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ORIGINAL ARTICLE

About human and learning factors impacting manual picking on assembly lines

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Abstract
In the pursuit of competitiveness, human capital remains a critical asset for companies. While automation offers unparalleled production efficiency and error reduction, often surpassing the capabilities of even the most skilled personnel, several factors -such as high initial investment costs, the diversity of products, and other operational complexities- ensure that production systems continue to rely heavily on human involvement as a key resource. This work focuses on assembly workstations, which are integral to a wide range of industries. At these stations, operators perform tasks such as selecting components, assembling parts, verifying outputs, labelling and packaging. The concept of "pick-to-assemble" is widely discussed in the literature, often accompanied by the use of selection support systems like "pick-to-light" technology, which assist operators in their tasks. Designing efficient workstations involves considering various factors, including Lean manufacturing principles and ergonomic design. In our study, we prioritized optimizing an assembly line designed to handle multiple product variations. The assistance systems were tailored to adapt to the operator's level of expertise and experience. By integrating Industry 4.0 concepts, we implemented real-time performance monitoring, enabling the system to dynamically support workers, even when new product references are introduced to the assembly line.

Keywords Pick-to-assemble · Pick-to-light · Learning curve · 4.0

1 Introduction

In the industrial sector of developed economies, automation is increasingly penetrating diverse production environments. Nevertheless, human intervention continues to deliver significant added value. Human error, whether in managing or executing work procedures, remains a topic of considerable economic importance. Even the press [1] often highlights these errors, sometimes overlooking the critical role human capital still plays. The ability to learn and adapt -especially in seemingly repetitive operations- continues to be a highly valuable asset.

The concept of learning curves has traditionally been employed to analyse a worker's performance over time. These models rely on prior knowledge of the tasks and the individuals performing them. However, in the era of Industry 4.0 and the Internet of Things (IoT), traditional models have lost some of their appeal to industries that now seek dynamic interaction with workers' activities [2, 3].This evolution marks the advent of the *Internet of People* (IoP) not merely as a marketing concept but as a framework for obtaining near-instantaneous insights into a worker's activities. In this context, it may be more fitting to refer to an "*Internet of Workers*" (IoW). The IoW presents new opportunities for applying learning curves to optimize productivity in modern industry, particularly in repetitive and automated processes. These advanced models enable accurate predictions of how operators improve with practice, reducing the time required per task, cutting costs, and enhancing workflow efficiency. Moreover, tracking learning curves facilitates qualitative

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evaluations of operator performance, allowing for the design of roles that reward and leverage individual efficiency [4].

This study focuses on assembly workstations, which are widely utilized across various industries. At these stations, operators perform tasks such as selecting components, assembling parts, verifying outputs, labeling and packaging. The concept of ”pick-to-assemble” is well-documented in the literature, often involving the use of selection support systems like ”pick-to-light” technology [4, 5].

When designing assembly workstations, several factors must be considered [4, 6], including Lean manufacturing practices [7] and the ergonomic design of the workstation. In this study, we concentrated on optimizing an assembly line designed for producing multiple product variations. The assistance systems were tailored to adapt to the operator's level of expertise and experience. Rather than relying on a static system, our approach incorporates Industry 4.0 concepts, enabling real-time monitoring of workers' performance. This dynamic adaptability ensures effective operations even when new product references are introduced into the assembly line.

In short, the proposed design allows necessary training to be carried out directly at the workstation (production), whether for the onboarding of new operators or for the assembly of new products (learning), without the need to duplicate facilities. To avoid a loss of production pace and reduced output, the aim is to progressively adjust the level of assistance provided to the trainee, using real-time data personalized for each individual.

2 Experimental learning curve models

The learning curve (LC) model is a method used to describe an organization's learning capability as it accumulates experience [8]. The concept of the learning curve model has been widely applied in industry since the late 1930s. The first study on learning curves was conducted by Wright [9] in 1936, within the aircraft industry. His model, known as the log-linear learning curve model, is expressed in Eq. 1.

The key premise of learning curves is that each time the production quantity doubles, the resources required to produce the product decrease by a fixed percentage of the previous resource requirements [10]. The Wright learning curve is defined as follows [9]:

$$Y_x = A \cdot X^{-b} \tag{1}$$

where:

Y : the time to produce the X-th unit;

X : the cumulative unit number;

A : the time required to produce the first unit;

b : the learning index.

Wright also observed that production time decreases at a consistent rate as the production quantity doubles. This rate, known as the learning rate, quantifies the reduction in resources required to produce output when the quantity doubles [10]. The learning rate can be calculated using Eq. 2.

$$\phi = 2^{-b} \tag{2}$$

where:

ϕ: the learning rate.

