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**Présenté par : Boursali Mohammed aze-Eddine**

Thème

# Optimizing Just-in-Time Scheduling: Comparative Analysis Using

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| | | | |
|---|---|---|---|
| M MALIKI Fouad | Maitre de conérence classe A | ESSA. Tlemcen | Président |
| M SOUIER Mehdi | Professeur | Université-Tlemcen | Directeur de mémoire |
| M Haddou Benderbal Hichem | Maître de conférence | Polytech Aix-marseille | Co- Directeur de mémoire |
| Mme SEKKAL Nourelhouda | Maître de conference classe B | ESSA. Tlemcen | Examinateur 1 |
| M HAMZAOUI Mohammed adel | Cherecheur/postdoctoral | Université Bretagne sud | Examinateur 2 |

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**ABSTRACT**

The advent of Industry 4.0 and the emerging concepts of Industry 5.0 have revolutionized manufacturing processes, emphasizing the integration of smart technologies and human-centric approaches. Industry 4.0 focuses on the automation and interconnectivity of manufacturing systems, while Industry 5.0 highlights the collaboration between humans and machines to enhance productivity and innovation. Despite the advancements brought by these industrial revolutions, a significant gap remains in the optimization of Just-In-Time (JIT) scheduling models, particularly when incorporating human factors. Traditional JIT scheduling primarily centers around machine efficiency, often neglecting the implications of human operator fatigue and the necessity for breaks. This oversight can lead to decreased productivity, increased risks of work accidents and health issues job completion times, and higher tardiness penalties. This project addresses this gap by proposing a comprehensive JIT precast production scheduling model that integrates human factors. Three distinct models were developed and analyzed: the first model focuses on JIT scheduling for fully automated machines, optimizing job completion without considering human involvement; the second model incorporates human operators without scheduling breaks, examining the impact of human factors such as fatigue and availability on job completion times and tardiness; the third model introduces scheduled breaks for human operators, aiming to mitigate fatigue and improve overall efficiency. By comparing these models, we evaluate the effects of incorporating human factors and breaks on key performance indicators (KPIs) such as job completion times, earliness, tardiness, and operational costs. The findings demonstrate the importance of human-centric scheduling in achieving sustainable and efficient production processes, underscoring the potential benefits of integrating breaks to manage operator fatigue.

**French:**

L'avènement de l'Industrie 4.0 et des concepts émergents de l'Industrie 5.0 ont révolutionné les processus de fabrication, en mettant l'accent sur l'intégration des technologies intelligentes et des approches centrées sur l'humain. L'Industrie 4.0 se concentre sur l'automatisation et l'interconnectivité des systèmes de fabrication, tandis que l'Industrie 5.0 met en avant la collaboration entre les humains et les machines pour améliorer la productivité et l'innovation. Malgré les avancées apportées par ces révolutions industrielles, un écart significatif subsiste dans l'optimisation des modèles de planification Just-In-Time (JIT), notamment en intégrant les facteurs humains. La planification JIT traditionnelle se concentre principalement sur l'efficacité des machines, négligeant souvent les implications de la fatigue des opérateurs humains et la nécessité de pauses. Cet oubli peut entraîner une diminution de la productivité, une augmentation des risques d'accidents du travail et des problèmes de santé, des délais d'achèvement des tâches plus longs et des pénalités de retard plus élevées. Ce projet aborde cette lacune en proposant un modèle de planification de production préfabriquée JIT qui intègre les facteurs humains. Trois modèles distincts ont été développés et analysés : le premier modèle se concentre sur la planification JIT pour des machines entièrement automatisées, optimisant l'achèvement des tâches sans tenir compte de l'implication humaine ; le deuxième modèle intègre des opérateurs humains sans planifier de pauses, en examinant l'impact de facteurs humains tels que la fatigue et la disponibilité sur les délais d'achèvement des tâches et les retards ; le troisième modèle introduit des pauses planifiées pour les opérateurs humains, visant à atténuer la fatigue et à améliorer l'efficacité globale. En comparant ces modèles, nous évaluons les effets de l'intégration des facteurs humains et des pauses sur les indicateurs clés de performance (KPI) tels que les délais d'achèvement des tâches, les avances, les retards et les coûts opérationnels. Les résultats démontrent l'importance de la planification centrée sur l'humain pour atteindre des processus de production durables et efficaces, soulignant les avantages potentiels de l'intégration des pauses pour gérer la fatigue des opérateurs.

Arabic:

إن ظهور الصناعة 4.0 والمفاهيم الناشئة للصناعة 5.0 قد أحدث ثورة في عمليات التصنيع، مع التركيز على دمج التقنيات الذكية والأساليب التي تركز على الإنسان .تركز الصناعة 4.0 على الأتمتة والترابط بين أنظمة التصنيع، بينما تسلط الصناعة 5.0 الضوء على التعاون بين البشر والآلات لتعزيز الإنتاجية والابتكار .على الرغم من التقدم الذي أحرزته هذه الثورات الصناعية، لا يزال هناك فجوة كبيرة في تحسين نماذج الجدولة في الوقت المناسب (JIT)، وخاصة عند تضمين العوامل البشرية .تركز جدولة JIT التقليدية بشكل أساسي على كفاءة الآلات، وغالبًا ما تتجاهل آثار تعب المشغلين البشريين والحاجة إلى فترات راحة .يمكن أن يؤدي هذا الإغفال إلى انخفاض الإنتاجية وزيادة مخاطر حوادث العمل والمشكلات الصحية، وزيادة فترات إتمام العمل، وارتفاع غرامات التأخير .يعالج هذا المشروع هذه الفجوة من خلال اقتراح نموذج شامل لجدولة الإنتاج المسبق بنظام JIT يدمج العوامل البشرية . تم تطوير وتحليل ثلاثة نماذج متميزة :يركز النموذج الأول على جدولة JIT للآلات المؤتمتة بالكامل، مع تحسين إكمال المهام دون مراعاة المشاركة البشرية؛ يدمج النموذج الثاني المشغلين البشريين دون جدولة فترات راحة، حيث يتم فحص تأثير العوامل البشرية مثل التعب والتوافر على فترات إتمام العمل والتأخيرات؛ يقدم النموذج الثالث فترات راحة مجدولة للمشغلين البشريين، بهدف تخفيف التعب وتحسين الكفاءة الشاملة .من خلال مقارنة هذه النماذج، نقيم تأثير دمج العوامل البشرية وفترات الراحة على مؤشرات الأداء الرئيسية (KPIs) مثل فترات إتمام العمل، التبكير، التأخير، وتكاليف التشغيل .تُظهر النتائج أهمية الجدولة التي تركز على الإنسان لتحقيق عمليات إنتاج مستدامة وفعالة، مما يبرز الفوائد المحتملة لدمج فترات الراحة لإدارة تعب المشغلين.

**Keywords:** Lean manufacturing, industry 5.0, just in time, human-centric, scheduling

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# General Introduction

The journey of manufacturing has been marked by remarkable milestones, each defined by unique technological breakthroughs and organizational frameworks. Beginning with Industry 1.0 in the late 18th century, the focus was on mechanization using the power of water and steam at that time it was a huge invention. This era ushered in fundamental changes to production methods, laying the groundwork for the modern manufacturing landscape. The mechanization of tasks previously performed manually led to significant improvements in productivity and efficiency, paving the way for future industrial revolutions [68].

The early 20th century witnessed the introduction of Industry 2.0, characterized by the advent of electricity and the assembly line, spearheaded by Henry Ford's mass production techniques. Fordism revolutionized the manufacturing sector by standardizing parts and processes, which enabled unprecedented levels of productivity and cost-effectiveness. The ability to produce large quantities of standardized products at lower costs made consumer goods more accessible to the general public. However, this approach often resulted in rigid production systems with limited flexibility, making it challenging to adapt to changes in consumer demand and preferences.[68]

The transition to Industry 3.0 in the mid-20th century was driven by the integration of automation and computerization. The introduction of programmable logic controllers (PLCs) and robotics facilitated more sophisticated and flexible manufacturing processes. The manufacturing industry has undergone significant transformations over time.

Advancements in technology have led to increased automation and precision, enabling the production of complex and high-quality goods. The rise of lean manufacturing and Just-In-Time (JIT) production systems, pioneered by Toyota, has emphasized minimizing waste, improving quality, and responding to market demands more effectively. By producing only what is necessary, when it is needed, and in the required quantities, companies have been able to reduce inventory costs and enhance efficiency.

Today, the manufacturing sector is experiencing the era of Industry 4.0, characterized by the integration of cyber-physical systems, the Internet of Things (IoT), and advanced data analytics. This transformation is enabling the development of smart factories where machines and systems are interconnected, allowing for real-time monitoring, predictive maintenance, and adaptive production processes. The focus has shifted towards enhancing flexibility, efficiency, and sustainability in manufacturing. Industry 4.0 technologies are enabling manufacturers to adapt more quickly to changes in market demand, customize products to meet individual customer needs, and operate more sustainably by reducing waste and energy consumption. As the industry continues to evolve, further transformations

driven by technological advancements and changing societal needs and expectations are anticipated [68].
The main contributions of this project can be organized as follows:

- **State of the art**: In this chapter, we conducted a comprehensive literature review focusing on key topics such as lean manufacturing, digital twins, meta-heuristics, artificial intelligence, and human-centric approaches. Our goal was to identify existing gaps in the research and explore less-explored combinations of these concepts. By doing so, we intended to provide a scholarly contribution that offers future researchers a clearer perspective on this expansive field. Additionally, we outlined various directions for future research, highlighting potential areas where further investigation could lead to significant advancements.

