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Heterogeneity and Variability on Human-Centered Assembly Systems

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Abstract

Manual work is often preferred to automation while assembling products. However, the human performance is variable by nature. The manufacturing companies are aware that the workers have variable performance, but have limited information about the quantification of these variations and the available literature on the subject is often inadequate. With the objective of quantifying and systematizing the knowledge about the heterogeneity of workers performance, data collection was performed in an industrial setting. These observations show that the workers performance varies significantly, and a mapping approach is proposed to systematize the quantification of the variations in terms of speed and variability. Since the human performance is influenced by the setting where the workers perform their job, several scenarios were studied concerning work flow policies. The heterogeneity of workers performance and the characterization the several types of performances was mapped for the following scenarios: workers performing assembly tasks paced by the system rhythm (system with margins); under a fixed time constraint (rigid pacing); and in unpaced conditions. Furthermore, simulation studies were performed to assess how different types of performances may affect an assembly system, demonstrating the need to characterize the workers performance – the key element of the assembly process.

Keywords: Worker Performance; Workers Heterogeneity; Manual Work; Manual Assembly Systems; Work Flow Policy; Empirical Research; Discrete Events Simulation.

Resumo

Nos sistemas produtivos de montagem, o trabalho manual é muitas vezes preferido à automação. No entanto, a performance humana é variável por natureza. Apesar dos fabricantes terem noção que os seus operadores têm desempenhos variáveis, a informação detida sobre a quantificação destas variações é limitada e a literatura disponível é muitas vezes desadequada. Com o objetivo de quantificar e sistematizar o conhecimento sobre a heterogeneidade do desempenho dos operadores, foram coletados dados em ambiente industrial. A análise destes dados demonstra que existe uma variação significativa destes desempenhos. É proposta uma abordagem de mapeamento para sistematizar estas variações em termos de velocidade e dispersão. Como o desempenho é influenciado pelo contexto em que os operadores se inserem, foram estudados vários cenários de acordo com diferentes condicionantes do fluxo de trabalho no sistema. As performances foram mapeadas e caracterizadas para as seguintes situações: operadores sujeitos ao ritmo do sistema (ritmo de trabalho com margens); com limitação de um tempo fixo; e na ausência de ritmo de trabalho. Adicionalmente foram realizados vários estudos de simulação para avaliar o impacto dos diferentes tipos de desempenho no sistema de montagem, demonstrando a necessidade de caracterizar o elemento essencial dos sistemas de montagem manuais – o operador.

Palavras-Chave: Desempenho dos Operadores, Heterogeneidade dos Operadores; Trabalho Manual, Sistemas de Montagem Manuais, Fluxo de Trabalho, Investigação Empirica; Simulação de Eventos Discretos

Dedication

To my family and especially to my nephews, Ricardo, Sérgio and Claudia Borges: which never asked me about my thesis and just wanted to play all the time.

To “Casa da Alegria”: it was the best of times.

To my friends, in particular David Castanho: for his support in my pursuit for knowledge, happiness and freedom.

To Ricardo Mata: for the love, the understanding and the new found sense that the distance does not matter.

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1. Introduction

The assembly process of a product is usually the last stage of the manufacturing process, and at this stage, there is a great deal of accumulated value added to the product. Therefore, it is of critical importance to manage assembly systems wisely, namely by identifying the factors affecting its performance and quantifying them. Of course, these factors depend on the system characteristics. In an assembly system with a high level of automation, factors such as the reliability of the equipment used are considered an important factor with a large influence on the system performance, while in systems with lower levels of automation the focus is on the probability of human error and variations while performing assembly tasks.

At a certain point of the assembly systems technological evolution, there was a strong tendency to automate the process as much as possible with the goal of mitigating variation problems caused by human involvement. Back in the 1980s, the leaders of this trend were automotive companies ranging from Volkswagen to Fiat and General Motors. In the end most failed to produce the desired results despite massive investments (MacDuffie *et al.*, 1996). In the present context, where products have shorter life cycles, higher model variety and demand uncertainty, the flexibility of the human factor is considered an advantage rather than a problem. In fact, in comparison to semi-automatic or fully robotized assembly, the use of manual work is still quite dominant for those reasons.

During the four years of this research, several visits were made to a company based in Portugal that produces kinematic products for automotive interiors, which allowed for an unprecedented view at the operations of such companies. This company engineers, manufactures and supplies these products for worldwide Original Equipment Manufacturers (OEM). During these visits, it was observed that at the assembly systems of this company, the workers performed most of the assembly process steps manually. As a result, the assembly systems performance was dependent on the workers ability and on natural variations in their performance when executing the assembly tasks required to the final product.

In manufacturing companies, such as the one in which the industrial field work of this thesis took place, the assembly systems are designed and/or implemented considering that for each workstation, the workers are able to perform the assembly tasks within a given average time. The average task time for the assembly is defined based on standard

times. These standard times are defined in an early stage of system design using predetermined motion and time systems, without the need of actual observation of the assembly process, since there are lists of basic motions required for each operation and the required time to perform them.

In reality, when the assembly system is in operation, workers perform the assembly tasks with some degree of variability, since in one repetition the worker may be quicker and in the next slower. These variations are often disregarded in the early system design stage. On top of that, the workers are different from one another: there may be differences in the speed and consistency while performing assembly tasks, some workers might be slower than others, and some workers might have task times more variable than others (or the other way around). Given the nature of manual processing it is expected some degree of heterogeneity in the performance, in terms of speed and consistency. In the daily production, the production management has then to deal with these variations on the workers performance, and make sure that the system output fulfils the customer order. However, the variations on performance are not quantified even if there is some empirical knowledge from the experience with such systems. The difficulty is to use this tacit knowledge in the improvement of these systems and future designs.

Consequently, there is a need of investigating the heterogeneity that can be expected on the workers performance, in order to verify if these differences in performance are in fact significant and if so, to quantify them in a systematic way. This is the main objective of this research work.

From the preliminary statistical analysis of the workers task times, the initial premise of this study could be accepted: in fact, the workers task times differ significantly in terms of average task time and variability. This result is supported by previous findings published on this subject, and adds knowledge to this field of study, since it was obtained from an industrial setting.

During the discussions about these findings with the management of the company where the observations took place, the conclusion that the workers task times can differ significantly was not necessarily surprising. The large experience they have on running such systems had already taught them that workers are heterogeneous. The main question was the quantification and characterization of those differences. In terms of previously published work on the subject, there seems to be gap in the quantification of

such differences in a systematic way, that both companies and researchers can actually refer to, when studying human-centered assembly systems.

In order to characterize the workers performance, a mapping approach to fulfil this objective is proposed. The proposed performance mapping enables the quantitative evaluation of the heterogeneity: both in terms of speed and of consistency.

The performance of a human-centered assembly system depends on the workers performance and consequently on the differences among the workers. However the workers performance is dependent on the system itself: if there is a modification to the system the workers are influenced by it. For instance, if the way the parts move inside the system change, it is likely that the workers performance will change and therefore the position of the performance in the previously mentioned maps will also change. Some research has already been done in the middle of the 20th century on the workers performance, when they are working under different workflow policies, namely with a pacing mechanism. Nonetheless, the useful but yet general conclusions of previous research, focus in defining an average performance which fits all workers under the different pacing conditions. The results often lack representativeness, since the heterogeneity of the workers performance is disregarded, even if recognized.

For the observed scenario at the company, the assembly system was paced by the work precedence constraints, and therefore workers interdependence among them, creating a system rhythm. A modification to this pacing was introduced to reinforce this rhythm: an equal time slot for every worker to fulfil the assembly work at their assigned workstations. With this modification a second scenario was created: if in the first scenario the workers were paced by the system rhythm, in the second the workers were rigidly paced by a time constraint. Therefore, another objective of this research is to understand if a rigid pacing influences the performance heterogeneity within a group of trained workers, and if there are gains in the assembly system productivity by introducing this control mechanism.

If a rigid pacing might influence the workers performance, a lack of pacing can also produce different results. In the available literature, the term “unpaced work” is used to describe a situation where the worker is performing the tasks at the rhythm he/she feels comfortable with, in other words, at his own natural pace. When a task is unpaced, the worker is free to decide when he/she will initiate a movement. The analysis of this third scenario, which represents another possibility of workflow policy for an assembly system, is also an objective of this research.

In this work, the heterogeneity of performance is characterized and quantified, using the proposed performance maps, in three different scenarios: paced by the system rhythm, paced by a time constraint and unpaced. The three scenarios considered, cover a large spectrum of the different types of pacing which can be used in human-centered assembly systems, helping both management and system designers to better understand the dynamic nature of the human element in such systems.

In order to demonstrate the possible effects of the imbalance caused by the different worker performance, serial assembly lines were simulated using Discrete Events Simulation (DES). Different possible combinations of performance were considered, meaning that the workers allocated to the system have different average and variability on their task times. These simulation studies demonstrate the impact of the performance heterogeneity in the system performance.

In summary, this research work has a broad objective to contribute to the knowledge of the human factor on manual assembly systems, a very important manufacturing process. In order to do so, several intermediate objectives were considered: to demonstrate that the workers performance varies significantly; the development of a mapping approach to assess the performances heterogeneity, by "translating" an implicit knowledge into an actual quantification; to cover a considerable spectrum of work-flow policies which can be used in human-centered systems, namely pacing by the system rhythm, pacing due to a fixed time-constraint and unpaced conditions. Several simulation studies were performed to assess how different types of performances may affect an assembly system, both in terms of average output and in terms of the variability of the output, demonstrating the need to characterize the workers performance – the key element of the assembly process.

The thesis document is organized in the following way: in the following chapter (Chapter 2), the literature review can be found, contextualizing the research topic, namely on types of assembly systems and of assembly tasks, previous studies on differences among paced and unpaced performances, and workers performance variability and heterogeneity.

Chapter 3 focuses on the research means and methods, where it is described in further detail the research problem formulation, and the methodology used to answer the proposed formulation. Since this research is fundamentally based on data collection in an industrial setting, a special section is reserved to describe the industrial framework, as well as advantages and limitations of data collection in this context.

Chapter 4 describes the assembly tasks observed in the industrial framework and the sampling process used to collect workers task times. It also contains the preliminary assessment of the workers task times using several statistical methods, in order to: analyse the type of distribution of the task times; to look for significant differences among distributions from different workers performing the same assembly task; and to look for significant differences among distributions the same worker performing different tasks.

The following chapter, Chapter 5, is focused on the analysis of task time performance in a tightly coupled asynchronous system, where the workers are paced by the system rhythm and there is a high interdependency among workers. This chapter gives insight to the development of the approach for mapping the heterogeneity in the workers performance. This mapping approach is then used to analyse the workers performance heterogeneity on the different studied scenarios.

In Chapter 6, the workers heterogeneity is analysed in a paced work scenario with a time constraint. It is described how the rigid pacing mechanism was introduced in the observed assembly system. Comparisons are made between the workers performance before and after the introduction of the time constraint, using the proposed performance maps and statistical analysis. In addition, the advantages experienced by the company when implementing such modification to the system are described. The assembly system output performance is compared with and without the introduction of this time constraint.

In Chapter 7 the analysis is focused on the task time performance for unpaced work – having the subjects working at their natural pace. This chapter describes how a laboratorial experiment was set up to replicate the assembly process in unpaced conditions. The sampling process, the statistical analysis made to the task time distributions and the results in the performance maps are also described.

In Chapter 8, the three studied scenarios are compared using the proposed mapping approach: when the assembly work is paced by the assembly system rhythm (Chapter 5), when there is an imposed time-constraint (Chapter 6) and when the subjects are performing assembly tasks at their natural pace (Chapter 7).

Chapter 9 describes the DES simulations of assembly systems, using inputs from the scenario described in Chapter 5, and assessments are made regarding the impact of workers performance heterogeneity in asynchronous assembly systems.

Finally, in Chapter 10, the main conclusions made throughout the course of this research for the last four years as a PhD student are gathered.

2. Literature Review

The motivation for this research is to characterize and quantify the heterogeneity among workers performance in different scenarios, in order to gain further understanding on the human factors within the field of production and operations research. This research is particularly focused on the assembly process, namely in assembly lines.

This chapter starts by introducing some definitions about assembly systems, regarding its classification in order to set a baseline for the terms used throughout this document. In the subsequent subchapter, the trends regarding the use of manual work in the assembly process and the common standardized work elements of manual assembly tasks are also described. Within the scope of manual work, the types of tasks usually found in an assembly system, regarding the cognitive and motor requirements from the worker, are presented as defined by previous authors.

The discussion of the existent research literature is then focused on the definitions and findings regarding workflow policies involving pacing. Following that topic, the previous research on variability and heterogeneity among workers performance is addressed emphasizing the need for further inclusion of human behaviour on production and operations research.

The literature review is then concluded by reviewing previous simulation studies, regarding the impact of workers performance on the assembly system performance.

2.1. Assembly Systems Classification

This section describes the types of systems according to equipment layout and more particularly according to the way the work flows between workstations.

In terms of production systems layouts there are three basic facility layouts: the process layout, the product layout, the fixed-position layout and one hybrid type, the cellular layout (B. Chase *et al.*, 2006) – Table 1. In the process layout type, the similar equipment is grouped together, and the product flows through the areas of different equipment to accomplish the sequence of operations dictated by its process plan. In the product layout, the equipment is arranged accordingly to the sequence of operations required to make the product. In the fixed position layout the product (given its weight or dimensions) remains at its location and the manufacturing equipment is moved rather than the product. In the cellular layout,

dissimilar equipment is grouped into work centres to process products that have similar processing requirements or shapes.

Table 1 – Types of layouts according to equipment grouping and product flow, based on Chase, Jacobs and Aquilano (2006).

	Equipment grouping	**Product Flow**	**Example**
Process Layout	Similar equipment grouped together	Product flows through different equipment areas	Dies and moulds
Product Layout	Equipment arranged by sequence of operations	Product flows in a straight line	Automobiles, Radios
Fixed-Position Layout	Equipment moved near to the product	Product is fixed due to weight/dimensions	Airplanes
Cellular Layout	Equipment arranged by sequence of operations	Product flows through different equipment areas	Hydraulic and engine pumps used in aircraft

Assembly lines are a special case of product layout, where the equipment is arranged in a given set of assembly sequences. By definition, in an assembly line the products visit workstations successively as they are moved along the line by some kind of transportation system (Boysen *et al.*, 2007). Assembly lines traditionally are configured in a serial line, where single stations are arranged along a straight conveyor belt moving at a fixed speed. This approach to the assembly system was introduced by Ford in the 1920s and complied with the mass production paradigm where extremely-high-throughput continuous-flow mass production (Womack *et al.*, 1991) was desired. With the evolution of production throughout the years, several "mutations" of this initial concept appeared.

Within this concept of an assembly line, where the product is transferred from workstation to another, there are two variations regarding the way this transfer takes place (Figure 1). It can be a transfer line, where workstations are connected by an entire conveyor system that moves one slot at a time synchronously (the approach used by Ford). The other possibility is when the work is complete at a given workstation, the semi-finished product joins the work-in-process (WIP) buffer at the next workstation or directly to the next workstation– this type of system is asynchronous (Altiok, 1997).

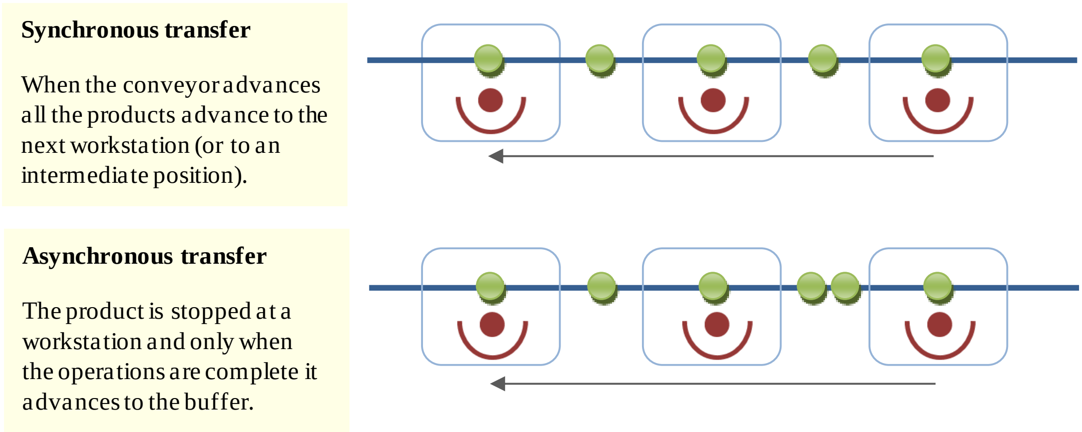


Figure 1 - Types of product transfer in serial assembly lines

In the case of a synchronous system, with or without work-in-process between workstations, the rule of First In-First Out generally applies. This might not be the case when we have asynchronous assembly lines: the work-in-process might not be queuing in a conveyor as in the case depicted previously, but simply a container with semi-finished products between workstations (Figure 2).

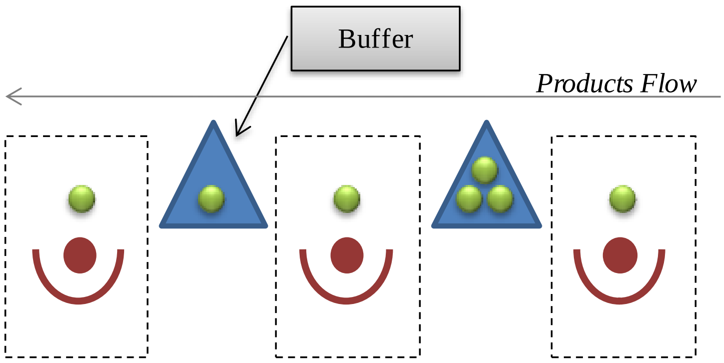


Figure 2 - Example of asynchronous transfer where the rule FIFO is not applied

Depending on how the input of raw material into the line is controlled, asynchronous lines may be further classified as open or closed (Hopp and Spearman, 2001). In a closed asynchronous line, the entry of a new product to be assembled is regulated by the amount of work-in-process in the line. Specifically, there are a fixed number of pallets/cards transporting the products circulating in the system, where each product is associated with a unique pallet/card. When the finished product arrives to the final station, the product is removed from the system and the pallet/cart returns to the beginning of the line at the entry point of the first station. A new product to be processed may enter the line, only when such

pallet/cart is available. An example of such type of systems is a closed loop conveyor assembly line, where the assembly process can be initiated on a product when a pallet is freed up by the completion of an assembly. In an open asynchronous assembly line, the assembly process can only be initiated when there is space available in the first station in the line or its buffer. That is, there is no mechanism regulating the entry to the front of the line that makes use of information beyond the first station.

Assembly lines can rely more or less on automation to transport products between workstations, to control the workflow rhythm or even to execute the assembly tasks on the workstations. In the following section, the trends regarding manual work in such systems are discussed.

2.2. Automation and Manual Work

Progress towards automating the assembly process has been slow, sporadic, and not all that successful. Back in the 1980s there was strong trend to automate assembly tasks as much as possible. Fully automated factories that would not have to consider the cost or variation problems caused by human involvement have been the ultimate goal of many companies. The leaders of this trend were companies ranging from Volkswagen to Fiat to General Motors. In the end most failed to produce desired results despite massive investments (MacDuffie *et al.*, 1996).

Automation has been implemented in many companies with false assumption regarding return on investment and often in an inappropriate manner. According to Bley *et al.* (2004), there are reports that a large number of companies that had invested in high automation have recognized that such approach was not suitable and again reduced their level of automation.

Industrial companies decreased the use of automation for several reasons (Figure 3), giving more importance to the needs of decreasing lot sizes and to the requirements for higher flexibility of capacity. Such change in the paradigm increased the inefficiencies when managing highly automated facilities and reduced the possibility to perform an advantageous amortization of the investment on such equipment during the production. This issue is particularly important for companies producing for markets requiring constant innovation – for such companies it becomes too expensive and too risky to invest in automated facilities, which would

be able to produce the desired product for that moment and for the following generations of that product. Flexibility on automation usually means high costs. These costs incur as a high initial investment, maintenance and repair costs during operation and on equipment modifications to produce new products, which can exceed investments for completely new facilities.

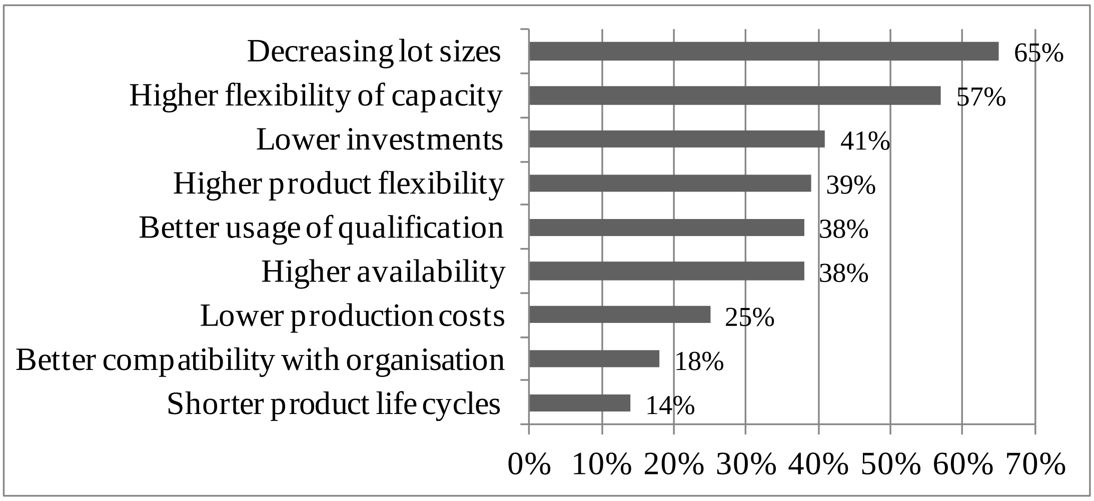


Figure 3 - Reasons for companies to reduce the amount of automation – adapted from (Bley *et al.*, 2004)

Therefore, the companies reduced high automation in production for a more efficient use of their qualified workforce and manual systems, demonstrated to have several advantages regarding flexibility to adapt to variations to production volumes, product variants and reduced product lifecycles. While automation has made some stages of the product manufacturing very efficient and less dependent on manual work cost, the manual processes are especially preferred in the final assembly of products (Butala *et al.*, 2002, Bley *et al.*, 2004, Michalos *et al.*, 2010). This preference is due to the adoption of a strategy which favours the postponement of customization, to the last stages of production, namely to the assembly (Yang *et al.*, 2004).

The manual assembly is advisable for situations where (Figure 4):

- The batch sizes are small;
- The required flexibility is high;
- The number of variants is considerable;
- The production volumes relatively low.

For other situations, “harder” automation solutions might be more advisable. However, the tendency regarding the customer demands point out to more flexible solutions.

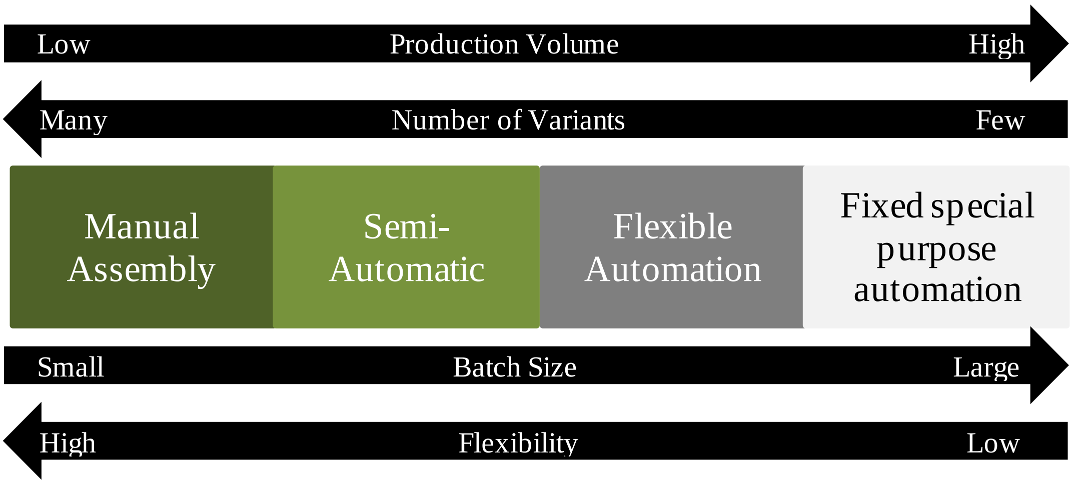


Figure 4 - Performance characteristics of assembly systems following different assembly principles – adapted from (Michalos *et al.*, 2010)

To assemble a product manually, the worker is required to execute a number of movements in a certain sequence. The following section will describe the content of the manual assembly task, according to the nature of each movement and the conditions under which it is made.

2.3. Work Elements

The research on manual assembly work in industrial settings dates back from 1881, when Frederick Taylor introduced the concept of work planning and standardization. However, the motion study field was pioneered with the collaboration of Frank and Lillian Gilbreth early in the 1900s (Niebel and Freivalds, 1999). They developed the motion study as an engineering and management technique. This interest in motion study first began with the observations of Frank Gilbreth of a brick-laying task. In studying bricklayers, he noted that the workers did not always use the same motions to build the brick-wall. These observations led him to seek a better way to perform tasks, by standardizing the workers movements – defined as work elements or “therbligs”, and keeping them to the minimum necessary.

While the Gilbreths developed the motion study to increase output through more effective use of time, Taylor focused on increasing speed and defining time standards. For Taylor, the time study "analysis" involved dividing a worker's job into its "simple elementary movements," discarding the "useless" ones, timing the quickest and best motions, and making their times the standard for the job (Price, 1992). The two techniques became integrated into a widely accepted method applicable to the improvement and upgrading of work systems, and spawned a variety of similar methods.

These methods became known as the predetermined motion time systems (PMTS), which are work measurement techniques with times established for basic human motions and used to make an (often) initial assessment of the average time for a task. Each work element is considered independent and additive; meaning, each element does not affect what happens before or after it. These systems are basically a database of basic motion elements and their associated normal time values, together with a set of procedures for applying the data to analyse manual tasks and establish standard times for the tasks. The most popular PMTS are Methods -Time Measurement (MTM), Work-Factor, Maynard Operation Sequence Technique (MOST), among others.

The basic motions identified in the MTM-1 system (Niebel and Freivalds, 1999) are described below. The MTM-1 is best suited to high production volume operations with relatively short cycle times. The identified basic motions consider the corresponding “therbligs” first defined by the Gilbreths.

- Reach (R): A basic motion element involving movement of the hand or fingers. Its purpose is to move the hand or finger to a new destination. The corresponding therblig is “transport empty”. If the hand is holding something during the motion, it is still classified as a reach if its primary purpose is to reposition the hand or fingers and not to move the object – for example, reaching for an object while holding a cigarette. The basic motion “Reach” depends on two work variables: (1) the distance moved and (2) the case under which the reach is performed. The case refers to such factors as whether the reach is toward an object in a known location or the object is jumbled amongst other object and must be searched out.

- Grasp (G): A motion element used by the fingers and hand to gain control of one or more objects. It is commonly employed as a prerequisite motion for performing the next basic motion, which is likely to be a move – for example grasping an object prior to moving it. There are five categories of grasp: (1) pickup, (2) regrasp, (3) transfer, (4) select and (5) contact.

- Move (M): A hand or finger motion whose primary purpose is to relocate an object. The corresponding therblig is "transport loaded". The move element includes pushing or sliding an object across a surface, so long as the hand controls the object. Move depends on three work variables: (1) the weight of the object being moved, (2) the distance of the move, and (3) the case under which the move is performed: (a) move object to other hand and stop, (b) move object to approximate or indefinite location, (c) move object to exact location.

- Position (P): A relatively short hand motion (no greater than 1in. (2.54cm)) employed to align, orient, or engage one object relative to another. It is usually preceded by a move. *Align* refers to the relative positioning of longitudinal axes of the objects; *orient* refers to the relative positioning of rotational axes of the objects; and *engage* refers to the insertion of one object into the other following either an alignment or an orientation. Accordingly, the position element may occur several times together depending on the number of separate positioning moves required. The work variables that affect the time for a position motion are the following: (1) pressure required to achieve the fit, (2) symmetry of the objects, and (3) ease of handling.

- Release (RL): A hand or finger motion element whose purpose is to surrender control of an object. There are only two cases of release: (1) the fingers open to the release and (2) contact release with no finger motion.

- Disengage (D): A hand and finger motion that causes the separation of two objects from one another, where the objects were previously held together by some force. Thus, disengagement breaks the force, resulting in recoil action by the hand.

The work variables that affect the time of a disengage motion are: (1) class of fit and (2) ease of handling.

- Turn (T): A basic motion element that involves rotation of the hand and wrist about the longitudinal axis of the forearm. The hand can be either holding an object (e.g. turning a dial on a machine) or empty. Turn depends on two work variables: (1) the degrees of turn and (2) resistance to the turn.

- Apply pressure (AP): An MTM-1 element that involves the application of force, but the force results in little or no movement. The force is usually applied by the hand and/or fingers, but the element refers to a force applied by any member of the body. There are two categories of apply pressure: (1) apply pressure alone and (2) apply pressure by a regrasp.

- Eye Travel, eye focus (EF) and reading: Basic eye usage motions that are important enablers for performing manual work. Frequently, the effect of the eyes during a motion element is usually already accounted. For example, a reach motion that required greater hand-eye coordination takes longer. However, there are situations when eye travel and/or eye focus are prerequisites for subsequent motions. In these cases, they must be counted as separate basic elements.

- Body, Leg and Foot Motion: Additional basic motions that involve moving the body, one or both legs, and/or one or both feet. The motions include walking, bending, stooping, standing from a seated position, and sitting from a standing position.

- Simultaneous Motions: Basic motion element that are performed at the same time. In general, it is desirable for more than one body member to be moving simultaneously. For example, it is desirable for both the right hand and left hand to be active during the task, not only sequentially but also simultaneously. When basic motion elements can be combined simultaneously, the time required for the combination is greater than the two parallel motions.

Other PMTS might be considered if: the task cycle times are long, it is more adequate for certain industries, it includes equipment handling, and so forth. These systems are used to define average times for the average worker, and consider that there are no significant differences among the workers. Manufacturing system designers use such standards to design the assembly system and balance it. There is a tendency to treat human performance in a similar way to machine functions by using "standard time" parameters for evaluations, and assume that any performance variations are considered in the time study techniques that are employed to derive these times (Fletcher *et al.*, 2008).

The manual assembly of products can require different types of human interaction. The following section, describes how the manual assembly tasks are classified from the point of view of the requirements towards the worker in a cognitive or motor sense, according to the existent literature on the subject.

2.4. Types of Manual Assembly Tasks

When studying the manual work and workers performance, it should be kept in mind that the human body is integrated with several sensory systems. These systems are stimulated by the interaction with the physical world, and carry information to the mind in order to produce an internal representation of those interactions. These representations are then processed by the cognitive system of the mind and are stored as memories within two levels: the long-term memory, which holds the mass of available knowledge, and the short-term memory. The short-term memory allows the use of the information, but in a limited way since it has limited storing capacity.

When the human element performs a complex task, it is required to retrieve information from the cognitive memories. The more complex the task the greater the need to go further into those cognitive memories and the longer it takes to activate the motor system to fulfil the task. Therefore, the tasks can be classified as motor tasks or cognitive tasks depending on the use of the cognitive system (Dar-El *et al.*, 1995). In order to assess the type of task in question it should be considered and analysed the need for making decisions when fulfilling the task. In a motor task, decision-making is seldom required, since all the steps are predefined – an example of such tasks would be to move an object between two pre-defined and

known locations. An example of a cognitive task would be to play chess, since each move requires evaluation and decision-making (Arzi and Shtub, 1997). In a manual assembly line, an inspection task will require more cognitive work elements than assembling components in a specific location. In a simple manual task, the use of the cognitive system is minimal. The first researchers pointing out the differences between the two types of tasks within the industrial context were Dar-El *et al.* (1995), focusing on the learning process. In order to better understand the cognitive and motor requirements of industrial tasks, these authors set up an experiment with two tasks involving the assembly of an electrical circuit. In one task, they had a diagram of the circuit to assemble and had to verify that the components where assembled in the right location in the circuit board, in order to obtain the correct sine wave signal. In the other task, they had to assemble the components without any regard to location or sequence. Therefore, the first task had larger cognitive requirements than the second task. These authors concluded that, as with many other industrial tasks, the cognitive requirements are dominant during the initial repetitions of the learning process. After a short number of repetitions, the motor elements tend to dominate the learning process (Figure 5). They also point out that this phenomenon is less dominant with simpler, manual tasks when cognitive elements play a minor role.

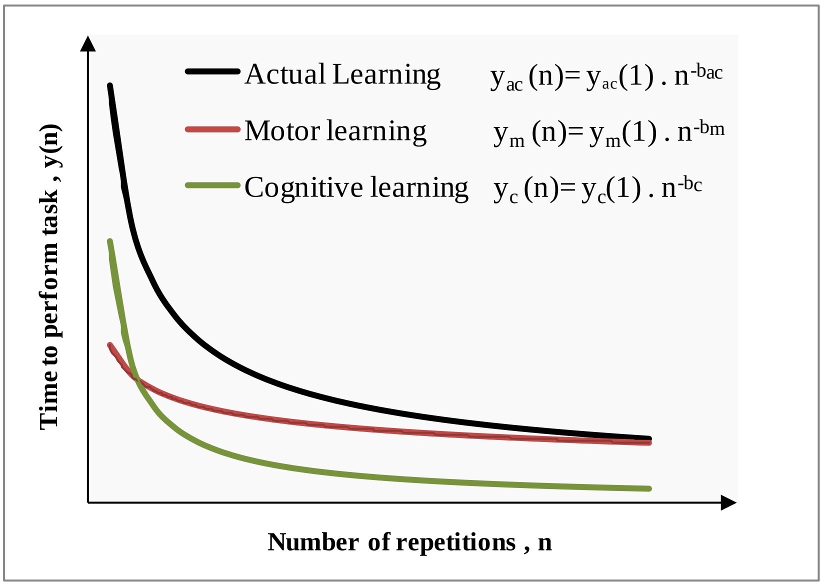


Figure 5 - Effect of the number repetitions, n, on the time to perform the task for motor learning, y_m, cognitive learning, y_c, and the combined effect, y_{ac} , with the respective learning rates b_m, b_c and b_{ac}– adapted from (Dar-El *et al.*, 1995)

Therefore, most of the industrial repetitive assembly tasks, for a fully trained worker, demand more of the motor elements rather than cognitive ones.

Nonetheless, several factors can influence the workers performance when executing an assembly task. The workers are integrated in a system as whole, consequently the way the system is configured to operate will affect the workers performance and the workers performance will consequently affect the system output performance. The following section, describes the previous findings on workers performance considering the influence of the assembly system policy on the worker, namely the pacing conditions.

2.5. Paced and Unpaced Work

The use of pacing comes from the approach of Ford to the assembly systems. Ford's approach was to not only standardize and simplify work, but also to impose a rhythm (through the use of a conveyor belt moving the product from one workstation to the next), to the workers performing the assembly work. The imposition of a rhythm assures a more constant and homogenous flow of the product in the system, since there is a pressure to perform the assembly tasks within a certain time interval and it also provides a degree of control over the workers performance. In addition, it is also important to understand how the different degrees of pacing might affect these performances. According to Dudley (1961), the distinction between a paced and unpaced operation is not always clear. In a more extreme case of pacing, the worker can have his performance rigidly paced by a machine, where the time available to perform the work is equal to time required to complete it. In the case of an unpaced work scenario, Dudley (1961) considers work situations "in which the speed of working is not determined or influenced by a machine, belt, or other worker". Nonetheless this author argues that there are several other factors, which might introduce some degree of pacing on the work, such as: presenting work in batches or as a continuous supply or articles. In the first case, the size of the batch and availability of further batches might introduce some pressure on the work. In the second case, expected or unexpected interruptions can influence the time to perform a task. In Dudley's laboratorial experiment (1961), he explores the differences between the two cases: unpaced work and pacing the system to the average speed measured in unpaced conditions. In his experiment, he

set up an apparatus involving a 1.524m (5ft) diameter turntable, near the circumference of which was located a number of fixtures equally spaced. In this apparatus, there was a supply of steel balls, provided in a drum mounted on a fixed table adjacent to a rotating disc. The balls were then fed down a chute to a fixed location on the platform in front of the subject performing the tasks, who had merely to grasp the ball and position it in the fixture of the disc (Figure 6).