There are several LC models proposed in the literature [11]; most notably (i) power models, such as Wright's, Plateau, Stanford-B's, DeJong's and the S-curve, (ii) hyperbolic models, and (iii) exponential models. Among these, Wright's model is the most widely recognized, primarily due to its simplicity and effectiveness in describing empirical data. Learning curve analysis is particularly valuable in scenarios that offer opportunities for improvement or reductions in labour time per unit.

As noted by [10], traditional models often require a priori knowledge. When examining the mathematical formulation of conventional parametric learning curve theories, it becomes evident that certain assumptions must be made beforehand. Learning curves can be applied also to individual processes performed by the operator, in our case study: picking componentes, assemble and packaging. The impact of learning on overall process capacity is reflected in the cycle time, which represents the total time required to complete all operations related to the final product [8]. It is also worthwhile to explore how the learning process progresses across different operations. Additionally, it is important to consider that learning curve models may vary for different product variants.

In conclusion, empirical investigations based on real-life data are rarely addressed in practical-level theory development. Several reasons may explain this, as outlined by Loske [12]: (a) logistics companies produce real live data through their daily business operations, but are not willing to share it with scholars, (b) scholars cannot use the real live data possibly provided by companies, (c) real-life cases often lack the a priori knowledge required to apply existing traditional learning curve models and (d) the volume and complexity of the a priori knowledge needed to apply conventional learning curve models to real-world scenarios are prohibitively challenging.

Nevertheless, the learning curve itself cannot be regarded as an objective at the industrial level. Instead, it serves as a tool to improve the scheduling of production processes or, as we will discuss below, to dynamically assess the maturity of a process. The ultimate goal is to achieve optimal production capacity as quickly as possible. Moussavi [13] proposes an approach for ergonomic job assignment by determining the ergonomic adequacy level between workers and workstations in a manufacturing system. The analysis should focus not so much on the workstation itself, but rather on the characteristics of the worker. The same study highlights four particularly significant factors: 1. Height, 2. Age, 3. Skill level, and 4. Experience level.

Therefore, with a global data approach, we would be missing out on most of the analytical potential. Thus, to analyze what happens at a workstation where different workers (W) perform their tasks and various products or product families (F) are assembled, the use of a disaggregated learning curve is proposed, so that:

$$Y_{x,W,F} = A_{W,F} \cdot X_{W,F}^{-b_{W,F}} \tag{3}$$

where:

$Y_{x,W,F}$: the time to produce the X-th unit of product F by worker W;

$X_{W,F}$: : the cumulative unit number of product F produced by worker W;

$A_{W,F}$: : the time required to produce the first unit of product F by worker W;

$b_{W,F}$: : the learning index of workwer W for product F.

We have already seen how Moussavi [13] placed the biometric factor as a top priority. When designing a workstation, the term ”ergonomic” is almost automatically included, although the development can be more advanced-ranging from the use of digital twins [14] to simply following the company's own ergonomic guidelines. Once the installation is in place, ergonomic problems may become evident, at worst, through worker injury, but they almost certainly lead to a loss in performance [12, 15]. The inclusion of a gender perspective in ergonomic diagnostics is a growing practice, as seen in the work of O'Sullivan [15].

Therefore, by deepening the diagnosis of a production system, we can personalize the analysis by increasing the level of disaggregation, including: global or individual processes performed, mode of assistance and also the gender perspective.

3 Workstation prototype

In our case, we developed a prototype assembly workstation integrated with a pick-to-light warehouse, a system that guides the operator in selecting the components for the next order. The workstation (Fig. 1) is designed as a ”pick-to-assemble” unit where the operator's learning process can occur, whether the worker is new to the job or needs to adapt to changes introduced by new variables in the product range. The system's assistance is tailored to the worker's proficiency level, defined by four operational stages: learning plus, learning, standard or expert (from the highest level of assistance to the lowest).

In our prototype unit, the assembly of industrial wheels was selected as a case study, though this choice is not critical to the research methodology. The variety of product configurations is determined by factors such as the characteristics of the supports, the material of the rolling surface, and the overall design, which dictate load capacity and suitability for specific work environments. This setup allows for the assembly of 24 distinct product variants within the unit. The operator works on a demand-driven basis, assembling products individually rather than in batches. In the initial implementation, a barcode-based ordering system is employed. The operator scans the barcode, which triggers the corresponding assembly process in the workstation.

The prototype is managed using Arduino and Raspberry as the core hardware components. These devices are programmed to collect and process real-time data, enabling precise time tracking. The design of the warehouse and work area incorporates fundamental ergonomic principles and warehouse management strategies, employing a Kanban-style flow for replenishing parts from the back.