- **Comparative analysis between two cases**: In this chapter, we undertook a comparative analysis between two scenarios within the learning factory context. The first scenario examined scheduling under the Just-in-Time (JIT) philosophy, focusing on operational efficiency and timeliness. In contrast, the second scenario incorporated human factors into the scheduling process, considering the influence of human capabilities and limitations on performance. By exploring these scenarios, our aim was to uncover insights and draw conclusions regarding their respective impacts on production efficiency, worker satisfaction, and overall operational outcomes.

- **The Digital model**: Creating a digital twin of the learning factory stands as a primary objective of this study. In pursuit of this goal, we successfully developed a digital model of the learning factory and conducted simulations. These simulations were instrumental in demonstrating how lean manufacturing principles can be effectively taught using modern digital technologies. This approach not only showcases the potential of digital twins in enhancing educational practices but also lays the foundation for future advancements in learning methodologies within industrial settings.

In the next chapters , we will find the first chapter I, where we define important aspects of manufacturing. This chapter gives a clear picture of what we aim to achieve. In the second chapter II, we extensively reviewed the literature on five key aspects that we identified as pivotal within our broad domain. Afterward, we proceed to Chapter **??**, where we defined the fundamental components of the learning factory that have our field of application. The comparative analysis was elaborated in the 4th chapter IV and finally to synthesize our work, we need to draw conclusions which is in chapter 5 IV.4.2;

# Chapter I

# Defining Key Aspects of Modern Manufacturing

## Introduction

In this chapter, we explored several key domains that were integral to modern production and operational efficiency. We began with lean manufacturing, a cornerstone of contemporary production management that emphasized demand-pull production to minimize inventory and associated costs. The principles and benefits of JIT were explored in detail, highlighting its impact on waste reduction and resource optimization. Next, we examined the realm of meta-heuristics, advanced algorithms designed to tackle complex optimization problems. These algorithms balanced exploration and exploitation to efficiently search for optimal solutions within vast solution spaces. In this part of the paper, We explored various types of scheduling, a critical function in both manufacturing and service industries, aimed at optimizing the use of resources and ensuring timely completion of tasks. By understanding and applying these concepts, organizations could enhance productivity, reduce costs, and maintain a competitive edge in the market.

## I.1 Lean manufacturing

The methodology of Lean Manufacturing has gained immense popularity in production management due to its systematic approach that prioritizes customer value while minimizing waste. Developed from the Toyota Production System (TPS), Lean Manufacturing emphasizes continuous process improvement and the elimination of non-value-added activities, also known as (Muda). These activities include overproduction, waiting, inventory, motion, transportation, rework/defects, and over-processing. The goal of Lean Manufacturing is to streamline workflows and increase productivity by prioritizing these principles.

The main objective of Lean Manufacturing is to reduce waste and increase efficiency. It is achieved through the implementation of various techniques and principles such as defining value from the customer's perspective, mapping value streams, establishing continuous flow, implementing pull systems, and striving for perfection. By applying these principles, Lean Manufacturing aims to make operations more agile, flexible, and responsive to market needs.

One of the key principles of Lean Manufacturing is defining value from the customer's

perspective. This principle emphasizes the importance of understanding the customer's needs and requirements. By identifying what the customer values, organizations can focus on delivering products and services that meet those needs, thus increasing customer satisfaction[45].
Another important principle of Lean Manufacturing is mapping value streams. This principle involves identifying all the steps involved in the production process and analyzing them to determine which steps add value and which do not. By eliminating non-value-added activities, organizations can reduce waste and increase efficiency.
Establishing continuous flow is also a crucial principle of Lean Manufacturing. This principle involves designing the production process in such a way that products move seamlessly from one stage to another without any interruptions or delays. By establishing continuous flow, organizations can reduce lead times and increase productivity.
Implementing pull systems is another key principle of Lean Manufacturing. This principle involves producing only what is needed when it is needed. By implementing pull systems, organizations can reduce inventory and minimize waste.
Finally, Lean Manufacturing strives for perfection. This principle emphasizes the importance of continuously improving processes to eliminate waste and increase efficiency. By constantly striving for perfection, organizations can achieve higher levels of productivity, quality, and customer satisfaction.
Lean Manufacturing is a methodology that has proven to be highly effective in maximizing customer value while minimizing waste. By following key principles such as defining value from the customer's perspective, mapping value streams, establishing continuous flow, implementing pull systems, and striving for perfection, organizations can achieve higher levels of efficiency and productivity.

### I.1.1 Muda

The elimination of Muda, a fundamental principle in lean manufacturing, pertains to any procedure or operation that consumes resources without providing any value to the final product or service from the customer's point of view. Muda comprises seven types of waste as we can see in I.7 including overproduction, waiting, transportation, unnecessary processing, inventory, motion, and defects.
1-**Overproduction**:
Producing more than what is needed or producing it too early. Excess inventory is generated, which ties up resources and raises storage costs.
[41] 2-**Waiting**:
The use of resources (such as workers, machines, and materials) in a productive manner that causes idle time. This includes waiting for materials, equipment, or information.[41]
3-**Transport**:
The eradication of Muda leads to increased efficiency, decreased expenses, and improved productivity and customer fulfillment.[67]
4-**Extra-processing**:
Engaging in activities that exceed the customer's needs or expectations, such as incorporating unnecessary steps into the production process, over-complicating designs, or implementing duplicate procedures.[57]
5-**Inventory**:
Inventory that is surplus to immediate requirements consists of raw materials, work-in-progress, and finished goods. This unnecessary inventory not only occupies valuable

storage space but also ties up capital. Additionally, it can mask production inefficiencies and imperfections.[41]

6-**Motion** :

Unneeded actions carried out by employees or equipment, such as unnecessary walking, stretching, or stooping. These actions may cause weariness or harm and also result in ineffectiveness in the task.[41]

7-**Defects**:

Defects are products and services that lack desired quality standards, hence failing to meet customer expectations. Examples of this type of waste include rework, scrap, and returns. To be more specific, defects stand for material, energy, time, and labor wastage; they also symbolize a dissatisfied customer base and harm to the reputation of the organization. The defects can be addressed by finding the root causes through quality control measures to ensure such flaws never happen again [35].

There are two other wastes, **the wasted potential of people** because Under-utilizing the skills and talents of employees leads to missed opportunities for improvement and innovation and **Environmental Waste** which is concentrated in any activity that causes harm to the environment, such as excessive use of resources, energy waste, and pollution [73].

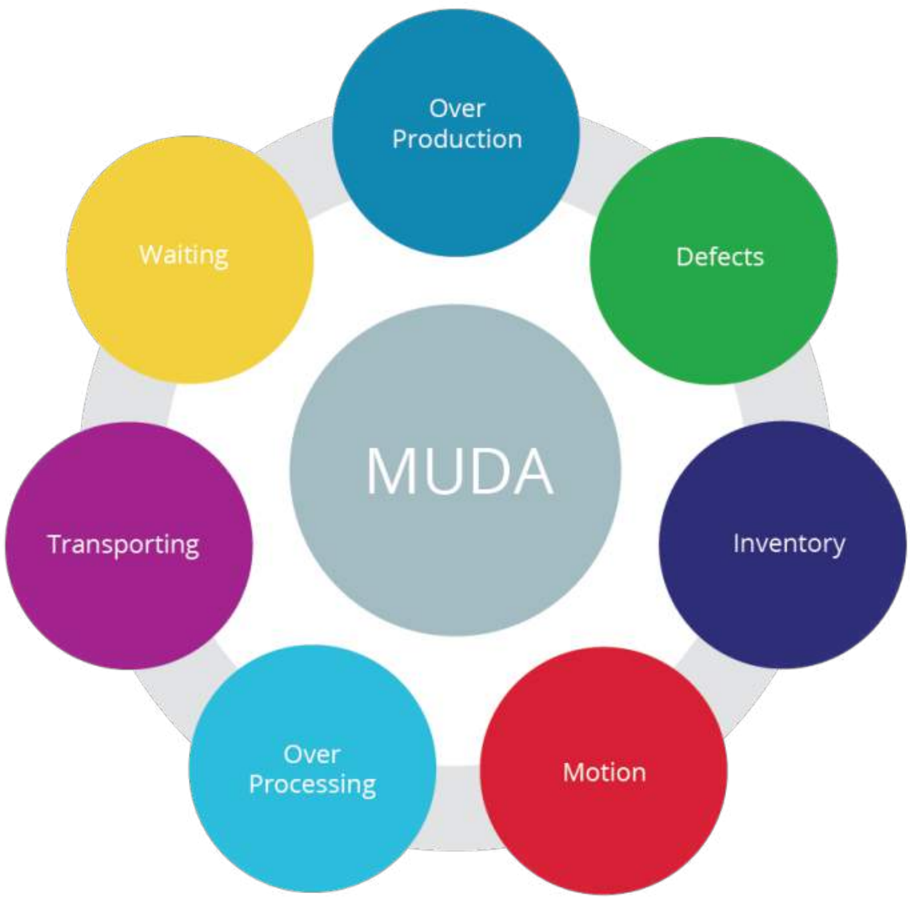


Figure I.1: 7 Muda

Additionally as shown in I.7, there is a wide array of methods and tools in this field. Here, we will highlight some of the key ones:

### I.1.2 5S

The 5S methodology is a systematic approach to workplace organization and standardization, originating from Japanese manufacturing practices [1]. It consists of five phases, each represented by a Japanese term starting with the letter "S":

- **Seiri (Sort)**: Remove unnecessary items from the workplace to eliminate clutter and improve efficiency.
- **Seiton (Set in Order)**: Arrange necessary items in a logical order for easy access and use.
- **Seiso (Shine)**: Clean the workplace and equipment regularly to maintain a neat and tidy environment.
- **Seiketsu (Standardize)**: Establish standardized procedures and schedules to maintain organization and cleanliness.
- **Shitsuke (Sustain)**: Foster a culture of continuous improvement and discipline to sustain the 5S practices.

