Effects of product complexity on human learning in assembly and disassembly operations

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Abstract

Purpose – The purpose of this paper is to investigate and quantify the impact of product complexity, including architectural complexity, on operator learning, productivity and quality performance in both assembly and disassembly operations. This topic has not been extensively investigated in previous research.

Design/methodology/approach – An extensive experimental campaign involving 84 operators was conducted to repeatedly assemble and disassemble six different products of varying complexity to construct productivity and quality learning curves. Data from the experiment were analysed using statistical methods.

Findings – The human learning factor of productivity increases superlinearly with the increasing architectural complexity of products, i.e. from centralised to distributed architectures, both in assembly and disassembly, regardless of the level of overall product complexity. On the other hand, the human learning factor of quality performance decreases superlinearly as the architectural complexity of products increases. The intrinsic characteristics of product architecture are the reasons for this difference in learning factor.

Practical implications – The results of the study suggest that considering product complexity, particularly architectural complexity, in the design and planning of manufacturing processes can optimise operator learning, productivity and quality performance, and inform decisions about improving manufacturing operations.

Originality/value – While previous research has focussed on the effects of complexity on process time and defect generation, this study is amongst the first to investigate and quantify the effects of product complexity, including architectural complexity, on operator learning using an extensive experimental campaign.

Keywords Quality management, Complexity, Learning curves, Customization

Paper type Research paper

1. Introduction

Increasing complexity within products, processes and manufacturing systems, as well as in the external environment, poses a significant challenge to modern industry (Codara and Sgobbi, 2023; ElMaraghy *et al.*, 2012). Therefore, it is crucial for companies to effectively characterise and measure complexity, along with developing models to understand its propagation from individual products throughout the manufacturing system (ElMaraghy *et al.*, 2012; Rodríguez-Toro *et al.*, 2003). Various approaches have been applied to investigate the sources of complexity in engineering design and manufacturing, given its significant impact on the quality and performance of production processes (Alkan *et al.*, 2018; Colledani *et al.*, 2014; ElMaraghy *et al.*, 2012). Particularly in manual assembly processes, recent research has used product complexity to predict assembly times and defect rates (Alkan, 2019; Galetto *et al.*, 2020a; Verna *et al.*, 2021). The power-law model, which shows that assembly times and defects increase disproportionately with complexity, has been particularly useful (Alkan, 2019; Galetto *et al.*, 2020a, 2020b; Sinha, 2014). With increasing customer demand for customised products, the industrial landscape is facing an ever-growing challenge: companies are now expected to produce smaller batch sizes, adding a layer of complexity to their operations. As a result, the role of operators has changed significantly. They are now expected to exhibit a high degree of flexibility, which requires the ability to adapt to a variety of tasks and respond quickly to unexpected events, such as the introduction of new orders or variant products (Dan and Tseng, 2007; ElMaraghy *et al.*, 2013; Ulonska and Welo, 2014; Wang *et al.*, 2017).

In the context of this evolving landscape, the importance of the learning effect comes to the fore. Traditionally, a learning effect has been observed in manual assembly operations where operators perform the same tasks repeatedly over long periods of time. This effect consisted of an initial learning phase or start-up phase, followed by a steady-state phase where learning plateaued (ElMaraghy *et al.*, 2012). During this steady-state phase, where large quantities of the same product were manufactured, the learning effect was often overlooked. However, in the current era of mass customisation and personalisation, such an assumption is no longer valid. Given the need for operators to show flexibility in their tasks and adapt to changes, such as the introduction of new orders or product variants, the learning effect can no longer be neglected (Cheung *et al.*, 2015; Er and MacCarthy, 2006; Roy *et al.*, 2011; Verna and Maisano, 2022). In this environment, the role of learning in the context of product and process complexity becomes paramount to understand and manage effectively.

Learning in and about complex systems is a critical factor in navigating the challenges posed by increasing complexity (Sterman, 1994). It involves a feedback process where decisions made by individuals alter the real world, and in turn, they receive information feedback that prompts revisions to decisions and mental models. However, barriers to learning, such as dynamic complexity, inadequate feedback, misperceptions and poor reasoning skills, can hinder effective learning in complex systems (Sterman, 1994). To overcome these barriers, effective methods for learning in and about complex dynamic systems must include tools to elicit participant knowledge, simulation tools to assess the dynamics of cognitive maps and methods to improve scientific reasoning skills and group processes (Sterman, 1994).

With the shift towards low-volume production and the need for sustainable manufacturing, it is crucial to assess the learning effect across different product types, which are typically characterised by different levels of complexity. It is also vital that product assemblies take into account subsequent disassembly and material reuse, contributing to waste minimisation (Desai and Mital, 2017; Qiu *et al.*, 2022; Tolio *et al.*, 2017).

Despite extensive research on the effects of complexity on assembly and disassembly processes and strategies to manage it (Alkan, 2019; Galetto *et al.*, 2020a, 2020b; Gulivindala *et al.*, 2021; Sinha, 2014; Verna *et al.*, 2021; Wang *et al.*, 2013), the impact of complexity on human learning is still under investigation and requires further exploration, as will be discussed in the next Section 2.

By investigating the effects of product complexity on operator learning in assembly and disassembly processes, the study makes a significant contribution to the understanding of manufacturing technology and management, providing practical implications for businesses operating in a dynamic and complex manufacturing landscape. Unlike previous research that has primarily focussed on process performance metrics, such as time and defects (Alkan, 2019; Galetto *et al.*, 2020a; Verna *et al.*, 2022a), this study specifically investigates the implications of product complexity on operator learning. The extensive experimental campaign involving 84 operators and products with varying levels of complexity allows for a comprehensive analysis of these effects.

The obtained findings not only shed light on how product complexity affects operator learning in terms of productivity, measured by task completion time and quality performance, assessed by the number of total defects that occur during task execution and in the final product, but also how these effects vary depending on the specific characteristics of the product being assembled or disassembled. These findings are valuable for companies seeking to improve their training programmes and improve manufacturing process efficiency by enabling the prediction of learning effects, guiding business decisions and supporting sustainable, quality production (Frederiksen and White, 1989; Tharenou *et al.*, 2007).

The paper unfolds as follows: Section 2 provides a comprehensive literature review. Section 3 establishes the theoretical background, focussing on the product structural complexity model and the learning effect model. In Section 4, the research approach is detailed, including the description of products, experimental setup and the analysis methodology. The findings are presented in Section 5, and the paper concludes in Section 6 with the discussion of key insights and implications.

2. Literature review

Learning curves (LCs) have proven instrumental in the field of production and operations management, shedding light on the learning progression of workers as they take on novel tasks (Anzanello and Fogliatto, 2011). The practical implications of LCs extend to worker-task assignment, production planning and cost reduction, positioning these models as invaluable assets in the manufacturing sector. Despite their widespread use and diverse applications, existing research has highlighted the limitations of LC models and opportunities for further research.

The improvement in operator performance as a result of repeated execution of a manual task has been the subject of extensive research in a wide range of industrial contexts, including electronics, automotive, construction, software and chemicals. The drivers of workers' learning processes are multifaceted, including the structure of training programmes, workers' motivation, prior task experience and, in particular, task complexity (Anzanello and Fogliatto, 2011).

In production economics, learning is conceptualised as the progression of performance over time as a function of accumulated experience (Grosse *et al.*, 2015). Myriad LC models have been designed to capture this phenomenon, but a striking research gap is the comparison of these models based on a rich empirical dataset. This investigation addresses this gap by collecting, categorising and analysing LCs and their associated empirical data, thus providing researchers with comprehensive guidance on model selection.

