Balancing of Manual Reconfigurable Assembly Systems with Learning and Forgetting Effects

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Abstract: Within the paradigm of Industry 4.0, digital reconfigurable manufacturing and assembly systems can rapidly adapt to dynamic market demand, modifying their capacity and functionality. In manual or hybrid reconfigurable assembly systems, the rapid and frequent variations in the performed tasks subject workers to a significant cognitive load, making relevant the learning-forgetting phenomenon. In fact, the operators carry out the assigned activities for a short time before a reconfiguration of the system takes place, assigning them tasks often different from those just performed. This paper aims at investigating how the tasks' execution time varies for operators working along a reconfigurable assembly line, depending on the learning forgetting effect. We applied a Kottas-Lau algorithm, considering the expected execution times updated according to a learning-forgetting curve. A numerical example, considering with five successive reconfigurations, allows to analyse the expected execution time trend for each operator-task pair and the variation in costs obtained as the operators learning rate and the variability of the operations change.

1 INTRODUCTION

The increased variability of market demand, both in the product range and the required quantity, is pushing forward the development of reconfigurable manufacturing and assembly systems. "Reconfigurability" signifies a system's capability of converting and modifying its processes in order to rapidly respond and adapt to market changing needs. This capability is supported by the utilization of digital manufacturing technologies, making the reconfigurable manufacturing and assembly systems part of the Advanced Manufacturing Solutions, the first of the Industry 4.0 key enabling technologies (Bortolini, Galizia, & Mora, 2018).

A reconfigurable system is a dynamic system, combining the strength of dedicated hard automation and flexible systems, generating a good compromise between functionality, production capacity and costs. Manual systems are the reconfigurable assembly systems (RAS) with the highest level of reconfigurability, since human being is highly flexible and can easily deal with changes and manage uncertainties (Bi, Wang, & Lang, 2007). Thus, in manual RAS the workers are requested to frequently move between cells and to rapidly change their tasks, making learning and forgetting mechanisms relevant to the assembly cycle time (Wang & Abubakar, 2017). The complexity of RAS, as well as the line balancing challenges have been widely investigated (ElMaraghy & ElMaraghy, 2016), however only a few authors studied the influence of workers' learning and forgetting effects on line balancing.

At the best of our knowledge, this is the first paper focusing on the balancing of manual RAS, analysing the influence of frequent line reconfigurations on the learning and forgetting of the workers, as well as the effect of the learning-forgetting on the line total costs. A model combining the Kottas-Lau heuristic for line balancing and the learning and forgetting curves is developed and analysed through a numerical example, demonstrating the importance of considering the human factor influence.

2 RESEARCH BACKGROUND

A literature review, bringing together the three main

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research fields concerning this paper, provides the research background of the study. As a result of the performed literature review, we found that no studies have yet been carried out on learning and forgetting applied to RAS balancing.

2.1 Reconfigurable Assembly Systems

According to Koren and Shpitalni (2010) reconfigurable assembly systems are systems *that can rapidly change their capacity (quantities assembled) and functionality (product type, within a product family) to adapt to market demand*.

A RAS is a key component of reconfigurable manufacturing systems (RMS), and must possess three of the six core characteristics of a RMS: customization, convertibility, and scalability. To meet the increasing challenging complexity raised by the mass individualization paradigm, allowing the production of cost-effective highly personalized products, a RAS must combine the advantages of machine/robot precision and repeatability and human adaptability. In this hybrid configuration, the time needed for the worker to complete her/his task is variable (Koren, Gu, & Guo, 2018).

2.2 Learning and Forgetting

Learning Curves were first studied and modelled by Wright (1936). The formulation allows to describe the variations in the performance of operators due to the repetition of the same task performed: memorization of the performed movements and familiarity with the tools allow to reduce the time to perform the same operation.

In learning models, different indicators can be used as a dependent variable that measures the performance of operators: the time to produce a single unit, the number of units produced in a time interval, the cost to produce a single unit or the percentage of non-compliant units (Lolli et al., 2016a). The main models can be classified as univariate and multivariate; a review of the learning curves and models can be found in (Anzanello & Fogliatto, 2011).