Figure 6 - Apparatus presented by Dudley (1961) to test the differences between paced and unpaced performance

Using this apparatus, the author of this research tested in a first stage the unpaced performance, with the turntable stationary. The subject being observed performed a very simple manual task: grasp the ball, move it and position it in the fixture, move back to the chute to grasp the next ball, and so on. Each subject had to repeat this procedure, until the task time was considered stable. The author then set the turntable speed to this value and required the subjects to perform a 15 min run (in order to avoid fatigue) in these conditions. The conclusions of this experiment indicated that, little or no change was found in terms of output between the unpaced scenario and the scenario where the subjects were paced to their average speed (assessed during the unpaced scenario).

Two years after the publication of this previously mentioned research work, Murrell (1963), performed another laboratorial experiment where the differences between subjects' performance are mentioned. This author makes a more detailed distinction

between types of pacing based on previous studies. Murrell (1963) considers that there are two types of pacing: rigid systems and systems with margins. For the rigid systems, the author defines that in those situations there is a fixed period of time during which some task must be carried out. For the systems with margins, the author states that pacing of this type is often found when the workers are working at conveyor belts and must remove a part from the belt, process the part, and return it to the belt before the next part passes out of reach. In the referred study, the intent was to simulate an industrial task of repetitive inspection of electrical components. The subject had to place the component in a fixture and then perform a reading to check if it was in conformity. In the first part of the experiment, it was considered an unpaced scenario, and in a second a scenario of a system with margins. The experiment also included variations concerning the pace rates. Seven subjects (all female) were observed performing the inspection task and the output rates, in units per hours, were registered. With this experiment, the author concluded that, in general, the increasing speed in the pacing rate increased the number of misses. Moreover, there was a very restricted range of machine rates over which the subjects could be expected to produce the greatest output and that speed was below the mean speed in the unpaced scenario. In addition, the maximum output was obtained when a proportion of misses were allowed, and if no misses were permitted then the pacing speed had to be substantially below the unpaced scenario (ranging from -7% to -40%). In terms of differences among the observed subjects, Murrell (1963) reported that in fact, the pacing speeds for no misses varied greatly among the observed subjects, also that the mean output in unpaced conditions was considerably different from subject to subject, and that the optimum pacing rate for optimum output was also substantially different among subjects. In summary, there were large differences between subjects performing the inspection tasks, in any scenario. According to Murrell (1963), these differences were observable during the experiment:

> “G was grimly determined not to "miss" even if she wore herself out in the process, while D (who had had much more industrial experience) was calm and placid and produced a very consistent performance.”

Nonetheless, Murrell (1963) did not perform further analysis to investigate these differences.

More research on the differences between paced and unpaced performance was performed within the same period, but considering an industrial environment instead of a laboratorial experiment (Sury, 1964). This author, observed three workers, performing manual assembly of torch bulb holders. The worker tasks consisted in picking up a key part from an ample supply provided in the workstation (unpaced scenario) or from a conveyor (paced scenario). The main part was manually assembled to two other parts, which were contained separately in the boxes at the work place. The sub-assembly was then placed on a conveyor belt in front of the worker, standing vertically when being carried away on the conveyor belt. In the paced scenario, the rhythm was imposed by presenting new work to the worker at a constant feed rate with the delivery of new work passing beyond her control after a specific time interval. The main part had to be removed from the conveyor to process the work required and, after completion of the work task, the final assembly was returned to the conveyor. The feed rates were selected by reference to each worker average unpaced task time. Sury (1964) concludes, similarly to Murrell (1963) that the individual differences found in an unpaced working scenario are reflected in paced performance and that for maximum efficiency in paced work it is necessary to set different pacing rhythms for different workers. It is also concluded by the author that the task time distributions tend to become more “symmetrical” and closer to a normally distributed variable when such rigid pacing is imposed, as it had been previously pointed out in previous studies (Dudley, 1961, Dudley, 1963, Murrell, 1963). The conclusions of this author also indicate that the number of missed parts, increases exponentially with the increasing of the pacing rhythm, and that if misses cannot be tolerated then the feed rate should be 10% below the unpaced average performance. In addition, according to the results, a speed up effect can create a reduction in the average time of 8 to 10 %, at a feed rate of 10% above unpaced performance. Further research on this subject supports these findings (Franks and Sury, 1966).

Several years later, a study was published in collaboration with one of the referred authors (Knott and Sury, 1987) which focused on the task time distributions for unpaced work. These authors gathered data on eight experienced workers performing light assembly tasks in unpaced conditions. They observed that the task

time distributions tended to exhibit a positive skew and that the individual distributions showed a marked difference from the average value. In their paper, Knott and Sury (1987) reinforce their doubt on the possibility of homogeneity of the work-time distributions of individual subjects or the use of a "representative" distribution. In addition, they found marked differences in the coefficients of variation (average time divided by the standard deviation), ranging from 22% to 57%, which underlined limitations in the use of a "typical" coefficient of variation which would represent the normal worker variability. No further work, describing the heterogeneity on workers performance in scenarios involving different types of pacing could be found since then.[1]

At a certain point, the research on paced and unpaced work focused on the stress and other health related issues. For example, Johansson *et al.* (1978) studied workers on a Swedish sawmills factory and established a relation between the repetitiveness, physical constraint machine-regulation of work pace and high demands or continuous attention, and psychosomatic illness and absenteeism. However, there was not a consensus about how/why the workers might be adversely affected by paced work. According to other studies (Sheppard, 1974, Wanous, 1974) it was suggested that the stress effects of machine-paced work were in some way mediated by individual worker characteristics. Although the speed or rate of work can influence worker well-being and physical health, especially when the speed is controlled (Carayon *et al.*, 1999), the interactions between the person and their various environments (the psychosocial and organizational contexts) have a large influence in determining the experienced levels of stress (European Agency for Safety and Health at Work *et al.*, 2000). In addition, in the case of light assembly tasks, increasing the work pacing speed does not necessarily show to have an adverse impact in terms of biomechanical exposures and muscle fatigue (Bosch *et al.*, 2011).

The workers might respond to the same stimuli in completely different ways, both in terms of their psychological/physiological response as in terms of their performance on the job, underlining the prevalence and nature of human performance variability within organizations. In the next section, focus will be given to the heterogeneity and variability on the context of manufacturing systems.

[1] To the best knowledge of the author of this document.

2.6. Variability and Heterogeneity on Workers Performance

In any type of job which involves human factors, there will be naturally some amount of variability in the produced output. There have been research efforts in order to predict the amount of variability on the job, which attempted to define typical values which would represent the "normal" worker for different types of job. According to Hunter *et al.* (1990) review on academic literature about this subject, the different kind of jobs involving workers are divided in low, medium, or high complexity requirements. Moreover, they reported the following average coefficients of variation of the workers task times in service industry jobs:

a) 17.3% for routine jobs (low complexity), for example, grocery checker, telephone operator, customers inspector, clerks, and others;
b) 27.8% with decision making (medium complexity), that is, mail distribution, supply specialist, claims authorizer, and claims evaluators;
c) 46.2% for professional judgment (high complexity), that is, cartographic technician, attorneys (partners), physicians, and dentists;
d) 96.6% for life insurance sales;
e) 42.3% for non-insurance sales.

In fact, due to changes in the business paradigms, the focus on performance was broadened from simply looking for an average performance to extending the interest in variability. Variability reduction in systems has become the prevalent priority in many manufacturing and service organizations throughout the world for quite some time (Shunta, 1997, Tan, 1998).

Nonetheless, within the field of operations and production management it is frequent to find the assumption that the workers will perform their tasks all at the same pace and with the same amount of variability, under all conditions. In fact, simplification is a required step when designing or modelling a system. Even so, if researchers and managers do not have more solid information on the extent of these variations, they might not be aware of the consequences of these simplifications. According to Boudreau *et al.* (2003) there are several assumptions which are commonly used regarding the human elements in the manufacturing systems, such as:

- The workers are not a major factor of impact on systems performance, since many models consider machines without the workers, and therefore the human factor is completely omitted;
- The workers are independent, meaning that they are not affected by each other;
- The workers are deterministic and predictable. Their task times are deterministic and they are all identical, working at the same speed and responding to same incentives.

Assumptions like these might simplify the analyses. However such simplifications can have a significant impact on the accuracy of system performance prediction (Siebers, 2004). Differences in workers' average task times can cause blocking and starving in tightly-coupled systems and underestimating variability will cause the models to underestimate congestion and consequently be too optimistic in predicting system performance (Juran and Schruben, 2004).

As described by Baugous (2007), it should be accepted that the workers typically are not isolated but rather integrated in a system and their performance most often contributes to the performance of a system. On an assembly line, the level of performance of one worker will determine, in part, the level of performance of the next stage, and if any of these inter-dependent individuals vary their level of individual performance, the impact of the variation is multiplied throughout the process by the subsequent stations in the system. This author states, "The effective performance of an employee, regardless of how productivity is defined, should be viewed as an interaction between individual mean level of work performance and individual work performance variability."

There is some descriptive empirical work which investigates the magnitude of individual differences in work-rate variability (Doerr and Arreola-Risa, 2000). In the work of these authors, it is proposed that the worker performing the task may be the most significant source of variability in task completion times, even when the tasks vary a great deal. Doerr and Arreola-Risa (2000) performed an experiment in an industrial context, at a seafood processing plant, where the workers had to process different types and sizes of fish. They verified that the task or the day where the observations took place by itself, did not explain variability in the task times, while the worker and the worker-task interaction effects were significant. It

should be noted that in their experiment, it is considered that the manual fabrication line is unpaced, however, according to the description of the workflow policy in the observed system, there is interdependence between workers (therefore, some degree of pacing). Later on, Doerr *et al.* (2002) also consider the differences among workers and variability in the production and operations management field. These authors propose a theoretical model in which the workflow policy moderates the relationship between heterogeneity (between-individual differences in mean performance) and line performance, as well as the relationship between variability (within-individual differences in mean performance over time) and line performance. They propose that workflow policies can change the levels of heterogeneity and variability. Two workflow policies are considered, one in which the worker performs the assembly tasks within the workstation space and only passes the product to the following worker when he/she finishes the work, other where the workers are allowed to take over the work of another, proposing that being able to share the work would be more efficient. Following that work, the same authors (Doerr *et al.*, 2004) performed a laboratorial experiment of an order picking operation to measure the levels of worker heterogeneity and within-worker variability under these two conditions. They concluded that in fact, a work sharing policy did not improve the system efficiency. Nonetheless, they did observe that the slower subject was faster when work sharing was not permitted. In addition, they also concluded that the subjects' performance were more homogeneous in such conditions. They suggest that the research about the impacts of workflow policies on individual differences in average performance and variability should also focus on the behaviour of the group, besides the individual.

Regarding the interaction among workers, and its effect in individual performance, there is some work developed by Schultz *et al.*(2006) considering the hypothesis that the workers will adjust their speed to the speed of their co-workers. These authors performed factory observations, on a radio bezel assembly line, where the workers had to perform a number of aesthetic inspections and electronic testing. The workstations were configured in parallel, and there was some degree of system pacing, since there was a common buffer from where the workers had to pick up the components, which was fed at a fixed rate. It was observed that there was some degree of correlation between the speed of a worker and the speed of their co-workers. Nonetheless, they were not able to demonstrate that this correlation was

due to the workers reaction to their co-workers speed, as initially proposed. The lack of explanatory power of the regression is justified by the authors, by the large variation among workers, since one slope does not fit all workers. They conclude that workers do not react the same way as each other, and any model which merely looks for an average response leaves a lot of unexplained variability. It should be underlined, since the workers were picking up parts from a large buffer, some of the workers could in fact slow down or speed up the process at their workstation without causing a direct impact on the work of their peers, since the workstations were configured in parallel.

In fact, when the subjects' performances have some degree of interdependence, this can lead to free riding - the reduction of individual efforts due to the presence of others. This effect, documented in the field of Social Psychology (Williams *et al.*, 1981), results from the subjects realizing that their effort does not lead them to enjoy their full benefits, since these benefits are shared with their co-workers. Nonetheless, it can also have the opposite effect, since peer pressure might lead into increased effort (Kandel and Lazear, 1992). It is also suggested, that the free-riding effect is more frequent in low task attractiveness conditions, and that in high task attractiveness conditions, there is an increased effort from the subjects (Zaccaro, 1984). These mixed results are related to the previously mentioned research on interdependence among workers performance (Schultz *et al.*, 2006), since the individuals response to the same stimuli within a group working for a common goal might vary significantly from worker to worker.

However, in terms of variability among workers, there is evidence that setting productivity norms might not increase motivation in the work setting, but it can lead to a decrease in variability around the mean among group members (Schultz *et al.*, 1999). There is the suggestion that in such cases the slowest workers can sometimes speed up, but it is not assured that the fastest workers will not slow down.

In summary, there is variability on individual performance and evidence of heterogeneity on workers performance among a group. There are workflow policies which seem to have a moderating effect on both individual variability and variations among the group. Nonetheless, the amount of variation and how much of this variation is reduced or increased by the different policies is not clear on the published results until this date. In addition, an increased understanding of the

human factors in production and operations research is of great importance, and the human behaviour should not be seen as good or bad, but rather increase knowledge on what it means to have effective operations (Bendoly *et al.*, 2010).

Some authors have been using simulation as a tool to test the impacts of human variability and heterogeneity on assembly systems. In the following section, the available existent literature on this topic is discussed.

2.7. Simulation Studies on Human-Centered Assembly Systems

Simulation involves the development of descriptive computer models of a system and exercising those models to predict the operational behaviour and performance of the underlying system. Performance analysis was one of the first manufacturing systems applications of Discrete Event Simulation, and has proven to be one of the most flexible and useful analysis tools in this field (Smith, 2003). The major advantage of simulation models is that they enable experiments with the system without disturbing the real system in operation (Kelton *et al.*, 2009). In addition, because of the development of standard simulation software packages, simulation studies have become more accessible. However, as pointed out by Nyhuis *et al.* (2005) most simulation models only represent a single configuration of a real production system. As a consequence, the performance predictions indicated by the analysis of a simulation model apply to that particular configuration only.

Simulation was traditionally focused on technological aspects of the system (Ehrhardt *et al.*, 1994), such as machines, conveyors and robotics, while the workers were represented in the model often in a simplistic way, as a resource or a parameter of a technical device (Baines and Kay, 2002).

As discussed in the previous section, the non-deterministic behaviour of the workers, as well as the existent differences among a group of workers, is accepted as a characteristic of human-centered systems that needs to be further studied and dealt with. Some authors have been publishing work, integrating some of these aspects on simulation of systems performance. Shafer *et al.* (2001) use simulation to investigate how heterogeneous patterns of learning and forgetting effects found in empirical data affect the performance of an assembly line. These authors underline that the heterogeneity inherent to real populations of workers had not

been usually considered in previous studies, and that it can change the assembly line performance results significantly. Furthermore, with their study they demonstrate that considering only an average tendency for all the workers can result in substantial underestimation of the system productivity. Nonetheless, they do not consider variability on individual worker task times in their simulations. Tummaluri (2005) also addresses the dynamic behaviour of the workers task times. In his study, the author analysed the problem of assigning workers to various operations in a cellular system, with different skill levels and variations to those skills due to learning and forgetting over time, using discrete-event simulation. This author demonstrates that there is a large difference in the output results when using the classical approach of standard times or considering variability and variations on skill levels. However, Tummaluri's study (2005) has significant limitations since the assumptions made on workers task times were made with no empirical data support.

Some studies consider the variability on task times, supported by empirical data, as the one done by Lassila *et al.* (2005). These authors collected data on a human-centered assembly line in an automotive manufacturing company, in order to extract the processing time variations (minimum, mode, and maximum) in each observed workstation to use as an input in their simulation model. They also included random temporary unavailability from the workers. They make several recommendations for the system improvement based on the gathered data. Nonetheless, they do not include any difference among the workers observed. Therefore, they do not consider heterogeneity among workers.

Some authors considered other effects such as aging and variations on performance due to the circadian rhythms (biological endogenous cycles of 24hours, which for instance regulate sleep) (Baines *et al.*, 2004) to "fill" the gap between the simulation results and the actual output of the real system. These authors concluded that the performance output performance of the system modelled was not largely affected by variations of workers performance, caused by circadian rhythms or aging.

Once again, these authors did not consider any differences among workers.

There is work published in which the heterogeneity among workers is considered in the simulation models, meaning that both the average time and variability might be different from worker to worker (Juran and Schruben, 2004). Juran and Schruben

(2004) considered a two-worker, three-machine serial work sharing production cell, in which all three machines are identical. These authors constructed a physical prototype of the system in a laboratorial environment, gathered data on both task times and system output performance. They used Discrete Events Simulation to compare actual system performance and the simulation model output performance, including the heterogeneity in the workers performance. Their conclusions indicate that there is large difference in the obtained results between considering the workers with equal task time distributions or a scenario where each worker might have a different performance.

The simulation studies found in the available bibliographic references are considering more and more the variations in the workers performance. Several studies included temporal variations in average performance due to learning, forgetting due to production breaks (Shafer *et al.*, 2001), aging and physiological rhythms (Baines *et al.*, 2004), and others variability on the task times (Juran and Schruben, 2004, Lassila *et al.*, 2005). Nonetheless, little is found considering heterogeneity on performance, which concerns both differences in average and variability. There is also some lack of studies which use industrial data as an input, probably due to a decreased representativeness of the results.

3. Research Means and Methods

This chapter describes the research problem formulation and the methodology used to approach the research problem. Since this research is fundamentally based on the collection of industrial data, it is important to characterize the industrial framework where this data collection took place and its relation with the research problem formulation. In this chapter, the discussion on the advantages and limitations of the data collection in the industrial context is also discussed.

3.1. Research problem formulation

The assembly process of any product requires a set of tasks, which often are required to be performed manually. In order to design the assembly system, the time required for each manual task to be performed by the average worker, is assessed using time standards. Therefore, for each workstation there is an average time in which it is expected that the worker will have enough time to perform the assigned tasks. Nonetheless, in reality, when the system is running, the worker performs those assembly tasks with some degree of variation relatively to that average time – there is dispersion (or variability) on the task times, or in other words, in one occasion the worker takes less time to perform the task and in another more time than expected. In addition, each worker might have more or less variability in his/her task time distribution and work, in average, slower or faster than the other workers. Consequently, the system performance depends on the variable nature of the manual assembly process performance and the heterogeneity of the workers performance. Since the system performance is connected to the worker performance, it becomes important to quantify these variations in performance.

A lack on previously published work was found on the quantification of these differences from worker to worker, and on comparing how changes in the workflow policy, namely different types of pacing affect these variations.

In a preliminary stage of the research, data was collected on the workers task times in an industrial setting of actual operating system, and it was observed that the task times distributions varied greatly from worker to worker performing the same assembly work. Such type of variations is often the motivation for the introduction

of buffers between workstations even in balanced lines, to avoid starving and blocking of workstations, which *per se*, can also have an influence on the workers performance. Therefore, there is the need to further investigate such differences and analyse its extent and significance in a systematic way.

To compare task times among workers, two measures can be used to analyse the differences: the average task time and the dispersion (or variability) on those task times, since they are the most typical measures to describe a task time distribution. The average time provides the central tendency for the time a worker requires to perform an assembly task, and the dispersion gives information about how variable those observed times are. The dispersion on task times can be described by the following measures: standard deviation, variance, mean deviation, among others. However, the standard deviation becomes more practical to use since it is in the same units as the data. Data was collected on several workers performing the same tasks, and tested to ascertain if significant differences could be found in the dispersion of the task times (if there were workers with significantly more variable times than others), and in the average task times (if there were workers which were significantly slower or faster than others).

This preliminary assessment (further details on Chapter 4) revealed that in fact there were statistically significant differences in the workers performance, which further motivates the search for a solution for the quantification of those differences within a workers population. Therefore, one of the main objectives of this work, is to develop an approach which will help to quantify and map the differences within a workers population using the two aforementioned measures (average time and dispersion), in terms of deviation to a given expected performance of the workers population. Such approach enables the analysis of common behaviours when performing such type of assembly tasks, and an assessment of the differences among a group of workers in the two dimensions of performance, which more informally can be called speed (average time) and consistency (dispersion).

The next step of this research study is to analyse if differences in the workflow policy have a significant impact in the workers performance, using the proposed mapping approach. The term workflow policy is used to describe all of the methods management has available to control workflow. Previous research, indicated that changes in the workflow policy have an effect on the workers performance, and that those effects might be different from worker to worker. Based on previous studies

(Conrad, 1955, Dudley, 1961, Dudley, 1963, Murrell, 1963, Sury, 1964) it is expected that the existence of a time limitation to fulfil a task, will consequently impact on the workers' task time distribution. For any given task, there will be a minimum task time below which it is impossible to complete the task with an appropriate level of quality and stamina. In theory there is no upper limit, in practice however the controls of the system, management and peer pressure ensure that a task is completed in a reasonable time (Baines *et al.*, 2003). There is also evidence that the interdependence among workers has an effect on their performance (Schultz *et al.*, 2006). By setting a productivity norm (in this case a time limitation) to each worker, besides a common productivity goal, the pacing becomes more rigid. It is important to understand how the introduction of a time limitation affects the task times distributions within the group and individually.

In this study, two scenarios were considered: in one the workers are paced by a common productivity goal (system output in parts/h) and interdependences (serial line with reduced buffer space) and in the other a time limitation is added in each workstation. It is investigated, if the introduction of an imposed task time as a method of rigid pacing has a moderating effect on the deviations the workers have relatively to the expected performance.

In both scenarios, where the workers are paced by the system rhythm or an imposed task time, there is some degree of heterogeneity in the workers task times. These observations, gives motive to question what happens in the case the workers are working on their natural pace. It is proposed to investigate if in such scenario, the heterogeneity of performances is aggravated by the absence of a system or imposed rhythm, in order to understand the impact of the different workflow policies. This type of scenario can be found in assembly systems where the workstations are decoupled. An example of a decoupled system would be an assembly system with buffers between workstations large enough, that any workstation would never be starved or blocked.

After assessing the heterogeneity of performance in different scenarios, the research problem is further extended with the impact analysis of different types of workers performance in the performance of assembly systems. Considering different task times distributions, the objective at this point is to investigate how the several possible combinations of workers performance might affect the system output performance. In other words, to study the effect of workers heterogeneity, an

abstract situation is considered, in which the simulated assembly system is perfectly balanced (every workstation has the same work content) and unbuffered (the part can only leave the workstation to enter the following one, if the workstation is free). This way, the effect of the workers heterogeneity is analysed independently from the system balancing solution, and in an extreme scenario where the effects of the differences in task times are directly propagated from workstation to workstation. Several measures of performance can be used when evaluating the system performance. While it is important to assure that an assembly system is able to produce a given number of parts on average, the variability of the output also plays an important role on the system management on the short-term. Therefore, the system performance is analysed in terms of the inter-departure time distributions of each task time allocation scenario. The average time between parts exiting the system and the dispersion of those times is then extracted for comparison purposes with the baseline scenario – where in every workstation the allocated workers have the expected performance of the workers population (average task time and dispersion).

3.2. Research approach

This section describes the research approach and the main methods of analysis used during the course of this work.

As previously mentioned, the research began with the observation of an assembly system in operation, where it could be verified that there was a large dependence on manual work to perform the assembly tasks. From a initial data collection on workers task times, large differences from worker to worker were observed, there was the need to further investigate these differences. In the diagram presented in Figure 7, this step (hexagon in yellow) is represented as the trigger for the following steps. The next steps were the definition of sampling process used to collect further data on the workers task times and the analytical evaluation of the found differences (boxes in blue, representing the evaluation steps). The statistical tests (box in white) were used to analyse the task time distributions in regards to the normality of such distributions and the homogeneity of variances. Such tests were required to choose the type of tests to be used further – parametric or non-parametric. The details of these analyses are further discussed in Chapter 4. The

next step was the development of a mapping approach to visualize the differences assessed analytically (box in green). From that approach the possible types of performance were defined, based on the average task times and dispersions within a workers population. After defining the approach used to describe the different behaviours that could be found within a workers population, three diferent scenarios were considered (boxes in purple): the first scenario where the workers were paced by the system rhythm - Chapter 5, a second scenario where the system flow policy was modified in order to introduce a fixed time constraint – Chapter 6, and a third scenario where the subjects could perform the assembly tasks in an unpaced way – Chapter 7. For the two first scenarios the observations took place in an industrial setting (described in the diagram as Factory Observations) and the third scenario in a laboratorial environment (Lab Observations). For the second and third scenarios several statistical tests were rerun in order to verify the previous assumptions about normality and homogeneity of variances and to look for significant differences among workers task time distributions.

The results for the three scenarios were analised using the proposed mapping approach. Statistical analysis tools to compare the performance occurences for the three different scenarios, such as independency tests and correlation tests were performed.

At this point it was performed a comparison between the three scenarios which is discussed in Chapter 8.

The next step was to use the inputs from factory observations, regarding the different types of performance found in a workers population performing assembly tasks, and build simulation models of an assynchronous assembly system. These models were built using Discrete Events Simulation, in order to test the impacts of performance heterogeneity in such systems.

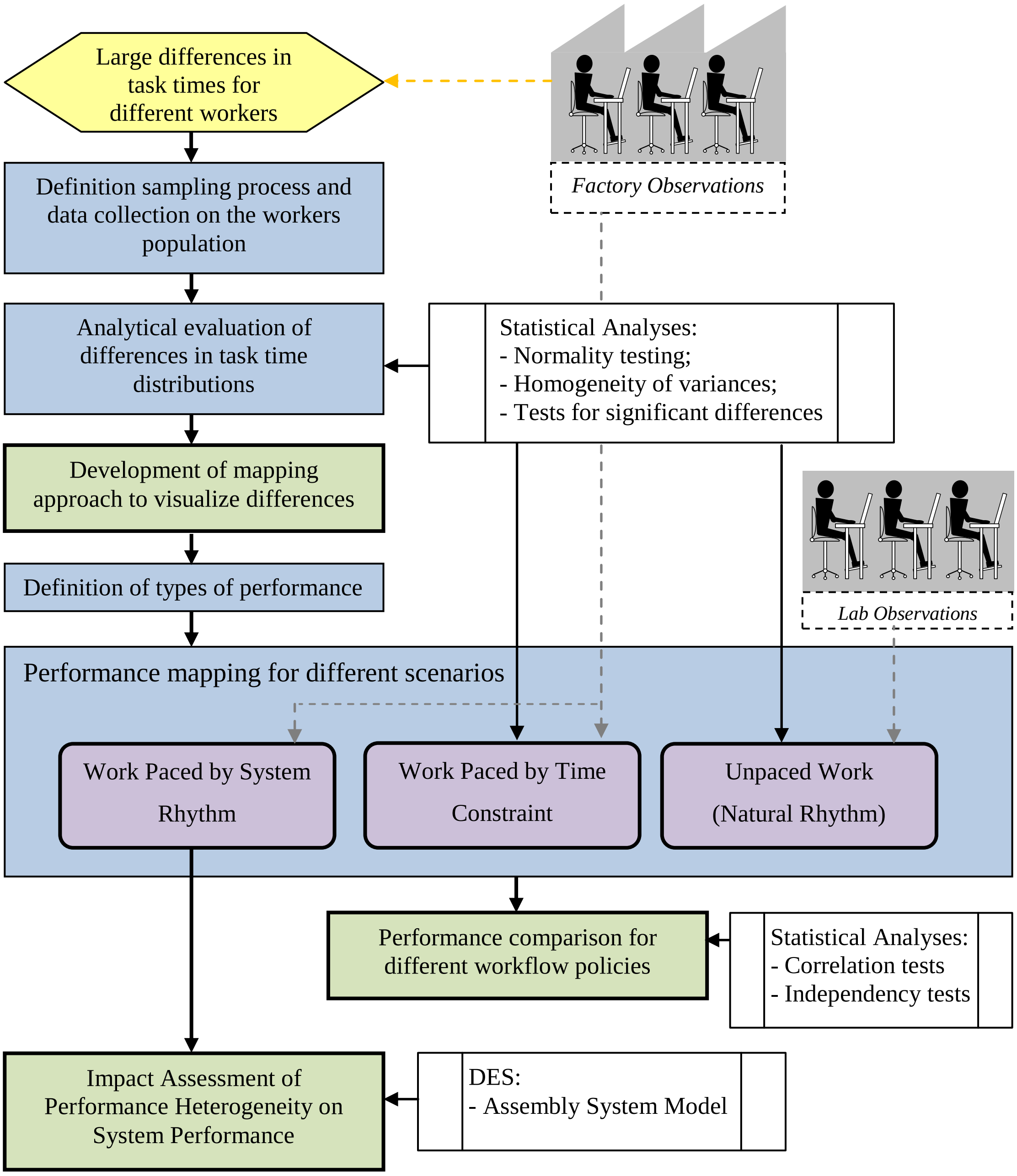


Figure 7 – Schematic diagram describing the research approach

3.3. Industrial framework

The workers performance cannot be accurately modelled in the same way as technological elements, as they are capable of independent actions and are susceptible to a much wider range of stimuli and responses. Laboratorial studies on human performance added valuable knowledge on this subject, but little is found

where industrial data is actually used. During the course of this research, whenever it was possible, it was opted to collect data on an industrial environment with the objective of describing workers performance in their “normal” working conditions, at the cost of not fully controlling the ambiance variables.

The data collection was performed with the collaboration of a manufacturing company located in Portugal. This company has competences in interior automotive kinematic components and their main products are components for the automotive interiors – namely kinematic components such as air vents, ashtrays, door handles, and radio bezels. The radio bezels are supplied to integrators, which then supply to the automotive manufacturers, while products like air vents and ashtrays are directly supplied to the automotive manufacturers.

The interaction with the selected company allowed the observation of an industrial reality where, beside other manufacturing processes, there was a dedicated area to the assembly processes of the produced kinematic components. The assembly processes within this company relied mostly in manual work tasks, as a large number of manufacturing companies do.

The assembly systems observed at the company were flow assembly lines connected by a loop conveyor (Figure 8). In this case, the product assembled on this assembly system was an automotive radio bezel. Several components (such as buttons), have to be assembled to the bezel (Figure 9), and the completed product verified, before being sent to the customer.

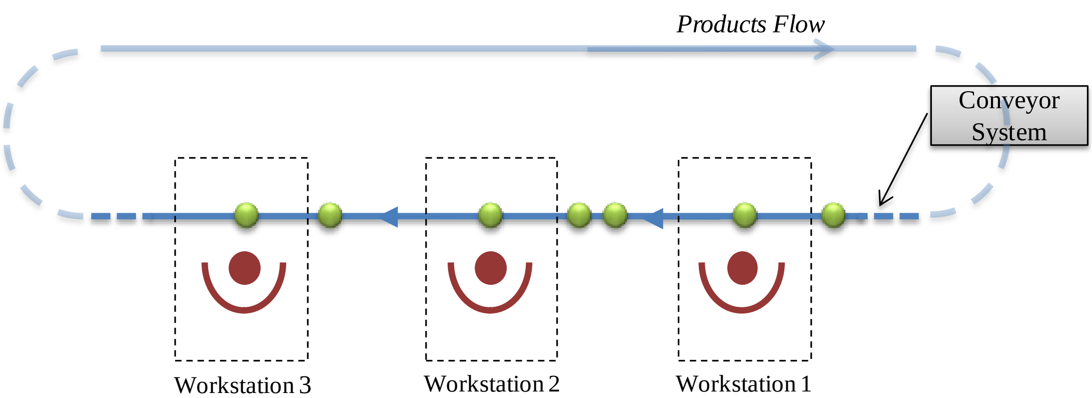


Figure 8 – Asynchronous closed loop assembly line observed at the industrial setting

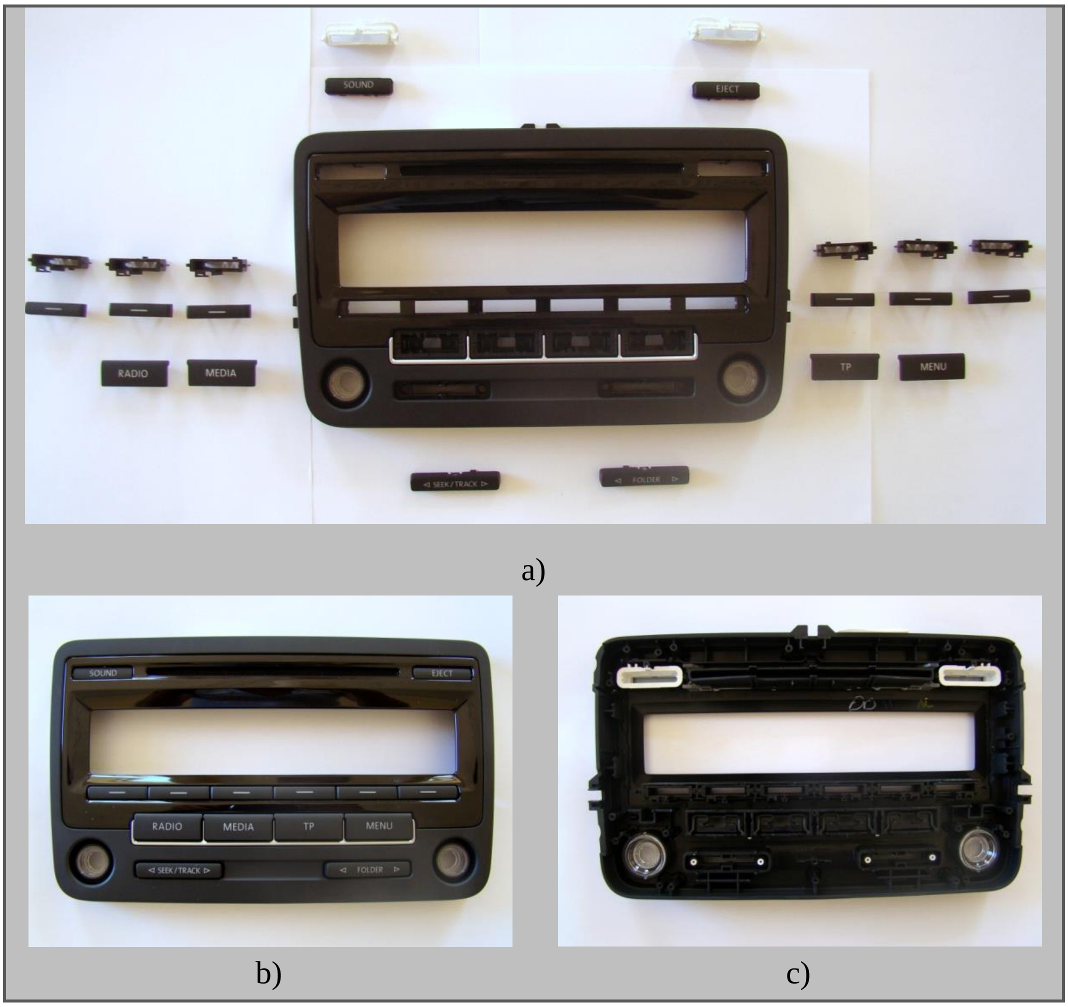


Figure 9 – Radio bezel assembled in the assembly line a) different components to be assembled b) product assembled - front c)product assembled - back

In such systems, there are dedicated jigs flowing in the conveyor, which provide a base to assemble the radio panel. This system limits the work-in-process, since it depends on the number of available jigs on the conveyor. Usually the number of jigs is the sum of the number of workstations with at least one jig between workstations (if the workstations have the same distance between them, and the line is balanced). In the observed system, the number of jigs was larger since the distance between workstations was not always the same. In such system every jig has to pass through every workstation to complete the assembly process. In the last workstation, the finished product is then removed from the jig, which (now empty) revisits the first workstation of the assembly system to initiate another assembly cycle. This kind of systems with circular transmission are referred as closed assembly lines since new

transmissions can only be released into the line when a jig is freed up by the completion of an assembly.