Recently, Glock *et al.* (2019) conducted a comprehensive literature review on LCs. They outlined a framework that includes typical LC models, fundamental LC characteristics and their practical implementation in production and operations management. While this body of work is enlightening, it also signals future research directions.

As mass customisation continues to proliferate in manufacturing and services, there has been a growing interest in multivariate LCs (Anzanello and Fogliatto, 2011). This area is relatively unexplored and warrants rigorous investigation. The proliferation of data measurement devices provides fertile ground for advancing the understanding of multivariate LC models. Grosse *et al.* (2015) echo this sentiment, arguing for a renewed research focus on group or organisational learning, with an emphasis on knowledge transfer and mathematical modelling.

The literature broadly underscores the continuing relevance of LC models for improving production and operations performance. However, there is a need for more empirically-based, data-driven research to extend and refine existing LC models and to inform model selection for different applications.

In the area of product complexity and operator learning, previous research (Kvålseth, 1978; Nembhard and Osothsilp, 2002, 2005) has investigated the effects of task complexity on human learning. In particular, Kvålseth (1978) found that task entropy, a measure of complexity based on information theory, significantly impacts learning improvement. Nembhard and Osothsilp (2002) further expanded on this by demonstrating the intricate relationship between task complexity and individual learning rates, forgetting rates and steady-state productivity rates. In their studies, task complexity was determined by relative assembly times, with the assumption that longer assembly times indicate greater information content and hence greater complexity level. In particular, they found increased variability in learning rates, forgetting rates and productivity rates as task complexity increased, especially for inexperienced workers.

These investigations have important implications for simulation studies and worker-task assignment strategies, especially in dynamic work environments undergoing continuous product and process changes. Building on this understanding, Nembhard and Osothsilp (2005) proposed a method for worker selection based on individual learning and forgetting characteristics tailored to tasks of varying complexity. They argued that this could potentially increase overall system productivity, particularly in low and high-complexity task environments.

Furthermore, recent studies have begun to explore the effects of Industry 4.0 (I4.0) on worker learning, with somewhat contrasting results. For example, Karacay (2018) and Fareri *et al.* (2020) argued that I4.0 technologies could increase task complexity, potentially hindering the learning process. Conversely, other authors (Fantini *et al.*, 2020; Tortorella *et al.*, 2021, 2022) found a positive correlation between employee engagement and technology adoption, suggesting that proper management of this relationship could yield performance benefits.

The approach proposed in this paper differs from the above studies by focussing on the effect of product complexity, understood in structural terms, on operator learning in assembly and disassembly operations. This involves quantifying and modelling the interplay between product characteristics and learning in terms of productivity, measured by task completion time and quality, assessed by the number of defects that occur during task execution and in the final product. While rooted in foundational research, this study introduces a new perspective by adopting a novel paradigm for modelling product complexity based on product variant structure. As such, this research extends the existing understanding of the impact of task complexity on operator learning, providing new insights and potentially bridging the research gap in this area.

3. Theoretical background

3.1 Product structural complexity model

In this section, one of the most accredited models in the scientific literature to assess product complexity from an objective standpoint is presented. This model was first proposed firstly by Sinha (2014), readapted by Alkan and Harrison (2019), and subsequently applied in different manufacturing contexts, including electronics, electromechanical and aerospace industries. In the proposed approach, this model is used to assess the complexity of different product varieties, relying solely on their structural characteristics. As a result, it serves as a valuable tool for assessing complexity, especially during the initial stages of product design (Verna *et al.*, 2022b; Verna *et al.*, 2023a).

Such a model draws its foundation from molecular theory (Hückel, 1932) and defines structural complexity of any network-based engineering system as a function of (1) the complexity of the individual parts, (2) pair-wise interaction complexity between connected parts and (3) the effects of the resultant system topology. In this analogy, structural complexity C is formulated as:

$$C = C_1 + C_2 \cdot C_3, \tag{1}$$

where C_1, C_2 and C_3 represent part, interface and *topological* complexity, respectively.

C_1 is the sum of component complexities, and is defined as:

$$C_1 = \sum_{p=1}^{N} \gamma_p, \tag{2}$$

where N is the total number of product parts and γ_p is the handling complexity of part p. γ_p denotes the technical difficulty associated with managing and interacting with the product part in isolated conditions. According to the context, γ_p may be estimated using different approaches, including an exponential function to derive a score from constituting elements of a part (2019), the so-called Lucas Method to derive a normalised handling index (Alkan *et al.*, 2017a), and a function of standard handling time (2019). The factor γ_p should be calculated based on the physical factors of size and weight, handling difficulties (delicate, flexible, sticky, tangible, nest, sharp/abrasive, etc.) and orientation (alpha and beta symmetry).

C_2, *i.e.* the complexity of connections/liaisons, is the sum of the complexities of pair-wise connections existing in the product structure, as follows:

$$C_2 = \sum_{p=1}^{N-1} \sum_{r=p+1}^{N} \varphi_{pr} \cdot a_{pr}, \tag{3}$$

where φ_{pr} is the complexity in achieving a connection between parts p and r, and a_{pr} is the $(p,r)^{th}$ entry of the binary *adjacency matrix* $\boldsymbol{AM}$ of the product. $\boldsymbol{AM}$ is a symmetric matrix of size NxN where each element designates the existence of an assembly liaison between two components. In detail, a_{pr} can assume two values: 1 if there is a connection between p and r and 0 otherwise. The complexity φ_{pr} can be assessed by the standard completion time of the connection in isolated conditions (Alkan, 2019), by a fraction of the connected component complexities depending on the nature of the connectivity (Alkan and Harrison, 2019), or by the normalised fitting index from the Lucas Method (Alkan *et al.*, 2017a). In the matrix $\boldsymbol{AM}$, if any type of connection exists between two components, they are considered connected (Sinha, 2014). The connection types may be generalised into the following four categories: physical connection (e.g. weld, bolt, socket, wiring), mass flow (e.g. toner, paper), energy flow (e.g. electrical, mechanical, chemical flow) and information/signal flow (e.g. diagnostics information to User Interface, sensors signals) (Sinha, 2014). Furthermore, in the case of physical connections, the contact may be a contact point, line or surface and the connections may be soft or hard. The different types of connections are included in the model through the complexity factors φ_{pr}, which may assume different values depending on the considered connection. Attributes that affect the estimation of factors φ_{pr} include the part placing (self-holding or holding down required), the part fastening and the need for tools (screwing, riveting, bending, mechanical deformation, adhesive, soldering or welding, etc.), the direction of the fitting, the insertion type, the visibility and the alignment.