Traceability is a key feature of the system, as it records various details, including: the worker assigned to the unit, the type of product being assembled, any unplanned production interruptions, the time the order was received (via barcode scanning), and the moment the last component for the assembled reference is collected. The prototype includes a warehouse capable of holding up to 16 components.

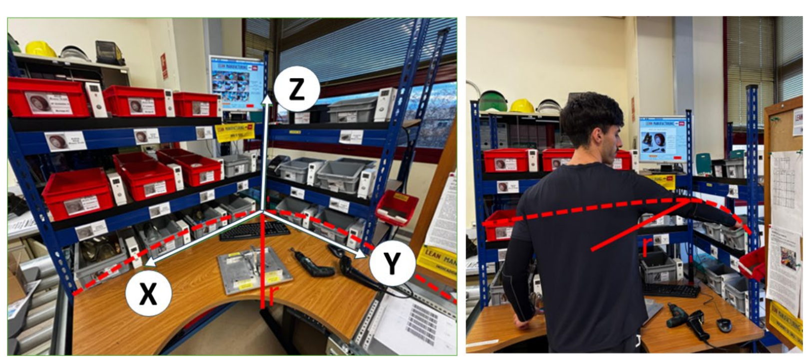

Fig. 1 Workstation prototype unit. Ergonomic design

Operators select components for each product variant with the assistance of a pick-to-light system. To ensure ergonomic efficiency, the warehouse is arranged with three height levels across six columns. This configuration also includes a dedicated column for quality defect management and another equipped with a monitor to assist operators or facilitate communication. Products are identified using a barcode reader, but the system also supports RFID-based identification through integrated tags in the container trays.

4 Learning curves and results

The system's functionality was validated by having multiple workers assemble different references based on a randomly generated demand. The total number of references was grouped into product families, considering factors such as the number of components and the similarity of the assembly procedures (e.g. we use F4 to identify the product family with 4 components). The assistance provided to the worker is controlled through a display showing a short video for each task or through the pick-to-light system, which can operate in either sequential or global mode. In sequential mode, each component must be selected in the prescribed order, while in global mode, the operator can choose components in any order that best suits their workflow. Figure 2 provides an overview of the four assistance modes.

Real-time data is collected, which will be used to estimate experimental learning curves. Data processing is done separately for each worker and each product family, as illustrated in Fig. 3, initiating the first level of disaggregation for diagnostics. This approach opens the possibility for tailoring the assistance based on individual worker performance. The individualisation of data collection also allows us to immediately address the gender perspective throughout the analysis.

We measured production time per unit and cumulative production volume using data from the production process to construct disaggregated learning curve models. The analysis was initially performed on a worker-by-worker basis. The model was updated with data from each completed product, so that by the end of two work shifts, a learning curve model of $Y = 108.73X^{-0.156}$ was obtained, which corresponds to a Learning Rate of 89.75 % (Fig. 4 for worker W1968, by the time 48 pieces have been produced). That is why we use the term disaggregated learning curve, to distinguish it from the typical learning curves used for a workstation.

As shown in Fig. 4, we present the production times for each unit, along with the time spent on picking (represented

Fig. 2 Modes of worker assistance: learning plus, learning, standard or expert (from the highest level of assistance to the lowest)

	Picking				Assemble			Packaging
MODE	Learning video	Summary image	Take one by one	Take as you want	Learning video	Summary image	Assemble	Take as you want
Learning +	→		→		→		→	→
Learning		→	→		→		→	→
Standard		→	→			→	→	→
Expert		→		→		→	→	→

Fig. 3 Data processing for the estimation of experimental learning curves

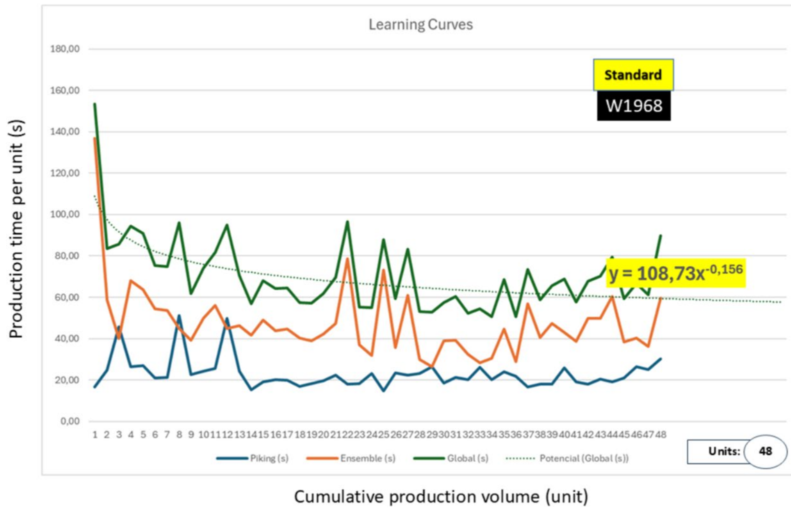

Fig. 4 General behaviour of the workstation. Production time per unit (s) and experimental learning curves, W1968 & X=48