### I.1.3 Kaizen

Kaizen is a Japanese term meaning "continuous improvement." It refers to the philosophy and practices that focus on incremental improvements in processes, products, or services over time. The Kaizen methodology emphasizes employee involvement at all levels, encouraging them to suggest and implement small, incremental changes that collectively result in significant improvements [47]. The main principles of Kaizen include:

- **Continuous Improvement**: Ongoing effort to improve products, services, or processes.
- **Employee Involvement**: Engagement and participation of all employees in the improvement process.
- **Standardization**: Establishing and maintaining standards to ensure consistency and quality.
- **Customer Focus**: Prioritizing the needs and satisfaction of customers in all improvement efforts.

### I.1.4 Jidoka

Jidoka, also known as "autonomation," is a principle in lean manufacturing that emphasizes the automation of processes with a human touch. It involves equipping machines and production lines with the ability to detect abnormalities or defects and automatically stop operations to prevent the production of defective products [47]. The main objectives of Jidoka are:

- **Defect Prevention**: Detect and address defects at the source to prevent their propagation.
- **Quality Control**: Ensure that only high-quality products are produced.
- **Empowerment**: Enable operators to focus on problem-solving and improvement rather than merely monitoring machines.

### I.1.5 Standard Work

Standard Work refers to the practice of establishing and documenting the most efficient methods and sequences for performing tasks. It serves as a foundation for continuous improvement and ensures consistency, safety, and quality in operations [41]. The key components of Standard Work include:

- **Takt Time**: The pace at which products must be produced to meet customer demand.
- **Work Sequence**: The specific order in which tasks should be performed.
- **Standard Inventory**: The minimum amount of materials or parts required to keep the process running smoothly.

### I.1.6 Heijunka

Heijunka, or production leveling, is a technique used in lean manufacturing to reduce the unevenness in production. It involves smoothing out the production schedule by distributing the workload evenly across all processes over a given period. The goals of Heijunka are:

- **Reduce Overburden**: Avoid overloading workers and equipment.
- **Minimize Inventory**: Reduce the need for excess inventory by leveling production.
- **Enhance Flexibility**: Improve the ability to respond to changes in customer demand.

### I.1.7 Kanban

Kanban is a visual scheduling system used in lean manufacturing to control the flow of work and materials. It utilizes cards or signals to represent tasks or items and their movement through the production process. The key benefits of Kanban include:

- **Visual Management**: Enhance visibility and transparency of work in progress.
- **Work in Progress (WIP) Limits**: Control the amount of work in progress to prevent bottlenecks.
- **Continuous Flow**: Promote a smooth and continuous flow of work through the production system.
- **Just-in-Time (JIT)**: Ensure materials and products are delivered exactly when needed.

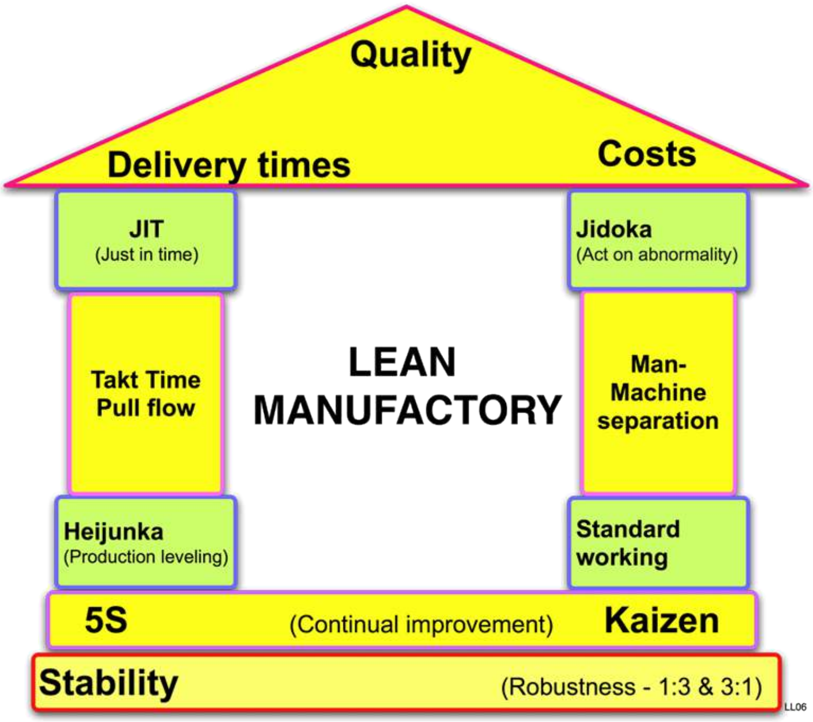


Figure I.2: Lean manufacturing aspects

## I.2 Manufacturing Strategies: A Deep Dive into Push and Pull Systems

In the world of production and inventory management, the distinction between push and pull systems is paramount for optimizing efficiency and responsiveness. The push system, rooted in conventional manufacturing practices, relies on forecasts and predetermined schedules to drive production, often leading to elevated inventory levels and potential overproduction. Conversely, the pull system, closely aligned with lean manufacturing principles, initiates production based on actual customer demand, thereby minimizing inventory and reducing waste. This section delves into the fundamental characteristics, advantages, and challenges of both systems, providing a comprehensive comparison to help identify the approach that best suits different production environments and objectives. By exploring the intricacies of push and pull strategies, we aim to shed light on their impact on overall operational effectiveness and adaptability in the ever-evolving market landscape [2].

### I.2.1 Push System

In the push production strategy, manufacturing and inventory levels are determined based on forecasts and predictions of future demand. This approach involves producing goods in anticipation of customer orders and then pushing them through the supply chain to reach the end consumers. While this method can result in overproduction and increased inventory costs, it enables companies to promptly fulfill customer requests from their existing stock. This production strategy contrasts with the pull system, where goods are manufactured in direct response to actual customer demand, minimizing the risk of overproduction and excess inventory. The push system prioritizes the ability to quickly fulfill orders, even if it means carrying higher inventory levels. By anticipating future demand, companies can ensure they have the necessary products on hand to meet customer needs. However, this proactive approach comes with the potential drawback of increased storage and handling costs associated with maintaining a larger inventory. Businesses must carefully balance the benefits of rapid order fulfillment against the financial implications of overproduction and excess stock. Overall, the push production strategy offers advantages in terms of responsiveness to customer demand, but it requires diligent forecasting and inventory management to avoid the pitfalls of inefficient resource allocation and higher operating expenses [3].

### I.2.2 Pull system

The pull system is a production strategy that puts the customer at the center of the manufacturing process. Instead of relying on forecasts to drive production, this approach responds to actual demand, initiating manufacturing only when a customer order is received. By producing only what is needed, when it is needed, and in the right quantities, the pull system aims to minimize waste and increase efficiency. Commonly associated with lean manufacturing, the pull system helps businesses streamline their operations, reducing inventory costs and improving their ability to adapt to market changes. Rather than stockpiling products based on predictions, this strategy ensures that resources are allocated effectively, with production closely aligned to real-time customer requirements. The result is a more agile and responsive manufacturing process, one that can quickly pivot to meet evolving customer needs. This customer-centric approach not only reduces waste but also enhances the overall efficiency of the supply chain, ultimately delivering greater value to the end consumer [24].

### I.2.3 Comparison table

Table I.1: Comparison of Pull and Push Systems

| **Aspect** | **Pull System** | **Push System** |
|---|---|---|
| Production Initiation | Based on actual customer demand | Based on forecasts and predictions |
| Inventory Levels | Minimizes inventory; produces only what is needed | Maintains higher inventory levels to meet forecasted demand |
| Flexibility | High flexibility; can quickly adapt to changes in demand | Lower flexibility; changes in demand can lead to over/under production |
| Lead Time | Generally longer, as production starts after order | Generally shorter, as products are produced in advance |
| Waste | Reduces waste by avoiding overproduction | Higher risk of waste due to overproduction |
| Production Control | Decentralized; each stage controls its own production | Centralized; production is controlled by forecasts and planning |
| Examples | Just-in-Time (JIT) manufacturing, Kanban | Traditional manufacturing, MRP (Material Requirements Planning) |
| Cost Implications | Lower holding costs but may incur higher setup costs | Higher holding costs but potentially lower setup costs |
| Risk | Risk of stockouts if demand spikes suddenly | Risk of excess inventory if demand decreases |