The observed type of system has an asynchronous transfer of products between workstations. The jigs are moved by the conveyor system, visiting each workstation, while the workers are usually fixed in their positions, with the jigs stopping (not the conveyor) at their workstation waiting for them to perform the assembly tasks assigned (Figure 10).

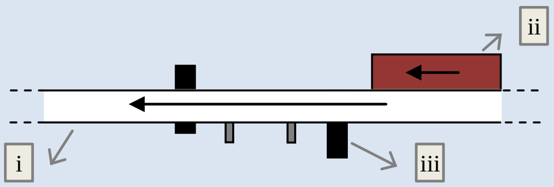
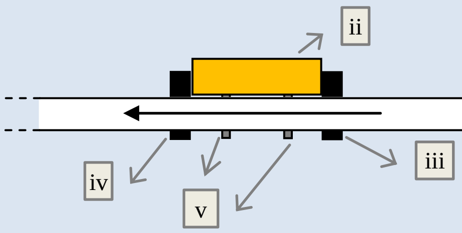
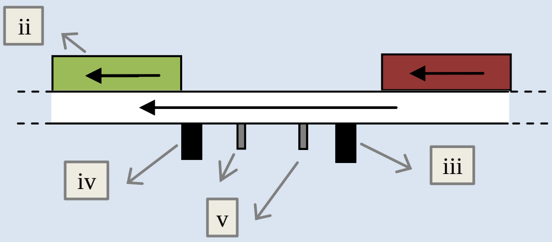
The loop conveyor (i) moves at a constant speed. The jig (with a part (ii) arrives to the workstation. The entrance is only allowed when the stop pin (iii) is down.	
The jig with a part (ii) remains at the workstation while the worker performs the assembly operations. The pin (iv) stops the jig movement, while other pins lift the jig from the conveyor (vi). The pins (iv) and (v) remain up whilst the worker does not signal the assembly tasks completion. During this time, no other jig is allowed to enter the workstation (iii).	
When the worker presses the pedal, signalling the assembly tasks completion, the pins (v) disengage from the jig and the pin blocking the jig movement (iv) moves down. The jig leaves the workstation (ii) becomes in contact with the conveyor and it is transported by it. Another jig can enter, since the pin at the entrance is down (iii).	

Figure 10 – Description of the mechanism controlling the entrance and exit of jigs in the workstation

In an asynchronous line, jobs are permitted to transfer between the stations independent of one another. Because arrivals to a station may not be coordinated with departures from that station, asynchronous lines may have buffers between the

stations to hold intermediate inventory, which in this case is limited by the number of jigs. In such type of assembly systems, a job is transferred from a workstation whenever it is completed, to the next if the buffer is not full (in this case if the number of jigs between workstations does not exceed the available space).

In the observed type of system, the workstations have a high degree of coupling between them, since it is a closed assembly line with low buffer levels. Therefore, if one workstation delays the release of a jig for too long, the next workstation will eventually starve. Moreover, if this delay is high enough, then the rest of the system becomes blocked and stops.

In terms of manual work within the observed systems, two significantly different types of tasks regarding the cognitive or motor requirements from the workers were identified:

- Tasks with a higher motor content than cognitive, where the workers are required to assemble the product physical components;
- Tasks with a higher cognitive content than motor, where the workers have to perform visual and functional inspections, implying a certain level of analysis and decision making regarding product conformity.

Most of the tasks at the observed assembly line have a high motor content, with the high cognitive content tasks located at the end of the assembly process. In the last workstations, the product has to pass the final aesthetic and functional inspections. If the product follows the defined quality standards, it is then packed to be sent to the customer. Although workers perform some kind of visual inspection during the high motor content tasks (they may have to reject or rework the in-assembly product), this is not their main function, which clearly relies on motor skills. The focus of this analysis is on the task times of high motor content tasks.

3.4. Advantages and limitations of data collection in an industrial framework

The data collection within an industrial framework brings significant challenges to conduct a research on human factors. Besides the ethical and practical issues, which impose natural barriers to the research on human beings, there are concerns about

the workplace and accessibility problems that further limit the research methods that can be used. Therefore, in order to perform research within a company compromises have to be made. The researcher when collecting data in such environment must be flexible and ready to use a variety of data collection and analysis methods to the addressed problems, as to take advantage of the presented opportunities.

The data collection approach in such context is determined by a combination of the research objectives, the industry purposes when collaborating in the research, and practical limitations in potential research settings available.

The laboratorial studies of human behaviour are an artificial setting to observe subjects reactions. The (industrial) field is a setting where it is possible to study the human behaviour in regards to the task at hand in its natural environment. The laboratory provides a highly controlled setting, in which experiments can be conducted so that the confident inferences can be drawn on the effects of a given variable. However, it typically lacks generalization or external validation. The field will often give greater external validity since it is the natural setting, but it is at the cost of losing control over the variables affecting the studied behaviours, due to limitations on research designs in the field (Spector, 2001).

The automotive industry is especially competitive and, as a natural result, there are strict limitations when performing observations in a company, which is part of such industry, due to confidentiality issues. In this case, the use of photographing/recording devices was off limits, meaning that all the time records collected at the industrial context were performed using a stopwatch and by one analyst – the author of the present document. The records were introduced in a personal computer where the data was stored in Excel files for analysis. In addition, in the context of the automotive manufacturers' suppliers, the contracts are often dependent on the approval of the assembly system used to build the supplied product. Therefore, the company had practical limitations to the modifications it could introduce in the studied assembly system. Further details on the data collection procedure can be found in Chapter 4.

Nonetheless, even with the natural limitations imposed by the research context, the data collection and analysis in such framework is a valuable input when studying human behaviour for both the industry and the academic field.

4. Data Collection and Preliminary Task Times Assessment

As mentioned previously this research relies on collecting task times of several workers operating under different assembly line flow policies. The data collection for the two first scenarios took place within an industrial framework, where there was the opportunity of registering task times in a factory environment.

This section describes the observed assembly tasks and the used sampling process to collect the data. The time distributions are described and analysed and the workers performance heterogeneity assessed.

4.1. Assembly tasks description

On the observed workstations, the workers have seats in front of the conveyor, and the workers can see the worker immediately ahead and behind. When a new jig enters in a workstation, the allocated worker assembles the required components. When the worker completes the assembly tasks, the worker presses a pedal in order to the jig to leave the workstation, so that another jig can enter to reinitiate the workstation assembly cycle. During this process, the worker has several components dispensers just in front of him/her from where the required components are available (in Table 2 the typical work content is described for a workstation, as well as the basic motion elements required). It is possible to have a queue of inbound jigs before each workstation, accommodating the impact of irregular output rates among workstations. The dimension of these waiting lines of inbound jigs is restricted to a few units, not only because of the space constraint between workstations, but also because of the limited number of available jigs.

Table 2 – Description of the work elements and basic motion elements required to assemble the buttons of the radio bezel

Work Elements Description	Basic Motion Elements
1. Approach both hands to the components dispensers placed in a fixed location;	Reach
2. Pick one component with each hand from the components dispenser;	Grasp
3. Move the two components close to the jig where	Move

the product is placed;	
4. Position the components in order to assemble them to the product;	Position
5. Apply small pressure with thumbs in order to assemble components to product;	Apply Pressure
6. Repeat steps 1 to 5 for the next two pairs of components (6 components in total);	-
7. Press pedal for the product to leave the workstation	Foot motion

The observed assembly system functions in an 8 hours shifts basis, working two shifts per day, and workers rotate their positions on the assembly system each two hours.

4.2. Sampling process

In order to establish the required number of readings (time measurements) of each worker performing the assembly tasks, it was used a statistical method, based on a preliminary study of 30 readings of two randomly chosen workers (Table 3). Equation 1 describes the calculations to obtain the required number of readings (n_i).

Equation 1– Calculation used to obtain the required number of readings, n_i

$$\boldsymbol{n_i} = \left(\frac{\boldsymbol{st}}{\boldsymbol{r\bar{x}_i}} \right)^2$$

Table 3 – Average times and dispersions for two randomly chosen workers

	Worker A	**Worker B**
$\bar{x}_i$ [sec]	10.9	11.6
s_i [sec]	1.5	1.9
n_i	32	45

This calculation is based on the sample standard deviation (s_i), the t-Student distribution value (t) for 29 degrees of freedom and for a 95% confidence level and

5% (r) maximum percentage of error, and the average value ($\bar{x}_i$) obtained for the 30 preliminary time readings for each of the two workers. To achieve the intended precision, according to Equation 1, 32 and 45 readings are required for the first and second measured worker respectively. It was considered that the number of readings should be rounded up to 50 to assure that the "natural" variability of the tasks processing by each and among all workers is captured with a high confidence level and low margin of error. Instead of observing a small number of workers performing the same assembly tasks for a long run, the objective of this study was to observe as many workers as possible and performing different assembly tasks to investigate the differences between the observed task times – meaning, the heterogeneity of performance.

During the assembly process in the described system, several situations may occur which are part of the productive process, but are not directly related with the worker motor time-performance. In some cases, the worker might be idle due to a blocking in an upstream or downstream point of the system; the worker might be working but not be assembling components, instead he/she is dealing with some non-compliance in the production process; the worker may have to assist an assembly system colleague; among other random situations. The goal of observing the workers was to analyse their task times when performing high motor content operation. Given the previous pointed facts, a valid reading was the time the worker actually took to fulfil the set of elementary assembly tasks assigned to his/her workstation. In the case the worker could not assembly a component at the first attempt, the reading was considered valid if the component wasn't rejected, to make sure the task times were not dependent on the quality of the components fed to the assembly system. Reflecting only the intended repetitive manual tasks, the registered time measurements were, as much as possible, independent of the assembly system balancing, production quality issues from previous production processes (such as plastic injection moulding and painting) and other unexpected events.

All the readings were made by the same analyst[2] and using the same digital chronometer. The observed workers were assured that the measurements were being made strictly for research purposes and that no personal identification would

[2] The author of this research.

be registered with the readings. During the initial observations, the workers got acquainted with the presence of the analyst and collaborated in clarifying doubts about the assembly process.

Four workstations (FL1A, FL1B, FL1C and FL2D) of high motor tasks content were observed in the described asynchronous flow line. All these workstations had the same type of basic motion elements as the ones described previously (Table 2). The differences between workstations were in the number of components required to assemble (repetition of the same sequence of basic motion elements) and small differences in the type of components to assemble (e.g. size of the button to assemble).

4.3. Observed task time distributions

It was possible to collect data from 26 different workers, and 46 sets of time readings (some of the workers were observed working at different workstations). All of the observed workers were female and had at least a 4-week training period in that assembly process. A short questionnaire at the end of the readings, assured that none of the workers observed had any job related health issue in the last two months and were working in assembly processes. The workers were very collaborative and did not pose any objection to answer to these questions.

Several workers were observed performing assembly tasks at different workstations. From the initial collected data for workstation FL1A, it was verified that there were large variations in terms of average and standard deviations (Table 4).

Table 4 – Average times and dispersions registered at workstation FL1A for the different workers observed

Worker *i*	$\bar{x}_i$ [sec]	s_i [sec]
ID1	11.29	1.31
ID2	14.31	1.62
ID3	12.70	1.45
ID4	10.23	1.01
ID5	10.62	1.12

ID7	12.63	1.56
ID8	11.18	1.47
ID9	15.00	1.89
ID10	11.33	1.54
ID11	12.25	1.91
ID13	11.64	1.74
ID21	12.66	1.35
ID22	13.17	1.90
ID23	13.90	1.82
ID24	12.11	1.51

Therefore, having as focus the performance heterogeneity, in a first approach the objective is to reply to the following question: If different workers are observed performing the same assembly task, are their task times significantly different from worker to worker?

In statistical studies, when there are several populations to compare, the Analysis of Variance or ANOVA is a common procedure to test hypotheses concerning means (*NIST/SEMATECH*, 2012). When using this procedure, the cases should be independent, the sampled populations must be normally distributed and must have equality (or "homogeneity") of variances, called homoscedasticity- meaning, the variance of data in groups should be the same.

The assumption of normality in the time distributions of each worker might be debatable, and there are several researchers that published work on the use of other distributions with a better fitting to the empirical data than the normal distribution. In addition, attempts to fit particular statistical models with sparse statistical information per worker might bring to the analysis an uncomfortable level of systematic uncertainty, which often lead to accuracy problems.

In order to assure the proper use of the ANOVA, the following paragraphs describe the required assumptions testing.

The statistical tests were performed using the SPSS version 18, software commonly used for statistical analysis.

To test the assumption of normality it was used a well-known test of normality: Shapiro-Wilk Test (Shapiro and Wilk, 1965). The Shapiro-Wilk test is more appropriate for small sample sizes (< 50 samples) but can also handle sample sizes

as large as 2000. In this case, the sample size (*n*) for each observed worker is equal to 50. This test checks the normal assumption by constructing the *W* statistic, which is constructed by considering the regression of ordered sample values on corresponding expected normal order statistics, which is linear for a sample from a normally distributed population (Royston, 1992). *W* is positive and less than or equal to one.

The null hypothesis is that the population is normally distributed, and the alternative hypothesis is that it is not normally distributed. If the probability, *p*, of obtaining a test statistic at least as extreme as the one that was actually observed is below the significance value, *α* (in this study it is considered 0.05 as acceptable), then the data significantly deviates from a normal distribution.

According to the test results (Table 5 and Table 6), there are several sets of observations, in which it is not possible to assume normality ($p \leq 0.05$), therefore the first assumption when using ANOVA is violated.

Table 5 - Shapiro-Wilk test results for normality of time distributions – Workstations FL1A and FL1B

	FL1A					FL1B			
Worker	***W***	***n***	***α***	***p***	**Worker**	***W***	***n***	***α***	***p***
ID1	0.986	50	0.05	0.809	ID1	0.919	50	0.05	**0.002**
ID2	0.941	50	0.05	**0.015**	ID2	0.879	50	0.05	*
ID3	0.982	50	0.05	0.628	ID3	0.984	50	0.05	0.709
ID4	0.977	50	0.05	0.417	ID4	0.988	50	0.05	0.884
ID5	0.957	50	0.05	0.067	ID7	0.921	50	0.05	**0.003**
ID7	0.975	50	0.05	0.366	ID8	0.977	50	0.05	0.450
ID8	0.951	50	0.05	**0.037**	ID9	0.968	50	0.05	0.183
ID9	0.982	50	0.05	0.637	ID10	0.961	50	0.05	0.096
ID10	0.976	50	0.05	0.404	ID18	0.954	50	0.05	0.052
ID11	0.971	50	0.05	0.244	ID20	0.946	50	0.05	**0.022**
ID13	0.973	50	0.05	0.313	ID21	0.977	50	0.05	0.444
ID21	0.977	50	0.05	0.444					
ID22	0.960	50	0.05	0.086					
ID23	0.945	50	0.05	**0.021**					
ID24	0.967	50	0.05	0.168	* *p*<0.0005				

Table 6 - Shapiro-Wilk test results for normality of time distributions – Workstations FL1C and FL2D

	FL1C					FL2D			
Worker	***W***	***n***	***α***	***p***	**Worker**	***W***	***n***	***α***	***p***
ID1	0.942	50	0.05	**0.016**	ID241	0.985	50	0.05	0.774
ID2	0.973	50	0.05	0.301	ID242	0.952	50	0.05	**0.040**
ID3	0.971	50	0.05	0.256	ID243	0.975	50	0.05	0.364
ID4	0.974	50	0.05	0.344	ID244	0.970	50	0.05	0.223
ID7	0.921	50	0.05	**0.003**	ID245	0.981	50	0.05	0.611
ID8	0.974	50	0.05	0.326	ID246	0.963	50	0.05	0.115
ID9	0.968	50	0.05	0.183	ID247	0.952	50	0.05	**0.043**
ID10	0.913	50	0.05	**0.001**	ID248	0.961	50	0.05	0.098
ID18	0.962	50	0.05	0.106	ID249	0.969	50	0.05	0.206
ID20	0.948	50	0.05	**0.028**					
ID21	0.973	50	0.05	0.308					

In statistics, Levene's test is an inferential statistic used to assess the equality of variances in different samples (Levene, 1960). Is the most practical test for heteroscedasticity, since it is less dependent on conditions of normality in the population (*NIST/SEMATECH*, 2012). It tests the null hypothesis that the population variances are equal. The significance of the test statistic *F*, is calculated from the F-distribution with degrees of freedom $df1=k-1$ (number of groups, in this case, workers, subtracted by one) and $df2=w-k$ (total number of samples, in this case, total number of registered task times ($n \cdot k$), subtracted by the number of observed workers).

If the resulting p-value of Levene's test is less than the critical value (α), the null hypothesis of equal variances is rejected and it is concluded that there is a difference between the variances in the population. SPSS calculates the absolute difference between each observation and the group mean variance and then performs an ANOVA on those differences.

The results (Table 7) indicate that the assumption of homoscedasticity is violated. These results were not surprising, since the observed dispersions showed large variations from worker to worker, in every workstation.

Table 7 – Levene's test results for homoscedasticity of performance in workstations FL1A, FL1B, FL1C and FL2D

Workstation	Levene's test results
FL1A (k=15 workers)	$F(df1=14, df2=735)= 3.971$, $p<0.0005$, $\alpha=0.05$
FL1B (k=11 workers)	$F(df1=10, df2=539)= 9.279$, $p<0.0005$, $\alpha=0.05$
FL1C (k=11 workers)	$F(df1=10, df2=539)= 9.475$, $p<0.0005$, $\alpha=0.05$
FL2D (k=9 workers)	$F(df1=8, df2=441)= 2.883$, $p=0.004$, $\alpha=0.05$

The previous stated evidences demonstrate that the ANOVA test is not suitable to evaluate the differences between the workers task times. In such cases, there are testing alternatives, as the Kruskal-Wallis test (Kruskal and Wallis, 1952). It is a distribution-free (non-parametric) test. The Kruskal–Wallis test does not assume a normal population. It is similar to ANOVA, but uses rank-transformed data. The test statistic, H, approximates a chi-square distribution with k-1 degrees of freedom if the null hypothesis of equal populations is true.

4.4. Significantly different task times

The tests were performed for all the four workstations where the readings were collected. For workstation FL1A it was possible to conclude that the null hypothesis (H0: all samples are drawn from the same population, or equivalently, from different populations with the same distribution) should be rejected since $H(df=14)= 301.378$, $p<0.0005$ and $\alpha=0.05$. This means that at least one sample median is significantly different from the others, and therefore at least one worker performs differently from the others. The same conclusions were drawn for the workers observed performance in the other workstations (Table 8).

Table 8 – Kruskal-Wallis test results for workstations FL1A, FL1B, FL1C and FL2D

Workstation	Kruskal-Wallis test results
FL1A (k=15 workers)	$H(df=14)= 301.378$, $p<0.0005$, $\alpha=0.05$
FL1B (k=11 workers)	$H(df=10)=305.451$, $p<0.0005$, $\alpha=0.05$
FL1C (k=11 workers)	$H(df=10)=290.280$, $p<0.0005$, $\alpha=0.05$
FL2D (k=9 workers)	$H(df=8)=213.372$, $p<0.0005$, $\alpha=0.05$

At least one of the samples is different from the other samples, but the test does not identify where the differences occur or how many differences actually occur. In order to understand if there is more than one worker that has a significantly different time distribution, it was performed a Kruskal-Wallis 1-way ANOVA pairwise comparison. This test is an extension of the Mann-Whitney test and the nonparametric analogue of one-way analysis of variance (Sheskin, 2004).

All possible pairwise hypotheses were tested for the all the workers, k, observed at each workstation, and it was considered a significance value of α=0.05. There are $k(k-1)/2$) possible combinations. To decide if the assessed pairs can be considered the same, the SPSS uses an adjusted p-value (p_{adj}) in order to reduce the Type I error rate, that is, the probability of rejecting at least one pair hypothesis given all pairwise hypotheses are true. The adjusted p-value is calculated by multiplying the p-value by the number of possible combinations. From the results for FL1A (Table 9), it could be observed that it is not the case that only one worker is affecting the results of the Kruskal-Wallis test. There is in fact a large heterogeneity among the workers performance observed at this workstation.

Table 9 - Pairwise comparisons for workers at FL1A - Detailed outputs in Annex A.1

FL1A	ID1	ID2	ID3	ID4	ID5	ID7	ID8	ID9	ID10	ID11	ID13	ID21	ID22	ID23	ID24
ID1		○	○	■	■	○	■	○	■	■	■	○	■	○	○
ID2			○	○	○	○	○	■	○	○	○	○	○	■	■
ID3				○	○	■	○	○	○	■	■	■	■	■	■
ID4					■	○	■	○	■	○	○	○	○	○	○
ID5						○	■	○	■	○	■	○	○	○	○
ID7							○	○	■	■	■	■	■	■	■
ID8								○	■	■	■	○	■	○	○
ID9									○	○	○	○	○	○	■
ID10										■	■	■	■	○	○
ID11											■	■	■	■	○
ID13												■	■	■	○
ID21													■	■	■
ID22														■	○
ID23															■
ID24															
■= $p_{adj} \geq 0.05$ (51 pairs out of 105); ○= $p_{adj} < 0.05$															

For workstations FL1B and FL1C, the results are similar. The results of the pairwise comparisons indicate that the performance are also quite heterogeneous – Table 10 and Table 11. Using this approach for FL2D (Table 12) it was noticed, that there was just one worker with task times significantly different from all the others, therefore the Kruskal-Wallis test was performed again, removing the observations of worker ID248. Once more the output indicated that, the task times could not be considered the same ($H(df=7)=129.869$, $p<0.0005$, $\alpha=0.05$).

Table 10 - Pairwise comparisons for workers at FL1B - Detailed outputs in Annex A.2

FL1B	ID1	ID2	ID3	ID4	ID7	ID8	ID9	ID10	ID18	ID20	ID21
ID1		○	○	■	○	○	○	■	○	○	○
ID2			■	■	■	○	○	○	○	■	■
ID3				■	■	○	○	○	○	■	■
ID4					○	○	○	■	○	○	■
ID7						○	○	○	○	■	■
ID8							■	○	■	■	■
ID9								○	■	■	○
ID10									○	○	○
ID18										○	○
ID20											○
ID21											

■= p_{adj}≥0.05 (21 pairs out of 55); ○= p_{adj}<0.05

Pairwise comparisons for workers at FL1B

Table 11 - Pairwise comparisons for workers at FL1C - Detailed outputs in Annex A.3

FL1C	ID1	ID2	ID3	ID4	ID7	ID8	ID9	ID10	ID18	ID20	ID21
ID1		○	■	■	○	○	○	■	○	○	○
ID2			○	○	■	○	■	○	■	■	■
ID3				■	○	■	○	■	○	○	■
ID4					○	■	○	■	○	○	○
ID7						■	○	○	○	■	■
ID8							○	■	○	■	■
ID9								○	■	■	○
ID10									○	○	○
ID18										○	○
ID20											■
ID21											

■= p_{adj}≥0.05 (23 pairs out of 55); ○= p_{adj}<0.05

Table 12 - Pairwise comparisons for workers at FL2D - Detailed outputs in Annex A.4

FL2D	ID241	ID242	ID243	ID244	ID245	ID246	ID247	ID248	ID249
ID241		○	○	○	■	■	○	○	○
ID242			■	■	○	○	■	○	■
ID243				■	○	○	■	○	■
ID244					■	■	■	○	○
ID245						■	○	○	○
ID246							○	○	○
ID247								○	■
ID248									○
ID249									
■= p_{adj}≥0.05 (14 pairs out of 36); ○= p_{adj}<0.05									

The tests performed indicate that the workers have significant differences when the task times are compared between them. Additionally, it was verified that it is not just one or two workers that are performing in a different way from all the others by chance. There is sufficient reason to believe that the workers performance varies greatly from worker to worker.

4.5. Influence of the workstation work content

The observed task times for different operators at the same workstation cannot be considered all the same. As it was stated out previously, a group of workers was observed repeatedly performing assembly tasks at different workstations. There is reason to believe that the same worker will perform similarly, independently of the workstation he/she is allocated to, since the workstations have the same type of basic motion elements.

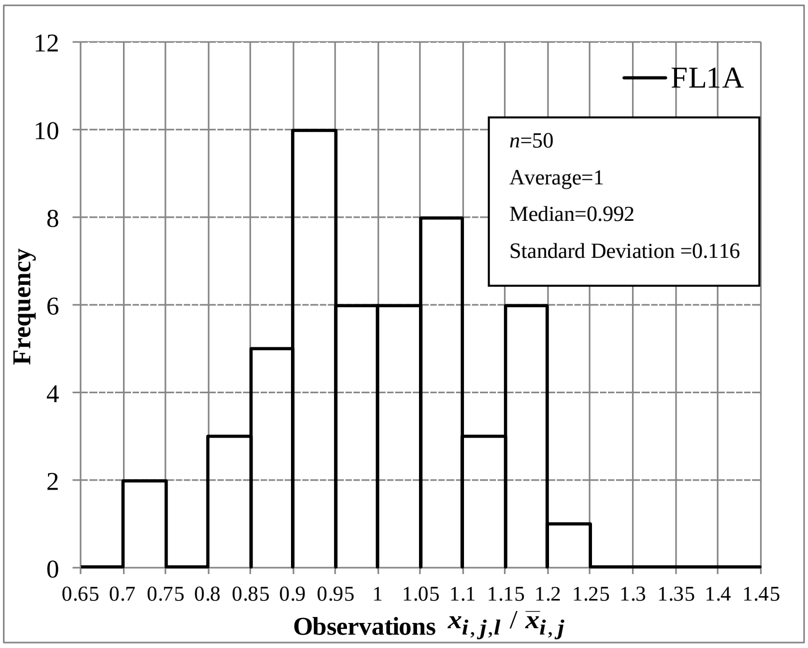
Before formally investigating this question it should be noted that each workstation has its own cycle time, since the assembly system is not perfectly balanced. If the cycle time of the workstation is larger, the average and the dispersion (standard deviation) of the worker task time are expected to be larger. In fact, the work content of each workstation is a sum of several elementary operations that need to

be performed. A larger task will require more basic motions elements. Each basic motion element has its own time variance. So the time variance of a larger task, as the sum of basic motions variance, becomes also larger.

In order to compare the time distributions of the same worker, working at different workstations, each time reading was divided by his own average time. To describe this calculation, it is considered that $\bar{x}_{i,j}$ represents the average time the worker *i*, presented in workstation *j*. Note that for each worker, *i*, was sampled *n* (*l*=1,2,…*n*=50) times. Therefore, each one of the *n* readings, was divided by $\bar{x}_{i,j}$. The proposed scaling is described by the relation $x_{i,j,l} / \bar{x}_{i,j}$. When performing this scaling for each task time observation, the distributions suffer a shift (the average is set to 1) but its shape is kept, (the coefficient of variation remains the same) allowing comparisons among all similar workstations (Figure 11). The average task time in each workstation can be different (since in workstation with more work content, the worker will take longer), but with this scaling the time distributions become adimensional.

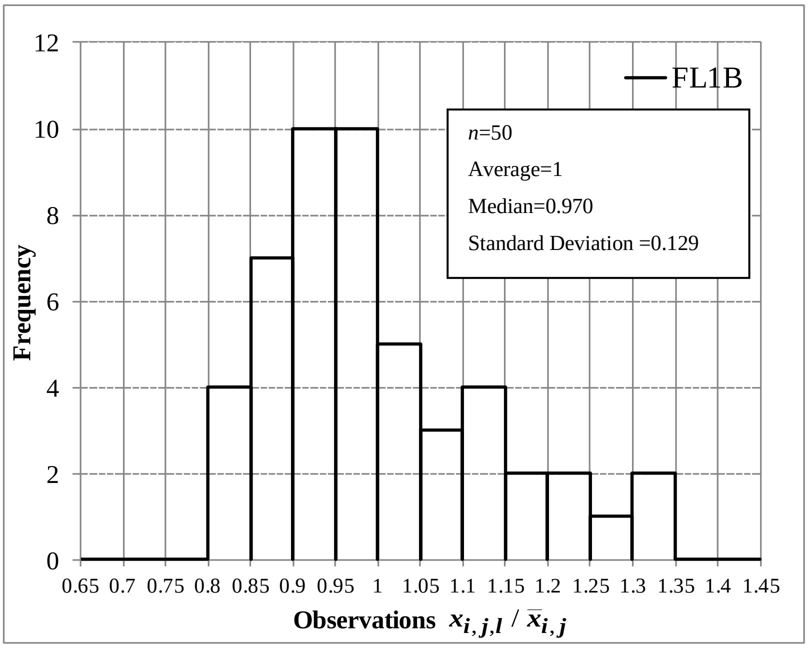
However, if the workstation content differs in terms of cognitive content, use of tools, or due to any other factor not taken into account, then differences in other distribution parameters, such as the median value could be expected.

Note that with this scaling, depending on the workstation where the worker was observed, the average is the same but the median can be different. The objective is to analyse if those differences are significant, using the Kruskal-Wallis testing procedure.



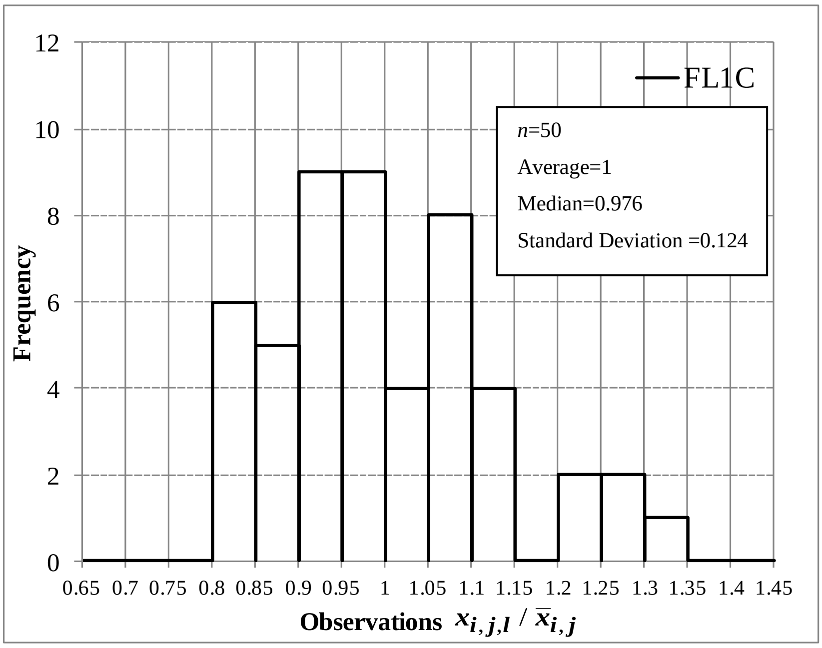
FL1A
n=50
Average=1
Median=0.992
Standard Deviation =0.116
Frequency
Observations $x_{i,j,l} / \bar{x}_{i,j}$

a)



FL1B
n=50
Average=1
Median=0.970
Standard Deviation =0.129
Frequency
Observations $x_{i,j,l} / \bar{x}_{i,j}$

b)



c)

Figure 11 - Histograms for the task time distributions scaled for worker ID1 at workstation a) *j*=FL1A, b) *j*=FL1B, c) *j*=FL1C

There was a set of eight workers that were observed repeatedly at workstations FL1A, FL1B and FL1C during the same week. The scale factor was applied to all the readings as described previously. To ensure that the task time distributions were not significantly different for each one of the workers observed in the three workstations, the Kruskal-Wallis testing procedure was applied. For all of them the null hypothesis can be accepted since the p-value was much higher than the significance level (Table 13). The type of tasks performed at each observed workstation was in fact very similar (the same basic motions elements required). The test results, coupled with the prior knowledge that the work content of each workstation is similar, indicate that the time distribution, and therefore the performance of each worker is similar no matter the workstation where the observations took place.

Table 13 – Kruskal-Wallis test results using the scaled task time distributions for workers observed repeatedly at workstations FL1A, FL1B and FL1C

Worker	Kruskal-Wallis test results
ID1	$H(df=2) = 0.294$, $p=0.863$, $\alpha=0.05$
ID2	$H(df=2) = 0.290$, $p=0.865$, $\alpha=0.05$
ID3	$H(df=2) = 0.071$, $p=0.965$, $\alpha=0.05$
ID7	$H(df=2) = 0.760$, $p=0.684$, $\alpha=0.05$
ID8	$H(df=2) = 0.145$, $p=0.930$, $\alpha=0.05$
ID9	$H(df=2) = 0.070$, $p=0.966$, $\alpha=0.05$
ID10	$H(df=2) = 1.037$, $p=0.595$, $\alpha=0.05$
ID21	$H(df=2) = 0.008$, $p=0.996$, $\alpha=0.05$

Nonetheless, this issue will be revisited later in Chapter 5, using the proposed mapping approach.

4.6. Results summary

From the analyses performed up to this point it can be concluded that:

- The collected workers task times cannot be considered normally distributed;
- The dispersion on task times is significantly different from worker to worker;
- Workers have significantly different task times when compared between them;
- The workstation work content is similar enough, so it does not affect the observed workers task time performance significantly.

Considering the previous statements, the worker task time seem to be a variable which is highly difficult to characterize, but that in fact depends highly on the worker. These results are in line with the results of previous authors (Doerr and Arreola-Risa, 2000) and validate the premise of the present work.

These results were presented to the company where the data collection took place. The conclusion that the workers are in fact quite different in terms of speed and consistency did not surprise the management. However, the company now had analytical proof of the tacit knowledge they had about the nature of manual processing, since statistically speaking the average task time and variability of the task times distributions varied significantly from worker to worker. The main issue

is the quantification of those differences in a systematic way, which helps in understanding more about the characteristics of the performance heterogeneity.

Instead of considering further statistical analyses, the following was considered: a worker might be slower or faster than the average and/or have more or less dispersion than average. One can conjecture that four types of performance can be considered, depending on these combinations.

The following section describes a useful way of looking into these behaviours and the obtained results for the performance assessed for work paced by the assembly system rhythm.

5. Workers Performance Paced by the System Rhythm

From the previous section, it was concluded that the task times observed on workers performing manual assembly tasks vary in a significant way: both in terms of speed and consistency. In order to understand the extent of such variations among the workers performance, it is important to quantify these variations within a workers population. This section describes how a mapping approach was developed and the resulting map for a scenario where workers are performing assembly work in an asynchronous assembly line.

5.1. Mapping Task Time Performances Heterogeneity

When a production manager evaluates the time required to perform the assembly tasks of a given workstation, he/she “targets” what he/she considers as a “normal” worker (with experience in performing the required tasks, in apparent normal working conditions, willing to have his/hers times measured and hopefully not affected by the time recording process). The measurement of task times, allows the manager to evaluate the actual time the worker requires to perform a task. However, by doing so, the manager is assuming that the worker has a deterministic behaviour, and that the all workers perform in the same way: eventual differences in those average times among the workers are small enough so they can be disregarded. These are typical assumptions, as described by previous authors in the field of production and operations management (Bendoly *et al.*, 2010), which can result in an overestimation of the system performance.

In the previous chapter, it was concluded that in fact those differences are substantial: there are significant differences on the average times within a group of workers. Furthermore, the amount of variability in a group of workers varies significantly from one worker to the other. Therefore, as it was previously suggested by previous authors (Knott and Sury, 1987), there is not one task time distribution which could effectively represent all the workers.