C_3 is the *topological* complexity and represents the complexity related to the architectural pattern of the assembled product. It is obtained as follows:

$$C_3 = \frac{E_{AM}}{N} = \frac{\sum_{q=1}^{N} \delta_q}{N}, \tag{4}$$

where E_{AM} is the matrix (or graph) energy of the *adjacency matrix*, which is designated by the sum of the corresponding singular values δ_q of $\boldsymbol{AM}$, and N is the total number of parts. As the *adjacency matrix* is a symmetric matrix of size NxN with the diagonal elements being all zeros, the singular values correspond to its absolute eigenvalues (Li *et al.*, 2012; Sinha, 2014). Matrix energy regimes can be divided into *hyperenergetic*, *hypoenergetic* and *intermediate* or transition regimes (Li *et al.*, 2012). The *hyperenergetic* regime is defined by graph energy greater than or equal to that of a fully connected graph, *i.e.* $E_{AM} \geq 2(N-1)$, and the *hypoenergetic* regime is defined as $E_{AM} < N$. Hence, in terms of *topological* complexity metric, the regimes are defined as *hyperenergetic* when $C_3 \geq 2(1-1/N)$ and *hypoenergetic* when $C_3 < 1$. Note that for *hyperenergetic* regimes, C_3 can be approximated to 2 when N is sufficiently large. In terms of system architectural pattern, *hyperenergetic* regimes are associated with distributed architectures, *hypoenergetic* regimes with centralised architectures, and *intermediate* regimes with hierarchical, or layered, architecture. Accordingly, C_3 increases as the system topology shifts from centralised to more distributed architectures (Sinha, 2014). Examples of real systems characterised by distributed architectures are printing systems and aircraft-geared turbofan engines (Sinha, 2014), as shown in Figure 1, while laptops have more centralised architectures as most components are connected to their base panel (see Figure 2).

It has to be noted that the proposed model aims to assess the complexity of a product and does not include aspects that may affect the complexity of assembly operations, such as assembly attributes and their influence on assembly planning (Gulivindala *et al.*, 2020; Raju Bahubalendruni *et al.*, 2015) and geometric feasibility (Kumar *et al.*, 2022; Prasad *et al.*, 2022).

The methodology of structural complexity quantification has been applied to various real engineering systems from the electronics, electromechanical and aerospace industries. In this section, the assembly of a laptop is taken as an example (see Figure 2).

In Figure 2, the exploded view, the liaison diagram and the related binary *adjacency matrix* $\boldsymbol{AM}$ of a laptop are represented. The assembly consists of 13 components (from A to M) and 17 connections. The analysis of component and connection complexities, estimated by the normalised handling and completion connection times, results in $C_1 = 8.77$ and $C_2 = 8.60$. The graph energy of matrix $\boldsymbol{AM}$ is 14.34 and accordingly, complexity of product topology is $C_3 = 1.10$, indicating a hierarchical architecture. According to the results, the overall complexity of product assembly C is estimated as 18.47.

3.2 Learning effect model

Industrial learning and the learning curve phenomenon were first reported by Wright (1936). The learning effect denotes that the longer the staff works on a particular task, the more efficient the staff will be on that task in terms of cost, productivity and quality performance

(a)

(b)

Source(s): Xerox's website and Pratt & Whitney's website

Figure 1.
Examples of industrial products with distributed architectures: (a) printing systems and (b) aircraft-geared turbofan engines

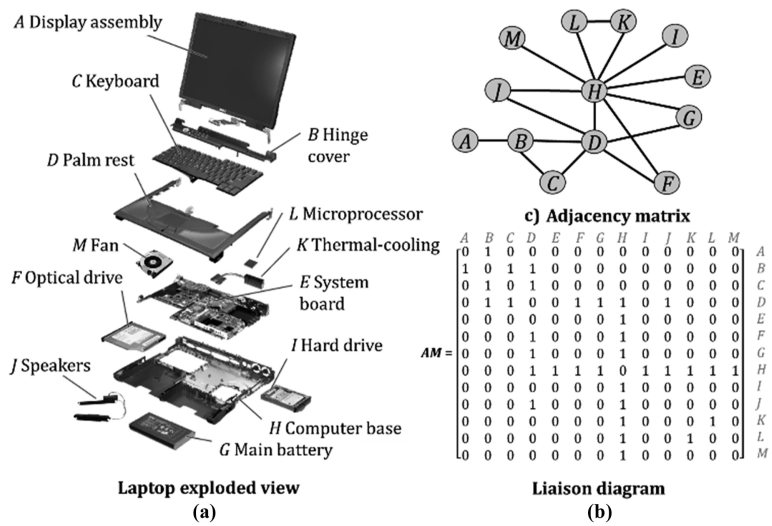

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Figure 2. Example of a laptop assembly: (a) exploded view (adapted from Dell® Website), (b) liaison diagram and (c) binary *adjacency matrix*

(Li and Boucher, 2017; Otto and Otto, 2014; Wu and Sun, 2006). The learning curve has been widely applied to various areas, and a comprehensive review of empirical models for the learning curve was proposed by Yelle (1979). The effect of learning is typically ignored in assembly and production lines. Indeed, for short cycle times and large batch sizes, typical of most traditional assembly lines, process times level off quickly and the learning effect is only significant during the start-up phase (Dar-El and Rubinovitz, 1991).

In the present paper, the learning effect denotes that the longer an operator works repetitively on a particular task, he will always need less time to complete it and the fewer defects he will introduce. The learning model adopted in this study uses a power-law learning curve that follows the mathematical function (Yelle, 1979):

$$Y = k \cdot X^{-b}, \tag{5}$$

where:

(1) X is the cumulative unit number;

(2) Y is the per-unit process time (or, alternatively, the number of defects) related to the assembly/disassembly of the Xth unit;

(3) k is the process time (or, alternatively, the number of defects) related to the first unit, *i.e.* the initial productivity (or, alternatively, the initial quality performance);

(4) $b = -ln\, r/ln\, 2$; $(0 < r \leq 1)$, b is the *learning factor*, r is the learning percentage, according to which $S = 1 - r$ is defined as the *progress ratio*. The smaller the value of r, the larger the value of b and the higher the learning effect (Wu and Sun, 2006).

4. Research approach

4.1 Products

The effects of product complexity on operator productivity and quality performance have been investigated through a set of different tests involving the assembly and disassembly of six different products with varying levels of complexity. Products adopted in the experiments are molecular structures assembled and disassembled using balls and sticks. The use of molecular structures to represent real cyber-physical products is a well-established approach in the scientific literature. By using atoms to represent product components and bonds to represent connections, molecular models can effectively emulate real assembly and disassembly processes (Alkan *et al.*, 2017a,b; Alkan and Harrison, 2019; Sinha, 2014; Verna *et al.*, 2022a,b). The assembly of ball-and-stick structures is primarily a constructive activity, involving the processing of visual and/or geometric information and the ability to assemble and disassemble a certain structure. Thus, the reason behind the choice of such structures is the concern of (*1*) isolating and controlling the effects of structural complexity alone on learning, while (*2*) minimising confounding effects that would occur in real production settings, such as dynamic and organisational aspects of engineering systems. Accordingly, studying the effects of complexity on learning using molecular structures allows the identification of generalisable patterns and mechanisms that inform the understanding of learning in real-world manufacturing processes, as the underlying principles of learning, such as information processing and cognitive abilities, are expected to apply across different domains.

In the proposed case study, organic molecular structures were built using a molecular modelling kit (Orbit™ by 3B Scientific®) based on clear 2D and 3D work instructions. Six different ball-and-stick structures with varying levels of complexity were selected to simulate the assembly and disassembly of real products (see Figure 3 and Table 1).