## I.3 Just-in-time

The Just-in-Time philosophy is one of the cornerstones of modern production management today. It has revolutionized the approach to efficiency and waste reduction among manufacturers. Having borrowed from the TPS, or Toyota Production System, JIT puts much emphasis on a demand-pull production model in which production is only done on demand to bring down the extent of inventory levels and their associated carrying costs. The two major goals of JIT are to increase productivity and efficiency through better planning and control, which keep production schedules very near to what is demanded in the market, in order to reduce wastes and optimize resource utilization [35].
The JIT methodology is harnessed with four basic principles: demand-pull production, waste elimination, quantitative inventory control, and continuous improvement. Because it takes off from real customer demand, not forecasts, JIT aids the organization in avoiding excess production and consequent excess inventory. This approach, which is pull-based, ensures that the products are manufactured just in time to customers' needs, drastically reducing storage and holding costs [53].
The other core principle of JIT is waste elimination, referred to as "muda" by lean terminology. Waste may be inflicted on many aspects, for instance, overproduction, waiting times, excess inventory, non-essential transportation, overprocessing, and defects. JIT endeavors to eliminate these activities devoid of added value so as to create a lean process that enhances efficiency.
Inventory management under JIT means keeping a low stock with materials and components arriving precisely when production needs them. The function reduces storage requirements, minimizes the risks of obsolescence, and ensures resources are better and more effectively utilized. To this end, good, collaborative relationships with suppliers are imperative in ensuring the timely delivery of quality materials [41].
Another very important principle of JIT is continuous improvement, or "Kaizen." It fosters constant assessment and improvement of processes, thereby involving every rank of employee within a given organization in the search for waste and in the fixing of problems. This commitment to ongoing improvement enables an organization to maintain high standards of quality while at the same time responding quickly to changes in market conditions [47].
High-quality standards are part of JIT, too, where the aim is to get it right the first time so no rework or scrap will have to be done. Total Quality Management practices are often used to ensure a quality product will come out the end of the line [48].

### I.3.1 JIT and the Pull System

The Just-in-Time philosophy is inextricably linked with the pull system, a technique in which production is incited by real customer demand, not speculation about what customers might purchase. In the case of a pull system, production activities are driven by customer orders. The idea is that each stage in the production process gets set to work in such a manner through which real-time demand can be met. This approach is different from the traditional push system whereby goods were produced according to forecasts and then pushed through the supply chain, which quite frequently resulted in excess inventory and increased waste [41].
Basically, the implementation of a 'pull' system under JIT means that only what's required will be produced and at the time and in quantities required. Through this approach,

synchronous customer demand helps reduce excessive production and inventory held at any particular time. The pull system enables an agile and responsive production process through which the manufacturer can easily respond to any changes in demand and reduce lead times [41].
application of the principles is toward a lean, efficient, and responsive production system in JIT. Significant advantages of the JIT technique are cost reduction by way of reduced inventory and waste and efficiency, productivity, improved product quality, and customer satisfaction from quick response during demand. On the other side, successful implementation of JIT demands careful planning, good relations with suppliers, and a continuous improvement culture to help surmount the challenges of disruptions to the supply chain and variability in demand [33] I.7


Figure I.3: JUST-IN-TIME

### I.3.2 Why do we have to use JIT philosophy

The just-in-time (JIT) approach is commonly used in pull-based production, where manufacturing is driven by real customer orders instead of forecasted demand and high stockpiles. Unlike the push system, the pull method only produces goods when there is a specific order, leading to reduced inventory levels. This approach offers several advantages, which we will examine in detail.[41]

1-**Lowering Inventory to Reveal Problems**:
Through keeping inventory to a bare minimum, the Just-In-Time (JIT) approach brings production challenges and inefficiencies to the surface. This allows for faster detection and resolution of issues, stopping them from happening again down the line as we can see in III.2 .

2-**Reducing Waste**:

JIT, or ”just-in-time” production, aims to cut down on unnecessary waste. Instead of making more than is required, JIT focuses on creating only what is needed, exactly when it is needed. This approach helps to avoid overproduction, excessive inventory, and the wastage of materials. As a result, resources are used in a more efficient and cost-effective manner.[4]

3-**Improved Quality**:
Just-in-time manufacturing encourages a culture of ongoing enhancement and prompt responses, resulting in enhanced product excellence. By closely aligning production with customer needs, any quality problems are swiftly detected and addressed, boosting client contentment [5].

4-**Increased Efficiency**:
Streamlining production through JIT (Just-In-Time) strategies minimizes the time and resources required to transport materials and parts, leading to a more efficient production process with fewer disruptions and delays. This, in turn, enhances overall productivity by optimizing the flow of the manufacturing operations.[6]

5-**Greater Flexibility**:
Agile production planning through JIT empowers companies to swiftly adapt to shifting customer needs and market dynamics. This flexibility is indispensable in the fast-evolving, competitive business landscape of today [11].

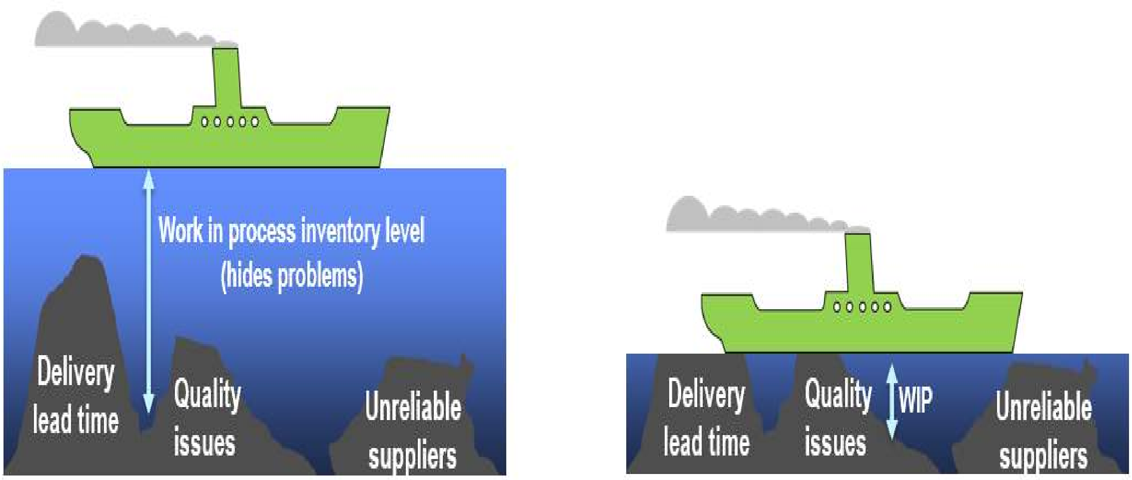


Figure I.4: Results of lowering inventory

# I.4 Meta-heuristic

Meta-heuristics are a class of advanced algorithms designed to tackle intricate optimization problems by efficiently searching for optimal solutions within a reasonable time-frame. These techniques are particularly useful when traditional methods fail to achieve the desired results due to the vastness or complexity of the solution space. Meta-heuristics aim to strike a balance between two key strategies: exploration and exploitation. Exploration involves searching through diverse areas of the solution space to avoid being trapped in local optima, while exploitation focuses on refining solutions in promising regions. By striking this balance, meta-heuristics can effectively explore the solution space and uncover optimal solutions in a relatively short period of time.[29]

There are several types of meta-heuristic algorithms that are commonly employed, including Genetic Algorithms, Simulated Annealing, Particle Swarm Optimization, and Ant Colony Optimization. Each of these algorithms has its own unique strengths and weaknesses, and the choice of algorithm depends on the specific nature of the optimization problem at hand. For instance, Genetic Algorithms are inspired by the process of natural selection and evolution, and they work by mimicking the mechanisms of genetic recombination and mutation to generate new candidate solutions [28].

Simulated Annealing is a technique inspired by the principles of thermodynamics, aiming to find the lowest energy state by gradually cooling down the system. Particle Swarm Optimization, as the name suggests, emulates the movement of particles in a swarm, adjusting their velocity and position to uncover optimal solutions. Ant Colony Optimization, on the other hand, is based on the remarkable ability of ants to discover the shortest path between their nest and food sources.[58]

Nature-inspired meta-heuristics have gained substantial attention due to their capacity to mimic natural phenomena and behaviors in order to tackle complex problems as we can see in the III.6. Genetic Algorithms, for instance, are modeled after the evolutionary process of natural selection, where the fittest individuals are chosen to reproduce and produce the next generation. This approach allows for a diverse exploration of the solution space and the potential to discover highly optimized solutions. Similarly, Simulated Annealing takes inspiration from the annealing process in metallurgy, involving the heating and slow cooling of a material to reduce defects, analogous to finding a global optimum in an optimization problem by occasionally allowing uphill moves to escape local optima.[60]

Fish swimming in coordinated groups adapt their movements based on their own and their neighbors' previous actions, allowing them to efficiently explore their surroundings. Similarly, the Ant Colony Optimization algorithm, modeled after the way ants find food, uses chemical signals left by other ants to guide the search for the best solutions to routing and scheduling challenges. Regardless of the particular approach employed, meta-heuristic methods are renowned for their flexibility, robustness, and capacity to address a wide range of optimization challenges across diverse domains III.7. These techniques have been effectively deployed in numerous fields, including engineering, logistics, finance, and artificial intelligence. Meta-heuristics present a promising avenue for identifying optimal solutions within a reasonable time-frame, making them a valuable tool for tackling complex optimization problems. As the meta-heuristics domain progresses, we can anticipate the emergence of even more sophisticated algorithms and techniques, capable of addressing increasingly complex problems with greater efficiency and precision.[71]