In fact, the workers are not isolated but rather integrated in the assembly system and their performance contributes to the performance of the system. If any of these inter-dependent workers vary their level of individual performance relatively to an average/expected performance, the impact of the variation is multiplied throughout

the process by the subsequent workstations in the system. Therefore, this analysis will be focused on the differences found among workers, in terms of deviations to an average/expected performance.

To address these practical matters, in this section the analysis is focused on the deviations to the average workers population performance, both in terms of average task time and dispersion. The approach used to perform such analysis is a mapping that enables the visualization and quantification of typical behaviours.

5.1.1. Task time performance maps

Considering that the average time to perform the workstation *j* work content, is based on the average of the workers population $\overline{X}_j$ (Equation 2), it's then possible to calculate the percentage deviation $\Delta\bar{x}_{i,j}$ of the average task time of worker *i*, to that time (Equation 3):

Equation 2 – Average time of the *k* workers observed at workstation *j*

$$\overline{X}_j = \frac{\sum_{i=1}^{k} \bar{x}_{i,j}}{k}$$

Equation 3 –Deviation in % of worker *i* average task time, to the average time of the workers observed at workstation *j*

$$\Delta\bar{x}_{i,j} = \frac{\bar{x}_{i,j} - \overline{X}_j}{\overline{X}_j} \times 100$$

The deviations to the average value are not the only measure of performance being considered. It is also important to characterize the dispersion of task times that can be observed in different workers and compared it to an average value of dispersion found within the workers observed, $\overline{S}_j$ (Equation 4). Similarly to the analysis made to the average task time, the deviation $\Delta s_{i,j}$, of the worker *i* time dispersion, $s_{i,j}$, to the workstation *j* expected dispersion is also calculated in terms of percentage (Equation 5).

Equation 4 - Average dispersion of the *k* workers observed at workstation *j*

$$\overline{S}_j = \frac{\sum_{i=1}^{k} s_{i,j}}{k}$$

Equation 5 – Deviation in % of the worker i dispersion, to the average dispersion of the workers observed at workstation *j*

$$\Delta s_{i,j} = \frac{s_{i,j} - \overline{S}_j}{\overline{S}_j} \times 100$$

Given that workers performance can be described in terms of deviations to the workstations average task time and average dispersion, makes it possible to define classes of workers performance based on these two dimensions, for this type of assembly system and assembly tasks.

Therefore, four types of performance can be considered in terms of deviations to the average values obtained for the workers population:

- The worker is slower completing the assembly task and the task times are more disperse (with more variability) than the average;
- The worker is faster completing the assembly task and the task times are more disperse than the average;
- The worker is faster completing the assembly task and the task times are less disperse (with less variability) than the average;
- The worker is slower completing the assembly task and the task times are less disperse than the average.

When these deviations are plotted in frequency histograms (pooling the results from the different workstations), it can be observed that the deviations range in non-symmetrical way, both in terms of $\Delta\overline{x}_i$ (Figure 12) and Δs_i (Figure 13). More than 50% of the times, the workers have deviations to the average between -20 % and 0 %, while the rest of the times, the workers can have performance up

to + 40% slower than the average. The deviation to the average dispersion ranges from -40 % to +80 %. Just looking at these histograms might be misleading, since the variables $\Delta\bar{x}_i$ and Δs_i can be correlated. If that is the case, then by knowing beforehand that a worker is slower than expected, it can give us an indication if the worker performs the assembly tasks with more or less variability than expected.

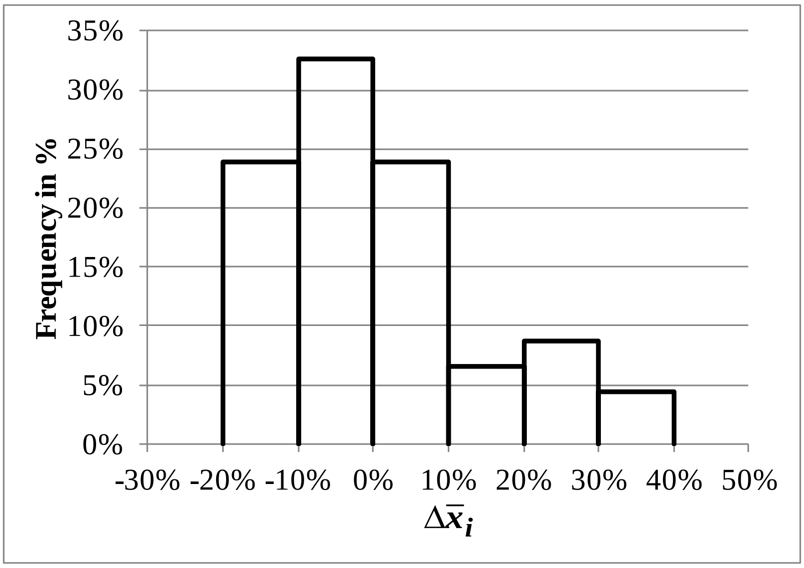


Figure 12 - Observed deviations to the average time of the workers population

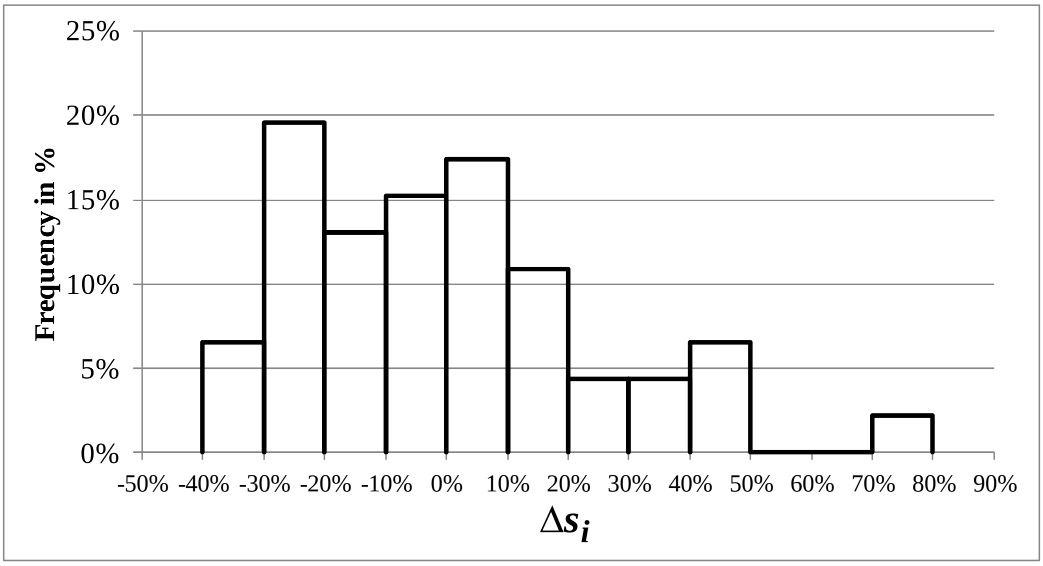


Figure 13 - Observed deviations to the average dispersion of the workers population

In order to visualize the relation between these two variables $\Delta\bar{x}_i$ and Δs_i, a graphic is proposed where the origin represents the average value of the workstation task time, considering the average time required to fulfil the assembly tasks as well as the expected dispersion of that time, based on all the sampled workers. The horizontal axis represents the deviation of a worker average time to the average time required to perform the assembly task at the workstation; and the vertical axis represents the deviation of a time dispersion of a worker to the average dispersion at this workstation (Figure 14). For example, if a given observed performance was located in the coordinates (+ 20 %, +30 %) it means that in average this worker took 20% more time than the average to complete the assembly, and the dispersion of his/her task times was 30% higher than the average based on the overall population observed on that workstation.

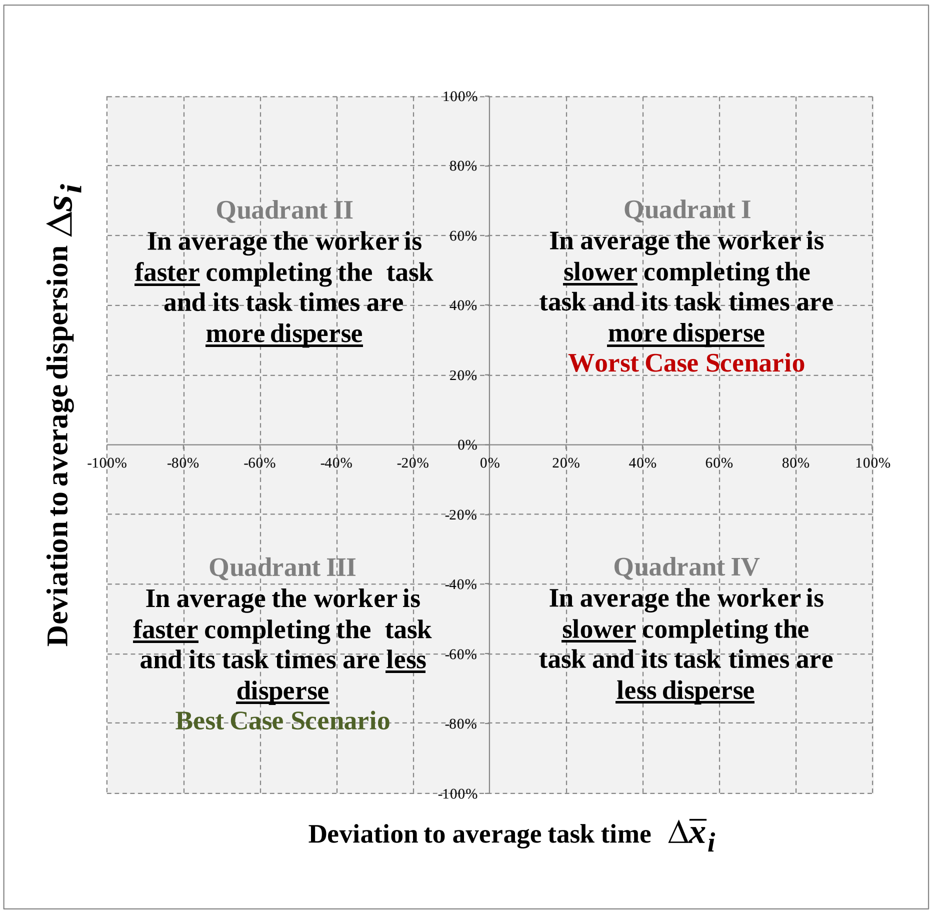


Figure 14 - Representation of the four types of performance in terms of individual deviations to the average task time and dispersion of the workers population

Representing the performance in such way, allows the evaluation of the different observations in terms of percentage deviations to the average performance of the workers population, as well as the visualization of the relation between $\Delta\bar{x}_i$ and Δs_i. In addition, by using the proposed mapping, the distribution and frequency of performance in each quadrant can be compared.

In the following section, the proposed mapping approach will be applied to the gathered data and analysed.

5.1.2. Task time performance map for work paced by the system rhythm

The individual performances (46 data sets) were calculated in terms of deviations to the average performance in each workstation ($\Delta\bar{x}_i ; \Delta s_i$) and plotted using the proposed graphical approach described in the previous section (Figure 15). In such way, the information described previously by the two histograms is combined in one map. It can be observed that there is a relation between the two variables.

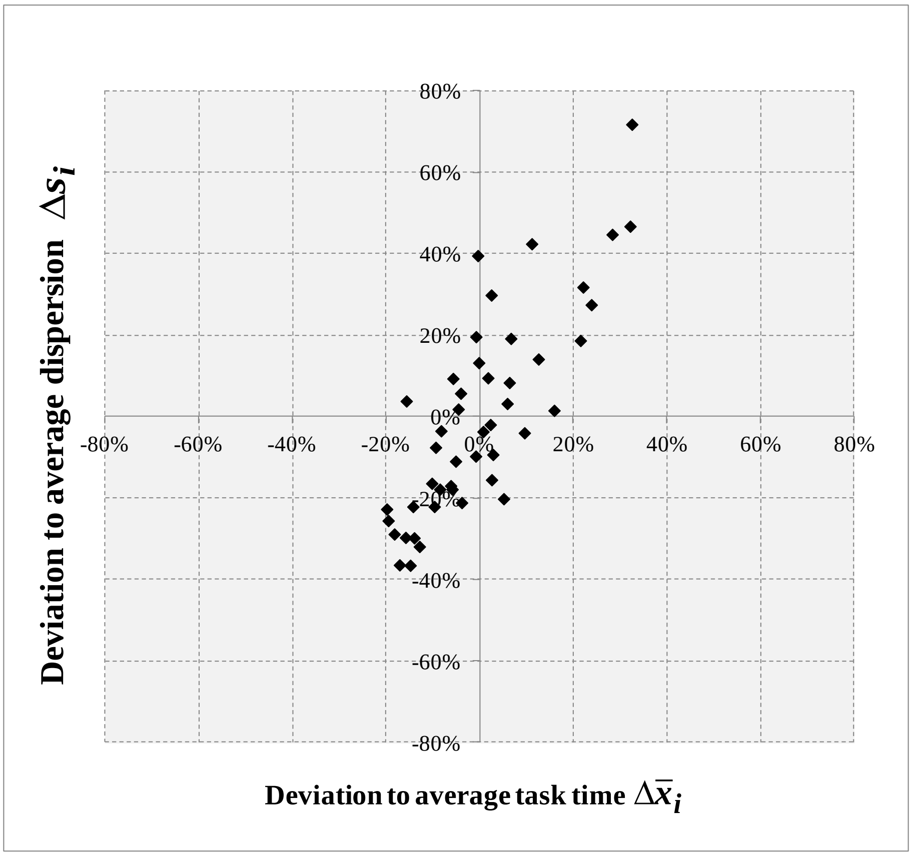


Figure 15 - Performance map for work paced by the system rhythm

However, before further analysing the previously presented map, it should be verified that in fact there are no differences according to the workstation where the workers were observed. In the previous chapter, it was concluded that for the same worker, performing in different workstations, there were not significant differences on the task time distribution. Therefore, the workstation where the worker was allocated to, did not affect her performance. Nonetheless, each pair of coordinates ($\Delta\bar{x}_{i,j}$; $\Delta s_{i,j}$) per worker was re-plotted differentiating the points per workstation (Figure 16). It was also plotted the linear regression per each workstation. By observing this map, it can be verified that, independently of the workstation where the data sets were collected, the performance tends to be distributed in the same way amongst the quadrants, since the slope of each line does not vary considerably. Nonetheless, for the case of the worker observed in the workstation FL1A, the slope is slightly less steep, meaning that slower performance presented lower dispersion in task times, when compared to the observation in the other workstations (where the slopes are practically coincident). The number of observations in each workstation was also different therefore these results might be affected by this fact. To further investigate the relation between the two variables ($\Delta\bar{x}_{i,j}$; $\Delta s_{i,j}$), observed in each workstation, the strength of the correlation between them will be calculated, using an appropriate statistical test.

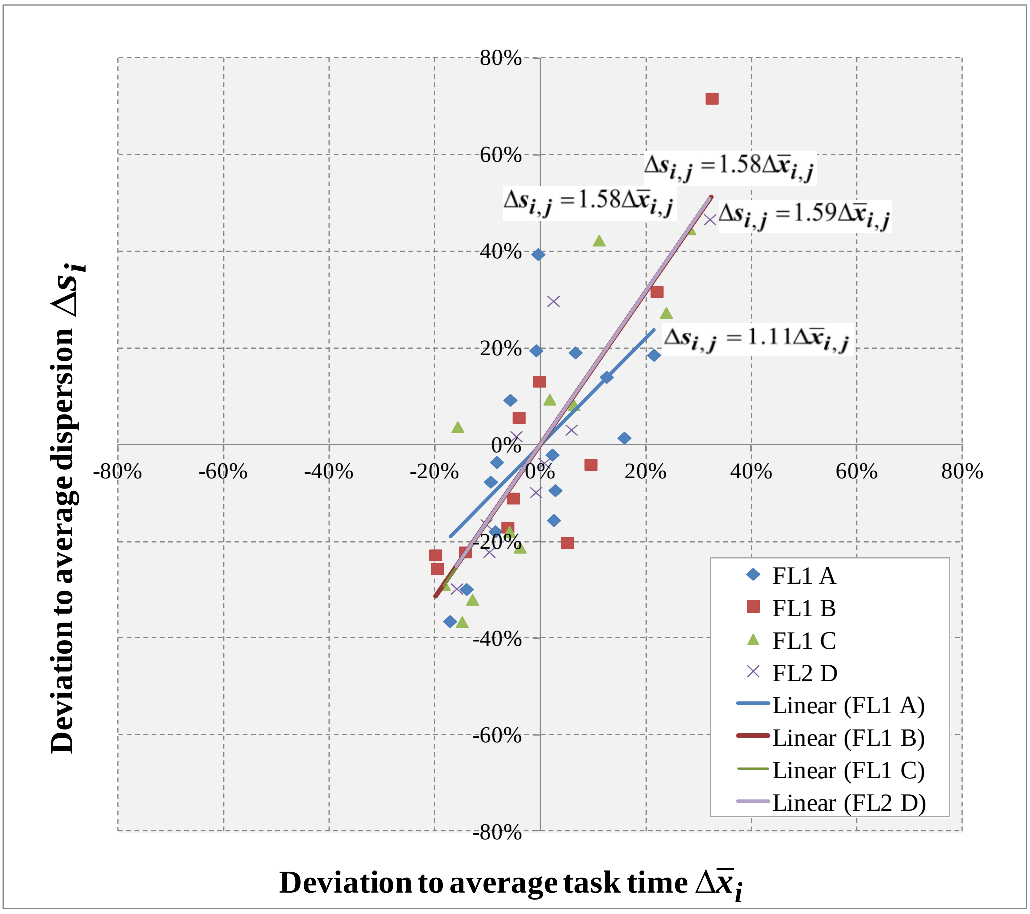


Figure 16 - Performance map for work paced by the system rhythm with differentiation per workstation

In order to verify the strength of the correlation between the variables $\Delta\bar{x}_{i,j}$ and $\Delta s_{i,j}$, for the different workstations, it was used a bivariate test procedure which calculates the Spearman Rank Order Correlation coefficient, r_s. This is a non-parametric measure of the strength and direction of association that exists between two variables measured on an ordinal scale (Sheskin, 2004). In order to perform this test SPSS rank orders the data (the ranked-ordered data can be found in Annex). To use this test, it is assumed that the variables have a monotonic relationship. This correlation coefficient can range from −1 to 1. Usually it is considered that a coefficient between 0.5 and 1 indicates a strong positive correlation between the variables (between 0.3 and 0.5 a medium positive correlation, between 0.1 and 0.3 a week positive correlation, and between 0.1 and 0 none or very week positive correlation). This coefficient in the analysis of the correlations was used, instead of a parametric one, since the

distribution of the variable $\Delta \boldsymbol{s}_{\boldsymbol{i},\boldsymbol{j}}$ for workstation *j*=FL1B, could not be considered to be normally distributed according to the Shapiro-Wilk test results (Table 14).

Table 14 – Shapiro-Wilk test results for normality of the distributions for the variables $\Delta \bar{\boldsymbol{x}}_{\boldsymbol{i},\boldsymbol{j}}$ and $\Delta \boldsymbol{s}_{\boldsymbol{i},\boldsymbol{j}}$ - Workstations FL1A, FL1B, FL1C and FL2D

Workstation	Tested Variable	Shapiro-Wilk test results
j= FL1A	$\Delta \bar{\boldsymbol{x}}_{\boldsymbol{i},\boldsymbol{j}}$	$W(k=15)=0.970$, $p=0.856$, $\alpha=0.05$
	$\Delta \boldsymbol{s}_{\boldsymbol{i},\boldsymbol{j}}$	$W(k=15)=0.981$, $p=0.975$, $\alpha=0.05$
j= FL1B	$\Delta \bar{\boldsymbol{x}}_{\boldsymbol{i},\boldsymbol{j}}$	$W(k=11)=0.936$, $p=0.471$, $\alpha=0.05$
	$\Delta \boldsymbol{s}_{\boldsymbol{i},\boldsymbol{j}}$	$W(k=11)=0.819$, $\boldsymbol{p=0.017}$, $\alpha=0.05$
j= FL1C	$\Delta \bar{\boldsymbol{x}}_{\boldsymbol{i},\boldsymbol{j}}$	$W(k=11)=0.915$, $p=0.283$, $\alpha=0.05$
	$\Delta \boldsymbol{s}_{\boldsymbol{i},\boldsymbol{j}}$	$W(k=11)=0.915$, $p=0.276$, $\alpha=0.05$
j= FL2D	$\Delta \bar{\boldsymbol{x}}_{\boldsymbol{i},\boldsymbol{j}}$	$W(k=9)=0.857$, $p=0.088$, $\alpha=0.05$
	$\Delta \boldsymbol{s}_{\boldsymbol{i},\boldsymbol{j}}$	$W(k=9)=0.923$, $p=0.420$, $\alpha=0.05$

The results of the correlation test (Table 15) indicated that there is a strong, positive correlation between $\Delta \bar{\boldsymbol{x}}_{\boldsymbol{i},\boldsymbol{j}}$ and $\Delta \boldsymbol{s}_{\boldsymbol{i},\boldsymbol{j}}$, which was statistically significant for all the workstations. However, these results indicate that there's the same type of correlation between the variables in each workstation, but it doesn't compare the regression lines.

Table 15 - Correlation coefficients, r_s, between the variables $\Delta \bar{\boldsymbol{x}}_{\boldsymbol{i},\boldsymbol{j}}$ and $\Delta \boldsymbol{s}_{\boldsymbol{i},\boldsymbol{j}}$, per workstation *j*

Workstation	Spearman Rank Order Correlation Coefficients and Significance
j=FL1A	$r_s(k=15)=0.571$, $p=0.026$, $\alpha=0.05$
j=FL1B	r_s $(k=11)=0.855$, $p=0.001$, $\alpha=0.05$
j=FL1C	r_s $(k=11)=0.836$, $p=0.001$, $\alpha=0.05$
j=FL2D	r_s $(k=9)=0.917$, $p=0.001$, $\alpha=0.05$

In order to understand if the data from the different workstations can actually be pooled, the linear regression coefficients must be compared. In order to do so, it is required to do Analysis of Covariance (ANCOVA) to check for significant differences between the regressions. The ANCOVA is a general linear model which blends ANOVA and regression. ANCOVA evaluates whether population means of a dependent variable (in this case $\Delta s_{i,j}$) are equal across levels of a categorical independent variable (workstation, *j*), while statistically controlling for the effects of other continuous variables, known as covariates ($\Delta \bar{x}_{i,j}$) (Sheskin, 2004).

To use this test, the first assumption to check is whether the dependent variable follows a normal distribution.

As it was previously pointed out previously, the distribution of the $\Delta s_{i,j}$ for workstation FL1B could not be considered normal. To avoid violating the assumption of normality when performing the ANCOVA, the data was rank ordered (as in the Kruskal-Wallis test – check Annex fur further details) and new linear regression models calculated using these new data points (Olejnik and Algina, 1984). The Shapiro-Wilk test was then reapplied to check the assumption of normality on the dependent variable, and the results indicate that this assumption is not violated (Table 16).

Table 16 – Shapiro-Wilk test results for the dependent variable rank ordered for each workstation

Workstation	Linear regression for rank ordered data	Shapiro-Wilk test results for the dependent variable
j=FL1A	$\Delta s_{i,j}{}^{*}=0.660\,\Delta \bar{x}_{i,j}{}^{*}+8.522$	$W(k=15)=0.946$, $p=0.460$, $\alpha=0.05$
j=FL1B	$\Delta s_{i,j}{}^{*}=0.711\,\Delta \bar{x}_{i,j}{}^{*}+5.777$	$W(k=11)=0.906$, $p=0.221$, $\alpha=0.05$
j=FL1C	$\Delta s_{i,j}{}^{*}=0.890\,\Delta \bar{x}_{i,j}{}^{*}+2.626$	$W(k=11)=0.896$, $p=0.165$, $\alpha=0.05$
j=FL2D	$\Delta s_{i,j}{}^{*}=0.944\,\Delta \bar{x}_{i,j}{}^{*}+1.955$	$W(k=9)=0.969$, $p=0.889$, $\alpha=0.05$

Before conducting an ANCOVA the homogeneity of variances assumption must be verified. The variances of the dependent variable ($\Delta s_{i,j}$*) must be equal for all levels of the independent variable (workstation, *j*) and the covariate ($\Delta \bar{x}_{i,j}$*).

The underlying assumption of homogeneity of variance for the one-way ANCOVA was also met according to the results of the Levene's test: F(*df1*=3, *df2*=42)[3]= 0.722, p = 0.544, α=0.05.

Another assumption of this test is the homogeneity-of-regression. The objective of this test is to evaluate the interaction between the covariate ($\Delta \bar{x}_{i,j}$*) and the independent variable (workstation, *j*) in the prediction of the dependent variable ($\Delta s_{i,j}{}^{*}$).The slope of the line predicting the dependent variable from the covariate must be equal for each level of the independent variable. That is, the covariate must not have differential effects on the dependent variable at different levels of the independent variable. This assumption is violated when there is a significant interaction between the independent variable and the covariate.

The obtained results suggest the interaction is not significant, *F*(*df1*=3, *df2*=42) = 0.443, p = 0.724, α=0.05. The regression lines although parallel might have different intercepts.

The ANCOVA test produced non-significant results (*F*(*df1*=3, *df2*=42)=0.068, p=0.977, α=0.05). Finally, if the workstation, *j*, effect is not significant nor its interaction with the $\Delta \bar{x}_{i,j}$*, this means there is a single regression line.

Considering that the data points can be pooled, the correlation coefficient was recalculated[4] considering the original data points. The deviations are strongly positively correlated ($r_s(n=46)$ =0.789, p<0.0005, α=0.05). In Figure 17 this correlation can be observed: the dashed black lines indicate the prediction interval where it is expected that 95% of all data points to be located, and the red dashed lines the confidence interval where it is 95% sure to contain the best-fit

[3] Note that *df1* is equal to the number of groups tested minus one, in this case it is the number of workstations minus one; *df2* is equal to the number of samples minus the number of groups, in this case number of data points minus the number of workstations.

[4] Note that when the results are pooled without differentiating the workstation where they were observed, the Shapiro-Wilk test results for the normality of the distributions of the variables $\Delta \bar{x}_i$ and Δs_i, indicate that they cannot be considered as normally distributed (for the $\Delta \bar{x}_i$: $W(k=46)$=0.951, p=0.051, α=0.05; and for the Δs_i : $W(k=46)$=0.940, p=0.020, α=0.05). Therefore, the use of a non-parametric correlation coefficient is more advisable in such cases.

regression line. In fact, the strong positive correlation between the variables and the observed confidence interval for the slope indicates that there is a significant tendency for a worker, which is slower than the average to also have more dispersion than the average. This means that, these workers have a central tendency to be slower than the other workers but work with higher speed variations when compared to the others. Alternatively, workers which are faster than the average have the tendency to have lower dispersion in the task times, meaning that their performance tend to be more consistent. Therefore, there are two predominant types of performance: QI and QIII.

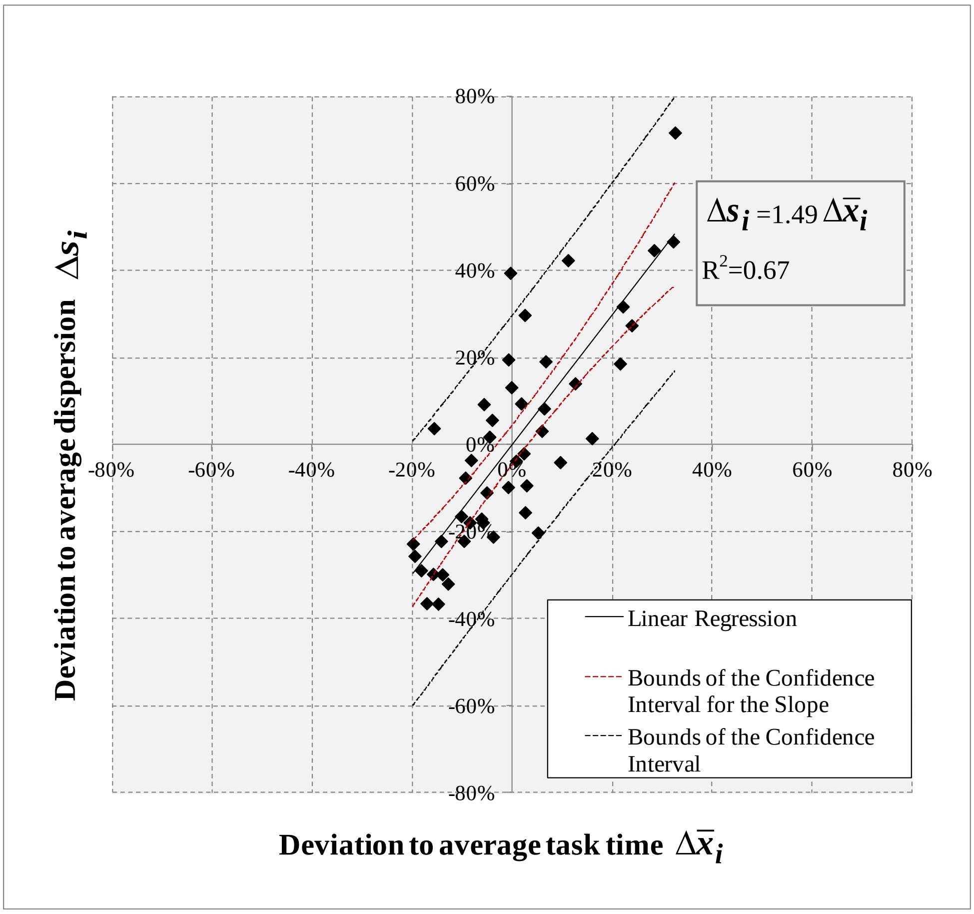


Figure 17 - Performance map for work paced by the system rhythm with linear regression and $CI_{95\%}$ for the slope and data points

However, besides two predominant types of performance, there are occurrences in the other two quadrants (also within the prediction interval). In addition, the distance of the occurrences to the origin is different from quadrant to quadrant. From the analysis of Table 17, it can be found that:

- There are less worker performances on QII (worker faster than average, but with more dispersion in his/her task times) and QIV (worker slower than average, but with less dispersion than average), but in fact they occurred;
- When the workers performances are in QI, they tend to be more distanced from the origin than performance in any other quadrant;
- More distanced deviations (average distance to the origin) in QI are balanced by a higher frequency of occurrences in QIII.

Table 17 - Percentage of observed occurrences per quadrant and average distance to the origin with worker paced by the system rhythm

Type of Performance	% of Observed Occurrences	Average Distance of Observed Occurrences to the Origin*
QI	30.4%	32.0 pp%
QII	15.2%	15.9 pp%
QIII	41.3%	24.6 pp%
QIV	13.0%	10.6 pp%
* $d_i = \sqrt{\Delta\bar{x}_i^2 + \Delta s_i^2}$		

The centroid of the points in each quadrant was used as a measure of the four types of performance (Figure 18). From the results, it is observable that the average worker of QI take 16% more time to complete the assembly cycle with 26% more dispersion than the expected. A worker having an average performance in the opposite quadrant takes less 11% of the time with 21% less dispersion, when compared with the expected values.

Each quadrant is interpreted as a potential type of performance (slower/faster than the average population, more/less dispersed than the average population), and the centroids are used as representative measures of the performance in each quadrant. The location of these centroids within the performance map outlooks the task time distribution of each type of performance.

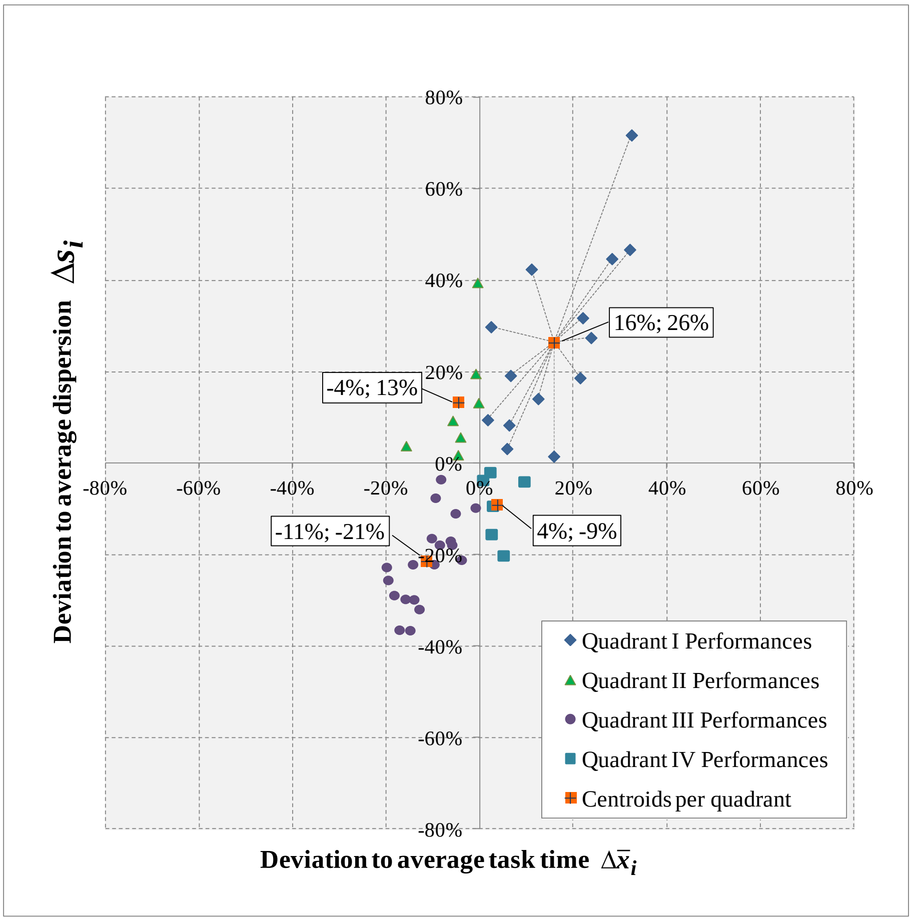


Figure 18 - Performance map for work paced by the system rhythm with centroids of performance per quadrant

Studying a system performance considering that all the workers have one type of performance (an expected performance corresponding to the origin of the map, which was calculated by the average of all the observed performance) might be underestimating the effects of the heterogeneity on the results. This research proposes considering four other types of performance based on the deviations to that expected performance. The position of the workers in the system with different types of performance can also vary and consequently influence the system performance. This issue will be revisited later in Chapter 9, where these values are used as an input in simulation studies in order to understand the impact of such heterogeneity.

5.2. Potential for assessing assembly system work flow policies

By mapping the performance in the proposed way it is possible to better visualize how different the performance spread in terms of average and dispersion and which performance are more frequent. If the workflow policy changes, namely if a rigid pacing mechanism is introduced, it is expected that the performance to be distributed differently when mapped in terms of deviations to the average and dispersion.

A modification to the observed system at the company was introduced to reinforce the pacing rhythm: an equal time slot for every worker to fulfil the assembly work at their assigned workstations. The workers became rigidly paced by a time constraint. By collecting new observations on the workers under these new conditions, it will be investigated if a rigid pacing influences the performance heterogeneity within a group of trained workers, and if there are gains in the assembly system productivity by introducing such type of control mechanism. With the proposed performance mapping it can be investigated if there is still a correlation between deviation to the average and dispersion, if there is still more frequent occurrences of certain types of performance and if in general the average and dispersion of the average type of performance in the re-sampled population changes.

The next chapter describes the company motivations to introduce the time constraint, the evaluation of the system productivity before and after the modification and the performance maps for this new scenario.