by the blue line) and assembly (represented by the orange line). From this, we can observe the stability of these operations and estimate a learning curve for overall production. Additionally, we could derive separate learning curves for picking and assembly processes. The learning curve for picking develops more quickly, as the process is intuitive and the times are easily predictable. In contrast, the assembly phase exhibits greater variability, due to the inherent complexity of the task and the need to handle parts containers. Although a Kanban system with three circulating containers is in place, when the current container is emptied, the operator must place it on the replenishment line. The learning curve is continuously updated with production times at each step, providing data that can be used to apply machine learning systems for the automatic selection of the optimal assistance mode for each operator and product family.

But the power of the diagnostic method improves when we begin to compare data across different disaggregated parameters. Figure 5 shows a snapshot of how production is being carried out. Working in the standard assistance mode, we visualize the curves for two workers, W1968 and W1999. At the top, we see the evaluation when they are working with product family F4, while at the bottom, we have product family F5.

Having disaggregated data allows us to understand to what extent a particular worker adapts to the different operations or processes of specific products. In particular, Fig. 5 shows how the picking operation is very intuitive, and improvement over time is barely significant. Occasionally, increases in time occur due to the need for control operations or the use of poka-yokes. The reduction in times due to learning is more significant for product family F5, regardless of the operator.

When introducing the gender perspective into the disaggregation, it was observed that picking times for the group of women were slightly higher than for men. It was identified that this was not due to a shortcoming of the control group used but rather the poor ergonomic adaptation of the

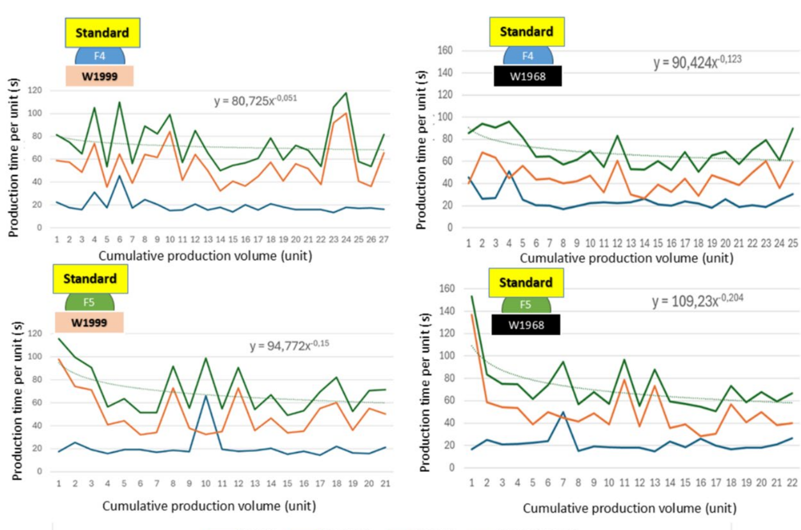

Fig. 5 Experimental disaggregated learning curves for workers W1999 and W1968, for product families F4 and F5, in standard assistance mode

workstation. For assembly, this problem was not significant. It is likely that the same ergonomic adaptation problem occurs among men of different sizes, but with the disaggregation parameters used, no conclusion could be drawn.

A new factor identified was the possible onset of tiredness, more significant in some workers, which would increase production times, offsetting improvements gained through increased skill.

Figure 6 shows an estimation of the learning curves based on the selected assistance mode in the system. The ”learning plus” mode significantly increases production times, so its usage should be minimized. This mode could be used for the first few units (e.g., 1 or 2) that an operator assembles or in cases where the worker’s work has been interrupted (such as after long breaks or shifts spanning several days). The ”learning” mode is more effective in reducing variability in production times and is particularly useful when adapting to new product references. In contrast, the ”expert” mode offers greater flexibility to the worker, though it may also increase the risk of errors in component selection.