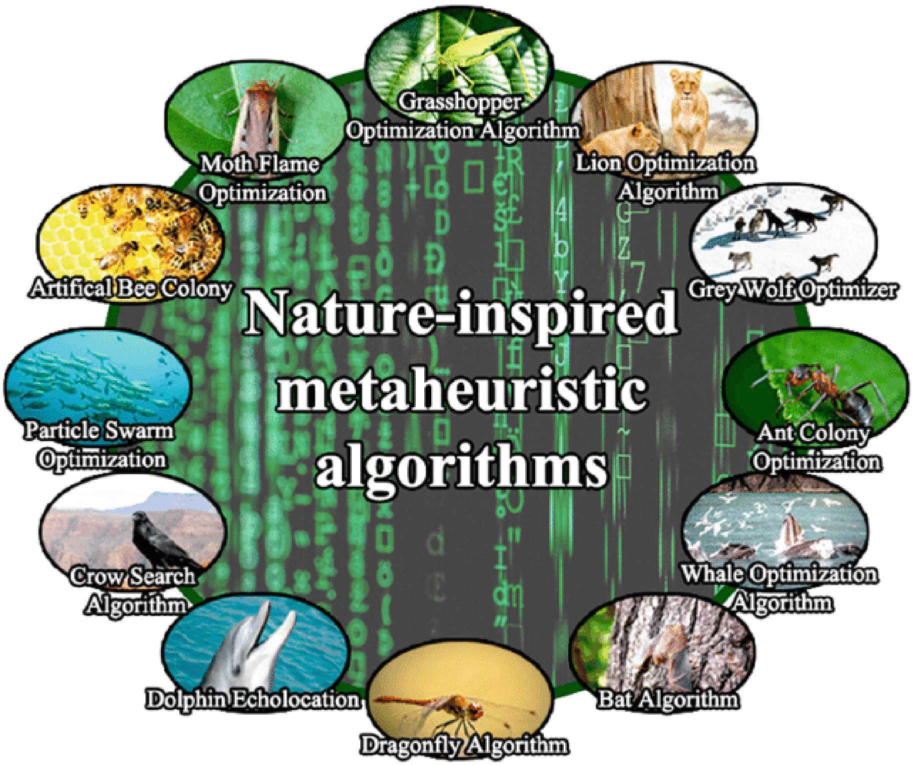


Figure I.5: Different meta-heuristics inspired from nature

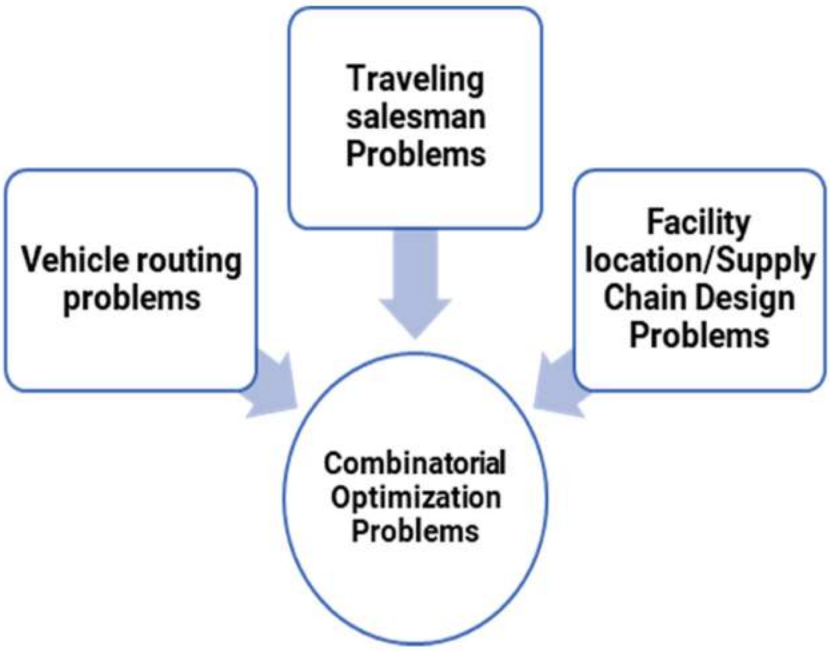


Figure I.6: Different meta-heuristics inspired from nature

## I.5 Scheduling

Organizing and managing the timing and order of diverse activities is a crucial aspect of any successful business or production process. This practice, known as scheduling, plays a vital role in streamlining workflows and ensuring efficient resource utilization, such as time, labor, and equipment.[51]
The primary objective of scheduling is to minimize production time and costs, enhance productivity, and meet deadlines effectively. By strategically planning the sequence of tasks, businesses can optimize the use of resources, minimize downtime, and ensure the timely completion of all operations. This optimization ultimately leads to increased profitability, improved customer satisfaction, and a competitive edge in the market.[18]
Scheduling is a fundamental function in various industries. In manufacturing, it is crucial for ensuring efficient production lines and the desired rate of product output. In transportation, effective scheduling enables optimal vehicle utilization and punctual deliveries. Similarly, in the computing sector, scheduling ensures the efficient execution of tasks and processes to maximize system performance [7]

Figure I.7: Scheduling

### I.5.1 Types of scheduling

1-**Production Scheduling**:
Manufacturing production scheduling is defining production tasks, their sequence, and timing in manufacturing so that the use of resources is maximal, with little idle time, and the production target will be met. It involves tasks ranging from resource allocation and setting production sequences to the management of production flows [51].
2-**Transportation Scheduling**:
The planning and organizing of transporting goods, people, or vehicles from one location to another is called transportation scheduling. The task entails arranging routes, assigning vehicles, and guaranteeing prompt delivery or pickup [58].
3-**Project Scheduling**:

In project management, project scheduling is an important step for planning and executing project tasks. It comprises creating a well detailed project schedule with tasks, milestones, resource allocation, and deadlines to ensure that projects are well aligned within the timing and the budget constraints [51].

4-**Employee Scheduling**:

Engaging in activities that exceed the customer's needs or expectations, such as incorporating unnecessary steps into the production process, over-complicating designs, or implementing duplicate procedures [8] .

5-**Task Scheduling**:

Organizing tasks within a project or work process is the focus of task scheduling. This involves determining the importance of each task, assigning the necessary resources, and setting time-frames to guarantee efficient task execution [58].

6-**Service Scheduling** :

Scheduling services is a widespread practice across various sectors, such as healthcare, customer service, and maintenance. This process involves arranging appointments, service calls, or maintenance tasks to fulfill customer needs and meet service level commitments [9].

### I.5.2 Types of Workshops and the Impact of Scheduling

1-**Flow shop scheduling**:

In a flow-based manufacturing setup, the production process follows a standardized sequence of steps that is applied consistently across multiple products. Flow shop scheduling involves organizing these jobs in a way that ensures each one travels through the same series of machines or workstations. Effective scheduling in this environment aims to minimize production time and idle time, enabling a streamlined and uninterrupted workflow. The primary goal is to shorten the makespan, which represents the total time needed to complete a given set of jobs. Proper scheduling can help mitigate bottlenecks and increase overall productivity [31] .

2-**Job shop scheduling**:

In a job shop setting, the production process is more versatile, as each job may have a unique path through the machines or work areas. This flexibility means the scheduling process is more intricate, with different operations required for various jobs. Effective scheduling in this environment concentrates on minimizing the time needed to complete jobs, lowering the inventory of work-in-progress, and making the most efficient use of available resources. The goal is to ensure timely delivery of customized products while handling the complexities arising from the diverse job requirements [1].

3-**Open Shop Scheduling**:

In an open workshop setting, there is no fixed sequence of tasks for the jobs. Any project can be carried out in any order on the available machines. Effectively planning the optimal order of operations for each job is crucial to minimize the total time required for completion in open workshops. The flexibility inherent in open workshops allows for dynamic adjustments based on real-time circumstances, making scheduling a critical factor in maintaining productivity and meeting deadlines [14].

4-**Hybrid flow shop scheduling**:

A hybrid flow shop fuses characteristics from both flow shops and job shops. It has multiple phases, with each phase potentially containing parallel machines. The goal of scheduling in a hybrid flow shop is to optimize the movement of jobs through the various phases while navigating the complexities of having multiple machines per phase. Efficient scheduling minimizes idle periods, distributes the workload evenly across machines, and guarantees jobs are completed on time [22] .

#### I.5.2.1 Impact of scheduling on workshop types

Effective scheduling makes a huge difference in the efficiency and productivity of different workshop types. In flow shops, proper scheduling will ensure smoothness in production without experiencing bottlenecks, thus maximizing throughput. In job shops, it controls the complexity and variability of the custom jobs—not only ensuring timely delivery but also using resources in the best possible manner. In open shops, scheduling enables flexibility and allows for real-time adaptation to changes, optimizing job sequences dynamically. For hybrid flow shops, the scheduling at each stage and on each machine aims to balance the workload, reducing idle times to improve overall efficiency.

By knowing the type of workshop and the kind of scheduling that should be applied to it, the business will be better positioned to optimize its operations, cut down costs, and improve customer satisfaction. One of the major functions that each business owner or manager should be equipped with in order to attain operational excellence and sustain a competitive advantage in the market is scheduling [10].

## Conclusion

As we observed in this chapter, the domains of Just-In-Time (JIT) production, meta-heuristics, and scheduling were vast and continuously evolving. The JIT philosophy, with its focus on reducing waste and improving efficiency, revolutionized production management. Meta-heuristic algorithms offered powerful tools for solving complex optimization problems, leveraging nature-inspired techniques to find optimal solutions. Scheduling, a fundamental aspect of various industries, ensured the efficient utilization of resources and timely completion of tasks. The depth and breadth of these fields highlighted their significance in achieving operational excellence. As these domains continued to develop, they presented numerous opportunities for innovation and improvement, enabling businesses to thrive in an increasingly competitive landscape.