6. Workers Performance Paced by a Time Constraint

In this chapter the workers task times are investigated in a scenario where there is a rigid pacing mechanism. Together with the company these modifications were introduced in the assembly system and it was possible to gather the workers task times after introducing a time constraint for the assembly tasks completion. It is described how the time constraint was implemented in the assembly system, the implementation plan developed with the company, the evaluation of the preliminary stages of implementation – the Pilot Project, the full implementation and the results obtained that focused on the observed time distributions in such scenario.

The results for this scenario are then compared with the observed performance for the previous work scenario (where the existing pacing results from the interdependence between the workstations), focusing on the changes in the way the individual performances are spread in the proposed performance maps, due to the implementation of a time constraint.

6.1. Motivation and mechanism used to implement a time constraint

The company where the data was collected performed modifications in the studied assembly line in order to introduce a rigid pacing mechanism. These changes were partially motivated by the findings described in Chapter 5.

The performance maps presented at the company enabled the visualization of the performance heterogeneity within a group of trained workers. From the analyses made to this map, it could be verified that within the group of workers the average time and dispersion can vary within a large range of values, when compared to the expected performance. Since the workers are positioned in a serial configuration with a very limited buffer level, if a worker has a slower performance relatively to others, her workstation can become the bottleneck affecting not only the upstream workstations by blocking them (the upstream workers cannot pass the part forward when they finish the assembly work at the workstation), but also the downstream stations by starving them (workers do not receive parts to work on).

In addition, the average task time and dispersion have a strong positive correlation, meaning that the workers with higher average task time also have larger dispersion

in the task time distribution. In other words, slower workers tend to be more variable.

One of the objectives of the company was to reduce the heterogeneity of work performance, namely by reducing the occurrence of extreme performance in QI (workers performing slower and with more dispersion than the average). This way the work flows more smoothly from workstation to workstation and potentially avoid the occurrence of random bottlenecks throughout the system.

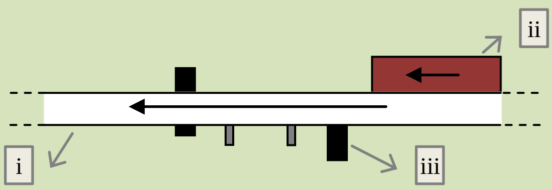
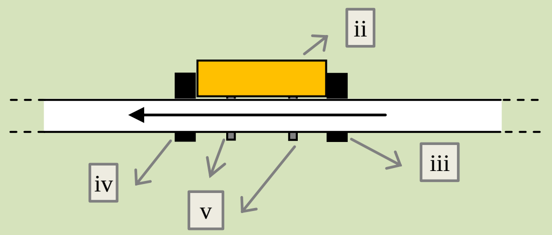
With the implementation of a fixed time to perform the task, the task time distributions become constrained to that maximum value. With this constraint, not only it is expected that the dispersion of the task time distributions to decrease (working in a more consistent way), but also the average task time to decrease as well (since this way random long cycles are not permitted). Therefore, with this modification to the system, it was expected to influence mostly the QI performance. By reducing the deviations to the origin in that quadrant, would potentially influence the expected performance of the group (the average task time and dispersion).

This opinion was shared by the company and the author of this research. However, at this point it was not clear how the QIII performance could be affected. With this pacing mechanism, the workers have to adapt their task time distribution to the available time and even if they complete the assembly operations faster than the set time, the jig does not leave the station before. On one hand, there is a time constraint, which can reduce the number of occurrences in QI, or/and their distance to the origin, but on the other, it is possible that workers with QIII performance slow down their performance.

Another consequence the company expected/desired by introducing the time constraint in each workstation was that the assembly system management would become more demanding. When managing a system without a time constraint in each workstation, the workers could speed up the assembly in case there would be a disturbance on the system operation and unintentionally “camouflage” this disturbance. With a time constraint, there would be no tolerance for these events. For instance, if the feeding of the components to the system was not made with the adequate rhythm, the workers could not wait for the components and speed up the work on the next cycle to compensate the delay; if a sensor to verify if all the

components had been assembled (poka-yoke[5]) would need readjustment due to false errors, this problem would be flagged more quickly. These are some examples of situations, which the company considered that the introduction of a time slot could increase the alertness to.

Before the introduction of a time limitation, the jig with the part would arrive to the workstation, transported by the loop conveyor, and stopped at that position (while the conveyor continued moving) and leave when the worker pressed a pedal – signalling the conclusion of the assembly tasks at that workstation – as previously described in Section 3.3 . After the modifications, a time constraint was introduced by programming the pins movements. When the sensors signal that a jig is at the workstation ready for the assembly tasks to start, the lifting pins are actuated and a timer is set. During a predetermined time, the pins do not allow the jig to leave the workstation. After that amount of time, the pins automatically go down and the jig is then be able to depart from the workstation, transported by the continuously running loop conveyor (Figure 19).

The loop conveyor (i) moves at a constant speed. The jig (with a part (ii) arrives to the workstation. The entrance is only allowed when the stop pin (iii) is down.	
The jig with a part (ii) remains at the workstation for a fixed time. The pin (iv) stops the jig movement, while other pins lift the jig from the conveyor (vi). The pins (iv) and (v) remain up during the defined time in which the worker must complete the assembly tasks. During this time, no other jig is allowed to enter the workstation (iii).	

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[5] Poka-yoke is a Japanese term that means "fail-safing" or "mistake-proofing". A poka-yoke is any mechanism in a manufacturing process, which helps a worker to avoid mistakes. Its purpose is to eliminate product defects by preventing, correcting, or drawing attention to human errors as they occur (Shingo, 1986).

When the time is up, the pins (v) disengage automatically from the jig and the pin blocking the jig movement (iv) moves down. The jig leaves the workstation (ii) becomes in contact with the conveyor and it is transported by it. Another jig can enter, since the pin at the entrance is down (iii).

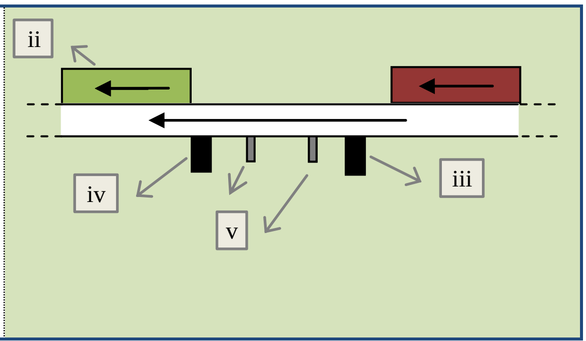


Figure 19 – Mechanism controlling the entrance and exit of jigs in the workstation according to the time constraint

6.2. Implementation plan

This subchapter concisely describes the implementation plan developed with the company. In the company, there was a team of several elements involved: the plant manager, two assembly systems managers, one equipment technician, and the human resources responsible, which planned the implementation of the rigid pacing mechanism to be executed in several phases. In the planning phase this team, with the collaboration of the author of the present work, gathered to discuss the concept and the inherent advantages, disadvantages, possibilities of implementation, and possible difficulties inherent to the process. During this phase, the plant manager, besides moderating the discussion, had as an objective to engage every involved element in this modification in order to reduce the resistance to change: the apparent reticence – or outright opposition. The plant manager was aware that this potential resistance to change could have several reasons. The available literature on management issues (Kotter and Schlesinger, 2008) indicates that people might be concerned with the effect the change will have on themselves and their own interests; they may not fully understand the needs for, and goals of, the change; people may value security, stability, and consistency and therefore be naturally resistant to any change, regardless of what it is; there may be disagreements with the solution or the reasons behind the decision to make the change. The role of the plant manager throughout the process was to mitigate the apparent reticence from the several participants in the process.

During this discussion, one source of resistance had to do with the functioning of the auxiliary systems of the assembly (components feedings and poka-yokes), since if they failed the workers would most certainly have difficulties in finishing their assembly work within the time slot. The plant manager pointed out this fact as an

advantage, since this way any problems with these systems would be flagged and solved more quickly. It was agreed during this planning, that a Pilot Project phase was required, which would serve as time to solve any potential problems related to the auxiliary systems and check if the modification to the system was in fact producing the desired results.

In addition, during this planning phase, the team discussed how this system modification was going to be communicated to the workers: namely the objectives of this modification was to reduce variations in term of speed and consistency while performing assembly tasks, and that initially there would be a Pilot Project phase to identify problems to solve before the full implementation The participation and involvement of the workers was underlined to be of the outmost importance, since they were the key elements implementing the change and without their commitment, the plan could not go through.

In the system, there was an automatic workstation which would inscribe symbols in the buttons which the workers had previously assembled in the bezel. This automatic workstation required 12 sec per part to perform the inscribing. Therefore it was decided by the company that they would use this value for the time constraint in each manual processing workstation. When the 12 sec time constraint is compared to the observed expected average time in each workstation (Table 18) it can be observed that it is slightly larger (for FL1A) or very close to the expected average time (for FL1B and FL1C). However, since the company had seen the analysis of the performance maps (Table 19), and they were already aware that most of the workers (QII+QIII=56.5%) had average task times lower than the expected values. Therefore this time constraint would influence mostly workers in the remaining quadrants.

Table 18 - Observed expected average time and dispersion in each workstation before the time constraint

Workstations	**Nº observed workers**	$\bar{X}$ **[sec]**	$\bar{S}$ **[sec]**
FL1A	15	12.4	1.6
FL1B	11	11.7	1.6
FL1C	11	11.8	1.7

Table 19 – Observed occurrences % per quadrant with the workers performance paced by the system rhythm

Type of Performance	% of Observed Occurrences
QI	30.4%
QII	15.2%
QIII	41.3%
QIV	13.0%

The following phase was the Pilot Project, where the time constraint was implemented in one of the shifts. The assembly line was programmed so it could work with or without the 12 sec limitation in each workstation. The plant manager, assembly systems managers, and the human resources representative communicated the new concept to the workers, which accepted the modification well and agreed to engage in the plan.

Then followed the Evaluation phase, where the system managers evaluated the system output and workers feedback resulting from the Pilot Project phase. In addition, data was gathered regarding the workers performance and a survey used to address their feedback, which is further discussed in the following section. Some technical problems were identified together with the company during the Pilot Project phase, regarding the time constraint which will be described in the next section. The next phase was the Full Implementation, where this modification was implemented in the remaining shifts and new data was gathered on the workers performance in order to map them (see Figure 20 with the summary of the Implementation Plan).

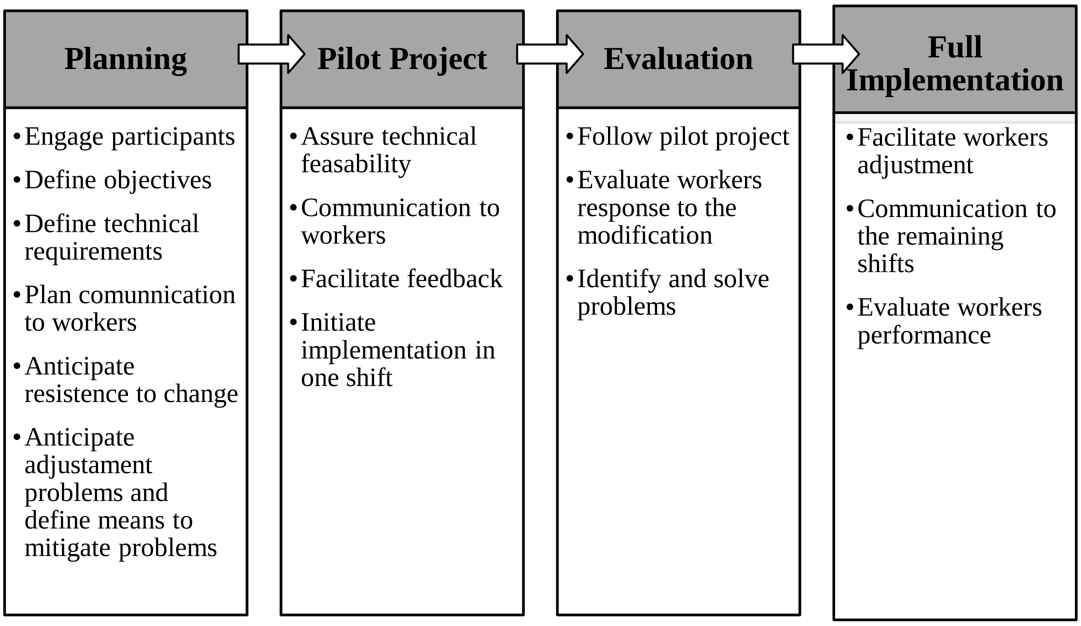


Figure 20 - Implementation plan for the introduction of a time constraint in each workstation

The modifications in the assembly line were introduced as stated previously, and the workstations were programmed to have a 12sec time constraint.
In the following section, the results obtained during the Pilot Project are discussed.

6.3. Pilot project evaluation

As described in the previous section, during the Pilot Project Phase the time constraint was set to 12 sec in each workstation. During this phase, the time performance for 9 workers was collected in order to evaluate their task times under this time constraint. Data was collected on the task times of 4 workers at FL1A, 3 workers at FL1B and 2 workers at FL1C. It could be observed that there was a reduction in the average time the workers required to perform the assembly tasks in each workstation, as well as a reduction in the average dispersion with the exception of workstation FL1A (Table 20). Nonetheless, using the proposed mapping approach it is possible to have a better visualization of the deviations the workers presented relatively to the workstation performance. In the observed workers, none of them had performance located in Quadrant I or IV. The performance varied from -1% to -30% in terms of deviation to the average time of the workers previously observed, $\Delta\bar{x}_i$, and +29% to -35% in terms of deviation to

the average dispersion previously observed, Δs_i, which demonstrates a considerable heterogeneity in the observed performance. It can be observed that in overall terms, the workers became 15% faster than previously and with less 5% dispersion on their task times (as indicated in the Figure 21).

Table 20 - Observed global average time and dispersion in each workstation evaluated during the Pilot Project

Workstation	Nº observed workers	$\bar{X}$ [sec]	$\bar{S}$ [sec]
FL1A	4	10.3	1.8
FL1B	3	9.0	1.4
FL1C	2	11.6	1.3

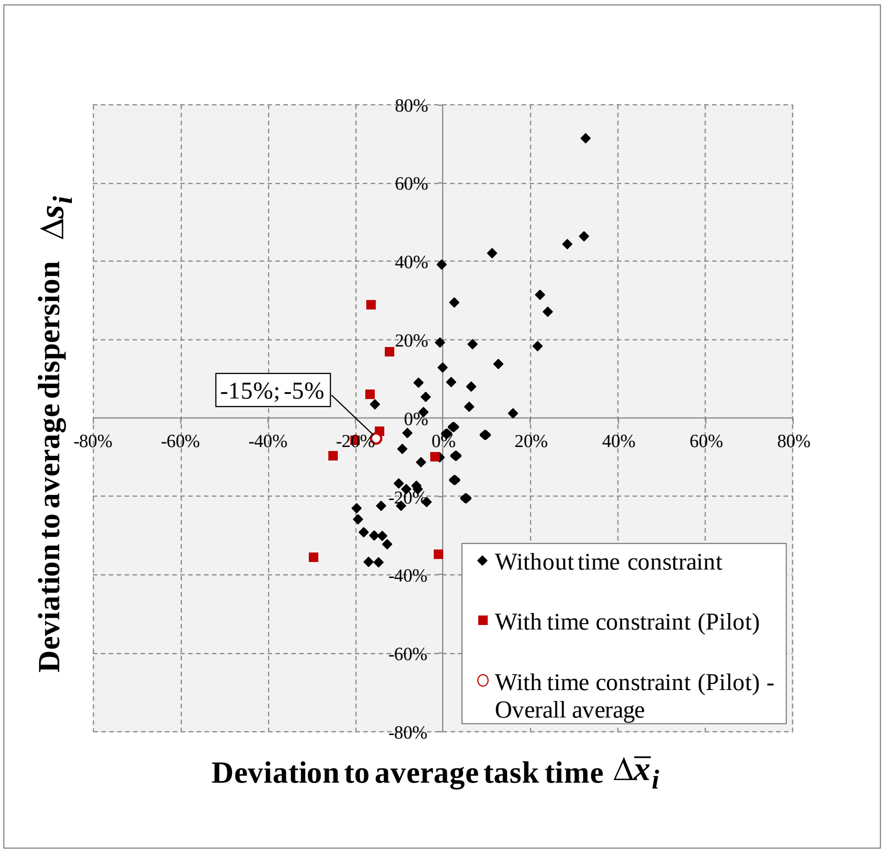


Figure 21 - Performance map for work paced by the system rhythm and with a 12sec time constraint

The performance of the sampled workers indicated that the imposition of the 12 sec. time constraint was making the workers perform faster than previously. However they were missing parts during the process. Each time they could not fulfil the assembly tasks within the 12 sec time slot, the incomplete part was taken out of the system, influencing the system output performance. To evaluate the

performance of the system, the hourly system output was sampled and compared to the target value (240 p/h ready for packaging). It could be observed (Figure 22) that the output of parts was in average was 8% below the target value even if the workers were performing faster, meaning they were missing parts since they could not cope with the pacing rhythm.

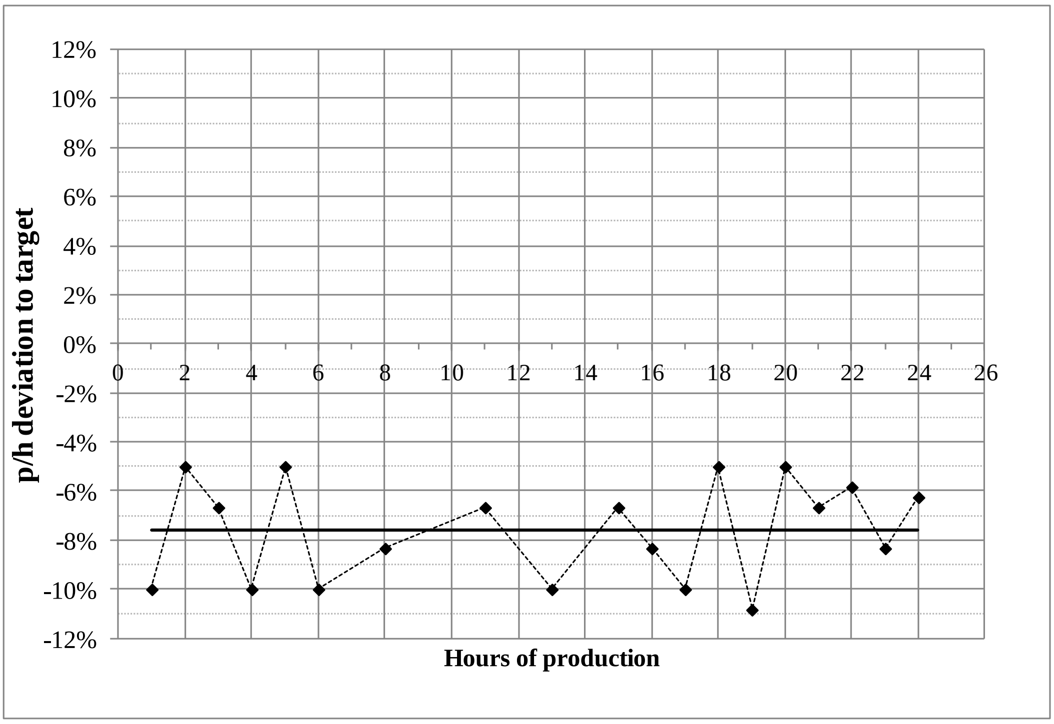


Figure 22 - System output performance compared to the target with the 12 sec time constraint

As it was stated previously, during the Pilot Project it was important to evaluate not only the individual performance of the workers and the system output performance but also the feedback of the workers towards this new workflow policy. It was important to gather the workers opinion on this policy and if they felt if they could cope with this speed increase. The workers were asked to fill out a short anonymous questionnaire to express their opinion, in a 5 points scale, making a comparison between working with the time constraint or without. They were asked to make a general comparison between the work with the time constraint and without, how did they assess the work rhythm, and the tiredness level at the end of the shift. They had also the possibility to justify their answers if they chose to.

A total of 16 workers answered the questionnaires (Table 21) and it was verified that 75% considered that in general the time constraint was a better "working

method". One of the workers, who had justified their opinion, referred that the workstation operation mode was more organized this way, in the sense that by setting a fixed rhythm, everyone had to work a given minimum. This opinion, is related to the free-riding effect (Williams *et al.*, 1981), previously described in Chapter 2.6: the workers considered that the working rhythms had become more independent and less affected by variations of the co-workers performance.

Nonetheless, the questionnaires also confirmed that the workers were working faster than before, since 75% of the responses indicated so. In addition, a large percentage (38%) of the workers considered they were feeling more tired at the end of the shift than before, while 19% considered they were much more tired. The answers to this questionnaire indicated that the workers generally accepted this workflow policy, but that the time constraint required an adjustment.

Overall, this adjustment was required since, even if the individual performance were faster than previously, the workers were feeling strained and the target output for the system performance was not being obtained.

Table 21 - Workers feedback on the 12 sec time constraint implemented in each workstation

Required Qualitative Comparison	Possible Answers	Results
General – Working with a time constraint or without	• Much Worse	-
	• Worse	-
	• Same	25%
	• Better	75%
	• Much Better	-
Work Rhythm - Working with a time constraint or without	• Much Faster	25%
	• Faster	75%
	• Same	-
	• Less fast	-
	• Much less faster	-
Tiredness Level - Working with a time constraint or without	• Much More Tired	19%
	• More Tired	38%
	• Same	38%
	• Less Tired	6%
	• Much Less Tired	-

Sample: 16 workers

Given the results obtained during the Pilot project was concluded that it should be given a plus 2 sec tolerance. Therefore, the time constraint was set for 14 seconds, so that the jig was fully immobile for 12 sec and 2 sec tolerance was allowed for the task if necessary.

After this adjustment, the system output was re-sampled in order to evaluate if it was according to the target value of 240 p/h (Figure 23). It could be observed that in average the produced output was (2%) higher than the target value. Therefore, given this data, it was considered that the time constraint was correctly adjusted and the workers were not missing enough parts that would reduce the output below the considered target.

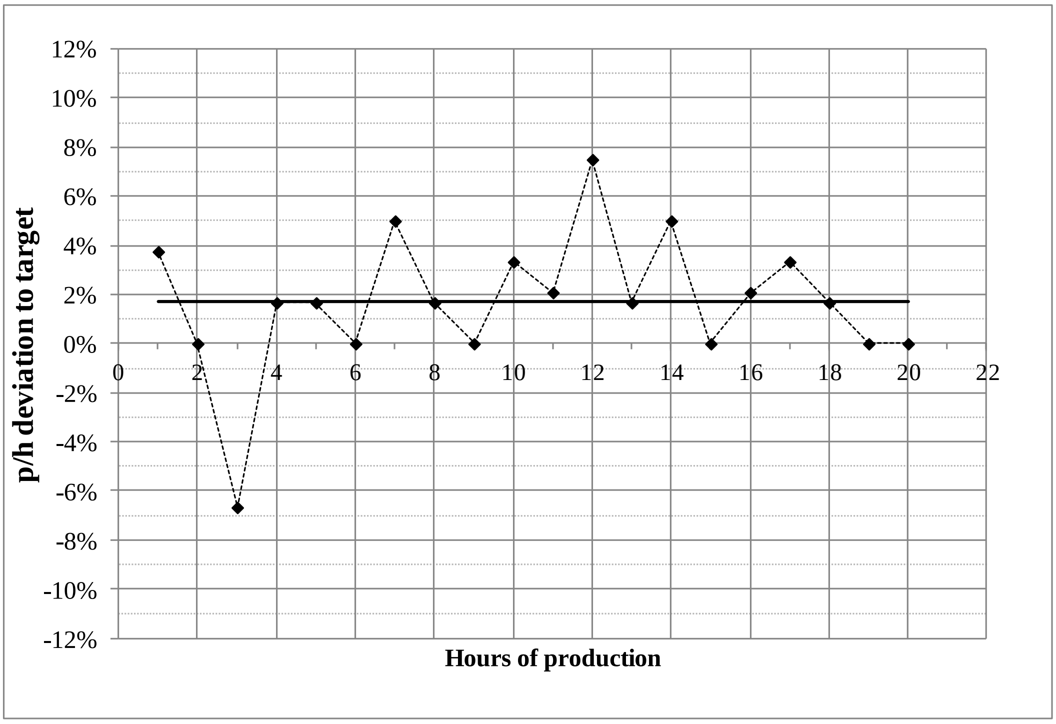


Figure 23 - System output performance compared to the target after readjusting the time constraint to 14 sec

This evaluation during the pilot project resulted in an adjustment of the time constraint from 12 sec to 14 sec, which resulted in better results in terms of system output. The modified workflow policy was then fully implemented to the system, and the workers performance reassessed as it is described in the following section.

6.4. Task time performance map for work paced by a time constraint

The time constraint was implemented as previously described, and in each workstation the workers had 14 sec available to perform the assembly tasks. In this section, the workers performance are evaluated in order to analyse the differences on the workers heterogeneity in a system where the workers were paced by the system rhythm and subjected to variations in performance of their co-workers, and in a system where a fixed time-constraint each worker had the same time available to perform the assembly tasks.

Data was collected on workers performing assembly tasks on workstations FL1A (seven workers observed), FL1B (six workers observed), and FL1C (six workers observed) with the adjusted pacing rhythm[6].

In order to verify if the task time distributions of the observed workers followed a normal distribution, it was used the Shapiro-Wilk test, previously described in Section 4.3. According to the test results (Table 22, Table 23 and Table 24), there is only one set of observations in workstation FL1B (Table 23), in which it is not possible to assume normality since the p-value is lower than the significance value (α=0.05). This outcome agrees with the results of previous authors (Dudley, 1963) which demonstrated the time distributions of trained and experienced worker on repetitive work have a marked tendency to yield a much more nearly normal distribution in rigidly paced conditions.

Table 22 - Shapiro-Wilk test results for task time distributions observed at workstation FL1A after the introduction of the 14 sec time constraint

Workstation FL1A			
Worker	W	n	p
ID1	0.963	30	0.368
ID4	0.952	30	0.197
ID5	0.983	30	0.904
ID8	0.933	30	0.061
ID9	0.972	30	0.582
ID10	0.961	30	0.322

[6] Note that the number of observations, n, per worker performed in this scenario was 30. The number of observations was lower than in the first scenario. The required sample size for a 95% confidence with 5% error rate for the average, had reduced significantly according to the calculations using Equation 1 (maximum n_i= 10). However it was opted to keep the 30 readings for the following analyses.

ID14	0.974	30	0.663
α=0.05			

Table 23 - Shapiro-Wilk test results for task time distributions observed at workstation FL1B after the introduction of the 14 sec time constraint

FL1B			
Worker	*W*	*n*	*p*
ID1	0.935	30	0.068
ID2	0.946	30	0.129
ID8	0.990	30	0.993
ID11	0.951	30	0.176
ID12	0.930	30	**0.050**
ID15	0.972	30	0.600
α=0.05			

Table 24 - Shapiro-Wilk test results for the task time distributions observed at workstation FL1C after the introduction of the 14 sec time constraint

FL1C			
Worker	*W*	*n*	*p*
ID3	0.968	30	0.488
ID6	0.971	30	0.554
ID7	0.972	30	0.591
ID8	0.954	30	0.215
ID13	0.986	30	0.954
ID14	0.962	30	0.341
α=0.05			

In order to verify if the task time distributions of the observed workers have similar variability, it was used the Levene’s test, previously described in Section 4.3. When the time distributions are analised in terms of variance homogeneity, it could be concluded that for the workers observed in workstation FL1A and FL1B, the variances do not vary significantly, but that for FL1C they cannot be considered homogenous (Table 25). However, these results indicate that the time constraint

had an effect on the observed variability, since the amount of variability on the task time distributions from worker to worker became more similar.

Table 25 - Levene's test results for the task time distributions of the workers observed after the introduction of the 14sec time constraint

Workstation	**Levene's test results**
FL1A (k=7 workers)	$F(df1=6, df2=203)= 1.146$, $p=0.337$, $\alpha=0.05$
FL1B (k=6 workers)	$F(df1=5, df2=174)= 1.992$, $p=0.082$, $\alpha=0.05$
FL1C (k=6 workers)	$F(df1=5, df2=174)= 2.486$, $p=0.033$, $\alpha=0.05$

In order to analyse if the differences in the task time distributions for the different workers were significant after the introduction of the time constraint, it was used the Kruskal-Wallis test. Similarly, to the results obtained before the introduction of the time constraint, the task time distributions are significantly different in each observed workstation according to the test results (Table 26). Therefore, the workers' task times even in a system with rigid pacing can vary significantly. The performance maps will help to quantify and visualize better these differences.

Table 26 - Kruskal-Wallis test results for the task time distributions of the workers observed after the introduction of the 14sec time constraint

Workstation	Kruskal-Wallis test results
FL1A (k=7 workers)	$H(df=6)=29.314$, $p<0.0005$, $\alpha=0.05$
FL1B (k=6 workers)	$H(df=5)=58.843$, $p<0.0005$, $\alpha=0.05$
FL1C (k=6 workers)	$H(df=5)= 66.168$, $p<0.0005$, $\alpha=0.05$

Each worker performance was then calculated in terms of deviations to average time and average dispersion to the performance values for each workstation before the introduction of the pacing mechanism. By doing so, it is possible to compare the changes in performance using as baseline the initial scenario (workers performance paced by the system rhythm). From these calculations, it could be observed that in general the deviations to the average $\Delta\bar{x}_i$ shifted for lower values (Table 27), indicating the workers are performing faster, but that the range of variation (difference between maximum and minimum value of $\Delta\bar{x}_i$) is very similar to what was observed in the previous scenario. When the values for the deviations to the dispersion Δs_i, are compared before and after the introduction of

the time constraint (Table 28), it can be observed that there was also a shifting for lower dispersions, but also that the range of variations reduced 21 pp%.

In order to verify if there was a significant correlation between the two types of deviations $\Delta\bar{x}_i$ and Δs_i, a correlation test it was performed. The results of the correlation test indicated that there is not a statistically significant correlation between $\Delta\bar{x}_i$ and Δs_i ($r_s(k=19)$ =0.381, p=0.108, α=0.05). From these results and the comparison to the initial scenario, there is some indication of how the performance will be scattered on the performance map.

Table 27 - Deviations to the expected average before and after the introduction of the 14 sec time constraint

	$\Delta\bar{x}_i$	
	Without the time constraint	**With 14sec time constraint**
Upper Limit	+33%	+11%
Lower Limit	-20%	-40%
Range of variation	53 pp%	51 pp%

Table 28 - Deviations to the expected dispersion before and after the introduction of the 14 sec time constraint

	Δs_i	
	Without the time constraint	**With 14sec time constraint**
Upper Limit	+72%	+40%
Lower Limit	-37%	-48%
Range of variation	109 pp%	88%

As expected the performance deviations plotted in the performance map (Figure 24) seem like to have little to no correlation with the deviations to the average dispersion (as indicated by the correlation test). This means that under this work rhythm there is no longer a tendency for the slower workers to have higher dispersion, since longer task times are no longer permitted due to the time constraint. In terms of the expected performance in this scenario, the expected average is 10% faster than previously and the expected dispersion decreased to -2%.

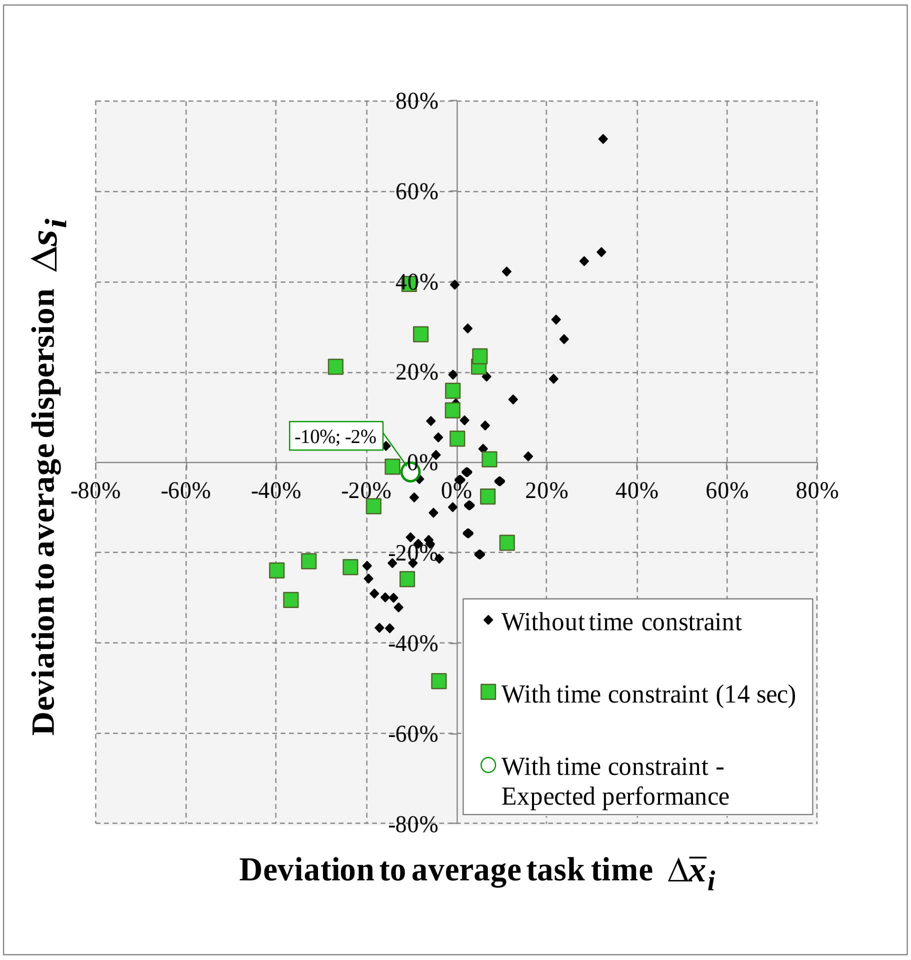


Figure 24 - Performance map for work paced by the system rhythm and with a 14 sec time constraint

When the results are analysed in terms of occurrences frequency in each quadrant (Table 29), it is concluded that when compared to the scenario with no time constraint, the occurrences frequency in Quadrant I (slower and more dispersed task times than the average – meaning the worst case out of the four combinations) reduced from 30.4% to 21.1%.

However, the sample size was different in each scenario (46 sets of task times were collected in the scenario before the time constraint implementation versus 19 with the time constraint implemented). In order to investigate if having the time constraint affected the number of occurrences per quadrant, a chi-square (χ^2) independence test was performed. This test is applied when there are two categorical variables from a single population. It is used for comparing frequencies (counts) of nominal or ordinal level data for two samples across two or more

subgroups displayed in a cross tabulation table (Sheskin, 2004). The calculated test statistic χ^2 is compared with the value of the χ^2 distribution, for $df=(a-1)(b-1)$, where a is the number of rows and b the number of columns (the cross tabulation is available in Annex A.6). The null hypothesis (H0) considered was that the number of occurrences in each quadrant (QI, QIII or QII+QIV)[7] is independent on the workflow policy. From the results of the chi-square independence test, it wasn't possible to verify that these two variables were in fact dependent ($\chi^2(df=2)=0.751$, $p=0.687$, $\alpha=0.05$). Therefore, the type of work flow policy (with and without the time constraint) is not affecting the frequency of each type of performance, QI, QIII or QII+QIV.

Table 29 - Percentage of observed occurrences and average distance to the origin per quadrant with and without the 14 sec time constraint

Type of Performance	**% of Observed Occurrences**		**Average Distance of Observed Occurrences to the Origin***	
	Without time constraint	*With time constraint*	*Without time constraint*	*With time constraint*
QI	30.4%	21.1%	32.0 pp%	13.6 pp%
QII	15.2%	26.3%	15.9 pp%	25.3 pp%
QIII	41.3%	42.1%	24.6 pp%	32.1 pp%
QIV	13.0%	10.5%	10.6 pp%	15.4 pp%
			* $d_i = \sqrt{\Delta\bar{x}_i^2 + \Delta s_i^2}$	

However, when the average distance of the performance to the origin in each quadrant are compared between the two scenarios, the differences are quite large[8], namely in QI where the average distance to the origin reduced 18.4 pp%. This means that with the pacing mechanism the range of the most extreme performance of this type of performance (QI) in average reduced. In QIII the distance to the origin increased in 7.5 pp%, indicating that more extreme performance (more distanced from the origin) of this type occurred when compared with the previous scenarios. This means that the observed task times with the time constraint became

[7] The occurrences in QII and QIV were summed, or else the expected counts in the cross table for paced work would be less than five, violating the main condition and consequently reducing the test reliability in terms of variability (Sheskin, 2004).