On the other hand, in recent years the impact of the workers' forgetting on the manufacturing process has been recognized (Lolli et al., 2016b). The forgetting phenomenon occurs when the operator must stop performing a task (due to illness, a vacation, a strike or a change in in product specifications). The operator, once the execution of a task has been interrupted for a long enough period, will take a longer production time than what was necessary before the task was interrupted. According to Nembhard and Osothsilp (2001), the main factors influencing the phenomenon of forgetting are the length of the interruption, the amount of experience learned before the interruption, the nature of the task (procedural or motor), the type of activity carried out during the interruption. Hoedt et al. (2019), have been suggested that the activity that the worker performs during the forgetting phase, does affect the level of retention: a more similar job results in a better retention of the reference job. It has also been shown that operators who learn quickly are the same ones who tend to forget just as quickly (M.Y. Jaber & Kher, 2002). A classification of the models describing the forgetting are presented in the review compiled by Nembhard and Osothsilp (2001).

2.3 Assembly Line Balancing Problem with Learning and Forgetting

Although it is now recognised that learning is a key factor, influencing both the line total costs and the correct line balancing, there are still few discussions on these issues in the literature. The first study on learning phenomena within an assembly line balancing is proposed by Chakravarty and Shtub (1988), and only recently the definition of "Assembly Line Balancing Problem with Learning Effects" has been given for the first time (Otto & Otto, 2014).

An overview of the main publications that aim at combining the two topics are presented below, classified according to the type of problem addressed.

2.3.1 Minimization of the Number of Stations

Among the earliest studies on learning along assembly lines are those carried out by Cohen et al. (1998), to find the minimum number of stations that allows to minimize the costs and to maximize the profit. Toksari et al. (2008) implemented the learning phenomenon within the study of simple and U-shaped assembly lines, to minimize the number of stations during line balancing and update the execution times. By applying the algorithm to the well-known Jackson 11 problem (Jackson, 1956), they show that the inclusion of the learning effects allows to open fewer stations than theoretically foreseen. A mixed non-linear mathematical model can solve the proposed problem, introducing the concept of task deterioration (Toksari, Işleyen, Güner, & Baykoç, 2010).

Otto & Otto (2014) tackle the ALBP-1 problem by introducing a learning rate for each task to be executed, thus defining a different decreasing rate of the execution time for each task. Here, the authors focus their attention on minimizing the number of stations and propose a heuristic to allocate the tasks to stations on the basis of a decreasing priority rule.

Lolli et al. (2017), for the first time, investigate the role of learning in the stochastic balancing problem of an assembly line with repetitive tasks through the use of the Kottas-Lau (1973) heuristic. To consider the effects of operator learning in manual assembly lines, the authors implement the Kottas-Lau algorithm, in which the expected execution times of the tasks follow the power law with plateau learning curve, while the variance changes keeping constant its ratio with the mean time. To include the human-machine collaboration, Lolli et al. (2018) implemented a new learning curve, to allow the subdivision of tasks into subtasks performed partly manually and partly in an automated way.

2.3.2 Minimization of the Cycle Time

Cohen (2006) studies the optimal allocation of tasks within the stations, taking into account a homogeneous learning, in order to minimize the makespan in a production of numerous products, each with relatively low demand. To do this, the author proposes a non-linear programming model and demonstrates how homogeneous learning and small batch sizes make a non-homogeneous task allocation between stations more efficient than a balanced one. Furthermore, he shows that the savings that occur from balancing the line, increase with the number of stations in the line, with the constant learning and with the reduction of batch sizes.

2.3.3 Multi-objective Optimization

In considering the balancing of assembly lines with a learning effect, many scholars have used a multi-objective perspective, to evaluate the optimality of the solutions.

Hamta et al. (2013) deal with the multi-objective optimization of a balancing problem of a single model assembly line; in the line the operating times, which depend on the learning of the operator or the machine, are not known, but only the upper and lower limits of them, for each task, are known. In this problem, the objectives considered simultaneously are the minimization of the cycle time, the minimization of the total cost of the equipment and the minimization of the smoothness index. The problem is addressed by the authors with a new solving approach that combines the particle swarm with the variable neighbourhood search metaheuristics.