# Chapter II

# Investigating Modern Lean Scheduling Methodologies within Industry 4.0 and 5.0 Frameworks

## II.1 Introduction

Improving manufacturing efficiency is crucial, and optimizing production scheduling techniques is key to achieving this. Although conventional scheduling methods have been the foundation, they often struggle to keep up with the demands of dynamic and complex production settings. However, the emergence of lean manufacturing and advanced optimization algorithms, including genetic algorithms and machine learning models, provides promising answers to these issues. This section examines the current state of production scheduling research, tracing the progression from traditional techniques to modern, algorithm-driven approaches. I will expose some of the related works and also some works related to lean manufacturing, digitalization, showcase their practical applications, and pinpoint the gaps that our study aims to fill within the context of a learning factory setting.

## II.2 Key aspects

### II.2.1 Digitalization in Lean Manufacturing and Industry 4.0

Talking about the digital side, in [43], the authors exposed the problem that was about production process re-engineering (Production process re-engineering involves the redesign and optimization of existing manufacturing processes to improve efficiency, quality, and productivity. This typically involves analyzing current workflows, identifying bottlenecks or inefficiencies, and implementing changes to streamline operations and enhance overall performance) and they have addressed the challenges faced by SMEs (Small and Medium Enterprises). They've proposed a methodology that combines the VSM and the digital twin technique.

On the other hand, in [52], we explored the automated data collection process facilitated by the DINASORE software, which effectively reduces sensor costs. Additionally, we examined the development of a dynamic Yamazumi diagram aimed at identifying system characteristics such as bottlenecks, operational inefficiencies, and workload distribution along the line. Leveraging key performance indicators (KPIs) like cycle time, the Yamazumi diagram provides real-time data, thereby enhancing our decision-making capabilities.

Staying in the digitalization domain, this time with some focus on flexibility management, the work in [62] addressed the challenge of enhancing flexibility management and decision-making in cyber-physical systems within the Industry 4.0 context. It proposed solutions by integrating digital lean principles with brain-inspired computing pattern recognition techniques. By leveraging machine learning algorithms and advanced digital tools, the study aimed to optimize manufacturing operations, improve responsiveness, and enhance decision-making processes in complex and dynamic production environments.

Moreover, the digitalization of lean manufacturing tools and methods didn't stop here, because in [49], the authors discussed the impact of Industry 4.0 on lean manufacturing practices and the potential for digital transformation to enhance traditional lean tools and methods. They explored the theoretical and practical implications of integrating lean principles with Industry 4.0 technologies, such as IoT, Big Data, and autonomous robots. They analyzed case studies of e-VMB (visual management board) and e-SMED to demonstrate the possibilities of digitalizing lean tools and developing new lean methods in the context of Industry 4.0. The discussion also delved into the challenges and opportunities presented by this convergence, highlighting the importance of adapting lean practices to the current digital landscape to drive operational excellence and innovation.

Talking more about modern intelligent aspects, intelligent VSM was discussed in the paper [46]. The element that triggered this research was the lack of information and studies about more sophisticated VSM and non-traditional VSM, despite the existence of multiple researches about VSM. In this regard, the authors decided to address this gap by implementing a VSM model and integrating Industry 4.0 technology, focusing on reducing lead time and predicting uncertainties, which provided more modern solutions in this domain.

### II.2.2 Meta-Heuristics and Scheduling

Switching fields from trending technologies to the scheduling domain where we will discuss synergy between scheduling, meta-heuristics and lean manufacturing founded in several works, we can can find the example of [21] that have exposed the assembly Line Balancing Problem (ALBP) which is a crucial challenge in manufacturing. Traditional methods often fail to consider the significant impact of worker skills and performance on line efficiency, even if we design a good scheduling philosophy and even with the application of the optimal task sequence employed, cycle time minimizing, the production line still cannot be balanced in most of cases.

Recent research [21] has addressed this gap by integrating meta-heuristic approaches, such as Ant Colony Optimization (ACO), with a hierarchical assignment of workers based on their competence. A modern technique was proposed to solve (ALBP) using ACO to assign workers based on their Competence Index (CIg), which considers factors like work quality, labor efficiency, and attendance, this synergy between meta-heuristics and the human factors was the spark that triggered a new solution in the manufacturing domain. Theoretically talking, this approach has shown some good results and has enhanced production line balance, significantly improved efficiency and quality, and ultimately boosted company revenues. The effectiveness of this method was validated in a real-world case study within a garment company, demonstrating its practical applicability and benefits in optimizing workforce assignments and enhancing production line performance.

Staying in the same domain, but this time talking more about precast scheduling and production planning, The paper [37] tackles the shortcomings of conventional construction techniques by introducing a Genetic Algorithm-Based Decision Support System to streamline precast production planning. The system employs a Multi-Objective Genetic Algorithm to strike a balance between competing goals, such as reducing costs and production duration, while accounting for constraints like restricted buffer capacities. The researchers verified their method through benchmark evaluations and a real-life case study, proving that the Genetic Algorithm-Based Decision Support System markedly improves production performance and decision-making in precast construction.

Furthermore, in the precast scheduling firm, The research paper [64] addressed the challenge of improving and enhancing production management in precast component plants. This was a big obstacle to the widespread adoption of off-site construction, despite its many benefits. The authors recognized the primary issue as the difficulty in managing production scheduling and workforce aspect in precast manufacturing. To address this, they proposed a formal modeling framework that quantified worker competence within a competence score, considering both professional skills and learning skills gained from the amount of years the worker have passed in this work (experience). The solution combined a genetic algorithm to optimize the scheduling of production processes, taking into account the competence scores of workers. This approach aimed to not only boost short-term productivity but also support long-term workforce improvement, addressing both immediate and future needs of precast production management. The authors suggested that future research should explore the balance between minimizing short-term costs and maximizing long-term competence to further refine the strategy for production facility owners which is real modern aspects, we are talking here about one of the pillars of the industry 5.0.

In order to introduce the next work, i allow to myself to bring a statement from [65] "The performance of precast construction is highly dependent on the effectiveness of production planning for the precast components (PCs)" which means that the success and efficiency of constructing buildings or structures using precast components—sections manufactured off-site and assembled on-site—are greatly influenced by how well the production of these components is planned. Effective planning ensures that the right components are made at the right time and delivered when needed (just in time philosophy), which is very important for the timely and cost-effective completion of construction projects. Other way of explication, good production planning is the main key to the general success of precast construction projects. In this regard the authors proposed a solution, called multi-agent based precast production planning model (MAPMPP), they have addressed the rigidity of traditional optimization methods and the inefficiencies of purely multi-agent system (MAS) approaches. At the heart of the model is a two-hierarchy resource constraint-based production scheduling optimization method. This modern innovative target to deliver on-time, minimize waiting and extension times, and enable flexible decision-making in a distributed production environment.

The key innovation lies in the combination of MAS with heuristic algorithms. This synergistic integration allows the model to predict the limitations of old/traditional optimization techniques and the inherent challenges of MAS. By pulling the strengths of each approach, (MAPMPP) delivers a comprehensive solution for precast production planning. To validate the model's effectiveness, the researchers conducted a case study that demonstrated significant cost savings compared to traditional/old scheduling methods and actual industry practices. This compelling evidence highlights the transformative potential of the MAPMPP model in optimizing precast construction planning.

Additionally, Recent advancements in manufacturing have exposed the limitations of traditional methods that handle process planning and scheduling as separate tasks [40]. This disjointed approach often results in sub-optimal resource utilization, production inefficiencies, unbalanced machine loads, and conflicting optimization goals. To address these challenges, researchers have proposed a hybrid algorithm that combines the strengths of Genetic Algorithm (GA) and Variable Neighborhood Search (VNS). GA is renowned for its robust global search capabilities, while VNS excels in local search. By integrating these techniques, the algorithm aims to enhance overall productivity and resource utilization in modern manufacturing systems. The proposed solution incorporates a novel procedure, innovative encoding methods, and advanced local search techniques to improve search efficiency. Empirical validation was conducted using 37 well-known benchmark problems, where the algorithm demonstrated superior performance compared to state-of-the-art methods, achieving new best solutions. Furthermore, the practical utility of the algorithm was confirmed through its application to a real-world case in a packaging machine workshop at a machine tool company in China, effectively resolving complex IPPS challenges. This integration represents a significant advancement in the optimization of process planning and scheduling, showcasing the potential for enhanced manufacturing productivity and flexibility.

Furthermore, the [39] research paper presents a deep investigation about the complex problem of simultaneous due-date determination and sequencing of jobs with normal random processing times on a single machine. The study focused on a real scenario where processing times of each job submitted a normal random distribution, adding an additional layer of complexity to the problem. Traditionally, such due-date and sequencing problems have been challenging to solve, especially for large-scale instances with a huge number of jobs required. The main goal was to determine the optimal due dates and schedule to optimize the expected total earliness and tardiness (E/T) fees. Two efficient insertion-based constructive heuristics were proposed, bringing by that the robustness needed against disruptions and achieving the optimal results. These constructive heuristics, validated through a set of 1700 problems with up to 2000 jobs.