[8] Since the number of occurrences in each quadrant for the paced scenario is less than 10, the average distances could not be statistically compared, since the results would be unreliable with such a small sample size per quadrant.

faster and less dispersed than the previous observed task times in QIII without the pacing mechanism.

In summary, the time constraint increases the expected speed in which the sampled workers population performed the assembly tasks, but the expected dispersion remains practically the same.

In addition, the deviations to the average and the deviation to the dispersion are no longer correlated: meaning that if the workers have a fixed time constraint there is no longer a tendency for workers with lower dispersion than expected to also have a lower average task time. This effect is observable since the $\Delta\bar{x}_i$ range of variation is similar to the scenario where there was not a time constraint, while the Δs_i range of variation decreased drastically (from 109pp% without the time constraint to 88pp% with time constraint). In terms of frequency of occurrences in each quadrant, a significant difference between the two scenarios could not be found. Nonetheless, the registered task times under the time constraint became less deviated from the expected performance (origin of the performance map) for QI performance type and more deviated for the remaining quadrants QII, QIII and QIV. For QIII, it could be observed that this type of performance became faster and less dispersed than previously.

In terms of system performance, there were significant gains in productivity. The introduction of a rigid pacing mechanism reduced the expected average task time (10 %) besides controlling the performance heterogeneity. In order to analyse the gains in the system output performance, several hours of production were sampled from two different periods: before and after the modification. It was possible to gather the output rate (p/h) from 10 different days (sampled one 8-hour shift per day) from each scenario. From the analysis of this data, it could be concluded that the company, by introducing the time constraint in that assembly system and consequently controlling the amount of allowed deviation to the average time performance, obtained a significant gain in productivity: in average, the assembly system was producing 13% more parts per hour than previously. The coefficient of variation (standard deviation divided by the average) of the part per hour also reduced from 3.7% to 2.8%, meaning that the variability of output was also reduced.

For the company this modification in the assembly system was considered as beneficial, since by controlling the heterogeneity of performance, they obtained an immediate result on the system output performance. For the assembly system managers, they considered that this way any issue related with the auxiliary systems were easily identified and therefore more quickly addressed. In addition, the system management had become easier – "if there are jigs queuing in some point in the system we know that something is wrong, while before it wasn't so obvious since it could be just a variation on the worker performance". This feeling was shared by the workers "if there is some malfunction in a sensor or any other equipment, we can't do our job within the established time, and we start missing parts, therefore everyone is more keen in being faster and more effective in solving these problems". The workers also considered that this workflow police help them maintain the working rhythm more stable during the shift, and therefore less tiring.
The plant manager gave a good analogy interpreting this feeling stated by workers: "you can drive from Lisbon to Porto sometimes at 90 km/h and other times at 150 km/h (…and risk getting a fine for speeding or even worse, an accident); or you can drive always at 120 km/h, in the end you can take the same time doing the trip, but you'll spend less fuel."
Given this results in this assembly system, the plant management plans to perform the same modifications to the remaining systems of this type.

6.5. Research problem extension

The performance maps approach demonstrated benefits in the visualization and discussion of the results. It enables the observation of how the performances are scattered in term of deviations to an average performance of the workers population, evaluate relations between the two types of deviations to the average performance, and evaluate occurrences in terms of four possible types of performance.
So far a comparison between the observed task times before and after the introduction of a rigid pacing using the performance maps was performed. Significant differences were found both in terms of the average performance and in terms of variations within each scenario.

In the first studied scenario, the workers were observed performing assembly tasks in an asynchronous assembly line. Because arrivals to a station may not be coordinated with departures from that station, asynchronous lines such as this one may have buffers between the stations to hold intermediate inventory, which in this case was limited by the number of jigs. However, in the observed type of system, the workstations had a high degree of coupling between them, since it was an assembly line working in a closed loop with low buffer levels. In addition, no job was allowed to overtake another. Therefore, if one workstation delayed the release of a jig for too long, the next workstation would eventually starve. Moreover, if this delay was high enough, then the rest of the system became blocked and stopped.
Since the observed system had such interdependence among workers, these could speed up the assembly process if they observed that they had jigs accumulating before their workstation and/or the following workstation was starving. Alternatively, they could slow down their assembly tasks completion if they observed that their workstation was becoming starved and/or if the buffer between their workstation and the following was reaching the maximum capacity. The time constraint in this case, reduced the interdependence over the workers task times, since whether or not the next workstation was starving and/or jigs were accumulating before their workstation, there was no point in speeding up the assembly process due to the control in the jigs release. Slowing down the assembly process was also limited to the time constraint. Nonetheless, both QI workers and QIII speeded up their performance.
Another important question to analyse is a scenario where the worker has the absence of interdependence with his/her co-workers. This situation can be found when the workstations are not coupled at all, considering for instance, that there is a large buffer between the workstations, large enough so it would never run out of parts, then the workers would not be pressured by their peers to perform slower or faster. It would be like each worker could perform at her/his own rhythm, and therefore in unpaced conditions. In this research work, one of the objectives is to analyse what are the differences in the task times among workers in such conditions. In this case, there is no pressure due to queuing before the workstation or starving from the following ones, neither a pressure due to an imposition of a limited time to fulfil the tasks. Therefore, it could be expected that the range of deviations in such workflow policy (or lack of it) would increase. In order to

investigate the effect of the lack of pacing will have on the workers performance, and consequently observable in the performance maps, a laboratorial physical simulation was performed , which is described in the following chapter.

7. Unpaced Work

As described previously, one of the goals of this research is to understand and quantify the workers tasks time distributions heterogeneity through data collection, statistical analysis, and development of new approaches to analyse those differences. At this point, it is questioned what is the impact in the workers' performance heterogeneity if the work is performed in unpaced conditions. The objective is to investigate if the workers performance heterogeneity is aggravated by the absence of a system rhythm.

Since this scenario could not be observed in the industrial framework, a physical simulation was set in laboratorial environment that mimicked the actual assembly tasks. In this section, it is described how this physical simulation was carried out using LEGO®-based assembling workstation, the sampling process, the time distribution observed and how those performances are scattered using the developed mapping approach.

7.1. Physical simulation using LEGO®

The use of LEGO® has been a common practice in research studies concerning manual assembly tasks in the last years. Researchers have been using these building blocks to investigate phenomena like the effect of grouping parts in the reduction of the average time to assemble parts (Madan *et al.*, 1995), assembly training procedures (Schlüter and Stodtko, 2011), physical and mental fatigue when performing manual repetitive tasks (Zadry *et al.*, 2009) and virtual reality in assembly and maintenance tasks (Adams *et al.*, 2001, Alem and Li, 2011).

Within the scope of this research, the LEGO® building blocks are used to mimic the type of assembly tasks carried out in the system observed in the industrial context.

A kit was built resembling the dimensions and components location where the components should be assembled of the actual radio bezel. In Figure 25 the model of the described kit with the components assembled can be observed, and in Figure 26 the schematic diagram with the main dimensions and indication of components location (buttons in grey).

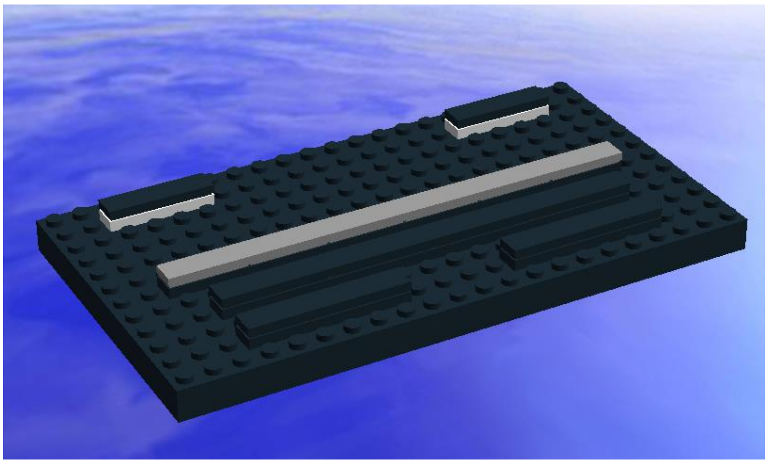


Figure 25 - Model of the LEGO kit representing the radio bezel

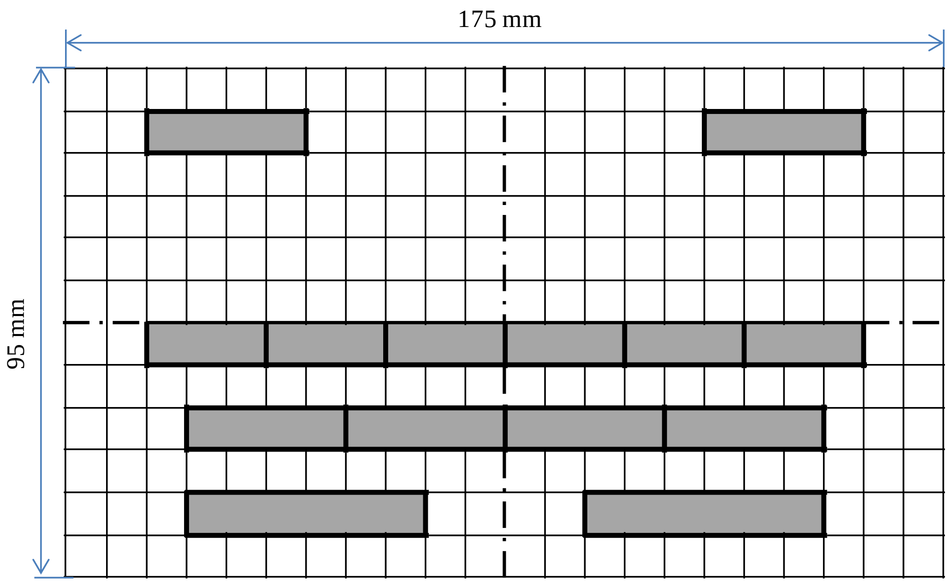


Figure 26 – Schematic diagram of the LEGO kit representing the radio bezel with main dimensions and location of the components to be assembled

In the actual company, it was observed that in the actual radio bezel the components should be assembled from top to the bottom and from the sides to the centre, using both hands simultaneously. This configuration of movements is common practice in the manual work design. When the right hand is working in the normal area to the right of the body and the left hand is working in the normal area to the left of the body, a feeling of balance tends to induce a rhythm in the workers performance. By using dual fixtures to hold two components, both hands can work at the same time, making symmetrical moves in opposite directions. It is natural for

both hands to move in symmetrical patterns. Deviations from symmetry in a two-handed workstation results in slow, awkward movements of the worker. Therefore, it is advisable to move the hands symmetrically and simultaneously to the centre of the body (Niebel and Freivalds, 1999). Consequently, in the laboratorial experiment with the LEGO kit, the assembly process followed the same logic observed in the company (which is a representative case of the common practice). In terms of basic motions elements required during the assembly process, it was also assured the same type of basic motions as in the assembly of the radio bezel would be used. In this case, they only differed in the last step, where in the assembly workstation observed in operation, the worker had to press a pedal to signal the part completion. In this case, the subject had to move the assembled kit to a box (Table 30).

Table 30 - Basic motions elements required to assemble the LEGO kit

Work Elements Description	Basic Motion Elements
1. Approach one hand to the box with the kits to be assembled placed in a fixed position	Reach (R)
2. Pick one kit with one hand from the box	Grasp (G)
3. Move the kit to the table and place it there.	Move (M)
4. Approach both hands to the components dispensers placed in a fixed location;	Reach (R)
5. Pick one component with each hand from the components dispenser;	Grasp (G)
6. Move the two components close to the jig where the product is placed;	Move (M)
7. Position the components in order to assemble them to the product;	Position (P)
9. Apply small pressure with thumbs in order to assemble components to product;	Apply Pressure (AP)
10. Repeat steps 4 to 9 for the next two pairs of components (7 in total);	-
11. Move the kit from the table to the box with the assembled kits;	Move (M)
12. Approach one hand to the box with the assembled kits placed in a fixed position and places the assembled kit there.	Reach (R)

7.2. Sampling process

For the experiment a total of 28 subjects (15 male and 13 female) were gathered, representing undergraduate students (22) from the Production Management course, graduate students enrolled as PhD students (3), and professors from IST (3).

None of the subjects had experience in performing assembly tasks of this type in an industrial context. Moreover, previous published research (Madan *et al.*, 1995) indicates that there are no substantial differences in the task times due to formal training (high school, vocational school or college level) involving manual assembly of LEGO® parts, therefore it was considered that the sample was homogenous regarding this matter.

All the sessions were performed in a laboratory at a normal temperature. Each observed subject was seated in an office ergonomic chair with the back vertical and the feet in full contact with the floor (Figure 27).

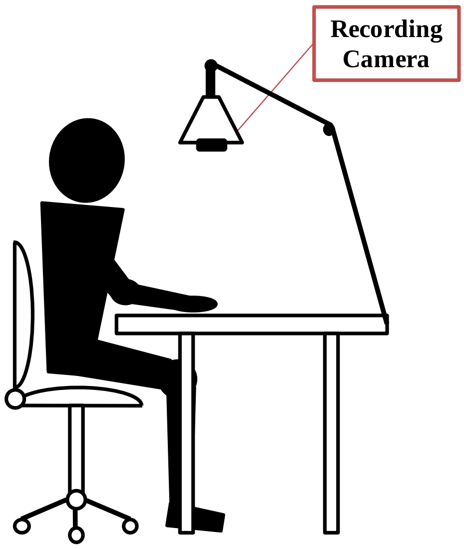


Figure 27 - Illustration of the workspace used to observed the assembly of the LEGO kit

To become familiar with the experimental equipment and procedures, the assembly instructions were posted in front of the workstation at the eye level, the assembly process was explained to each one of the subjects and demonstrated by the analyst. In order for the subjects to be acquainted with the assembly process, they were able to experiment the assembly process for approximately 3 min. The subjects were informed that there would be a camera recording only their hand movements (Figure 28). The subjects were requested to assemble the kits, following the

instructions, for 15 min. It was also underlined during the this short briefing that the objective was not to perform as much parts as possible within that time, but to work at a rhythm they felt comfortable with. The objective was to capture the subjects' task times, without them being constrained by time or any other pace rather than their own. The recorded sessions were then analised and the assembly times registered in Excel format.

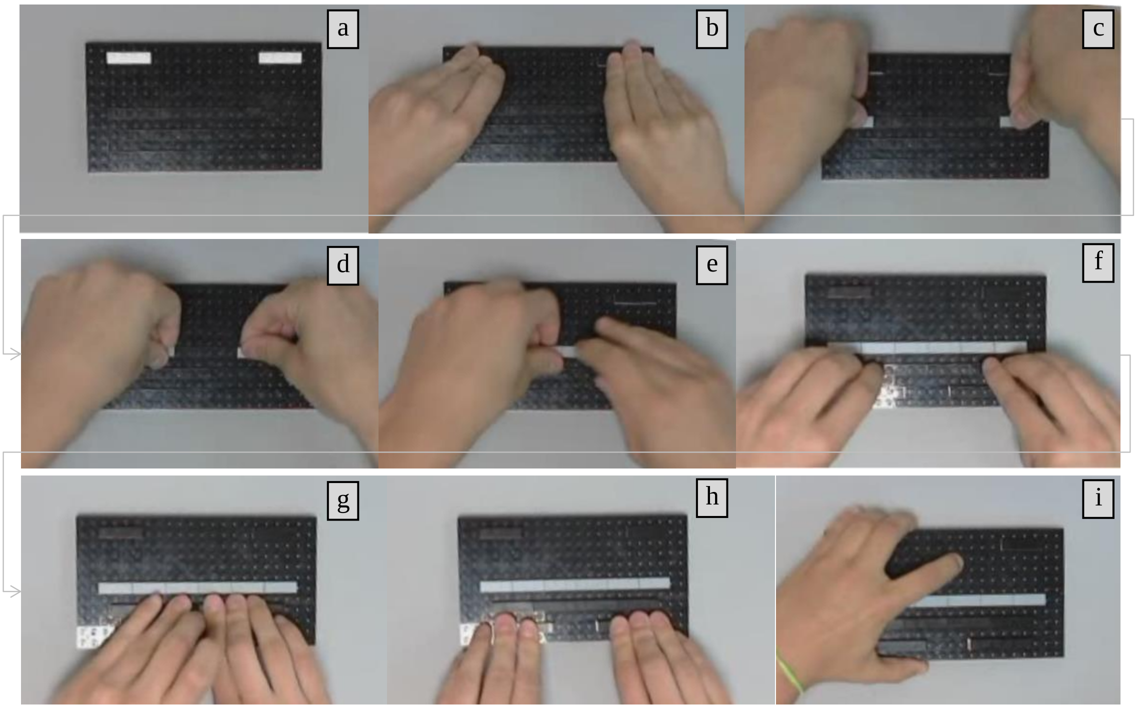


Figure 28 - Snapshots of the assembling process of the LEGO kit

7.3. Observed task time distributions

The task times for the 28 subjects were registered and treated in order to analyse the differences in performance from subject to subject.

After collecting the task times of the observed subjects it was verified that the average time of all the observed subjects was 23.16 sec and the average dispersion in the times was 2.20 sec. In comparison to the assembly process observed at the company, the coefficient of variation is 9%, which is lower than the average coefficient of variation observed at the company (which was 13%). This is an indication of an overall lower variability in unpaced conditions.

When the individual average task times and dispersion are calculated it can be observed (Table 31) that there is a large variation on the average times and on the dispersions of the registered times. For example, worker IDL21, took in average

28.99 sec to fulfil the assembly tasks with a dispersion of 3.64 sec, while worker IDL6 took in average 20.14 sec and presented a dispersion of 1.56 sec. Appropriate statistical tests were used to investigate the significance of these differences.

Table 31 - Average task times and dispersion observed in the assembly of the LEGO kit simulating unpaced working conditions

Subject *i*	$\bar{x}_i$ [sec]	s_i [sec]
IDL1	21.61	2.05
IDL2	22.09	1.71
IDL3	20.48	1.49
IDL4	26.84	3.10
IDL5	27.75	2.73
IDL6	20.14	1.56
IDL7	20.27	1.86
IDL8	20.32	2.04
IDL9	26.29	3.21
IDL10	21.53	2.28
IDL11	22.98	2.25
IDL12	22.27	2.00
IDL13	25.53	1.70
IDL14	24.76	3.25
IDL15	23.09	1.88
IDL16	21.75	2.22
IDL17	20.21	1.94
IDL18	22.99	1.66
IDL19	23.15	1.60
IDL20	22.79	2.83
IDL21	28.99	3.64
IDL22	21.10	1.55
IDL23	20.83	2.00
IDL24	22.91	2.48
IDL25	23.08	1.46
IDL26	26.79	1.67
IDL27	24.01	3.26

IDL28	23.99	2.19
Average	$\bar{X}$=23.16	$\bar{S}$ =2.20

Before analysing the significance of the observed differences in the task times, it is required to test for normality and homogeneity of variance of the task time distributions, to choose the appropriate testing procedure correctly.

In order to verify if the task time distributions could be approximated to the normal distribution, it was performed the Shapiro-Wilk test (Table 32) previously described in Section 4.3, and verified that for two of the subjects the null hypothesis had to be rejected. In other words, for some cases the time distributions significantly deviate from a normal distribution, therefore the use of a parametric testing procedure is not advisable.

Table 32 – Shapiro-Wilk test results for task time distributions of the subjects observed assembling the LEGO kit

Subject *i*	***W***	***n***	***p***
IDL1	0.872	16	**0.029**
IDL2	0.981	24	0.907
IDL3	0.945	25	0.198
IDL4	0.969	16	0.823
IDL5	0.915	18	0.107
IDL6	0.922	16	0.181
IDL7	0.956	27	0.306
IDL8	0.902	15	0.103
IDL9	0.940	18	0.292
IDL10	0.906	20	0.054
IDL11	0.946	19	0.341
IDL12	0.939	18	0.279
IDL13	0.970	20	0.761
IDL14	0.924	20	0.117
IDL15	0.950	18	0.431
IDL16	0.953	22	0.360
IDL17	0.932	25	0.096
IDL18	0.954	20	0.433
IDL19	0.946	20	0.310
IDL20	0.909	22	**0.046**
IDL21	0.972	20	0.792

IDL22	0.974	21	0.823
IDL23	0.963	24	0.500
IDL24	0.971	23	0.711
IDL25	0.955	18	0.501
IDL26	0.935	17	0.265
IDL27	0.955	21	0.427
IDL28	0.985	21	0.979
α=0.05			

In addition, in order to verify if the observed individual dispersions are significant different the Levene's test was used. The test result indicate the violation of the assumption of homoscedasticity ($F(df1=27, df2=536)=3.117$, $p<0.0005$, $\alpha=0.05$). This means that the dispersions from subject to subject are significantly different.

In order to check for differences in the time distributions, the Kruskal-Wallis test procedure was used. As in the previous scenarios, the test results indicate that there is a significant difference among the time distributions ($H(df=27)=286.669$, $p<0.0005$, $\alpha=0.05$), supporting the previous findings.

In the observed sample, there were both female and male subjects. Therefore, there was the concern that these variables might introduce heterogeneity to the group and that the results would not be comparable to the industrial scenario, where all the workers were female. In the industrial scenario, the reason for this choice had to do with the empirical experience gathered throughout the years while running this type of assembly systems. Their experience had made them prefer female workers since they considered that there was a difference in the general attitude towards the attention to details, hence an increased responsibility on the quality of the product being manufactured. However, they had no indication that the time performance could be different among men and women.

Therefore, the Kruskall-Wallis test was rerun for the following situations:

- Only male subjects' task times, to check if the performances could be considered homogenous within this group. The test results indicate that there are significant differences among the performances ($H(df=14)=120.358$, $p<0.0005$, $\alpha=0.05$).
- Only female subjects' task times, and once more the test results led to significant differences ($H(df=12)=159.453$, $p<0.0005$, $\alpha=0.05$).

These results indicate that within male or female subjects the observed task times are significantly different. Nonetheless, the gender factor could yield differences in the average times, since from the experience of observing the subjects assembling the parts there was the feeling that some male subjects seemed more in a hurry to finish the experiment than any of the females observed. In order to compare the performances between these two groups, their average task times were compared using a t-test.[9] The calculated test statistic, *t*, is compared with the Student's t-distribution for $df=kf+km-2$, where *kf* is the number of subjects in the group with only female subjects and *km is* the number of male subjects. There were no significant differences between the female subjects' average task times (M_f=23.56 sec, SD_f=2.94 sec) and the male subjects (M_m=22.82 sec, SD_m=1.96 sec) average task times ($t(df=26)=-0.791$, $p=0.436$, $\alpha=0.05$), and therefore, no gender differentiation was considered in the following analyses. Note that the company where the observations took place considered that there were gender differences in regards to responsibility towards the quality of the product being produced. However, in order to support or refute this statement, further studies should be considered which fall outside the scope of this research.

As demonstrated in the previous chapters, the proposed mapping is a practical approach to visualize and analyse the heterogeneity of the performances within the observed group of subjects. In the following section, the analysis to performances heterogeneity is performed using this approach.

7.4. Task time performance map for unpaced work

With the objective of characterizing the subjects' performances heterogeneity, the data points for the 28 subjects were calculated in terms of deviation to the global average time, $\Delta\bar{x}_i$, and global dispersion, Δs_i. It was verified, that the range of $\Delta\bar{x}_i$ reduced 15 pp% (Table 33). The maximum and minimum values for $\Delta\bar{x}_i$ in the LEGO case reduced 8 pp% and increased 7pp% respectively. The range of

[9] Note, the task times for each worker might not be normally distributed, but the distribution of the averages within each group are, according to the results of the Shapiro-Wilk test: Male subjects: $W(km=15)=0.930$, $p=0.271$, $\alpha=0.05$; Female subjects: $W(kf=13)=0.916$, $p=0.223$, $\alpha=0.05$. For both female and male subjects, the average task times are normally distributed. Also the Levene's test results ($F(df1=1, df2=26)=3.983$, $p=0.057$, $\alpha=0.05$) assure equal variances on the averages between groups. Therefore, the assumptions of normality and homoscedasticity when using the t-test are not violated.

deviations for the, Δs_i, (Table 34) is quite similar when compared to the industrial scenario (where several workers were observed performing the same type of assembly tasks paced by the assembly system rhythm). The Δs_i maximum and minimum are also slightly less extreme (reduced 7 pp% for the maximum and increased 3 pp% for the minimum). Therefore, it can be concluded that the location of the observed extreme values is quite similar.

Table 33 - Deviations to the average for work paced by the system rhythm (without time constraint) and for unpaced work

	$\Delta\bar{x}_i$	
	Paced by System Rhythm	**Unpaced Work**
Upper Limit	+33%	+25%
Lower Limit	-20%	-13%
Range of variation	53 pp%	38 pp%

Table 34 - Deviations to the average dispersion for work paced by the system rhythm (without time constraint) and for unpaced work

	Δs_i	
	Paced by System Rhythm	**Unpaced Work**
Upper Limit	+72%	+65%
Lower Limit	-37%	-34%
Range of variation	109 pp%	99 pp%

In addition, when the number of occurrences in each quadrant is compared between the industrial and the LEGO scenario (Table 35), a smaller proportion of occurrences in QI can be noticed in the latter case, meaning that there are less occurrences of performances slower and more dispersed than average. Nonetheless, since the sample size was different in each scenario (46 sets of task times were collected in the industrial scenario versus 28 in the LEGO scenario), an independence test was performed (the cross tabulation can be found in Annex A.7). The objective was to investigate if the total lack of pacing was affecting the number of occurrences per quadrant or not (H0: the number of occurrences in each quadrant (QI, QIII or QII+QIV) is independent from the type of work considered). From the

results it can be concluded that in both scenarios the frequency of occurrences in each quadrant is not significantly different ($\chi^2(df=2)=0.818$, $p=0.664$, $\alpha=0.05$).

Table 35 - Percentage of observed occurrences per quadrant for work paced by the system rhythm (without time constraint) and unpaced work

	% of Occurrences	
Type of Performance	Paced by System Rhythm	Unpaced Work
QI	30.4%	21.4%
QII	15.2%	17.9%
QIII	41.3%	50.0%
QIV	13.0%	10.7%

In terms of the calculated average distances to the origin per quadrant (Table 36), the largest distance occurred in QI. The occurrences in this quadrant were further away from the origin when compared with the industrial scenario (increased 15.6 pp%), meaning that the subjects with this type of performance were slower and more dispersed when compared to the industrial scenario, where the workers were paced by the system rhythm. In QIV the distance also became larger, but only by 8pp% meaning that the subjects were slightly slower but less variable, but given the number of occurrences it was considered that this difference was dismissible. The average distances to the origin in the remaining quadrants were reduced overall, but not considerably as it can be seen from the results.

Table 36 - Average distance of observed occurrences to the origin per quadrant for work paced by the system rhythm and unpaced work

	Average Distance of Observed Occurrences to the Origin*	
Type of Performance	Paced by System Rhythm	Unpaced Work
QI	32.0 pp%	47.6 pp%
QII	15.9 pp%	9.9 pp%
QIII	24.6 pp%	20.7 pp%
QIV	10.6 pp%	18.6 pp%
	* $d_i = \sqrt{\Delta\bar{x}_i^2 + \Delta s_i^2}$	

It was observed in the performance map for unpaced work (Figure 29) that, similarly to what was observed in the industrial scenario (with the workers paced

by the system rhythm), there is a significant positive correlation between the two types of deviations ($r_s(k=28)=0.447$, $p=0.017$, $\alpha=0.05$).

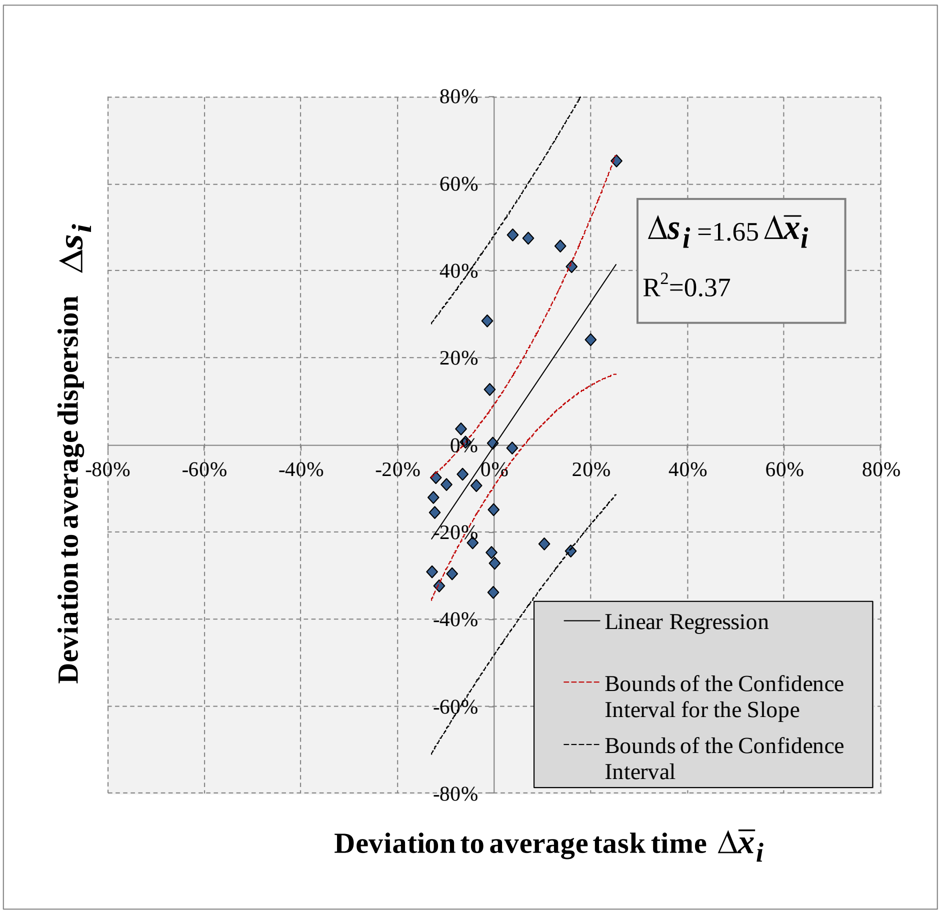


Figure 29 - Performance map for unpaced work

When the values for the slope (m) in the scenario where the workers were paced by the system rhythm are compared to the values for this scenario, unpaced work conditions, it can be verified (Table 37) that the slope (m) is steeper for unpaced work. This difference indicates that those subjects with slower performance tend to have more dispersed performances than in the industrial scenario. Nonetheless, the 95% confidence interval for the slope is wider in this case, indicating more uncertainty in the regression.

Table 37 – Correlation coefficients, slope and $CI_{95\%}$ in the scenarios when the work is paced by the system rhythm and in unpaced conditions.

	Paced by System Rhythm	**Unpaced Work**
Correlation coefficient, r_s	0.789 (k=46, p<0.005, α=0.05)	0.447 (k=28, p=0.017, α=0.05)
Slope, m	1.489	1.645
Confidence Interval for m, $CI_{95\%}(m)$	[1.174;1.805]	[0.801;2.489]

Given the previously mentioned facts, no significant differences were found between the performances observed in the industrial scenario and in the LEGO scenario.

In the industrial scenario, the workers were observed while performing assembly tasks in a highly coupled assembly system. In the Lego scenario, the subjects were observed performing the same type of assembly tasks. In this case, they were only subjected to their own natural pace, since their working rhythm is not subjected to pressure from adjacent workstations. It can be concluded that the absence of a system rhythm does not aggravate the heterogeneity of performances significantly. However, the QI performances became (in average) more distanced from the origin. The occurrences in that quadrant were more distanced from the origin mainly due to an increase in dispersion, than when compared to the industrial scenario. The slower subjects tend to have more dispersion since there is no peer pressure constraining the eventuality of longer task times.

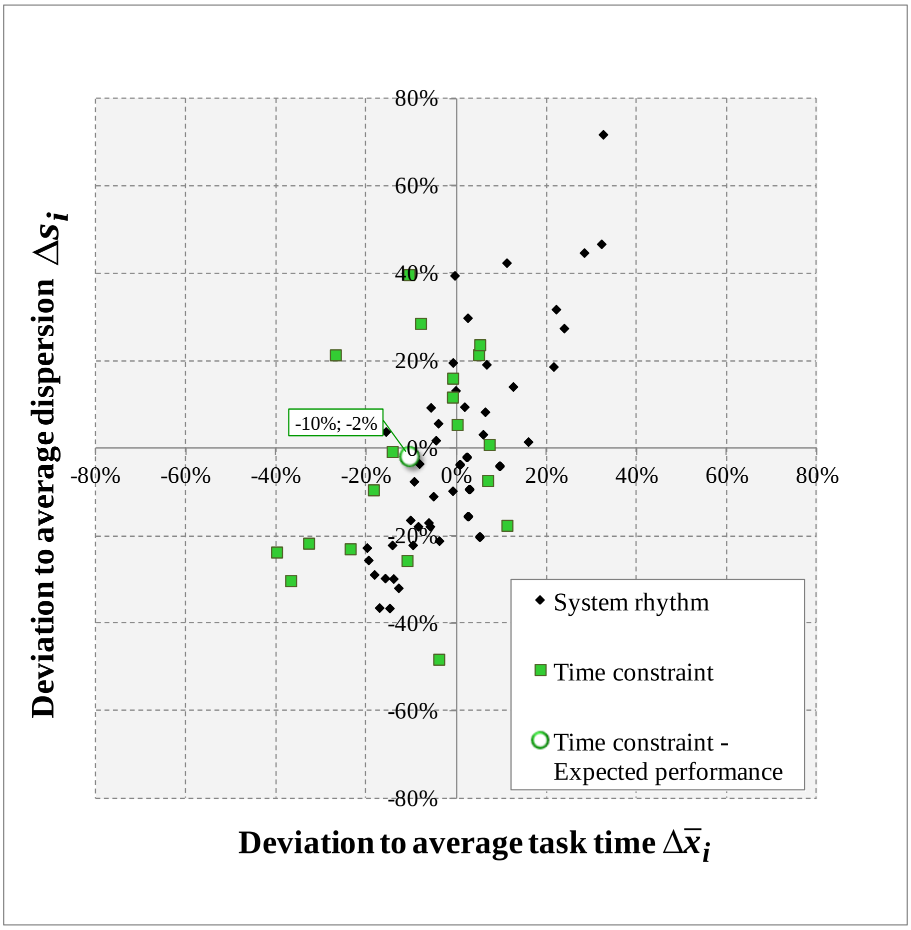
In the following chapter the three studied scenarios are compared among them, and the differences and similarities further discussed.