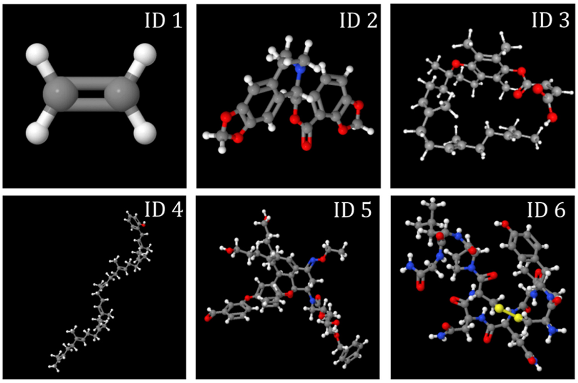

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Figure 3. 3D representation of the six molecular structures (ID 1 – ID 6), detailed in Table 1

Table 1. Technical specifications and complexity results of six ball-and-sticks molecular models

ID	Molecular formula	Total parts	Total connections	Single connections	Double connections	E_{AM}	C_1	C_2	C_3	C
1	C_2H_4	6	5	4	1	6.00	1.72	4.67	1.00	6.40
2	$C_{20}H_{17}NO_6$	44	49	42	7	52.41	12.65	45.55	1.19	66.90
3	$C_{33}H_{46}O_5$	84	85	76	9	89.79	24.14	78.75	1.07	108.32
4	$C_{46}H_{70}O$	117	117	106	11	123.29	33.63	108.28	1.05	147.73
5	$C_{50}H_{64}N_2O_{12}$	128	133	119	14	145.73	36.79	123.21	1.14	177.07
6	$C_{43}H_{66}N_{12}O_{12}S_2$	135	137	123	14	151.33	38.80	126.88	1.12	181.04

Source(s): Authors work

The molecular structures referred to in the case study are organic molecules that are made up of different atoms (i.e. balls) and bonds (i.e. sticks), in the quantities specified in Table 1. Regarding the atoms, 5 different typologies were involved: carbon (grey), hydrogen (white), nitrogen (blue), oxygen (red) and sulphur (yellow). On the other hand, two kinds of chemical bonds were included, i.e. rigid connectors for single covalent bonds and flexible connectors for double covalent bonds. These molecules can vary in size, shape and complexity depending on the number and types of atoms they contain and the way they are connected. The six molecular structures used as a case study are identified using their chemical formulae, which provide information about the types and numbers of atoms present in each molecule (see Table 1). For example, ID 1 (C_2H_4) is a molecule made up of two carbon atoms and four hydrogen atoms, while structure ID 6 ($C_{43}H_{66}N_{12}O_{12}S_2$) is a more complex molecule made up of 43 carbon atoms, 66 hydrogen atoms, 12 nitrogen atoms, 12 oxygen atoms and 2 sulphur atoms. In addition to the different number of atoms and bonds, each molecule has a different architecture, which influences the final complexity of the product. For example, as seen in Figure 3, structures ID 1 and ID 4 are linear, while structures ID 3 and ID 5 are more distributed.

The level of complexity of each structure, which depends on the number of atoms and bonds and the architecture of the structure, is derived according to the structural complexity model (see Section 3.1). Part complexity γ_p, see Eq. (2), is estimated as a function of the average handling time, *i.e.* the time to locate the box, move arm to pick position, pick the relevant atom and return the arm to the work position. Connection complexity φ_{pr}, see Eq. (3), was estimated by the average completion time of a connection between a pair of atoms in isolated conditions, involving (*1*) connector handling and (*2*) joining process. This latter requires locating the connection holes, orienting and positioning the atoms and bond, connecting the bond to both atoms, arranging the connection and a final check. To estimate the average times of the above activities, preliminary experiments were performed by the 84 operators by randomising the tasks to minimise learning effects. According to the results, the average handling time of individual atoms is 2.80 s, the average connection time using a rigid connector is 8.95 s and using a flexible connector is 9.75 s. Part and connection complexities are derived by normalising the average times based on the longest time, resulting in $\gamma_p = 0.29$, $\varphi_{pr} = 0.92$ for rigid connections and $\varphi_{pr} = 1.00$ for flexible connections. Accordingly, part, connection and topological complexities of each molecular structure are calculated by Eqs. (2)–(4), respectively, and the overall structural complexity by Eq. (1) (see Table 1).

4.2 Experimental setup

This study was structured to resemble real manufacturing scenarios while controlling confounding factors to focus on product complexity's impact on operator learning, productivity and quality performance.

Experimental trials were organised in 7 days. On each day, 12 operators were involved, for a total of 84 operators. This large and diverse sample size ensured robust data for analysis and accommodated variability amongst individuals for broader generalisation. Operators were divided into pairs: while the first operator was responsible for the assembly of a molecule randomly assigned, the second operator performed quality inspections and was responsible for the subsequent structure disassembly. Then, the operator who previously disassembled moved on to the assembly of a second molecule, always randomly assigned and the other operator performed the quality control and the subsequent disassembly. This division simulated real-world assembly line scenarios where tasks are typically shared amongst teams. After seven assembly-disassembly cycles per molecule, roles rotated. This rotation avoided monotony and allowed a comprehensive understanding of operator learning across both assembly and disassembly operations. Daily, each molecule was assembled and disassembled by two distinct operators, yielding 14 replicates per molecule. Repetition of assembly and disassembly operations seven times per operator mirrored assembly line work's repeated nature and aided the construction of learning curves, providing insights into how operator performance evolves with practice. Assembly and disassembly operations lacked a particular sequence, minimising sequence complexity effects, relevant in both assembly operations (Bahubalendruni *et al.*, 2019; Kumar *et al.*, 2022) and disassembly operations (Anil Kumar *et al.*, 2021; Gulivindala *et al.*, 2021).

For assembly, each type of atom and connector was located in a specific box (see Figure 4), where the operator selected the corresponding part following the given assembly instruction. For disassembly, specific empty boxes were prepared, one for each type of atom and connector, where operators could put the corresponding part (see Figure 4). It is worth noting that all the participants had no previous industrial assembly experience.

During assembly, the operator responsible for quality control was assigned to measure the total assembly time of each structure and count the number of process and product defects. Process defects are those errors occurring during assembly operations, which involve disassembling one or more parts/connections and repeating the operations to correctly complete the structure. On the other hand, product defects are those found by the quality inspector on the finished product after assembly (*i.e.* missing and/or incorrect atoms and bonds). During disassembly, the total disassembly time was measured by the quality controller, as well as the number of disassembly defects, *i.e.* the number of atoms and/or bonds put in the wrong box.

Figure 5 provides a detailed schematic representation of the adopted experimental setup, illustrating each operation's procedures, stages and responsibilities.

4.3 Analysis methodology

The outcomes of the experiments, *i.e.* (*1*) total assembly time, (*2*) total number of defects occurring during assembly (considering both process defects and defects remaining in the final product), (*3*) total disassembly time and (*4*) total number of disassembly defects, were recorded for each of the six molecular structures. Outcomes (*1*) and (*3*) can be considered a measure of the productivity of operators, while outcomes (*2*) and (*4*) provide an insight into quality performance. As outcomes (*2*) and (*4*) are closely linked to human errors, they can also be interpreted as indicators of worker reliability (Givi *et al.*, 2015). As mentioned above, 14