In addition to that, the paper [59] addressed the single-machine earliness/tardiness scheduling problem without forcing machine idle time. This challenge arose in production environments where the goal was to optimize the scheduling tasks on a single machine to minimize both early and late completion of tasks. The study proposed an innovative scheduling method that combine the Artificial Bee Colony (ABC) algorithm with local search aspects. This hybrid approach succeeded in minimizing the tasks' earliness and tardiness without causing forced machine downtime. The ABC algorithm, modeled after the foraging habits of bees, and a thorough local search, considerably improved the scheduling process. The solution's effectiveness was confirmed against well-known heuristics, showing by that its capability to enhance the efficiency of production schedules aligned with just-in-time manufacturing principles, ultimately improving operational efficiency and reducing waste.

Another work talked about the scheduling using (JIT) philosophy [70], This article aimed to address the convoluted challenge of precast production scheduling by proposing a dominance rule-based genetic algorithm. Before getting any-further, we should give a highlight about the problem. The problem was defined in two stages: off-site precast production and the on-site assembling process, during the off-site precast production stage, numerous steel box girders are prefabricated in a factory. Subsequently, in the on-site assembly stage, these steel box girders are transported to the construction site and assembled one by one in accordance with the on-site construction plan. Due to the huge aspect of the box girders (volume, weight), it will be very hard to store a significant number of these steel boxes, so before the solution have been proposed by the authors, the managers used to pick either one of the poisons. First one, the early production on the off-site which will cause a huge inventory and significant amount of the maintenance costs. Second one, delay the production which means a delay at the project planning level causing by that a huge tardiness penalty costs. The key contributions of the research were presented in three main parts.

First one, the researchers developed an innovative (JIT) precast production scheduling model to make the construction of precast components more fluid. The introduction of a job batching algorithm was a decisive step in this model, which organized individual jobs into efficient batches. The primary goal of implementing this job batching process was to simplify the overall solution approach by reducing the difficulty of the scheduling problem.

Second, the researchers delved deeper into the cost structure of the precast production process. They were able to demonstrate that the batch cost function is a piece-wise linear convex form. Leveraging this important theoretical aspect, the researchers then proposed an Optimal Shifting Algorithm (OSA) to determine the optimal start time for each batch. The main objective was to minimize the total batch cost by systematically adjusting the start times.

The last key contribution of the article was the development of a Dominance Rule-Based Genetic Algorithm (DBGA) to create the final precast production schedules, this algorithm was designed specifically for early/tardy scheduling problems, where jobs need to be completed within specific time windows. The novel approach of the genetic algorithm allowed the researchers to create more practical and efficient production plans that aligned better with the real-world requirements of the precast construction industry. This method enabled them to generate schedules that took into account the need to complete tasks within specific time frames. A recent work also talked about the efficiency of the scheduling using (JIT) philosophy [42].

### II.2.3 Implementing AI in Lean Manufacturing: Current Trends and Applications

Our review revealed a significant focus over the past five years on the synergy between LM and AI. It particularly highlighted terms such as smart manufacturing (SMM), sustainable manufacturing (SUM), meta-heuristics (MH), Industry 4.0 (I4.0), human factors (HF), and digitalization (DG). These concepts have been increasingly integrated with lean manufacturing to enhance its implementation and effectiveness across various industries. One notable study by [56] examined the integration of machine learning with lean manufacturing, identifying key factors that influence the implementation of lean manufacturing in the automotive industry. This study highlighted machine flexibility as the foremost factor influencing efficiency, followed by human factors.

The term "smart manufacturing" (SMM) is frequently associated with AI and meta-heuristics, yet little research has bridged these fields comprehensively. Studies like those of [13] and [17] have begun to integrate SMM with other key concepts like Industry 4.0 technologies—big data, IoT, augmented reality (AR), and virtual reality (VR). This integration imbues companies with both smart and sustainable characteristics, crucial for the current industrial landscape. Further studies such as those by [54, 19, 43, 52, 62], have integrated AI with lean manufacturing under the umbrella of Industry 4.0. These studies have employed digitalization tools like intelligent Visual Stream Mapping (IVSM) and Electronic Visual Management Boards (E-VMB) to pinpoint non-value-added times and visualize key performance indicators (KPIs) across organizational levels. These advancements exemplify how digitalization and AI are enhancing traditional lean methods.

Additionally, [49] discussed the optimization of manufacturing systems using lean methods and a fuzzy logic controller, demonstrating the integration of lean principles with manufacturing objectives. [46] introduced a novel approach by combining data envelopment analysis, genetic algorithms, and machine learning to optimize the production efficiency of a thermoelectric power plant using manufacturing sensor data. This represents a sophisticated amalgamation of Industry 4.0, meta-heuristics, and artificial intelligence.

Moreover, the literature reflects a significant alliance between human factors and sustainable manufacturing, a connection that is particularly poignant in the context of Industry 5.0, as noted by [25]. Additionally, a trending area in this field is zero defect manufacturing (ZDM), as discussed by [38]. The objective here is to use AI to foster knowledge creation specific to industrial applications, essential for achieving ZDM. Shifting focus to the human side of the story, in [20] fusing human know-how with AI's analytical prowess, this collaboration in quality control elevates manufacturing processes. AI's advanced analytics, including descriptive, predictive, and prescriptive insights, help pinpoint defects and suggest solutions. This integration enables proactive quality management, catching issues before they reach the customer. Take Whirlpool's model, where predictive quality strategies connect quality control of final products with design and production, enabling effective defect forecasting and resolution. This approach empowers workers to uncover and address potential failures efficiently through root cause analysis. Moreover, in studies like [27], humans play a very important role in strengthening Artificial Intelligence (AI) within real-world applications. By contributing their specialized knowledge, approving and improving data, transferring expertise, overseeing and controlling the process, and offering feedback for ongoing refinement, humans enable the development of more efficient and responsible AI-powered solutions.

### II.2.4 Machine Learning in Scheduling

Taking our literature somewhere else and focusing now about the integration of machine learning with scheduling domain, which is a very trending domain. [36] This paper investigated the integration of failure-prone machines in a multi-stage process line that processes a single type of product. In the other hand, this paper emphasizes the importance of the integration of the manufacturing paradigms with technologies taking the example of the industry 4.0 technologies, the authors succeeded to optimize the manufacturing systems to be more flexible and sustainable, focusing on energy efficiency and cost-effectiveness by integrating the reinforcement learning aspects with ad-hoc planning (An ad hoc network is one that is spontaneously formed when devices connect and communicate with each other) and scheduling to enhance the decision making in the manufacturing domain, they aim also to bring to the enterprise a greater profitability while enabling the green manufacturing practices, such as waste management and recycling.

Moving forward to the Neural Network field, where the authors of [32], have discussed the challenge of optimizing project schedules, where the completion time of sub projects varies depending on their start times, a class of issues known as Time-Dependent Project Scheduling Problems (TPSPs). The authors have identified the main problem as the inadequacy of traditional methods like shortest path algorithms and evolutionary algorithms to solve TPSPs effectively, especially under constraints like varying start and completion times. They propose a novel solution using a Time Wave Neural Network (TWNN) "TWNN is a novel approach to project scheduling that leverages the principles of neural networks and wave propagation to efficiently solve complex scheduling problems" [32] framework, which blended the neural network techniques with a modified Dijkstra's algorithm to dynamically adjust to time-dependent variables in project scheduling. This approach aims to find the optimal schedule by minimizing the project completion time through iterative learning and adaptation, addressing the complexities of TPSPs. The authors utilize various tools and datasets, including the Project Scheduling Problem Library (PSPLIB) and benchmarks from existing literature, to validate their framework. Finally they have achieved there goal by hitting a big success in the results demonstrating by that the improving marge that the TWNN framework has brought to the scheduling domain and how much it enhanced the efficiency and accuracy comparing to the old/traditional methods.

Furthermore, it demonstrated how machine learning can pinpoint specific areas for improvement within lean manufacturing processes. Additionally, the integration of digital technologies such as AI has been recognized as a crucial element in enhancing operational efficiency and empowering employees to work more effectively. [13] discussed how advancements in pragmatic AI are expected to reduce human involvement in many production processes. This utilization of AI-driven machinery not only augments the efficiency of task completion but also significantly reduces the time required, which is a critical parameter in manufacturing efficiency. This evolving landscape underscores the transformative potential of AI in refining and redefining lean manufacturing practices within modern industrial settings. Further, the integration of AI with lean manufacturing principles has been extended by [?], who employed machine learning and deep learning algorithms to minimize downtime in manufacturing systems. Their study achieved remarkable results through a proactive maintenance approach that optimized equipment lifespan, enhanced safety measures, and improved customer satisfaction. This approach not only maintains a positive brand image but also promotes sustainable growth. Notably, the models discussed in this study exhibited a wide range of accuracies, from as high as 99% to as low as 0-50%. After thorough comparison, the most effective model was selected to enhance the maintenance process.

### II.2.5 Human-centric in scheduling

As the industrial landscape evolves towards Industry 5.0, the integration of human-focused principles into production scheduling has become increasingly vital. This approach recognizes workers as essential contributors to sustainable and efficient production systems, prioritizing their well-being and capabilities. A crucial aspect of this human-centric approach is the consideration of worker fatigue, a critical factor that directly impacts productivity, safety, and job satisfaction. Incorporating fatigue management into scheduling not only enhances operational efficiency but also supports the overall sustainability of the manufacturing process. By incorporating human factors such as fatigue, companies can design more flexible and adaptive production schedules that accommodate the physical and mental limits of their workforce. This holistic view of production aligns with the core pillars of

Industry 5.0, which emphasize human-machine collaboration, sustainability, and resilience. This section will explore how recent research has addressed the fatigue parameter in production scheduling, highlighting the methodologies and frameworks developed to incorporate human factors into scheduling algorithms. By examining these advancements, we aim to showcase the practical applications and benefits of human-centric scheduling, paving the way for more sustainable and adaptive manufacturing environments.