Chutima and Naruemitwong (2014) solve the problem of mixed model sequencing along a two-sided assembly line, in which learning effects are also taken into account, through the Pareto optimization based on biogeography. They consider three contrasting objectives: the minimization of the variance of the production rate, the minimization of the total utility work and the minimization of the total set-up time depending on the chosen sequence.

3 PROBLEM FORMULATION

We consider a manual reconfigurable assembly line, where frequent changes occur.

The operators are then subject to a phenomenon of learning by doing, and to the forgetting phenomenon if the task is not carried out for a certain period. Thus, the time necessary for carrying out the task must be therefore continuously updated.

A single-station manual assembly line is considered, in which one and only one operator is assigned to each station, fixed during all reconfigurations. Each operator is characterized by a learning rate; the learning rate value is the same for all operators, independent from the type and number of tasks assigned, and by the previous training and experience. Each operator performs only the tasks assigned to her/his station and, when the station is not needed along the line, the operator is reassigned to another task for the necessary time.

3.1 The Learning-forgetting Model

For characterizing the learning-forgetting effect we used the learn-forget curve model (LFCM) presented by Jaber and Bonney (1996), where the learning component is modified by the assumption made by Lolli et al. (2017). The LFCM combines the Wright's power learning curve (Wright, 1936), with the forgetting curve relation introduced by Carlson and Rowe (1976), and allows to estimate the future performance of an operation within an intermittent production.

In our model, for the learning component we consider a modified Wright's curve with a plateau (1) according to (F. Lolli et al., 2017):

$$y_{ink} = \left((1-r)\cdot Y_{i1}\right)\cdot n^{-b_k} + r\cdot Y_{i1} \qquad (1)$$

where y_{ink} is the expected time for the task i after n products have been assembled by the station k; n is the number of products assembled; Y_{i1} is the initial expected time for the task i (the standard task time); b_k is the positive learning rate related to each assembly station k; r is the fraction, fixed for all the stations and tasks, of Y_{i1} that is unaffected by the learning process. The learning curve will then converge to the plateau value $r \cdot Y_{i1}$ for all stations, that is to the invariable part of the average processing time of each task.

The forgetting curve relation (2) assumed is the following:

$$\hat{T}_x = \hat{T}_1 x^f \tag{2}$$

where $\widehat{T}_x$ is the time for the x-th unit of lost experience; x is the amount of output that would have been produced if interruption did not occur; $\widehat{T}_1$ is the equivalent time for the first unit of the forgetting curve; and f is the forgetting slope. The LFCM model considers both the intercept $\hat{T}_1$ and the slope f of the forgetting curve variable.

3.2 Line Balancing Assumptions

The balancing of the reconfigurable assembly line uses a Kottas-Lau heuristic (Kottas & Lau, 1973).

Alongside the standard assumptions for the method (a to e), 4 extra assumptions (f to i) are considered to introduce the learning-forgetting effect:

a) The cycle time and the priority between operations are the only constraints considered when assigning the tasks.

b) An operation can only be initiated if all the preceding and following operations have been completed.

c) Each operator of the line is equally paid.

d) The tasks and their execution times t_k follow the normal probabilistic curve (3) and are independent of each other.

$$t_k \approx N(\mu_k,\ \sigma_k^2) \tag{3}$$

where μ_k is the expected time to execute the k-th operation and σ_k the standard deviation. The average time μ_k is characterized by a variable part, subject to learning, and by a fixed part, which represents the minimum time necessary to perform the task.

e) Whenever a task is incomplete, the unit keeps moving along the line and all operations with no priority constraints are completed. All incomplete or unexecuted operations are completed offline at a specific cost I_k for each k-th operation.

f) The learning and forgetting effects are described by eq. (1), where learning and forgetting effects are applied to a fraction of the average initial time of each task, the variable part of μ_k, while the fixed part forms the plateau of the curve.

g) The trend of the execution time of the tasks, due to learning and forgetting, affects the parameter μ_k for each operation k. According to (F. Lolli et al., 2017), the variance σ_k^2 (4) is defined so that its ratio to the processing time of the k-th operation remain constant:

$$\sigma_k^2 = s \cdot t_k \tag{4}$$

where s is the variability rate defined for the configuration and t_k is the execution time of the operation for the considered station. This definition allows the variance to adjust following the changes in the expected cycle time value, thus avoiding an unrealistic increase in the variability of the execution time following the learning effects.

h) The assembly line is completely manual and each station is assigned only one operator.

i) Each worker has her/his own learning rate and it depends only on the individual, and it is not influenced by external factors.