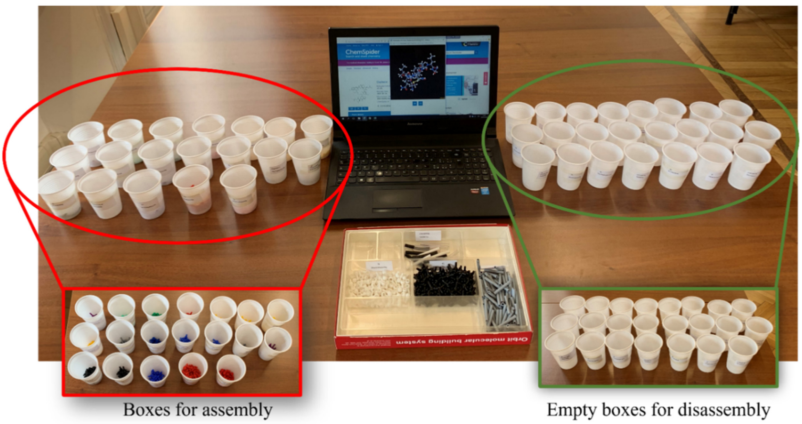

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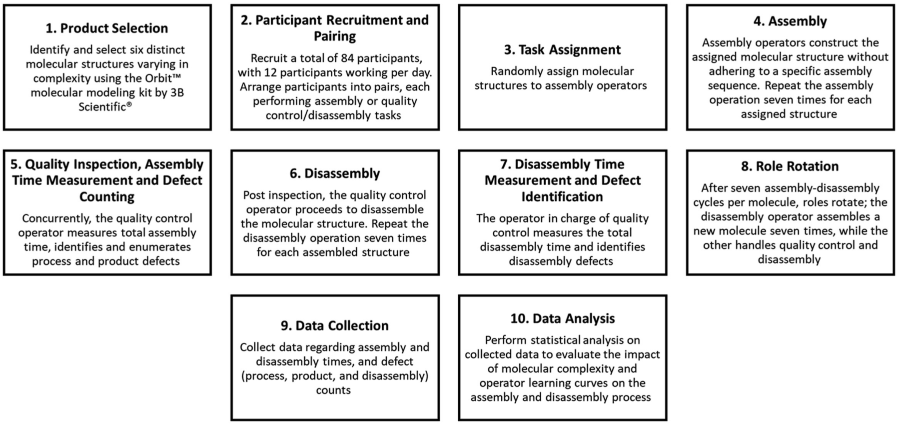
Figure 4.
Workstation and equipment used for assembly and disassembly tasks



Source(s): Authors work

Figure 5.
Schematic of the experimental setup

replicates of each structure's outcomes were obtained. For the analyses, the average values obtained from the 14 outcome measures were considered because of the high variability of individual data. The software *MINITAB*® is used for statistical analysis (Minitab, 2022). It has to be noted that nonlinear regression models are used to analyse data since logarithmic transformation–and subsequent linear regression–proved inaccurate in modelling near-zero data affected by variability, as in the case of defects, leading to a prediction bias. To ensure accuracy, the obtained models were evaluated via goodness-of-fit tests and residuals analysis. Statistical significance was assessed at the 95% confidence level, contributing to the results' validity and reliability (Bates and Watts, 1988; Seber and Wild, 1989).

5. Results

Four learning curves, one for each outcome mentioned in Section 4.3, were derived for all the products, according to Eq. (5), by nonlinear regression models. Figure 6 illustrates, as an example, the four learning curves for ID 4. On each plot of Figure 6, the experimental mean values, the regression line, the 95% confidence and the prediction intervals are represented.

Table 2 summarises the mean values of the regression parameters (k and b, see Eq. 5) of the learning curves related to productivity and quality performance of assembly and disassembly.

Below, the results of the regressions are analysed in detail. The 95% confidence and prediction intervals on the plot are represented, showing that the regression lines follow the curvature in the points closely and no systematic deviations from the fitted line appear (see Figure 6). Then, the statistical significance of parameter estimate is assessed by analysing the 95% confidence intervals for the parameters, calculated from the corresponding Standard Errors (SE) reported in Table 3. The parameter estimates are verified to be statistically significant in all learning curves since their 95% confidence intervals do not contain zero (Bates and Watts, 1988; Seber and Wild, 1989). Moreover, a lack-of-fit test is performed (Bates and Watts, 1988; Seber and Wild, 1989) when considering all the 14 replicates in the model. In Table 3, the p-values of the lack-of-fit tests are reported showing that, being larger than the significance level of 0.05% (the minimum p-value is 0.511 for the assembly quality learning curve for ID 3), no lack-of-fit is detected. Finally, regression residuals are analysed, revealing that the power-law models are adequate and meet the assumptions of the analysis.

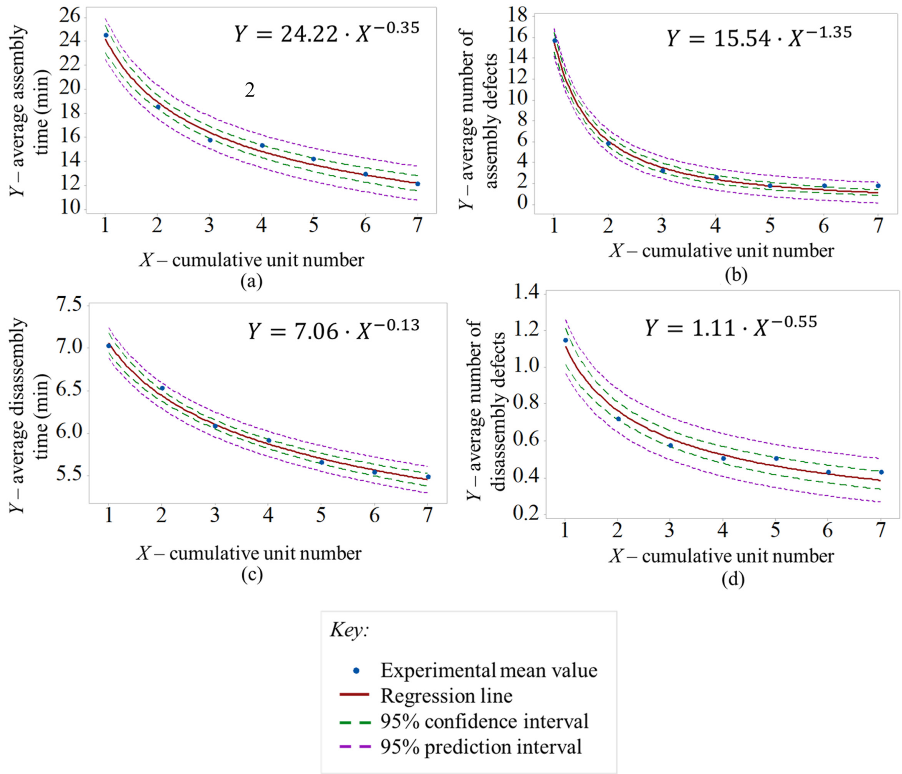


Figure 6.
Learning curve of structure ID 4 for (a) average assembly time, (b) average number of assembly defects, (c) average disassembly time and (d) average number of disassembly defects

Source(s): Authors work

Table 2.
Mean values of parameters of productivity and quality learning curves

	Productivity				Quality performance			
	Assembly		Disassembly		Assembly		Disassembly	
ID	k_{pa}	b_{pa}	k_{pd}	b_{pd}	k_{qa}	b_{qa}	k_{qd}	b_{qd}
1	0.71	0.31	0.29	0.12	0.71	2.09	0.21	1.62
2	13.46	0.43	3.43	0.20	3.40	0.60	0.43	0.03
3	22.25	0.34	5.19	0.15	8.72	1.00	0.66	0.76
4	24.22	0.35	7.06	0.13	15.55	1.35	1.11	0.55
5	40.66	0.37	9.21	0.18	13.32	0.77	1.39	0.21
6	51.74	0.40	9.90	0.17	16.71	0.64	1.47	0.18

Source(s): Authors work

Learning curve coefficients, *i.e.* k, the initial productivity in terms of times and defects, and b, the *learning factor*, see Table 2 in Section 5, are related to product structural complexity. Experimental results showed a statistically significant effect of structural complexity C on k, and it was found that their relationship follows a power law, both in assembly and disassembly (Finding 1). This outcome aligns with previous studies (Alkan, 2019; Galetto *et al.*, 2020b), wherein assembly times and defects increase more than linearly with increasing complexity. These findings reinforce and extend the scope of the existing knowledge base by providing empirical evidence for a similar power-law relationship in disassembly processes, as shown in Figures 7 and 8.

