$Wp5_1$, $SubT1_1$, $Wf5_1$	$Wp5_2$, $SubT1_2$, $Wf5_2$, Mp5	$Pup5_3$, $Mp5_3$, $Pp5_3$
	15min	15min	5min

In this example, the first step is to identify the product that has the sequence in which the products pass from the same order of machines.
In this case, we can identify P1 and P4 that have the same order, P2 and P3 pass from the same machine 2 in the first phase then they move to different machines, Then P5 has its unique order.
So now we have 3 families: (P1, P4); (P2, P4), and P5. The proposed order relies upon the observation that the first family represents more similarities than the second, and so on.
The order in the same family can be based on standard algorithms like generalized Johnson when the products present high similarities in subprograms and order. which means that for the first family we will have product 4 than product 1. When we are in the presence of few similarities between the products we based our analysis on the minimum time of execution of similar tasks, which means that for the second family we will start with P2 since the Time of execution on the machine M2 is less than the time of execution of product 3 on the same machine. We can also base our analysis on the examination of each product. Figure 2 presents a proposition of scheduling the 5 products-3 machines scheduling using the logic aforementioned. At this point, we can see that changes in the program will be reduced to a minimum, assuming that the tasks realized in a high collaboration between humans and Cobots are conducted in the fastest and best way possible. Which led to the second part of our proposition.

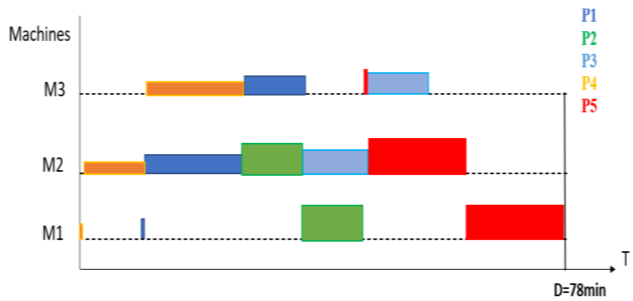

Fig 2: Scheduling of 5 Products- 3 machines

3.2 Dissociating human and robots' performance

The kernel of collaborative robots relies on the assumption that robots work hand in hand with operators in synergy and complementarity, several degrees of collaboration can exist: independent, simultaneous, sequential, and supportive [1].
Independent and simultaneous don't raise the issue of dissociating human and robot's performance as the time of execution must be in the first scenario attributed to the operator or machine. In the second one, humans and machines share the same time execution, which makes it easier to identify the performance.
However, in the sequential scenario, we must navigate from one task to another according to who does what!

In the supportive scenario, the average duration of execution can be calculated during the training process, of course, this duration must be corrected to embody the fact that not everybody is an expert from day one. When the duration time is higher than the standard time of execution, both robots and humans must assess the anomalies and validate them. This will imply that robots and operators can raise anomalies during the execution and support one another to resolve the issue raised.

3.3 Dynamic formulation of operator's performance

Operators' performance is highly linked to the time of execution of each task, this assumes that during the training, the trainee must be aware of the standard time of execution of each task. The performance factor is simply the ratio between the Real-Time Execution (TE) of task I and the Standard Time of Execution (TE_{is}) of task i. The quality and ratio consumption must be validated by the machine to avoid having products that don't meet the client's needs.

$$Wij = \frac{TEij}{TE\ is} \quad (2)$$

Where:

- W_{ij} is the operator j performance level for task i.
- TE_{ij} is the Real-Time Execution for operators j for task i
- TE_{is} is the Standard Time Execution for task i

Based on the second hypothesis mentioned in section 3, operators' performances must be collected from day one. Their social behavior must be also assessed: Learning curve, forgetting curve, fatigue parameters, and preferences. The calculated performance must depend on the number of times a similar task has been performed as well as the day of the week the shift number.

Several parameters must be defined as well: for example, we can state that after one week of not executing a certain task the forgetting curve gets activated and operators will be needing assistance from robots, supervisors, or colleagues to execute this particular task. The expression of execution time depends also on the fatigue that results from the occurrence of each task, this fatigue can be more pronounced in the last shift or on the last day of the week, and modifiers are proposed to embody this particularity. Preferences can also be deduced from asking operators, this aspect can increase the operator's motivations.
The Execution Time For operator j after a multiperiod where he performed Task i is:

$$TEij = TE_{nij}.Wm_j.SJM_j.P_{ij} \quad (3)$$

Where:

- TE_{nij} is the time of execution of operator j after n repetition of task i. In this case, we can use the right formula for the learning curve if repetition occurs in a week for example. If a week passes by, and operators did not use this particular program we will assume that the forgetting curve gets activated and announce that operator needs assistance [17].
- Wm_j is a weekly modifier that relies on the day the task occurs; each day of the week will have a personalized value for each operator j [20].
- SJM_j is a modifier that relies on the occurrence of the shift, in the morning, in the midday or the afternoon, it is always linked to the operator j [20].
- P_{ij} is the preference of the operator j of task i; it can add a subjective factor that might increase significantly the time of execution.

We can easily deduce the formulation of dynamic performance from (2) and (3):

$$Wij = \frac{TEnij.Wmj.SJMj.Pij}{TE\ is} \quad (4)$$

This phase will help measurably to orient the decision of the supervisor in terms of the operator's task allocation, with the proper review of their real performance, supervisors can propose the right operator for the right shift. They can also anticipate if they need the assistance of help with a certain task and be present at the moment, or find proactive solutions to empower operators to do the task properly. This will embody the concept of continuous learning and knowledge management.

4 Discussion

This paper aims to address several issues that make scheduling in a collaborative environment highly difficult. The high variety of products and the large number of tasks to perform can impair any attempt to propose an order with such a high number of constraints. Adding to that, performance notion can be very difficult to determine as the time of execution can be related to tasks executed by operators only, tasks executed by robots and operators, and tasks executed by robots. Operators can work on variable dependencies scenarios which makes it even harder de determine each entity's execution time to evaluate its performance. Another difficulty resides in the human factors: learning curve, fatigue, and preference are factors that characterize each operator and affect greatly their performances.

This paper gives a proposed schedule based on the assumption of similarities between tasks. It also proposes a way to dissociate human performance from robot ones. As well as a proposed equation to calculate real-time human performance. On one hand, this proposition has the advantage of using real-time performance value to decide who does what, it might also give an insight into whom might need assistance for certain tasks, which results in increasing collaboration and trust between robots and humans. On another hand, these solutions can put us on the right path to resolving highly complex scheduling problems.

5 Conclusion

In the framework of the collaborative robot, the suggested research attempts to handle an assignment workload problem as well as a scheduling issue. The scheduling difficulty arises from the unique characteristics of each product and the changing aspect of the operator's performance. On the one side, the high level of personalization can make scheduling more difficult. Operator job allocation, on the other hand, is based on the dynamic component of their performances. Another issue is the dependency between robots and operators, which might make it impossible to distinguish between operator and Cobot performance.

The purpose of this work is to address these three challenges and suggest solutions for fulfilling scheduling based on real-time data. The main drawbacks of our proposal are related to the acquisition of tacit knowledge and competencies while dealing with scheduling challenges. Future contributions will present a method to aid automate the operator's allocation, as well as handling the task's similarities to suggest a proper schedule using real-time data.

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