3.3 Solution Approach

According to the Kottas-Lau heuristic, once set the cycle time, the algorithm aims at establishing the minimum number of stations that guarantee the requested productivity. The novelty of this study is the inclusion of the learning-forgetting effect on the execution times, to use the methodology for balancing manual reconfigurable assembly lines. The algorithm has been implemented using Java language, in an Eclipse integrated development environment.

Together with the standard input data for the Kottas-Lau heuristic, the general parameters of learning and forgetfulness are added for each worker and task: the learning rate LR, the total forgetting time t_B, and the operations variability rate s. Furthermore, the fraction of the processing not subject to learning is provided.

The updating of the execution time due to the learning-forgetting phenomenon is regulated according to four possible cases:

1) the operation under consideration is assigned to a station for the first time; the worker has no experience. The time that this operator will take to carry out the same operation in the future is updated (5) on the basis of the learning that has taken place in the configuration just completed:

$$T_{d+1} = (1 - r)\, T_1 \cdot (d + 1)^{-b} + r\, T_1 \tag{5}$$

where the expected initial execution time is $(1- r) \cdot T_1$.

2) the operation has been assigned to a station where it was previously processed; two sub-cases can take place:

2.a) the operation is assigned to the same station in which it was carried out in the previous configuration; in this case, if the task was operating with interruptions a factor α, accounting for the remembered rate of experience (Jaber M.Y & Bonney, 1996), must be added (6).

$$T_{d+1} = (1-r)\,T_1 \cdot [(d+\alpha)+1]^b + r\,T_1 \qquad (6)$$

2b) the operation is assigned to a station where it has already been carried out, but not in the previous configuration; after updating the accumulated demand in the previous period, the (6) applies.
3) the operation is not assigned to a station in which it has not yet been entered; the execution time of this operation equal to the average time provided by the input data (7), as no learning or forgetting phenomenon has yet occurred on it.

$$T_{d+1} = T_1 \qquad (7)$$

4) the operation is not assigned to a station from which it has already been processed previously; according to the modelled forgetting phenomenon by (Jaber M.Y. & Bonney, 1997), the time needed to rerun the task for the first time after the break occurred is then updated (8):

$$\widetilde{T}_{q+1} = (1-r)\,T_1 \cdot (\alpha+1)^{-b} + r\,T_1 \qquad (8)$$

Lastly, the algorithm that updates the time, considers also the case in which a station, opened in a past configuration, is not opened in the current configuration. In this case, it is updated only the break time of all the operations that have been allocated to this station in the past configurations, at least once.

4 NUMERICAL EXAMPLE

The developed algorithm has been tested implementing five successive reconfiguration of a manual assembly system with six stations and twelve operations; a set of realistic data has been used for four configurations of the line, while for one of them we decided to use the data proposed by the Jackson 11 problem, to compare our line balancing including learning-forgetting effects with the results obtained without considering these effects.

To investigate the effect that the learning-forgetting phenomenon, firstly we balanced the line with fixed learning-forgetting parameters. We then performed the line balancing analysing the variation of the production costs as a function of the operations execution time variability rate s, with a fixed learning rate, and as a function of different learning rates with fixed s.

4.1 Line Balancing with Fixed Learning-forgetting

The input data representing the five successive reconfigurations are as in table 1 (variable data) and in table 2 (fixed data).

The five precedence diagrams are shown in the appendix (Figure A1), while the input data for each station are available upon request.

Table 1: Production time and market demand variations for the five configurations.

Config.	1	2	3	4	5
Production time	5040	8400	6300	5880	4620
Demand	560	700	630	588	462

Table 2: Fixed input data for all the configurations.