In each plot of Figures 7 and 8, the regression line, the 95% confidence and prediction intervals are represented. Nonlinear regressions are expressed in the form: $k = v_k \cdot C^{w_k}$. Since times and defects cannot assume negative values, plots have zero as lower limit of the ordinate axis and, consequently, negative values of confidence and prediction intervals are set equal to zero.

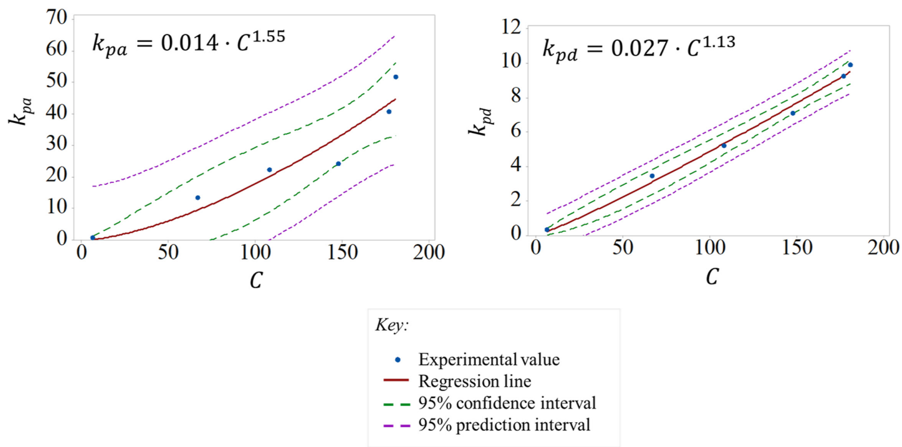
The adequacy of regressions is assessed by verifying the statistical significance of regression parameters through the 95% confidence intervals, calculated from the parameters standard errors reported in Table 4, and by analysing the residual plots. In this case, the lack-of-fit p-value cannot be calculated because the models do not contain replicates. As can be seen from Table 4, the estimates of the exponents (w_k) of the regression curves are all significant. However, this is not the case for all estimates of parameters v_k, being affected by high uncertainty probably due to the low number of data used for the regression. To obtain more robust parameter estimates, additional products with different levels of complexity will be considered in the future.

Comparing the curves (cf. Figures 7 and 8), and the mean values and standard errors of regression parameters (cf. Table 4), the variability of disassembly curves is lower than that of

	Productivity						Quality performance					
	Assembly			Disassembly			Assembly			Disassembly		
ID	k_{pa}	b_{pa}	Lack-of-fit p-value	k_{pd}	b_{pd}	Lack-of-fit p-value	k_{qa}	b_{qa}	Lack-of-fit p-value	k_{qd}	b_{qd}	Lack-of-fit p-value
1	0.034	0.041	0.562	0.008	0.020	0.975	0.081	0.530	0.880	0.043	0.595	0.797
2	0.535	0.037	0.814	0.095	0.022	0.679	0.449	0.139	0.704	0.432	0.049	0.999
3	0.469	0.018	0.993	0.213	0.032	0.993	0.931	0.1633	0.511	0.081	0.148	0.884
4	0.442	0.016	0.969	0.045	0.005	0.999	0.362	0.051	1.000	0.039	0.035	1.000
5	0.390	0.009	0.994	0.071	0.006	0.998	1.053	0.097	0.912	0.063	0.036	0.999
6	1.227	0.021	0.923	0.219	0.017	0.913	2.354	0.154	0.570	0.087	0.047	0.995

Source(s): Authors work

Table 3. Standard Error (SE) of parameters of productivity and quality learning curves and p-values of lack-of-fit tests



Source(s): Authors work

Figure 7. Initial productivity of assembly (k_{pa}) and disassembly (k_{pd}) as a function of structural complexity

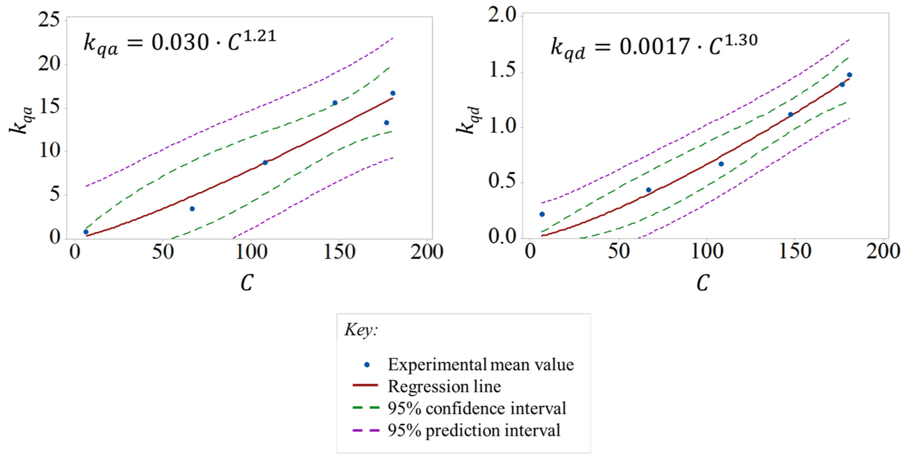


Figure 8. Initial quality performance of assembly (k_{qa}) and disassembly (k_{qd}) as a function of structural complexity

Source(s): Authors work

Table 4. Mean values and standard errors of regression parameters relating initial productivity and initial quality performance to structural complexity (see Figures 7 and 8, respectively). Nonlinear regressions are expressed in the form: $k = v_k \cdot C^{w_k}$

	Assembly				Disassembly			
	Mean value v_k	SE v_k	Mean value w_k	SE β	Mean value v_k	SE v_k	Mean value w_k	SE w_k
Initial productivity	0.014	0.032	1.55	0.44	0.027	0.013	1.129	0.097
Initial quality performance	0.030	0.051	1.208	0.333	0.002	0.002	1.299	0.207

Source(s): Authors work

assembly curves (Finding 2). The underlying reason can be that assembly operations are intrinsically characterised by greater variability and uncertainty due to the greater difficulty of the operations to be performed and the greater cognitive and physical effort required of the operator compared to disassembly operations.

Then, since initial productivity and quality performance in assembly and disassembly, *i.e.* k_{pa}, k_{pd}, k_{qa}, k_{qd}, are affected by variability (see Table 3 in Section 5), the final uncertainty can be derived by applying the law of variance composition (JCGM 100:2008, 2008; Montgomery *et al.*, 2009). The variability derived from the regression (see Table 4) is combined with the variability obtained from learning curves (see Table 3 in Section 5). As a result, an uncertainty interval at 95% confidence level can be associated with the predicted value of initial productivity/quality performance for each complexity value. Negative limits of uncertainty intervals are set equal to zero and are written in italic in Table 5.