8. Task Time Performance Maps Comparison

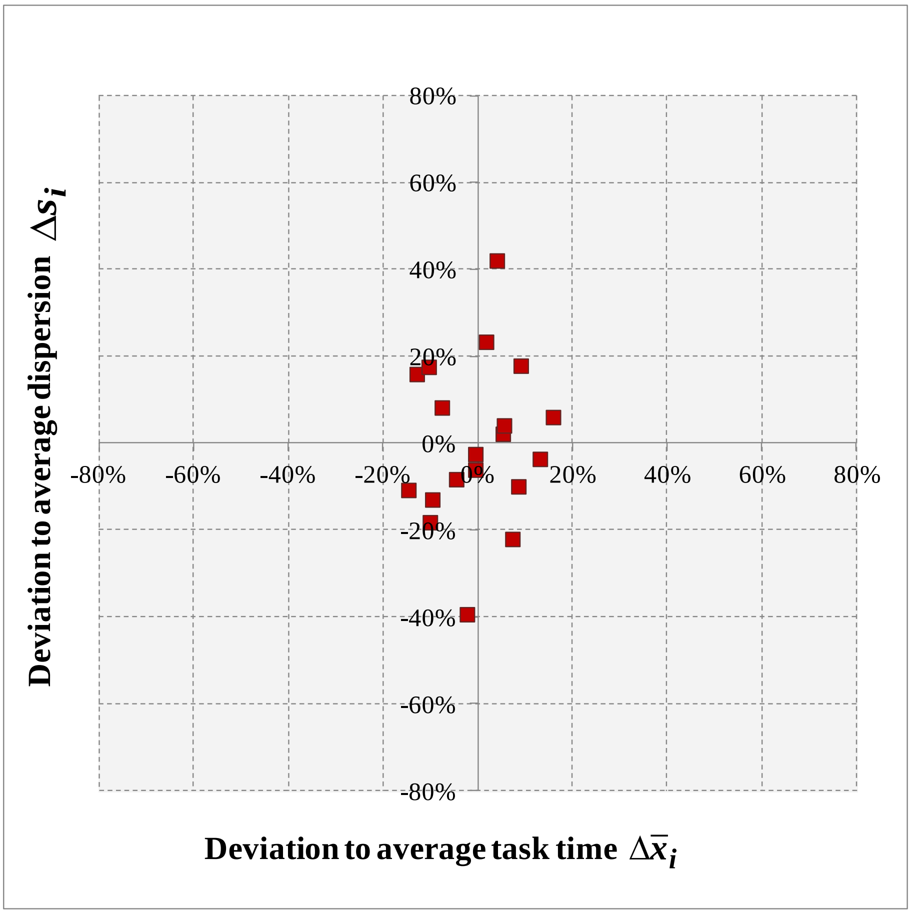
In this chapter, the three studied scenarios are compared using the proposed task time performance maps:

1) Workers performance paced by the system rhythm (without time constraint);
2) Workers performance paced by a time constraint;
3) Unpaced work (performance paced by the worker natural rhythm).

In the second scenario (workers paced by a time constraint), the performance maps data points were calculated in terms of deviation to the workstation average time and dispersion previously observed while the workers were paced by the system rhythm (Figure 30 a). Therefore, to compare the three scenarios it was necessary to redefine these points in order to make a direct comparison. The average task time and average dispersion per workstation was redefined based on the observed workers under the time constraint (Table 38). The deviations observed for each worker were plotted in the performance map (Figure 30 b).



a)



b)

Figure 30 – Performance maps for work paced by a time constraint of 14 sec a) based on the average time and dispersion observed in the scenario with the workers paced by the system rhythm and b) recalculated based on the workers average time and dispersion observed in this scenario

Table 38 – Expected performance for the scenarios Paced by System rhythm and Paced by Time Constraint

Workstation	Expected Performance Paced by System Rhythm	Expected Performance Paced by Time Constraint
FL1A	$\bar{X}$=12.35 ; $\bar{S}$=1.60 (15 workers)	$\bar{X}$=12.30 ; $\bar{S}$=1.90 (7 workers)
FL1B	$\bar{X}$=11.67 ; $\bar{S}$=1.62 (11 workers)	$\bar{X}$=8.20 ; $\bar{S}$=1.40 (6 workers)
FL1C	$\bar{X}$=11.77 ; $\bar{S}$=1.44 (11 workers)	$\bar{X}$=11.56 ; $\bar{S}$=1.68 (6 workers)

At this point it is possible to compare the three scenarios using the proposed mapping approach, since they are being treated as independent situations (see Figure 31 in page 126 with the three performance maps corresponding to each studied scenario).

The main numerical results for each scenario in Table 39 (page 127), summarize the findings in terms of:

- The differences in workers task time distributions;
- The range of deviations in terms of average and dispersion;
- The frequency and distance of the occurrences of performances of type QI and QIII;
- The correlations between the two types of deviations studied, as well as the values for the regression slopes.

From these results, it could be observed that, in every studied scenario of worker pacing, significant differences were found among the workers task times. This means that when workers are performing paced by the system rhythm, by a time constraint, or at their natural pace their differences on time performances are mainly due to individual differences.

When mapping the time performances in deviation to the average performance, these differences can be observed both in deviation to the average (worker slower of faster than the average) and in deviation to the dispersion (worker with more or less dispersion than the average).

The range (difference between maximum and minimum observed) of the differences between deviation to the average time and dispersion, are quite large in every scenario. However, if there is an imposed time constraint, the deviation to the average is contained between +16% and -14%, while the dispersion is contained between +42 % and -40%, which is a significant reduction in the maximum values when compared to the other two scenarios.

This result shows the effect of controlling the maximum time allowed to perform the assembly tasks, on the extreme performances observed within the sampled workers. Workers that have a large dispersion in their task time distributions will be faced with a cut-off value (equal to the time constraint) which will limit the maximum value for the task time. This has not only an effect on the dispersion, which is reduced, but also on the average time which also decreases.

It could be observed that the range of deviations is larger when the workers are influenced by the system pace. In this scenario the observed workers presented the fastest (-20% of deviation to the average) and the slowest performances (+33% of deviation to the average), and the most variable one (+72% of deviation to the dispersion). These observations indicate that the absence of pacing (either by the system

rhythm or time constraint) when performing assembly tasks, will not necessarily aggravate the values of the extreme performances, even if permitted by the workflow policy.

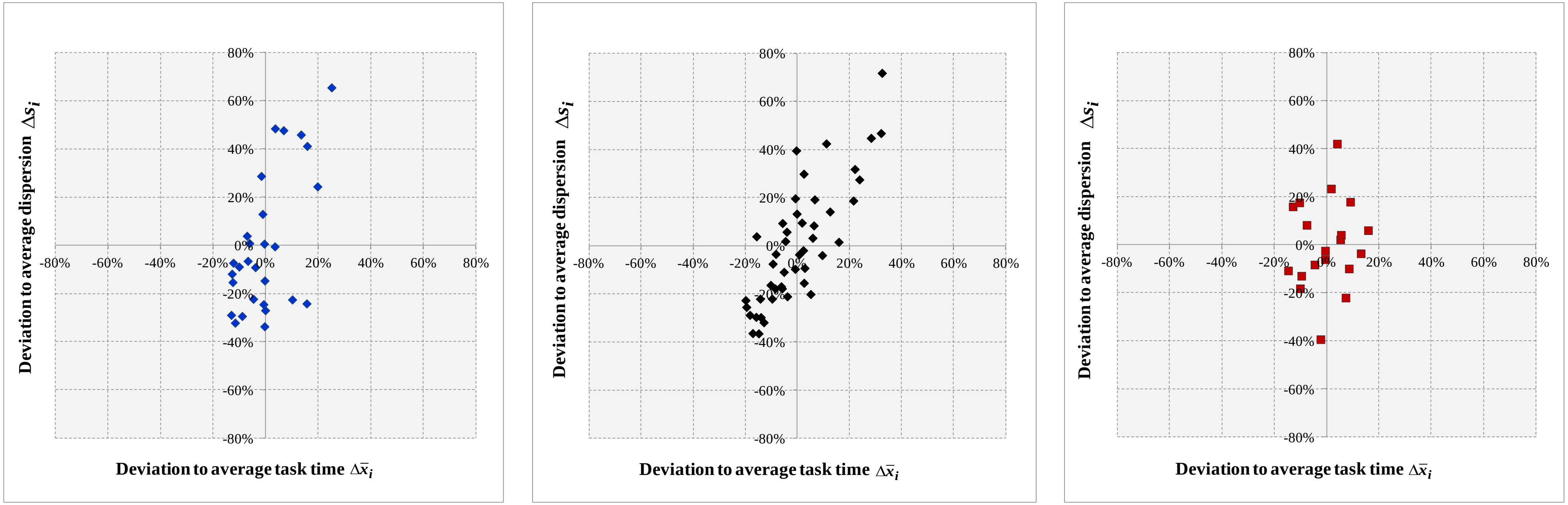
It could not be statistically proven that the frequency of occurrences per defined quadrant is in some way dependent on the workflow policy. Nonetheless, it was observed that in every scenario the performances were mostly located in QI (slower and more dispersed task times) and QIII (faster and less dispersed task times). However, in the scenario where there is an imposed time constraint, the distribution of occurrences become more homogeneous between these two quadrants (QI: 32%; QIII: 37%; QII+QIV: 31%).

When the values for the average distance to the origin are compared, it can be concluded that when the workers are performing assembly tasks at their own pace, they tend to have performances that are more deviated from expected performance. This happens mainly due to an increase in dispersion in their task times (see Figure 32 in page 128 with the centroids for each scenario), even if in terms of deviation to the average the value is close to what was observed in the scenario where the workers worked influenced by the system pace. The regression slope between deviation the average and deviation to the dispersion gives an indication of this phenomenon, since it is the steepest (but with a wider confidence interval).

In summary, three scenarios were studied, focusing on the effect that different kinds of pacing would have on the heterogeneity of workers performance. In addition, the proposed mapping approach enabled the comparison between the three different scenarios. With such mapping, four types of performance were defined based on the deviations to the average performance of the observed subjects. Using such maps, it was possible to visualize and obtain quantitative measures of the deviations observed for each scenario and compare them. Overall, a time constraint controls the amount of deviation to the average performance among the group of subjects performing the same task. On the other hand, in unpaced work, there is an increased tendency for the subjects to have more dispersion in their task times. However, in the industrial practice, the subjects work with some degree of interdependency between them.

In the scenario where the workers are paced by the system rhythm, there is more heterogeneity in the performances, compared to the scenario of a time constraint. Nonetheless, it is not always possible to impose this kind of mechanism to control the workers performance. Therefore, it becomes important to understand what would be the

sole impact of having workers with different performances. Using the centroids calculated based on the observations for the scenario where the workers had their performances paced by the system rhythm, an abstract assembly system to test the impact of the different performances will be modelled.



a) b) c)

Figure 31 – Performance maps for the different studied scenarios of worker pacing a) Unpaced Work, b)Paced by System Rhythm and c) Paced by a Time Constraint

Table 39 – Summary of the numerical results for the three different studied scenarios of worker pacing

<table>
<tr><td colspan="2">Data collection</td><td colspan="2">LEGO Experiment</td><td colspan="4">Industrial Setting</td></tr>
<tr><td colspan="2">Type of Worker Pacing</td><td colspan="2">Unpaced Work</td><td colspan="2">System Rhythm</td><td colspan="2">Time Constraint</td></tr>
<tr><td colspan="2">Differences in workers task times</td><td colspan="2">Significant</td><td colspan="2">Significant</td><td colspan="2">Significant</td></tr>
<tr><td rowspan="2">Observed Range of deviations</td><td>Average</td><td colspan="2">38 pp% (-13%;+25%)</td><td colspan="2">53 pp% (-20%;+33%)</td><td colspan="2">31% (-14%;+16%)</td></tr>
<tr><td>Dispersion</td><td colspan="2">99 pp% (-34%;+65%)</td><td colspan="2">109 pp%(-37%;+72%)</td><td colspan="2">81% (-40%;+42%)</td></tr>
<tr><td rowspan="3">Occurrences for each type of performance</td><td></td><td>Frequency</td><td>Average distance to origin</td><td>Frequency</td><td>Average distance to origin</td><td>Frequency</td><td>Average distance to origin</td></tr>
<tr><td>Slower and more dispersed (QI)</td><td>21%</td><td>48 pp%</td><td>30%</td><td>32 pp%</td><td>32%</td><td>14 pp%</td></tr>
<tr><td>Faster and less dispersed (QIII)</td><td>50%</td><td>21 pp%</td><td>41%</td><td>25 pp%</td><td>37%</td><td>15 pp%</td></tr>
<tr><td colspan="2">Correlation between deviation to the average and deviation to dispersion</td><td colspan="2">Significant
Positive</td><td colspan="2">Significant
Strong Positive</td><td colspan="2"><u>Non-Significant</u></td></tr>
<tr><td colspan="2">Regression slopes</td><td colspan="2">1.65 ($CI_{95\%}$=[0.8;2.49])</td><td colspan="2">1.49($CI_{95\%}$=[1.17;1.81])</td><td colspan="2">-</td></tr>
</table>

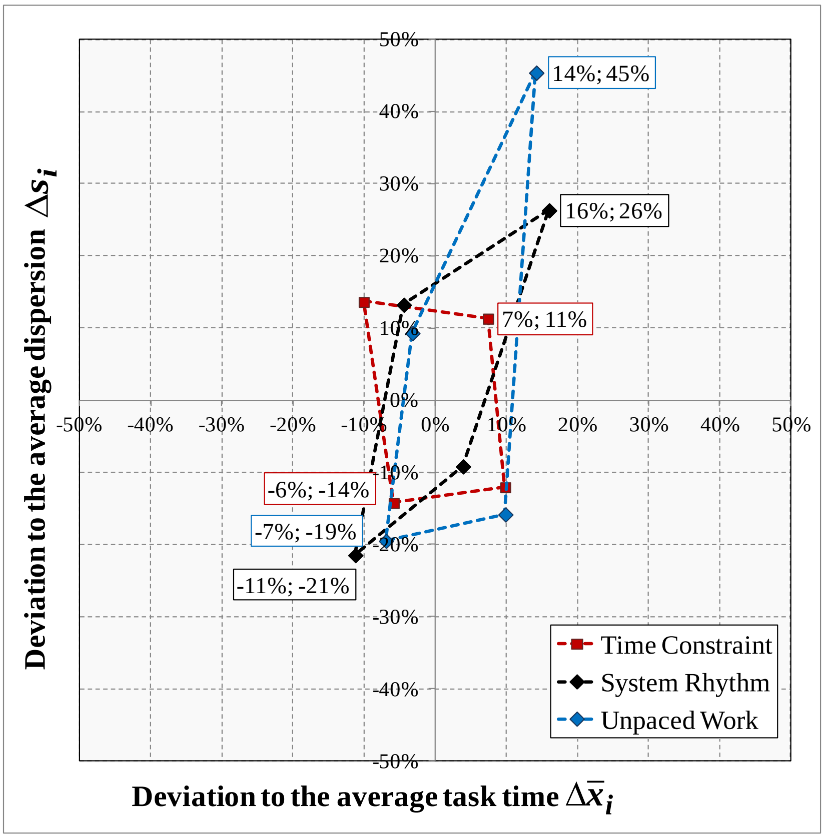


Figure 32 – Location of the centroids per quadrant for the three studied scenarios of worker pacing

9. Impact of Performances Heterogeneity in Asynchronous Assembly Systems

Assembly systems hinged on manually performed tasks are quite common in the industry. As it was previously demonstrated, the workers performance tends to be highly heterogeneous, and from the data obtained from the industrial setting, there was the indication that the heterogeneity of performances has in fact a considerable impact in the system performance. In order to investigate the possible effects of the imbalance caused solely by the different workers performance, Discrete Events Simulation was used to create a model of an assembly system and test its behaviour under different circumstances. A serial assembly line is considered, with an asynchronous operation mode and different possible combinations of performances, meaning that the workers allocated to the system have different average and variability on their task times.

This chapter describes the simulation model considerations and the inputs used for the task times. The models built are tested considering different workers performance: in a first approach that all the workers perform equally in terms of task times, and then scenarios are simulated with the allocated workers performing differently. Different assembly line lengths are also considered in order to perform a sensitivity analysis to the system behaviour under such conditions. The objective of the proposed simulation studies is to demonstrate the impact of workers performance heterogeneity and draw guidelines regarding the workers allocation in such scenarios.

9.1. Simulation Model

To test the impact of having significantly different task times, a serial assembly line was considered, with three workstations (as depicted in Figure 33). Each workstation has one dedicated worker. The part transfer between workstations is done asynchronously. This means that when the worker finishes the assembly tasks on his/hers workstation, he/she transfers it to the next workstation if it is idle (waiting for a part). If the next workstation is not idle (is either working or blocked), then the workstation becomes blocked. In this situation the worker has to wait and cannot accept any other part. The first workstation is never waiting and the last station is never blocked. There is no possibility of buffering parts between workstations, so that there is no buffering of the differences in performance. Also, in order to isolate the performance variations effect on the system, the work content in each workstation is

the same, meaning that the line is perfectly balanced. Any unbalance will then be caused by the workers performance variations, which is the objective of this analysis.

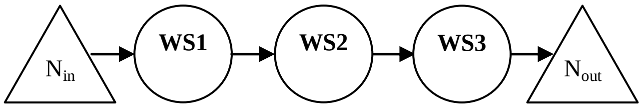


Figure 33 – Representation of the assembly line considered in the simulation model, with 3 workstations (WS_m) to produce (*N*) parts

The simulation model was implemented on MATLAB, using Object Oriented Programming (OOP). The program can test all the possible combinations of workers task times. To test the different scenarios of performance allocation, the model was simulated until it produced a given number of parts (*N*). It was considered that there was a customer order of *N*=1800 parts to fulfil.

For assembly line design purposes it is important to make sure that an assembly system is able to achieve a given output rate (average number of parts assembled per unit of time). However, the output variability also plays an important role on the daily planning and control of the system. If the output variability is high in some moments the system might be producing above target and other times below, increasing the uncertainty that the customer order will be met. Therefore, an assembly system producing with less output variability is more desirable (Tan, 1999), as long as the output is met. In this study, the focus is given to the average inter-departure time (*IDT*) and the inter-departure time variability (*SD*), as measures of the system performance, as well as to the total required time to produce the *N* parts. The developed model records each time a part leaves the system, therefore the *IDT* is obtained by subtracting the successive times in which the parts leave the system. The *SD* is obtained by calculating the average of the variances obtained for each run (out of 10) of 1800 produced parts and applying the square root to this value. Since a warm-up period is not considered, the first *IDT* value will be larger than the following ones.

The following section describes the task time inputs considered for each performance.

9.2. Task time inputs

As described previously, the worker performance can be measured in terms of deviations to the workstation expected performance (for the average time and dispersion). A worker might have a task time performance slower or faster than expected and/or be more or less dispersed than expected. Given that, four types of performance were considered in terms of deviations to the expected performance (E) and mapped accordingly:

- QI: The worker is slower completing the assembly task and the task times are more dispersed (meaning higher variability) than expected;
- QII: The worker is faster completing the assembly task and the task times are more dispersed than expected;
- QIII: The worker is faster completing the assembly task and the task times are less dispersed (therefore less variability) than expected;
- QIV: The worker is slower completing the assembly task and the task times are less dispersed than expected.

From the data collected in a scenario where the workers are paced by the system rhythm, the centroid of occurrences observed in each quadrant was calculated. The centroids are used as representative performance values in each quadrant. The location of these centroids within the performance map outlooks the task time distribution of each type of performance.

In the observed tasks, the average coefficient of variation, meaning the standard deviation divided by the average time of all the observed workers, is 13% (expected coefficient of variation). Therefore, considering that in each workstation, if the expected average time is 15 seconds, the standard deviation is 1.95 seconds. Using these values, the corresponding average task time and dispersion for each type of performance was calculated, using the coordinates of the centroids (Table 40). For instance, a worker with a performance QI, is considered to be +16% slower than expected and with +26% more dispersion than expected. Therefore, for this worker it will take in average 17.39 sec to complete the assembly task and with a standard deviation of 2.49 sec. In regards to distribution, it must be noted that with 50 task times per observed worker, different types of distribution can be fitted from worker to worker, given the sample size, and there is not a consensus among the reviewed literature on which distribution to use. In this case, a triangular distribution was

considered, which is the preferred distribution in project management problems. The triangular distribution was constructed with defined minimum and maximum values[10], and with the average equal to the mode.

Since a centred distribution is being considered, it is assumed that each worker has the same probability of fulfilling the assembly task faster or slower than his/her own average.

Table 40 – Inputs considered for each type of performance of the workers allocated to the system

Type of Performance	Quadrant Centroids	Average [sec]	Standard Deviation [sec]	Minimum [sec]	Maximum [sec]
E	(0%;0%)	15.00	1.95	10.22	19.78
QI	(+16%;+26%)	17.39	2.46	11.35	23.43
QII	(-4%;+13%)	14.33	2.21	8.91	19.74
QIII	(-11%;-21%)	13.30	1.53	9.55	17.06
QIV	(+4%;-9%)	15.58	1.77	11.23	19.92

The first scenario considers that every worker allocated to the system has the same task time distribution, meaning that when testing QI for instance, all the workers have task times only of the QI type. The following scenario considers that there is one worker with the less desirable type of performance QI (slower and more dispersed task times), with the remaining having E type of performance. The variation in this case, is made by changing the position along the assembly line where this worker is allocated. The analogous analysis will be performed, but this time considering that there is a worker with the most desirable type of performance (QIII), meaning this worker is faster and has less dispersion in his/her task time distribution. The last scenarios will be focused on the situation where there is a search for the allocation of workers with different performances, in order to minimize and maximize the output variability (*SD*). The scenarios of workers allocations for the three-workstation asynchronous assembly line considered in this analysis, are summarized in Figure 34.

[10] For a triangular centred distribution, Minimum=Average- Standard Deviation√6 and Maximum=Average+ Standard Deviation √6

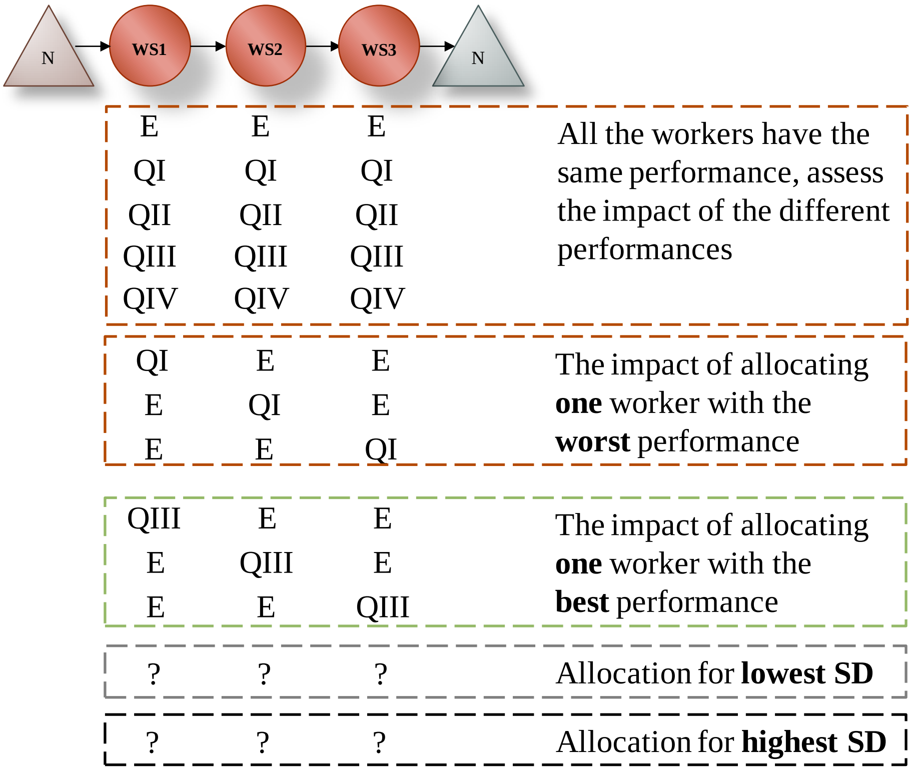


Figure 34 – Proposed analysis of allocation scenarios in the assembly line model

9.3. Every worker with the same type of performance

In a first approach, a set of scenarios were considered where the allocated workers have the same type of performance: either all Expected, or QI, or QII, or QIII, or QIV. In Figure 35 it is represented the distribution of the system inter-departure times obtained with the simulation runs for all the workers with the same type of performance. In each 1 sec interval the average frequency with which a part left the system was calculated. It can be observed that the interaction of the several workers in this system configuration, introduces some positive skewness on the output time distribution due to blocking and starving times, which increases the probability of the part spending more time in the system and therefore increasing the *IDT*.

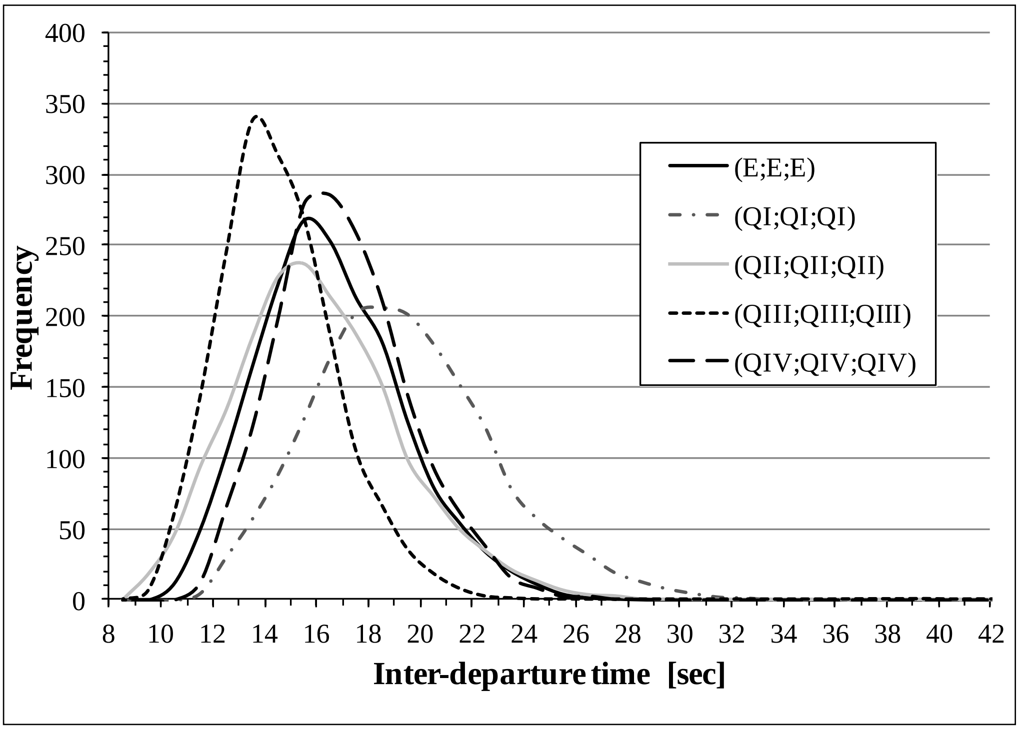


Figure 35 - Histograms of frequency for allocation scenarios where workers have the same type of performance on every WS

The increase on the average task time results in an increase of the average system *IDT* (Table 41). The same happens with the variability. If all the workers have a performance with higher average times and higher variability, the system *IDT* will also be higher and with higher variability (*SD*). As it would be expected, the best possible scenario is having all workers with QIII performance where it is possible to fulfil the customer order in 12% less time, and the worst is having them with QI performance. In this situation, it will take 17% more time to produce the full amount of parts. Nonetheless, if scenario (E;E;E) and (QII;QII;QII) are compared it can be concluded that the allocation of workers with QII performance (slightly faster but with task times more dispersed) increases the line performance since the system would produce the same amount of parts in less time. However, as it was concluded throughout the course of this research, there is a large heterogeneity of performances among a workers population.

Table 41 – Results of the simulation model when the allocated workers have the same type of performance on every *WS*

Type of allocated performance WS_m(m=1,2,3)	*IDT* [sec]	*SD* [sec]	Time Span [h:min]	Time Span Variation [%]
E	16.55	2.88	8:17	-
QI	19.34	3.64	9:41	+17%
QII	16.08	3.23	8:03	-3%
QIII	14.51	2.28	7:16	-12%
QIV	16.98	2.64	8:30	+3%

Since the focus of this research is on the heterogeneity of performances within a workers population, the following scenarios consider that the workers allocated to the system have different performances among them.

9.4. The effects of allocating one worker with worst /best performance

As it was demonstrated earlier in this research, within a workers population there are different types of performances. The most extreme, and most frequently observed, are workers with performances from Quadrant I or III. In this section, two examples are considered: one worker with a time distribution QI while the other two workers have an expected performance (E); one worker has a time distribution QIII while the other two have an Expected performance (E). This way, the effect of having such type of performance in the several possible positions in the considered system can be studied.
The simulation results (Table 42) show that if there is one worker with the worst type of performance (QI) while the others have an expected (E) performance, the system performance, in terms of time spent assembling the required number of parts is affected by at least 8%. This time varies slightly according to the workstation where this worker is allocated. The higher *IDT* is obtained when he/she is allocated to the middle workstation (E;QI;E). In this scenario, there are more chances of increasing the blocking situations on the first workstation (that the worker cannot pass his/her output to the following workstation) and starving in the last workstation (in which the worker is waiting for a part to work on). The variability in the inter-departure time (*SD*) is lower for the scenario where the worker is allocated to the last workstation, meaning that the system output flow will be smoother when compared with the other two scenarios. This result may seem counter intuitive, since this worker is the one

with the largest variability in his task times. Nonetheless, because this worker is the slowest, by being in the last workstation, even if there are variations in the task times upstream, he/she acts like a "buffer" for variability.

Table 42 - Results of the simulation model when there is one worker with QI performance in the different assembly line positions

Type of performances (WS1;WS2;WS3)	***IDT* [sec]**	***SD* [sec]**	**Time Span [h:min]**	**Time Span Variation [%]**
(E;E;E)	16.55	2.88	8:17	-
(QI;E;E)	17.88	3.40	8:57	+8%
(E;QI;E)	17.99	3.38	9:01	+9%
(E;E;QI)	17.90	2.84	8:58	+8%

In the case of having one worker with the best type of performance considered (QIII), then it will have a more positive impact (*IDT* and *SD* reduction) when such worker is allocated in middle workstation (Table 43). If such worker is in the last workstation of the system, then the variability of the inter-departure time is larger than in the other scenarios, since the workers upstream are slower and more variable, he will become idle more frequently and therefore affecting the time between the departures of completed parts out of the system.

Table 43 - Results of the simulation model when there is one worker with QIII performance in the different assembly line positions

Type of performances (WS1;WS2;WS3)	***IDT* [sec]**	***SD* [sec]**	**Time Span [h:min]**	**Time Span Variation [%]**
(E;E;E)	16.55	2.88	8:17	-
(QIII;E;E)	16.18	2.61	8:06	-2%
(E;QIII;E)	15.94	2.60	7:59	-4%
(E;E;QIII)	16.17	2.97	8:06	-2%

In summary, if there is one worker with a worse performance (QI) among the others (E), no matter the position where this worker is allocated, it will be required at least 8% more time to produce the required amount of parts. If there is one worker among the others that has a better performance (QIII), the amount of time required to produce the total amount of parts will reduce a maximum of 4% if it is allocated to the middle workstation, otherwise it's only possible to obtain a 2% total time reduction.

In the following section, the system performance is analysed in terms of inter-departure variability (*SD*).

9.5. Allocations for the lowest/highest inter-departure variability

For the performance of the assembly system it is not only important to evaluate the average time required to produce a part, but also the variability with which it does. If a system produces a stable output, there is more certainty in fulfilling customer orders. So, to identify the workers allocation combination that result in the smaller output variability, several simulation runs were conducted. The results indicate that the *SD* is lower in the (QIII; QIII; QIV) scenario, and not with the (QIII; QIII; QIII) (Table 44). The allocation of a worker with a higher variability in performance but slower when compared with QIII will result in lower variability output during the production of the 1800 parts (note that nonetheless, in this scenario more time is required to produce the parts than with (QIII; QIII; QIII)). This happens because the worker in last workstation has a performance with a higher average time, therefore the variability from the workers in the upstream workstations is “buffered”.

The combination with the highest output variability, is the (QI;QI;QII). In this case the worker in the last workstation is the fastest in average when compared to the others, causing an increase in variability in time between the completed parts departure of the system. Nonetheless there is a reduction in the amount of time required to produce the 1800 parts when there’s a QII performance type instead of a QI performance type on the last workstation (Figure 36).

Table 44 – Allocations for high/low *SD* compared with scenarios where the workers have the same performance

Type of performances (WS1;WS2;WS3)	*IDT* [sec]	*SD* [sec]	Time Span [h:min]	Time Span Variation [%]
(E;E;E)	16.55	2.88	8:17	-
(QIII;QIII;QIII)	14.51	2.28	7:16	-12%
(QIII;QIII;QIV)	15.82	2.01	7:55	-4%
(QI;QI;QI)	19.34	3.64	9:41	+17%
(QI;QI;QII)	18.86	4.18	9:27	+14%

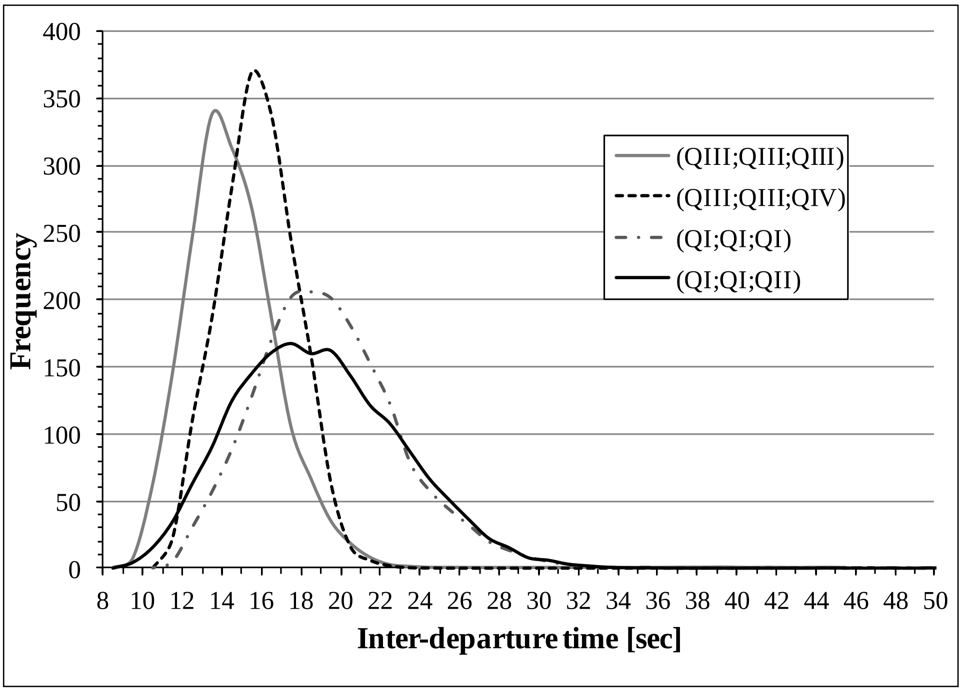


Figure 36 – Frequency histograms for workers allocations resulting in low/high *SD* output compared with scenarios where the workers have the same performance

9.6. Longer lines

In order to verify if a longer line would be more or less sensitive to workers with these types of performances, the system was simulated with eight workstations instead of three. Note that by considering a longer line the product assembled has more assembly tasks (and not a division of the work per more workstations). It was observed that the increase in the number of workstations increases the inter-departure time in every tested scenario, due to the coupling effect and consequent increase in the probability of starving and blocking due to variability when performing the assembly tasks (Table 45). Therefore, longer lines will be more sensitive to variability in the task time distributions, when considering that all the workers have the same task time distribution. The time span variations, when compared to the scenario where every worker has the expected (E) task time distribution (in this case the time span would be of 8h17min), are also similar to what was observed previously in the shorter assembly line.