Hourly cost	30.0
Hourly cost for inactivity	60.0
Cost for opening a station	25.0
Learning rate	0.9
Break time for total forgetting	300000.0
Variability rate of the operations	0.1

After each reconfiguration the performed calculation provides the line balancing and the production costs. Moreover, at the end of each configuration, for each open station the execution times are updated to the value they will assume in the next configuration.

The first balancing of the assembly is implemented without any variation of the data, as no learning or forgetting phenomenon has yet occurred. For each operation, the operator to whom the task has been assigned is affected by learning, and the related execution time recalculated according to the eq. (5).
Starting from the second reconfiguration, the effects of the forgetting are present. Where learning has taken place, the recalculated execution time is lower than the previous one, while where forgetting occurred, as the stations that previously performed the task, did not performed it during the last configuration, the execution time increases.

In the third line reconfiguration we consider the Jackson 11 problem. In this case, the line balancing is clearly affected by the learning- forgetting effect since the algorithm allocated all the tasks within 5 stations, unlike the classical solution of the Jackson 11 problem which provides for the opening of 6 stations, allowing a significant reduction in costs and greater efficiency for the system. It is interesting to notice that task 9, executed by station 3, had already been processed by the same station during the 1st configuration. The execution time by operator 3 for this operation is therefore updated using the equation (6).

After the fourth line balancing, the execution of the task 8 by the station 5, after starting in the 1st configuration, is interrupted for a time period (during the 2nd and 3rd configuration) and finally it is reallocated to the same operator in the current configuration. In this case, the execution time is updated considering the accumulated production demand without interruption of the 1st configuration to calculate the number of equivalent units remembered after the interruption occurred during the 2nd and 3rd configurations and then applying the equation (6).

In the last configuration we have the possibility to study the long-term effects of the phenomenon of learning and forgetting, since a significant number of reconfigurations of the system have already occurred.

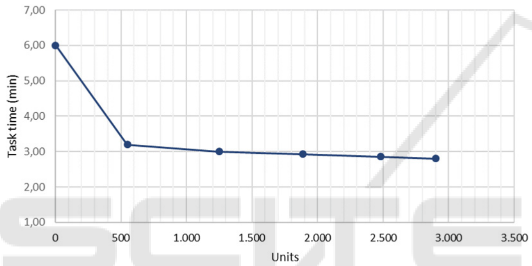

Figure 1: Task 1 execution time in the station 1.

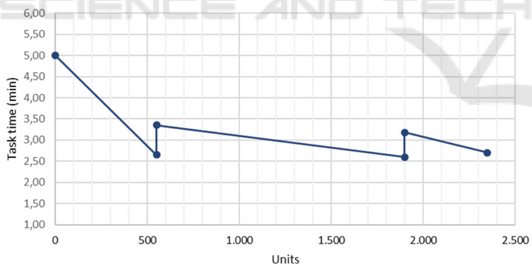

Figure 2: Execution time of the task 9 in the station 3.

Conversely, the operator 3 carries out operation 9 in alternate configurations: for this operator, therefore, there is a learning process followed by the forgetting of the considered task, due to the interrupted activity. This process is represented in figure 2, that reminds the trend of the learning and forgetting curves presented in (Jaber M.Y. & Bonney, 1996).

4.2 Production Costs vs s

In this scenario, the line balancing has been performed considering a fixed low learning rate (LR=9), and setting four classes for s, corresponding to a variance (σ_k^2, as defined in (4)) equal to 5% (low variability), 10%, 20%, 30% (high variability) of the average processing time.

The increase in the variability of operations generates an increase in the total costs of the assembly line, as can be seen in the figure 3. The cost growth starts from a constant cost component due to the fixed costs of the line, and grows until it reaches a plateau.

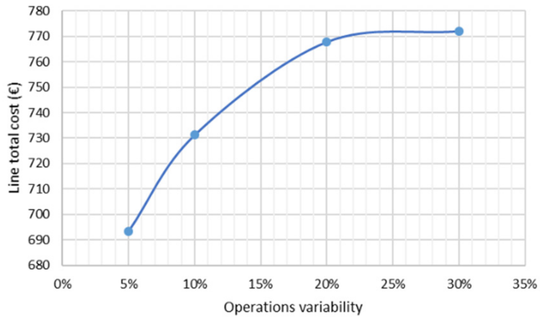

Figure 3: Cost trend as a function of the variability of the operations.