In detail, predicted values reported in Table 5 are obtained by using mean values of regression parameters given in Table 4. Such predicted values thus represent the values assumed by the regression curves (shown in Figures 7 and 8) at the considered complexities. The uncertainty intervals at 95% confidence level are obtained from the uncertainty s_{tot} reported in Eq. (6):

Table 5.
Predicted values and relevant uncertainty intervals (95% confidence levels) of initial productivity and quality performance of assembly and disassembly

		Assembly				Disassembly			
ID	C	Predicted k_{pa}	95% uncertainty interval	Predicted k_{qa}	95% uncertainty interval	Predicted k_{pd}	95% uncertainty interval	Predicted k_{qd}	95% uncertainty interval
1	6.40	0.25	(*0.00*, 17.08)	0.286	(*0.00*, 6.04)	0.21839	(*0.00*, 1.27)	0.01874	(*0.00*, 0.32)
2	66.90	9.56	(*0.00*, 29.49)	4.8615	(*0.00*, 11.82)	3.08647	(1.82, 4.35)	0.39475	(0.04, 0.75)
3	108.32	20.20	(0.01, 40.39)	8.7039	(1.99, 15.41)	5.32019	(4.11, 6.53)	0.7386	(0.39, 1.09)
4	147.73	32.69	(13.88, 51.50)	12.6617	(6.35, 18.97)	7.55273	(6.41, 8.69)	1.10538	(0.78, 1.43)
5	177.07	43.27	(23.33, 63.21)	15.752	(9.02, 22.48)	9.26341	(8.05, 10.48)	1.39809	(1.05, 1.75)
6	181.04	44.80	(24.34, 65.25)	16.1814	(9.31, 23.05)	9.49923	(8.26, 10.74)	1.43912	(1.08, 1.80)

Source(s): Authors work

$$s_{tot} = \sqrt{s_{pred}^2 + \mathrm{SE}^2}, \tag{6}$$

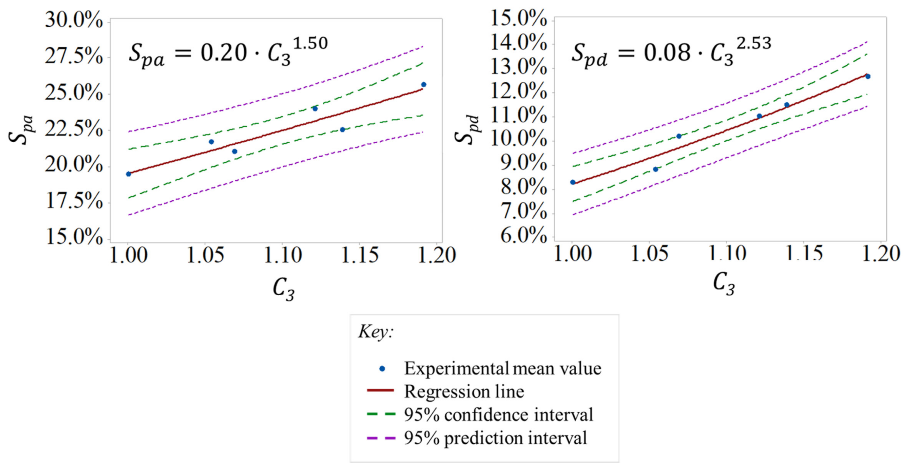
where:

(1) s_{pred}^2 is the variability of the prediction associated with the 95% prediction interval represented in Figures 7 and 8. It is calculated as $s_{pred}^2 = \mathrm{SE}^2(Fit) + {S_{regr}}^2$, where $\mathrm{SE}(Fit)$ is the standard error of the fitted value, and S is the standard error of the regression (Seber and Wild, 1989). Both values $\mathrm{SE}(Fit)$ and S_{regr} are outputs of the nonlinear regression implemented in Minitab®.

(2) SE is the standard error of parameter k (i.e. SE(k)) derived from the learning curves (see Table 3).

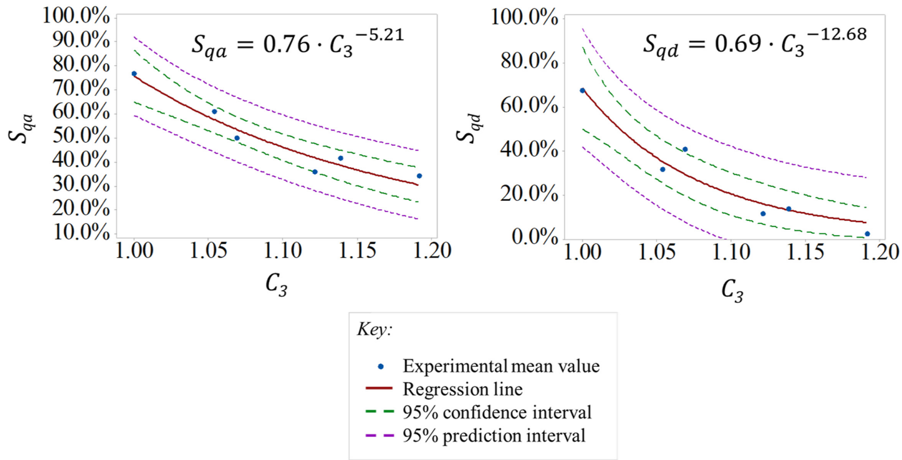
On the other hand, the *learning factor b* was found to be statistically affected by the sole *topological* complexity (C_3). In particular, as *topological* complexity C_3 increases, thus moving from centralised to distributed architectures, the *learning factor* related to productivity (*i.e.* process times) increases more than linearly, following a power law, in both assembly and disassembly (Finding 3). This result can be explained as the more distributed the structure becomes, *i.e.* the more atoms are connected to each other, the easier the operator can identify assembly/disassembly strategies that lead to significant time improvements. On the contrary, for the quality *learning factor*, an inverse proportionality relationship with *topological* complexity is observed (Finding 4). In fact, the more distributed the structure becomes, the fewer reference points there are and consequently, on average, the same defects are repeated. Instead, in centralised or layered structures (with low values of C_3), defect learning is greater because the structure, being more repetitive and easily visible, facilitates quality improvement.

For predictive purposes, instead of representing the *learning factor b*, the *progress ratio* (*i.e.* $S = 1\text{-}r$, where r is obtained as $e^{-b \cdot ln(2)}$, see Section 3.2) was related to the *topological* complexity, as it is more readily useable from an operational standpoint, see Figures 9 and 10. In detail, the 95% confidence and prediction intervals and the regression lines of progress ratio of productivity and quality performance are shown in Figures 9 and 10, respectively.



Source(s): Authors work

Figure 9.
Progress ratio of productivity of assembly (S_{pa}) and disassembly (S_{pd}) as a function of *topological* complexity



Source(s): Authors work

Figure 10. *Progress ratio* of quality performance of assembly (S_{qa}) and disassembly (S_{qd}) as a function of *topological* complexity

Nonlinear regressions are expressed in the form: $S = v_s \cdot C_3^{w_s}$. Mean values and standard errors of regression parameters are provided in Table 6. In analogy to the regressions presented above, the adequacy was checked using the appropriate techniques for nonlinear regressions (Bates and Watts, 1988). In such a case, according to Table 6, all parameter estimates are statistically significant.