Table 45 – Simulation model results for an 8WS assembly line considering that every worker has the same type of performance

Type of allocated performances WS_m(m=1,..8)	*IDT* [sec]	*SD* [sec]	Time Span [h:min]	Time Span Variation [%]
E	17.83	3.10	8:55	-
QI	20.96	4.58	10:29	+18%
QII	17.52	3.04	8:45	-2%
QIII	15.53	2.55	7:46	-13%
QIV	18.16	3.16	9:05	+2%

Similarly to what was done for the short assembly line scenarios, the effect of having one worker with a different performance from the others was studied in this longer system. A scenario was simulated where there is one worker with a QI type of performance in the first position in the assembly line, and another scenario where this worker is in the last position. Both scenarios outcomes are compared to the situation where all the workers have an expected (E) performance. The results (Table 46) indicate that the allocation of one worker with a worse performance (slower and more variable), increases the required time to produce the required amount of parts in 5%, independent of its location. Nonetheless, there is a slight difference in the inter-departure time variability. If the worker with a QI performance is in the last position, there is the effect of buffering the variability since it has a larger average time, as in the shorter lines previously considered. As the worker with QI type of performance is moved towards the end of the assembly line (Figure 37), the *IDT* practically does not change, while the *SD* decreases.

If a worker is allocated with a performance of type QIII, either in the first or last position of the assembly line, there is a time reduction of 1%. The variability in the inter-departure time is increased if this worker is in the last position, since this worker is faster, and therefore more susceptible of becoming “starved” due to the variations accumulated in the upstream workstations.

Table 46 - Simulation model results for an 8WS assembly line considering that, one worker has QI/QIII performance and variations regarding the position of allocation

Type of allocated performances WS_m(m=1,..8)	***IDT* [sec]**	***SD* [sec]**	**Time Span [h:min]**	**Time Span Variation [%]**
E	17.83	3.10	8:55	-
For m=1, QI	18.69	3.58	9:20	+5%
For m=8, QI	18.68	3.34	9:20	+5%
For m=1, QIII	17.70	3.02	8:51	-1%
For m=8, QIII	17.70	3.10	8:51	-1%

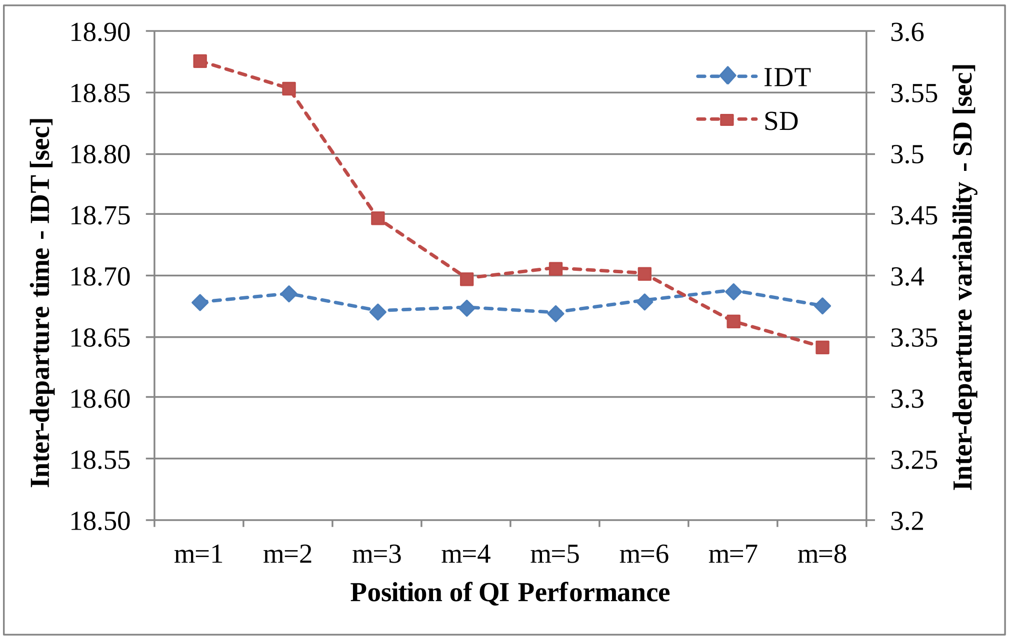


Figure 37 – Obtained *IDT* and *SD* by varying the position of the QI worker in the assembly line

9.7. Results summary of the simulation study

Workers task times can vary significantly from one to another, both in terms of average and dispersion of task times. The performed simulations studies indicate that if there is one worker with a worse performance than the others, the system *IDT* is more affected, if such worker is allocated to the workstations positioned in the middle section of the assembly line, than in any other position. Nevertheless, the position in which the best/worse time performing worker is allocated has a small impact on the system average inter-departure time. This effect is even further reduced when the lines are longer. Having one worker, which outperforms the others, does not have

such a large (positive) impact in the line output as compared to the (negative) impact of a worker which underperforms the others.

In terms of inter-departure variability, it will be reduced if the worker with the worst performance (slower and with more dispersion in their task times when compared to the others) is allocated in the last position. There is a “buffering” effect, since the worker in this position will not become idle so frequently. Nonetheless, this inter-departure variability reduction in shorter lines will be at the “cost” of increasing the inter-departure time, and consequently the amount of time to produce the total number of parts required by the customer.

In longer lines, the position where the worker with the worst performance is allocated does not affect the *IDT*, as it was previously stated, but it is possible to have smoother parts flow (reduce *SD*), if this worker is allocated in the final workstation. This way the accumulated variations throughout the process upstream, will not affect the processing in the last workstation, since this worker is slower. Therefore, this worker will not become “starved” so often.

Overall, the differences found on workers task times, both in terms of average times and dispersion, can have large impacts on the output performance of manually operated systems, and should be taken into account when modelling and managing tightly coupled systems. Having heterogeneity in the workers performances will inevitably affect the system performance, especially if these workers have extremely different performances. Therefore, it is recommended when performing simulations of systems which are manually operated, to consider performances of type QI (slower and with higher dispersion) and QIII (faster and lower dispersion), beside the expected performance, in order to have a more realistic output.

10.Conclusions and Further Developments

In the present context of the manufacturing paradigm, products have shorter life cycles, more model variety, and demand uncertainty. Often, an extended automation might not be possible, even if technologically there are means to do it. For a company faced with the uncertainties of the Automotive Industry, the manual assembly of the products supplied to Original Equipment Manufacturers is frequently an attractive choice. This preference for manual processing at the assembly stage could be observed in the visited company throughout the course of this research. Therefore, not only for this particular 1st tier supplier for the automotive industry, but for several others in the same situation, it becomes important to better understand the nature of the manual work and the heterogeneity of performances since companies rely on it, as they do on knowledge and innovation capacities.

In addition, for academic purposes, there was a gap in the existent literature, referring to the heterogeneity of performances that can be found within a workers team, which required further research. Moreover, there was a disconnection between the studies on the heterogeneity of performances and the influence of different types of pacing in an assembly system.

Previous researchers, performed studies addressing the effect of pacing in individual performances (Dudley 1961, Dudley 1963, Franks and Sury, 1966) and some reported that in fact there were considerable variations in the task times, depending on the subject that was being studied (Murrell 1963, Sury 1964, Knott and Sury, 1987). However, the quantification of these differences was not systematized by such authors.

On the other hand, later researchers focused on the heterogeneity of performances (Doerr and Arreola-Risa, 2000), and suggested that the subjects' performances should be investigated in a group perspective (Baugous, 2007, Doerr *et al.*, 2002, Doerr *et al.*, 2004, Schultz *et al.*,2006), since they might be affected by the performance of their peers. Nonetheless, the authors do no establish a connection of these findings to the different types of pacing in an assembly system.

Within the scope of this research, several objectives were proposed, namely: add knowledge to the study of the performances heterogeneity within an interdependent team of workers and understand how different pacing situations, which affect that interdependency, affect such heterogeneity.

Firstly, it was required to observe an actual group of workers and collect data in order to verify if in a group of fully trained subjects there would be significant differences among the task time distributions. These observations took place in a scenario where the workers were working as a group with a high degree of interdependency between them – which is the case often found in asynchronous assembly systems with limited Work-In-Process. During these initial observations and subsequent statistical analyses, it was verified that not only workers have different average task times, but also different dispersion in their task times. Therefore, there are significant variations from worker to worker in these two chosen measures of performance regarding the task time, and they should be addressed. In order to visualize and facilitate the analysis of this heterogeneity within the group of workers, it was developed a mapping approach for the different performances.

The assembly system output is a result of the performances of the several interconnected workers allocated to it. Therefore, if there are large deviations to that average performance of the group, the system output will be hampered. In the proposed mapping approach, the differences in performances are mapped in terms of deviations of the average task time and average dispersion of all the workers observed performing the same type of task. This way, the variations in performance could be analysed without "subtracting" the interdependence among workers. Moreover, such mapping could be used to compare different working situations, since there were no units associated to it.

Using this approach, it was possible to visualize that, for a situation where the workers are paced by the system rhythm (or system with margins, as defined by Murrell (1963)), there are large variations in both types of deviations. In result, it could be observed that:

- Some workers are the slowest and have more dispersion than the average. This means that in average they take longer than their co-workers to perform the required assembly tasks in the workstation, and that their task times are more variable;
- Other workers are faster but have more dispersion than the average. In other words, these workers even if faster than their peers, the amount of time required in fulfilling the assembly varies more than the average.
- Some other workers are even faster and have less dispersion than the average.
- Others, even if slower than the faster co-workers, have less dispersion in their task times than the average.

Moreover, having the performances mapped in such way, enabled the analysis of which type of performances occurs more frequently in such conditions. In fact, it was observed that there are two predominant types of performances: the workers are slower and have more dispersion, and the workers are faster and have less dispersion. There is in fact a high significant correlation between the deviation to the average task times and the deviation to the average dispersion. Therefore, there is a tendency that as the workers become slower they also have an increase in the dispersion of their task times. Another conclusion which is drawn from this analysis is that when workers have such type of performance, it is not symmetric when compared to the opposite case (lower average task times and less dispersed). In other words, when the workers have better performances than the group average, the workers with worse performances tend to deviate more (in absolute terms).

In such situations, where the workers are performing the assembly task in a serial assembly line, there is an influence of the tight interconnection between the workers performances. In part, it can be attributed to the "free-riding" effect, previously stated by earlier authors (Williams et al., 1981). Therefore, as way of controlling the amount of heterogeneity, a common goal for every worker can be set. As demonstrated by the implementation of a time constraint (or rigid pacing within the definition of Murrell (1963)) developed with the company, the occurrence of extreme performances is reduced and it can increase productivity. After implementing such modification in the asynchronous assembly system, there was an increase in the system products output of 13%. However, to obtain such results, this type of modifications in the assembly system should be implemented with appropriate planning and evaluation. From the analysis of the workers performances and comparison with the previous scenario, it was concluded that the average task time for the group improved. This speed up effect is due to the limitation of a maximum allowable value for the worker task time, which reduces the dispersion (longer cycles are not permitted) and consequently has an effect in the average task time.

Since the time slot in each workstation was fixed and the worker had no control over the inbound or outbound of products assembled, it had been considered that the occurrences of workers faster and less dispersed than average could be hampered by implementing such time constraint. It was verified, that in such case, the occurrences of such type actually improved. Nevertheless, it would be required the collection of further data to verify if this particular effect remains in a long-term perspective. In addition, this study can be extended in the future by further comparison of the two pacing situations, namely

in terms of the worker well-being. Previous work, indicates there is not an adverse impact in terms of biomechanical exposures and muscle fatigue (Bosch *et al.*, 2011), when controlling the work speed. Nonetheless there is contradictory work published that refers this might not be the case regarding the well-being in the long term (Carayon *et al.*, 1999). Therefore, a long term analysis to the well-being of workers compared to the non-rigidly paced situation would help to reduce possible reservations.

Further conclusions were made from the analysis of the performance map in this rigidly paced scenario. In such case, there is no longer a linear relation between the deviation to the average and the deviation to the average dispersion. Meaning that, in a scenario where each worker has a fixed time slot to fulfil the task, the slower workers do not have necessarily larger dispersions in their tasks times, neither the faster workers have less dispersion.

Another variation to the initial scenario where the workers were performing the assembly tasks paced by the system rhythm, is the absence of a pacing rhythm. In one sense, the introduction of rigid pacing constrained the interdependence among workers, since each one had the same time to fulfil the assembly tasks. On the other hand, working in unpaced conditions can also be seen as a reduction of interdependence (in this case a total elimination of that dependence). The two situations have completely different results. In unpaced work, the workers always have products to assemble and a place to dismiss them when they finish the assembly cycle, and they are free to work at the pace they feel comfortable. The results of the laboratorial experiment with LEGO's have shown that the lack of a pacing does not necessarily aggravate the performances heterogeneity observed in a group of subjects performing the same task. It could be concluded that, in fact, the distribution of performances was quite similar to what was observed in the scenario where the workers were tightly interdependent (paced by the system rhythm). The most evident change was a magnification of the dispersion, since the linear relation between the deviation to the average and the deviation to the average dispersion became steeper, although the correlation was less significant. Therefore, it could not be made a clear distinction between the two maps given the obtained data points, and it is concluded that the heterogeneity of performances is not necessarily aggravated in unpaced conditions. However the subjects which tend to be slower than the others tend to be have more dispersion, since there is no constraint to limit the longer cycles. It should be noted that this was a laboratorial experiment and not data obtained from fully trained workers, and

therefore the possible differences between these two settings should be further investigated.

From the three studied scenarios, it can be concluded that there are significant differences in terms of average time and dispersion of the task time distributions from worker to worker. In addition, by imposing a fixed time slot equal for every worker, the heterogeneity of workers performance is reduced, and this results in improvements in the system productivity. Nevertheless, it is not always possible to implement such time constraints. In order to test the impact of the different types of time performances allocations and understand in which cases of workers allocation this impact can be minimized, it was modelled an asynchronous assembly system (considering some simplifications for generalization purposes). The results of these simulation models demonstrated that having a worker which underperforms relatively to the others (slower and more variable), reduces the system productivity in the tested conditions. In terms of strategies of allocation, such workers should be in last position of the assembly line, since the fact of them being slower buffers the variations accumulated throughout the process. Nonetheless, further studies should be addressed in the future regarding variations of the system parameters, in order to broaden the scope of the analysis.

Overall, this research contibuted to the knowledge of the heterogeneity on human performance and group response under different working conditions, which hopefully can be considered for other areas of production and/or services in the future.

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Annex

A.1 - FL1A – Pairwise Comparison (Kruskal-Wallis) SPSS Output

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
4-5	-44.290	43.329	-1.022	.307	1.000
4-8	-112.910	43.329	-2.606	.009	.962
4-1	125.640	43.329	2.900	.004	.392
4-10	-137.880	43.329	-3.182	.001	.153
4-13	-173.880	43.329	-4.013	.000	.006
4-22	-227.870	43.329	-5.259	.000	.000
4-11	-231.530	43.329	-5.344	.000	.000
4-7	-283.550	43.329	-6.544	.000	.000
4-21	-288.470	43.329	-6.658	.000	.000
4-3	292.970	43.329	6.762	.000	.000
4-23	-323.350	43.329	-7.463	.000	.000
4-24	-400.770	43.329	-9.250	.000	.000
4-2	447.850	43.329	10.336	.000	.000
4-9	-484.140	43.329	-11.174	.000	.000
5-8	-68.620	43.329	-1.584	.113	1.000
5-1	81.350	43.329	1.878	.060	1.000
5-10	-93.590	43.329	-2.160	.031	1.000
5-13	-129.590	43.329	-2.991	.003	.292
5-22	-183.580	43.329	-4.237	.000	.002
5-11	-187.240	43.329	-4.321	.000	.002
5-7	-239.260	43.329	-5.522	.000	.000
5-21	-244.180	43.329	-5.636	.000	.000
5-3	248.680	43.329	5.739	.000	.000
5-23	-279.060	43.329	-6.441	.000	.000
5-24	-356.480	43.329	-8.227	.000	.000
5-2	403.560	43.329	9.314	.000	.000
5-9	-439.850	43.329	-10.151	.000	.000
8-1	12.730	43.329	.294	.769	1.000
8-10	-24.970	43.329	-.576	.564	1.000
8-13	-60.970	43.329	-1.407	.159	1.000
8-22	-114.960	43.329	-2.653	.008	.837
8-11	-118.620	43.329	-2.738	.006	.650
8-7	170.640	43.329	3.938	.000	.009
8-21	-175.560	43.329	-4.052	.000	.005
8-3	180.060	43.329	4.156	.000	.003
8-23	-210.440	43.329	-4.857	.000	.000
8-24	-287.860	43.329	-6.644	.000	.000
8-2	334.940	43.329	7.730	.000	.000
8-9	-371.230	43.329	-8.568	.000	.000
1-10	-12.240	43.329	-.282	.778	1.000
1-13	-48.240	43.329	-1.113	.266	1.000
1-22	-102.230	43.329	-2.359	.018	1.000
1-11	-105.890	43.329	-2.444	.015	1.000
1-7	-157.910	43.329	-3.644	.000	.028
1-21	-162.830	43.329	-3.758	.000	.018
1-3	-167.330	43.329	-3.862	.000	.012
1-23	-197.710	43.329	-4.563	.000	.001
1-24	-275.130	43.329	-6.350	.000	.000
1-2	-322.210	43.329	-7.436	.000	.000
1-9	-358.500	43.329	-8.274	.000	.000
10-13	-36.000	43.329	-.831	.406	1.000
10-22	-89.990	43.329	-2.077	.038	1.000
10-11	-93.650	43.329	-2.161	.031	1.000
10-7	145.670	43.329	3.362	.001	.081
10-21	-150.590	43.329	-3.476	.001	.054
10-3	155.090	43.329	3.579	.000	.036
10-23	-185.470	43.329	-4.281	.000	.002
10-24	-262.890	43.329	-6.067	.000	.000
10-2	309.970	43.329	7.154	.000	.000
10-9	346.260	43.329	7.991	.000	.000
13-22	-53.990	43.329	-1.246	.213	1.000
13-11	57.650	43.329	1.331	.183	1.000
13-7	109.670	43.329	2.531	.011	1.000
13-21	-114.590	43.329	-2.645	.008	.859
13-3	119.090	43.329	2.749	.006	.629
13-23	-149.470	43.329	-3.450	.001	.059
13-24	-226.890	43.329	-5.236	.000	.000
13-2	273.970	43.329	6.323	.000	.000
13-9	310.260	43.329	7.161	.000	.000
22-11	3.660	43.329	.084	.933	1.000
22-7	55.680	43.329	1.285	.199	1.000
22-21	60.600	43.329	1.399	.162	1.000
22-3	65.100	43.329	1.502	.133	1.000
22-23	-95.480	43.329	-2.204	.028	1.000
22-24	-172.900	43.329	-3.990	.000	.007
22-2	219.980	43.329	5.077	.000	.000
22-9	256.270	43.329	5.915	.000	.000
11-7	52.020	43.329	1.201	.230	1.000
11-21	-56.940	43.329	-1.314	.189	1.000
11-3	61.440	43.329	1.418	.156	1.000

11-23	-91.820	43.329	-2.119	.034	1.000
11-24	-169.240	43.329	-3.906	.000	.010
11-2	216.320	43.329	4.993	.000	.000
11-9	252.610	43.329	5.830	.000	.000
7-21	-4.920	43.329	-.114	.910	1.000
7-3	9.420	43.329	.217	.828	1.000
7-23	-39.800	43.329	-.919	.358	1.000
7-24	-117.220	43.329	-2.705	.007	.716
7-2	164.300	43.329	3.792	.000	.016
7-9	-200.590	43.329	-4.630	.000	.000
21-3	4.500	43.329	.104	.917	1.000
21-23	-34.880	43.329	-.805	.421	1.000
21-24	-112.300	43.329	-2.592	.010	1.000
21-2	159.380	43.329	3.678	.000	.025
21-9	195.670	43.329	4.516	.000	.001
3-23	-30.380	43.329	-.701	.483	1.000
3-24	-107.800	43.329	-2.488	.013	1.000
3-2	154.880	43.329	3.575	.000	.037
3-9	-191.170	43.329	-4.412	.000	.001
23-24	-77.420	43.329	-1.787	.074	1.000
23-2	124.500	43.329	2.873	.004	.426
23-9	160.790	43.329	3.711	.000	.022
24-2	47.080	43.329	1.087	.277	1.000
24-9	83.370	43.329	1.924	.054	1.000
2-9	-36.290	43.329	-.838	.402	1.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

A.2 - FL1B – Pairwise Comparison (Kruskal-Wallis) SPSS Output

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
10-1	1.350	31.782	.042	.966	1.000
10-4	51.440	31.782	1.619	.106	1.000
10-21	-129.160	31.782	-4.064	.000	.003
10-2	139.570	31.782	4.392	.000	.001
10-3	141.070	31.782	4.439	.000	.000
10-7	174.380	31.782	5.487	.000	.000
10-20	-239.630	31.782	-7.540	.000	.000
10-8	272.540	31.782	8.575	.000	.000
10-9	335.430	31.782	10.554	.000	.000
10-18	-361.670	31.782	-11.380	.000	.000
1-4	-50.090	31.782	-1.576	.115	1.000
1-21	-127.810	31.782	-4.021	.000	.003
1-2	-138.220	31.782	-4.349	.000	.001
1-3	-139.720	31.782	-4.396	.000	.001
1-7	-173.030	31.782	-5.444	.000	.000
1-20	-238.280	31.782	-7.497	.000	.000
1-8	-271.190	31.782	-8.533	.000	.000
1-9	-334.080	31.782	-10.512	.000	.000
1-18	-360.320	31.782	-11.337	.000	.000
4-21	-77.720	31.782	-2.445	.014	.796
4-2	88.130	31.782	2.773	.006	.306
4-3	89.630	31.782	2.820	.005	.264
4-7	-122.940	31.782	-3.868	.000	.006
4-20	-188.190	31.782	-5.921	.000	.000
4-8	-221.100	31.782	-6.957	.000	.000
4-9	-283.990	31.782	-8.936	.000	.000
4-18	-310.230	31.782	-9.761	.000	.000
21-2	10.410	31.782	.328	.743	1.000
21-3	11.910	31.782	.375	.708	1.000
21-7	45.220	31.782	1.423	.155	1.000
21-20	110.470	31.782	3.476	.001	.028
21-8	143.380	31.782	4.511	.000	.000
21-9	206.270	31.782	6.490	.000	.000
21-18	232.510	31.782	7.316	.000	.000
2-3	-1.500	31.782	-.047	.962	1.000
2-7	-34.810	31.782	-1.095	.273	1.000
2-20	-100.060	31.782	-3.148	.002	.090
2-8	-132.970	31.782	-4.184	.000	.002
2-9	-195.860	31.782	-6.163	.000	.000
2-18	-222.100	31.782	-6.988	.000	.000
3-7	-33.310	31.782	-1.048	.295	1.000
3-20	-98.560	31.782	-3.101	.002	.106
3-8	-131.470	31.782	-4.137	.000	.002
3-9	-194.360	31.782	-6.115	.000	.000
3-18	-220.600	31.782	-6.941	.000	.000
7-20	-65.250	31.782	-2.053	.040	1.000
7-8	-98.160	31.782	-3.089	.002	.111
7-9	-161.050	31.782	-5.067	.000	.000
7-18	-187.290	31.782	-5.893	.000	.000
20-8	32.910	31.782	1.035	.300	1.000
20-9	95.800	31.782	3.014	.003	.142
20-18	122.040	31.782	3.840	.000	.007
8-9	-62.890	31.782	-1.979	.048	1.000
8-18	-89.130	31.782	-2.804	.005	.277
9-18	-26.240	31.782	-.826	.409	1.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

A.3 - FL1C – Pairwise Comparison (Kruskal-Wallis) SPSS Output

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
1-10	-27.170	31.782	-.855	.393	1.000
1-4	-29.700	31.782	-.935	.350	1.000
1-3	-53.160	31.782	-1.673	.094	1.000
1-8	-124.410	31.782	-3.915	.000	.005
1-21	-147.060	31.782	-4.627	.000	.000
1-7	-183.670	31.782	-5.779	.000	.000
1-20	-226.020	31.782	-7.112	.000	.000
1-2	-243.660	31.782	-7.667	.000	.000
1-9	-329.870	31.782	-10.379	.000	.000
1-18	-341.710	31.782	-10.752	.000	.000
10-4	2.530	31.782	.080	.937	1.000
10-3	25.990	31.782	.818	.413	1.000
10-8	97.240	31.782	3.060	.002	.122
10-21	-119.890	31.782	-3.772	.000	.009
10-7	156.500	31.782	4.924	.000	.000
10-20	-198.850	31.782	-6.257	.000	.000
10-2	216.490	31.782	6.812	.000	.000
10-9	302.700	31.782	9.524	.000	.000
10-18	-314.540	31.782	-9.897	.000	.000
4-3	23.460	31.782	.738	.460	1.000
4-8	-94.710	31.782	-2.980	.003	.159
4-21	-117.360	31.782	-3.693	.000	.012
4-7	-153.970	31.782	-4.845	.000	.000
4-20	-196.320	31.782	-6.177	.000	.000
4-2	213.960	31.782	6.732	.000	.000
4-9	-300.170	31.782	-9.445	.000	.000
4-18	-312.010	31.782	-9.817	.000	.000
3-8	-71.250	31.782	-2.242	.025	1.000
3-21	-93.900	31.782	-2.955	.003	.172
3-7	-130.510	31.782	-4.106	.000	.002
3-20	-172.860	31.782	-5.439	.000	.000
3-2	190.500	31.782	5.994	.000	.000
3-9	-276.710	31.782	-8.707	.000	.000
3-18	-288.550	31.782	-9.079	.000	.000
8-21	-22.650	31.782	-.713	.476	1.000
8-7	59.260	31.782	1.865	.062	1.000
8-20	-101.610	31.782	-3.197	.001	.076
8-2	119.250	31.782	3.752	.000	.010
8-9	-205.460	31.782	-6.465	.000	.000
8-18	-217.300	31.782	-6.837	.000	.000
21-7	36.610	31.782	1.152	.249	1.000
21-20	78.960	31.782	2.484	.013	.714
21-2	96.600	31.782	3.039	.002	.130
21-9	182.810	31.782	5.752	.000	.000
21-18	194.650	31.782	6.125	.000	.000
7-20	-42.350	31.782	-1.333	.183	1.000
7-2	59.990	31.782	1.888	.059	1.000
7-9	-146.200	31.782	-4.600	.000	.000
7-18	-158.040	31.782	-4.973	.000	.000
20-2	17.640	31.782	.555	.579	1.000
20-9	103.850	31.782	3.268	.001	.060
20-18	115.690	31.782	3.640	.000	.015
2-9	-86.210	31.782	-2.713	.007	.367
2-18	-98.050	31.782	-3.085	.002	.112
9-18	-11.840	31.782	-.373	.709	1.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

A.4 - FL2D – Pairwise Comparison (Kruskal-Wallis) SPSS Output

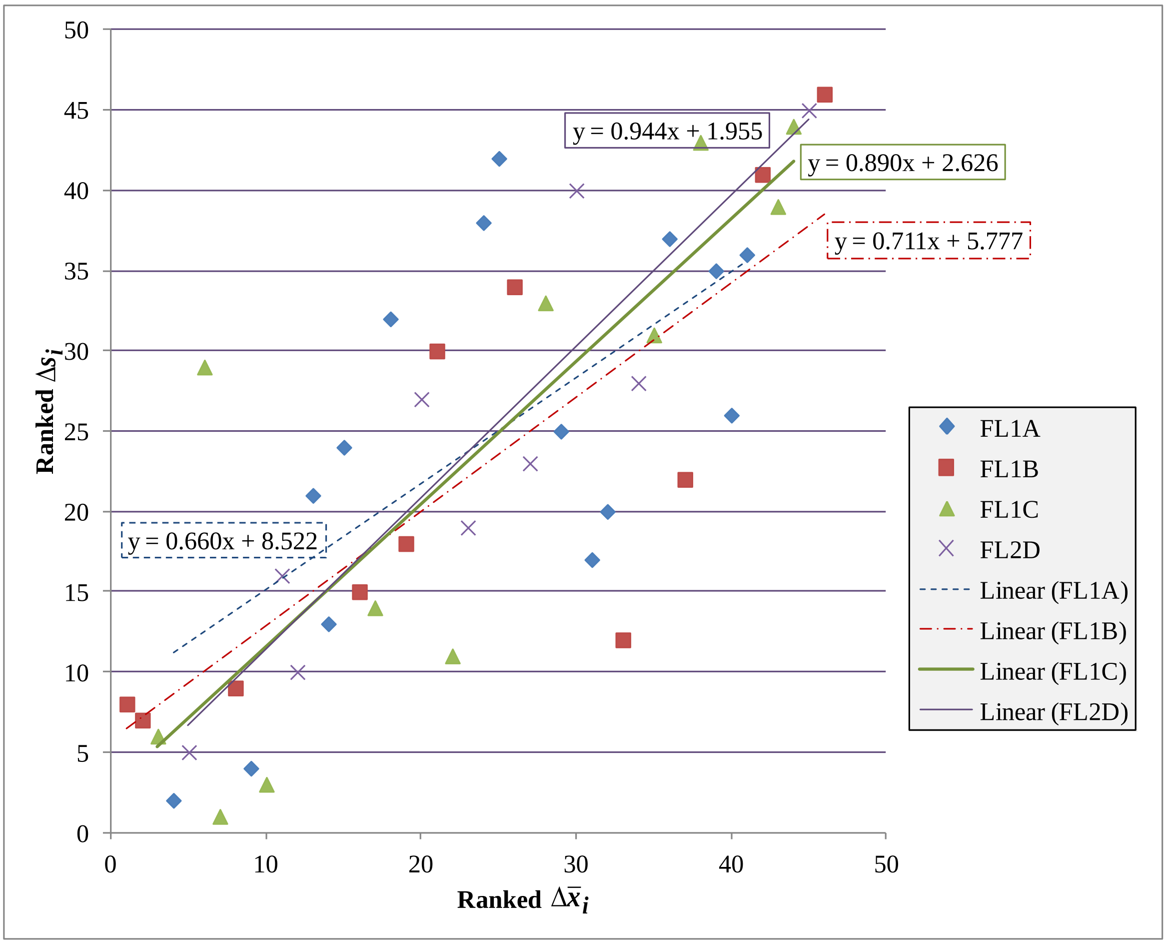
Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
241-245	-56.310	26.010	-2.165	.030	1.000
241-246	-58.780	26.010	-2.260	.024	.858
241-244	-112.280	26.010	-4.317	.000	.001
241-243	-150.930	26.010	-5.803	.000	.000
241-247	-160.800	26.010	-6.182	.000	.000
241-242	-171.690	26.010	-6.601	.000	.000
241-249	-212.770	26.010	-8.180	.000	.000
241-248	-317.180	26.010	-12.195	.000	.000
245-246	-2.470	26.010	-.095	.924	1.000
245-244	55.970	26.010	2.152	.031	1.000
245-243	94.620	26.010	3.638	.000	.010
245-247	-104.490	26.010	-4.017	.000	.002
245-242	115.380	26.010	4.436	.000	.000
245-249	-156.460	26.010	-6.015	.000	.000
245-248	-260.870	26.010	-10.030	.000	.000
246-244	53.500	26.010	2.057	.040	1.000
246-243	92.150	26.010	3.543	.000	.014
246-247	-102.020	26.010	-3.922	.000	.003
246-242	112.910	26.010	4.341	.000	.001
246-249	-153.990	26.010	-5.921	.000	.000
246-248	-258.400	26.010	-9.935	.000	.000
244-243	38.650	26.010	1.486	.137	1.000
244-247	-48.520	26.010	-1.865	.062	1.000
244-242	59.410	26.010	2.284	.022	.805
244-249	-100.490	26.010	-3.864	.000	.004
244-248	-204.900	26.010	-7.878	.000	.000
243-247	-9.870	26.010	-.379	.704	1.000
243-242	20.760	26.010	.798	.425	1.000
243-249	-61.840	26.010	-2.378	.017	.627
243-248	-166.250	26.010	-6.392	.000	.000
247-242	10.890	26.010	.419	.675	1.000
247-249	-51.970	26.010	-1.998	.046	1.000
247-248	-156.380	26.010	-6.012	.000	.000
242-249	-41.080	26.010	-1.579	.114	1.000
242-248	-145.490	26.010	-5.594	.000	.000
249-248	104.410	26.010	4.014	.000	.002

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

A.5 - Ranked Order Data – Workers Performance Paced by the System Rhythm

Workstation	Rank for $\Delta\bar{x}_i$	Rank for Δs_i
FL1A	14	13
FL1A	40	26
FL1A	32	20
FL1A	4	2
FL1A	9	4
FL1A	29	25
FL1A	13	21
FL1A	41	36
FL1A	15	24
FL1A	24	38
FL1A	18	32
FL1A	31	17
FL1A	25	42
FL1A	36	37
FL1A	39	35
FL1B	2	7
FL1B	21	30
FL1B	19	18
FL1B	8	9
FL1B	26	34
FL1B	37	22
FL1B	42	41
FL1B	1	8
FL1B	46	46
FL1B	33	12
FL1B	16	15
FL1C	3	6
FL1C	38	43
FL1C	10	3
FL1C	7	1
FL1C	28	33
FL1C	17	14
FL1C	43	39
FL1C	6	29
FL1C	44	44
FL1C	35	31
FL1C	22	11
FL2D	5	5
FL2D	30	40
FL2D	23	19
FL2D	20	27

FL2D	11	16
FL2D	12	10
FL2D	27	23
FL2D	45	45
FL2D	34	28



Ranked $\Delta\bar{x}_i$ versus ranked Δs_i and linear regressions per workstation

A.6 – Cross tabulation comparing the number of occurences per quadrant with and without the time constraint

Work Flow Policy * Quadrant Crosstabulation

a=2 workflow policies compared b=3 quadrant possibilities			Quadrant			Total
			QI	QII+QIV	QIII	
Work Flow Policy	With Time Constraint	Count	4	7	8	19
		Expected Count	5,3	5,8	7,9	19,0
		% within Work Flow Policy	21,1%	36,8%	42,1%	100,0%
		% within Quadrant	22,2%	35,0%	29,6%	29,2%
		% of Total	6,2%	10,8%	12,3%	29,2%
	Without Time Constraint	Count	14	13	19	46
		Expected Count	12,7	14,2	19,1	46,0
		% within Work Flow Policiy	30,4%	28,3%	41,3%	100,0%
		% within Quadrant	77,8%	65,0%	70,4%	70,8%
		% of Total	21,5%	20,0%	29,2%	70,8%
Total		Count	18	20	20	65
		Expected Count	18,0	20,0	20,0	65,0
		% within Work Flow Policiy	27,7%	30,8%	30,8%	100,0%
		% within Quadrant	100,0%	100,0%	100,0%	100,0%
		% of Total	27,7%	30,8%	30,8%	100,0%

A.7 – Cross tabulation comparing the number of occurences per quadrant for work paced by system rhythm (without time constraint) and unpaced work

Work Flow Policy * Quadrant Crosstabulation

a=2 workflow policies compared b=3 quadrant possibilities			Quadrant			Total
			QI	QII+QIV	QIII	
Work Flow Policy	System Rhythm	Count	14	13	19	46
		Expected Count	12,4	13,1	20,5	46,0
		% within Work Flow Policy	30,4%	28,3%	41,3%	100,0%
		% within Quadrant	70,0%	61,9%	57,6%	62,2%
		% of Total	18,9%	17,6%	25,7%	62,2%
	Unpaced Work	Count	6	8	14	28
		Expected Count	7,6	7,9	12,5	28,0
		% within Work Flow Policy	21,4%	28,6%	50,0%	100,0%
		% within Quadrant	30,0%	38,1%	42,4%	37,8%
		% of Total	8,1%	10,8%	18,9%	37,8%
Total		Count	20	21	33	74
		Expected Count	20,0	21,0	33,0	74,0
		% within Work Flow Policy	27,0%	28,4%	44,6%	100,0%
		% within Quadrant	100,0%	100,0%	100,0%	100,0%
		% of Total	27,0%	28,4%	44,6%	100,0%