4.3 Production Costs vs LR

The line balancing has been performed considering s=0.1 and five levels of learning: LR=1 (no learning), LR=0.9, LR=0.8, LR=0.7, and LR= 0.6 (high learning rate). The costs incurred increase (figure 4) as the operators' learning rate increases, that corresponds to a decreasing of the operators' learning capacity.

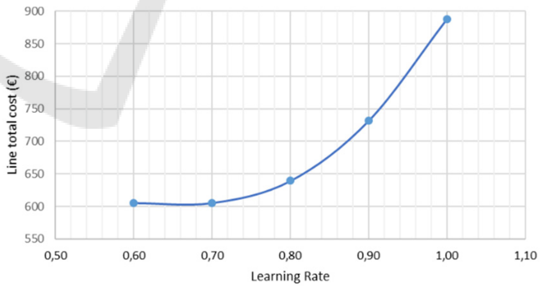

Figure 4: Cost trend as a function of the learning rate.

This is due to the fact that, since the operators are slower to learn for the same number of units worked, the operators take longer to carry out the tasks, thus increasing labour costs and, in the event that this involves opening a station, the fixed costs related to the stations. The greatest total cost occurs when the operators' learning and forgetting are not considered (LR = 1). In fact, in this case the execution times are constant and this implies higher costs.

5 CONCLUSIONS

The reconfigurable assembly systems are key components of a manufacturing system complying with the paradigm of mass individualization. In this study, we propose a model to take into account the workers' learning and forgetting to make a more precise allocation of the tasks within a given configuration, with respect to the present workforce, maximizing the efficiency of the system. We combined a learning-forgetting model with the Kottas-Lau heuristic to show how the learning and forgetting phenomena affect the balancing of a manual RAS and the related line costs. A preliminary numerical application allowed to test the model, and the use of the Jackson 11 problem showed that it is crucial taking into account these phenomena. This is only a first validation step, but, due to the relevance of the obtained preliminary results, we will apply the developed algorithm to a case study in industrial environment, to further improve and validate the methodology.

In addition, various research developments can extend the study presented in this paper. Among these, the possibility of considering specific learning rates for each operator will be investigated. To fully take advantage of the RAS capabilities, the problem of designing a reconfigurable layout and assigning tasks between operators and machines in an interdisciplinary way should be addressed. Then, the developed methodology should be adapted and applied to hybrid RAS, including new technologies such as autonomous robots that can help operators to better adapt to sudden system reconfigurations.

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APPENDIX

The five reconfigurations precedence diagrams are shown in the figure A1.

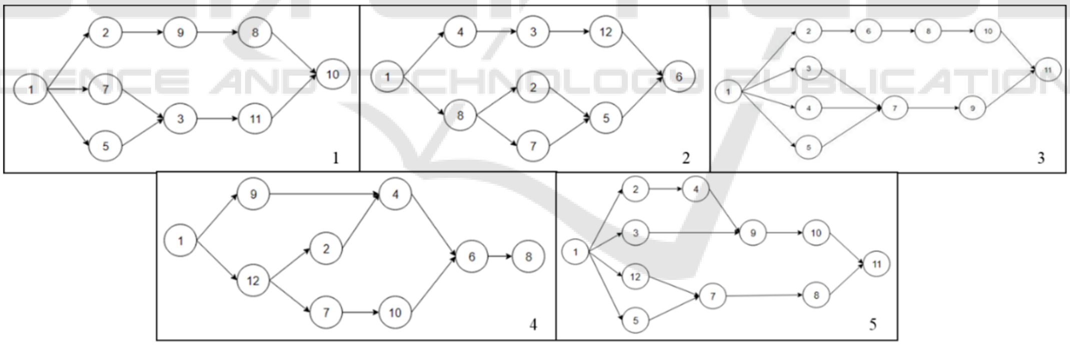

Figure A1: The five reconfigurations precedence diagrams.