Finally, an estimate of the effects of the assistance modes on production is shown. Figure 7 illustrates how the choice of assistance mode impacts production capacity. The learning curves provide personalized insights into production capacity for each worker and product family (in this case, worker W1968 and product family F5). This enables us to identify the most suitable worker for each product type and assess specific training needs [12] In a more intuitive way, the production output is presented as a percentage, with expert mode as the reference for maximum capacity. The integration of IoT technology, in a non-intrusive way, brings us closer to what could be considered the ”*Internet of Workers*” (IoW). This approach opens up the possibility of dynamically adjusting assistance modes, while ensuring full traceability of the entire process.

These results serve to highlight some of the success stories of the analysis methodology, given that the data obtained on worker behaviour -the subject of social sciences- presents a diversity inherent both to the study population and to external factors.

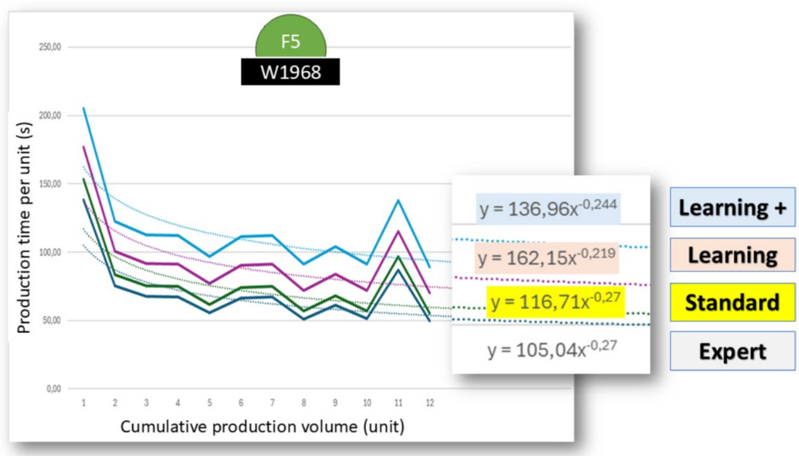

Fig. 6 Experimental learning curves for each of the four modes of assistance, W1968 & F5

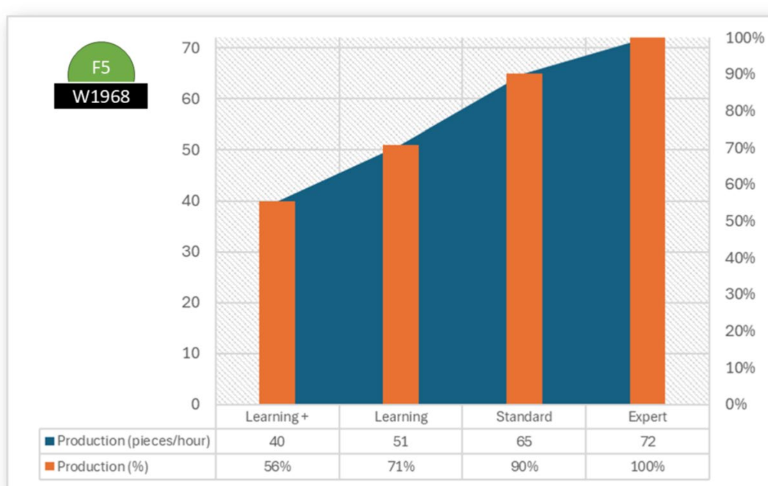

Fig. 7 Production capacity for each of the four modes of assistance.

5 Conclusions

Instead of relying on a passive system, the application of Industry 4.0 concepts allows for real-time monitoring of worker performance, even when new product references are introduced to the pick-to-assemble line. The following points can be considered as the main conclusions of this work:

- Progress has been made in the concept of the Internet of Workers (IoW) by identifying signals that provide insight into worker performance with minimal intrusion. The availability of such systems enables more advanced analysis compared to traditional passive picking systems.
- Real-time learning curves (LC) have been successfully generated, addressing the limitations of theoretical curves.
- Data discrimination allows for a deeper understanding of individual worker and product family behavior.The disaggregation of experimental data to obtain disaggregated learning curves opens new possibilities in diagnostics.
- The system allows us to collect sex-disaggregated data and gender-sensitive job information as a first step in gender-sensitive strategic planning. The application to ergonomic adaptation problems can be immediate.
- The application of machine learning techniques opens up new possibilities for production optimization.

Looking ahead, this study establishes the groundwork for comprehensive observational methodologies that will be progressively enriched with additional parameters -such as age and potential disabilities- thereby expanding their scope and enhancing generalizability. Subsequent investigations will increase the sample size and involve industry partners to broaden and diversify the cohort under observation.

Author Contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Manuel San-Juan, Elena Merino-Gómez and Francisco J. Santos. The first draft of the manuscript was written by Manuel San-Juan and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Declarations

Competing Interests The authors declare no competing interests.

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