Similar to initial productivity and quality performance, predicted values of progress ratio are obtained for each value of topological complexity, with the corresponding uncertainty interval at 95% confidence level, derived by combining the variability of regression parameters (see Table 6) and variability of progress ratio values. Predicted values reported in Table 7 are obtained by using mean values of regression parameters given in Table 6. The uncertainty intervals (95% confidence level) are derived by implementing Eq. (6), considering that *progress ratio* standard error, i.e. SE(S), has to be derived from *learning factor* standard error, i.e. SE(b) - listed in Table 3 in Section 5 - as follows:

$$\mathrm{SE}(S) = \sqrt{\left(\ln(2) \cdot e^{-b \cdot \ln(2)}\right)^2 \cdot \mathrm{SE}^2(b)}\,. \tag{7}$$

The resulting values are given in Table 7. Note that negative limits of uncertainty intervals are set equal to zero and are written in italic.

It has to be highlighted that progress ratio is very marked for quality performance, where it goes on average from about 35% for high values of C_3 to 80% for low values of C_3 in

Table 6. Mean values and standard errors of regression parameters relating *progress ratio* of productivity and quality performance to *topological* complexity (see Figures 9 and 10, respectively). Nonlinear regressions are expressed in the form: $S = v_s \cdot C_3^{w_s}$

	Assembly				Disassembly			
	Mean value v_s	SE v_s	Mean value w_s	SE w_s	Mean value v_s	SE v_s	Mean value w_s	SE w_s
Progress ratio of productivity	0.195	0.006	1.498	0.273	0.082	0.003	2.528	0.267
Progress ratio of quality performance	0.758	0.039	5.207	0.658	0.688	0.067	12.683	2.134

Source(s): Authors work

assembly (and from 2% to 70% in disassembly). On the other hand, progress ratio of productivity ranges, on average, from about 20% to 26% for assembly tasks and from about 8% to 13% for disassembly operations (Finding 5).

Below are some considerations on the validation and generalisation of the proposed approach. The six products used were chosen to cover a wide range of complexity (i.e. from 6.40 to 181.04) to quantify the effects that complexity has on operator learning in terms of productivity and quality. To validate the proposed approach, some of the molecular structures used or different ones (still within the adopted range of complexity) should be chosen and checked that the productivity and quality obtained fall within the 95% uncertainty intervals reported in Tables 5 and 7. Furthermore, to generalise the proposed method, it will be necessary to apply it to real products and verify that the learning curve trends obtained align with those obtained using the molecular structures. This will be the subject of future research.

6. Conclusions

In the modern industrial context, operators are required to be increasingly flexible to deal with sudden reallocations due to unexpected events, *e.g.* the introduction of different product variants or extra orders. This study addresses the urgent need to examine and evaluate the operator learning effect in relation to different product variants and their levels of complexity. Additionally, the subsequent disassembly process is also considered to align with sustainable production and waste minimisation objectives.

This study investigates for the first time the effects that product complexity has on operator learning in terms of productivity, *i.e.* process times, and quality performance, *i.e.* total number of defects, in both assembly and disassembly processes. An extensive experimental campaign–with respect to previous studies in the field–involving 84 operators was conducted, using six different products with varying levels of complexity. In detail, six ball-and-stick structures were repeatedly assembled and disassembled since molecular structures are typically considered in the scientific literature to effectively emulate real production processes.

This study contributes to the theoretical development in the field by modelling the relationships between product complexity and initial productivity and quality performance, as well as the relationships between topological complexity and the progress ratio of productivity and quality performance in both assembly and disassembly tasks. The findings of the study are as follows:

(1) The analysis of learning curves revealed that as the product complexity increases, both initial productivity and quality performance exhibit a power-law growth pattern.

Table 7. Predicted values and relevant uncertainty intervals (95% confidence level) of *progress ratio* of productivity and quality performance of assembly and disassembly

		Assembly				Disassembly			
ID	C_3	Predicted S_{pa}	95% uncertainty interval	Predicted S_{qa}	95% uncertainty interval	Predicted S_{pd}	95% uncertainty interval	Predicted S_{qd}	95% uncertainty interval
1	1.00	0.20	(0.13, 0.27)	0.76	(0.47, 1.05)	0.08	(0.04, 0.12)	0.69	(0.23, 1.15)
2	1.19	0.25	(0.19, 0.31)	0.30	(0.08, 0.53)	0.13	(0.09, 0.17)	0.07	(*0.00*, 0.30)
3	1.07	0.22	(0.18, 0.25)	0.54	(0.33, 0.74)	0.10	(0.04, 0.15)	0.30	(0.02, 0.57)
4	1.05	0.21	(0.18, 0.25)	0.58	(0.44, 0.72)	0.09	(0.08, 0.11)	0.35	(0.13, 0.58)
5	1.14	0.24	(0.21, 0.27)	0.39	(0.21, 0.56)	0.11	(0.10, 0.13)	0.13	(*0.00*, 0.35)
6	1.12	0.23	(0.19, 0.27)	0.42	(0.18, 0.65)	0.11	(0.08, 0.14)	0.16	(*0.00*, 0.39)

Source(s): Authors work

This finding (Finding 1) aligns with previous research (Alkan, 2019; Galetto *et al.*, 2020a; Verna *et al.*, 2023b) and contributes to understanding how complexity impacts learning outcomes. Moreover, this power-law relationship applies to both assembly and disassembly tasks, expanding the scope of previous investigations.

(2) The study also showed that disassembly curves demonstrate lower variability compared to assembly curves, signifying that disassembly processes could be inherently less prone to variation and uncertainty (Finding 2).

(3-4) The study highlights significant differences in learning outcomes between structures with different levels of topological complexity, which have not been previously explored. The results pointed out a superlinear relationship between the *learning factor*, and thus the *progress ratio*, of productivity and the sole *topological* complexity (Finding 3).

An opposite trend was found for the *progress ratio* of quality performance (Finding 4). Increasing *topological* complexity means moving from centralised to distributed architectures. Thus, the more distributed the structure becomes, the easier the operator can identify assembly/disassembly strategies that lead to significant productivity improvements. However, few reference points exist and, as a result, the same defects are repeated on average. Instead, in centralised or layered structures, which are more repetitive and easily visible, few strategies for assembling/disassembling the structure exist and, accordingly, productivity learning is low. Conversely, this facilitates quality improvement as the previous assembly operations and errors are easily memorised.

(5) Experimentally, topological complexity resulted in a more pronounced variation in the *progress ratio* of quality performance than in productivity (Finding 5).

These novel insights expand our understanding of the impact of complexity on learning and performance in manufacturing processes.

It should be emphasised that although molecular structures used in this study are not real industrial products, this does not limit the validity of the findings. In fact, although these objects may appear simple, in the scientific literature, they have fully considered reference structures whose results can have general validity, regardless of the type of product being assembled/disassembled. Therefore, the insights gained from studying molecular structures can be extended to real products, as the underlying principles of learning, such as information processing and cognitive abilities, are expected to apply across different domains. This investigation of complexity's effects on learning using molecular structures uncovers generalisable patterns and mechanisms contributing to understanding learning in real manufacturing processes.

Overall, this study highlights the importance of considering the effects of product complexity on operator learning in both assembly and disassembly processes. By understanding these effects, companies can make informed decisions to optimise their manufacturing operations, improve productivity and quality, and develop more effective training protocols in response to the challenges arising from the increasing product variety and customisation. Future research should focus on exploring the transferability of findings from molecular structures to real products. Comparative studies incorporating both molecular structures and real production settings will be essential to validate the observed relationships and generalise the findings. These research endeavours will bridge the gap between controlled laboratory settings and the complexities of real-world manufacturing systems, providing a comprehensive understanding of how product complexity influences operator learning and performance in practical industrial contexts. Given the potential influence of various external factors on learning, the effects observed in ball-and-stick models are expected to magnify in real engineering systems.

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