Fatigue is multidimensional, encompassing tiredness and lack of energy [66], physical exertion [15], physical discomfort [72], lack of motivation [23] and sleepiness [55, 61], as distinguished dimensions [12]. It is a common consequence of work [66] and leads to performance problems, adversely affecting judgment, causing omission of results, indifference to essentials, decreased efficiency and productivity, and increasing error rates and quality issues [26]. Chronic or excessive fatigue reduces a person's quality of life and can contribute to work-related disorders [16]. Rest breaks are essential as they help alleviate body fatigue and allow a worker to recover their normal strength and capacity.

In the article [30] the authors have addressed the impact of the rest breaks on the worker fatigue caused by the physical effort in several operations. Also integrating the collaborative robots aiming to improve the production efficiency and also minimizing the physical strain from challenging tasks designed in the production planning. The fatigue parameter was based on the difficulty level of tasks in the production system. A case study was conducted in a flexible job shop manufacturing system which will add modifications to the basic flow shop model especially considering the precedence constraints that this type of manufacturing shop requires us to adhere to. The authors of this paper have created a system to arrange the scheduling of activities in a manner that boosts the rest intervals for human employees. By planning the idle times carefully, the system guarantees that workers receive adequate rest to recuperate from the demanding nature of their responsibilities, because the short waiting time is not considered as a break generating by that the mental fatigue. The recovery parameter is set at the half of the fatigue one, which means that the recovery will take longer than the fatigue buildup. This technique is grounded in an ergonomic measure that evaluates the complexity of operations, enabling a more personalized and efficient distribution of break times. Finally, the researchers have managed to reduce the fatigue parameter by increasing idle time while maintaining the same makespan. Integrating these aspects will the solution more credibility in the manufacturing domain.

Fatigue has also been extensively studied in the context of the dual-resource constrained (DRC) job shop, In [34], the authors addressed the significant challenge of incorporating human fatigue and recovery into task scheduling within dual-resource constrained (DRC) systems. Traditional models had overlooked the dynamic nature of worker fatigue and recovery, leading to inefficient job rotation schedules that risked overburdening system operators and jeopardizing their health and safety. In this model, fatigue was specifically based on the physical effort required by workers during tasks, which were organized in cycles.To elaborate this issue, the authors developed a Mixed-Integer Linear Programming (MILP) model that integrated fatigue and recovery dynamics into DRC systems. This model aimed to optimize job rotation schedules, balancing productivity with worker well-being. The model, assuming each worker could handle two different tasks, explored various recovery scenarios ranging from no recovery to full recovery after each task. The study found that integrating partial recovery after each task was the most effective strategy for balancing productivity and fatigue.Consequently, the benefits of this solution highlighted the feasibility and advantages of incorporating fatigue and recovery into DRC systems, optimizing task schedules to improve productivity without overloading operators. Maintaining employee well-being was crucial for organizational success. Various aspects, such as work environment, job demands, and work-life balance, significantly impacted an employee's physical and mental health. By addressing these factors, employers could foster a healthier, more engaged workforce that was better equipped to contribute to the company's growth and productivity. Investing in programs and policies that prioritized employee wellness ultimately benefited the entire organization, leading to improved outcomes and a stronger, more resilient workforce. Fatigue also was exposed as one of the major factors in work accident and also a big aspect in lowering the efficiency and quality of the production system, The paper [50] addressed a significant challenge in the design phase of manufacturing systems, predicting workload exposures and their ergonomic impacts. Traditional design methodologies often overlook ergonomic considerations, which can lead to increased risks of musculoskeletal disorders and other health issues among workers. This oversight not only jeopardizes employee health and safety but also detracts from overall productivity and efficiency. The absence of early ergonomic assessments can result in inherently unsafe and inefficient work environments, necessitating costly post-implementation adjustments and modifications. To tackle this issue, the authors propose the use of discrete event simulation (DES) as a sophisticated ergonomic tool for predicting workload exposures during the system design phase. By simulating various production scenarios, DES can identify potential ergonomic risks and optimize system design to mitigate these risks. This proactive approach ensures that ergonomic assessments are incorporated early, facilitating the design of work environments that are both safe and efficient from the outset. The simulation models in this study are based on the physical effort required for tasks, considering factors such as task frequency, duration, and intensity and also body posture, which are directly linked to worker fatigue. By integrating these ergonomic parameters into DES, the study demonstrates how potential risks can be anticipated and addressed effectively, leading to the development of safer, more productive manufacturing systems. The authors call for further development and refinement of DES models to include more detailed ergonomic parameters and validation against real-world data, enhancing their predictive accuracy and practical utility.

The human-centric approach is a crucial aspect, representing one of the pillars of Industry 5.0, which emphasizes the integration of human well-being into advanced manufacturing and service systems. This focus is particularly relevant in the air traffic control domain, where the problem of fatigue in shift work has been prominently highlighted.The study on [63] effectively addressed this issue by proposing a sophisticated model that captures the variations in fatigue during work and rest periods through first-order ordinary differential equations. By coupling this model with an integer programming approach, the study aimed to optimize shift schedules to minimize peak fatigue levels. This approach considered various constraints such as holidays, manpower requirements, and work-hour restrictions, ensuring that the schedules are both practical and effective. The results showed that well-designed work schedules, which consider changes in workload and rest time, can greatly lower peak tiredness levels and help workers stay focused and productive. This is especially important in high-risk settings like air traffic control, where fatigue can have serious impacts. The research emphasized the need to incorporate human needs into scheduling and system planning, demonstrating how this can improve overall efficiency and safety. These insights from the study reinforce the broader objective of Industry 5.0 to create resilient and efficient work environments that prioritize human well-being. By focusing on human-centric design principles and considering the physical and mental demands on workers, it is possible to develop systems that not only optimize performance but also ensure the health and safety of the workforce. This approach contributes to the creation of more sustainable and human-friendly industrial and service sectors, aligning with the evolving goals of modern industry practices.

As solutions, The paper [44] underscored the necessity for a transformative shift in manufacturing paradigms, moving from a system-centric approach to a human-centric one. Historically, manufacturing has prioritized system efficiency, often at the expense of workforce well-being. This narrow focus has resulted in environments where human roles were marginalized and their needs inadequately addressed. The primary issue identified was the absence of a comprehensive model that prioritized human well-being within manufacturing processes, ensuring that technological advancements would enhance rather than diminish the human role. To address this, the authors introduced the "Industrial Human Needs Pyramid," an adaptation of Maslow's hierarchy of needs tailored to the manufacturing context. This model stresses the critical importance of addressing a broad spectrum of human needs, from fundamental safety and health to deeper needs such as belongingness, cognitive engagement, and self-actualization, thus fostering a more inclusive and supportive industrial environment.

To tackle these issues, the authors proposed a framework integrating enabling technologies crucial for human-centric manufacturing, such as human-centric AI, empathic machines, transparent and explainable AI, and lifelong learning systems. These technologies were aimed at augmenting human capabilities, fostering trust, and providing continuous learning opportunities. The paper also discussed the challenges of implementing this approach, including technology acceptance, team dynamics, ethical considerations, and performance measurement. The study concluded that achieving human-centric manufacturing required a holistic approach that integrated technological advancements with a deep understanding of human needs, aiming to enhance human well-being and foster sustainable industrial growth.

## II.3 Discussion of the state of the art's

This review tackled the current state of the art in production scheduling, lean manufacturing, and their digitalization as exposed by Industry 4.0. The reviewed literature demonstrates that advanced optimization algorithms, machine learning process models, and digital tools, integrated with traditional lean manufacturing methodologies, can disrupt the existing manufacturing structure and potentially result in higher productivity. These studies collectively contribute to the insights and methods for designing and diffusing solutions to support the complex demands of modern manufacturing settings.

In the digitalization domain, there have been advancements in methodologies, such as integrating Value Stream Mapping with digital twin techniques and using automatic data collection tools, which further enhance efficiency improvements and decision-making capabilities. Finally, integration between machine learning and advanced digital tools of cyber-physical systems is planned to show insight into flexibility and responsiveness in manufacturing. These developments underscore the adoption of digital lean principles as a requirement for Industry 4.0 to ensure operational excellence and innovation.

The application of meta-heuristic techniques to scheduling, as evidenced by applying Ant Colony Optimization (ACO) and Genetic Algorithms (GA) to complex production scheduling problems, highlights the potential of these methods. Especially when used in combination with human factors such as worker skills, these methods provide useful approaches for productivity management and planning of precast production lines. The above research has shown that hybrid algorithms and modern scheduling models play an effective role in improving resource utilization, minimizing costs, and enhancing overall productivity in manufacturing systems.

The application of machine learning in scheduling further marks the importance of adaptive and intelligent systems in modern manufacturing. In this regard, frameworks using reinforcement learning and neural networks have been successful in optimizing decision-making processes to improve project scheduling efficiency under dynamic conditions. Such approaches identify the changing landscape of scheduling methodologies in which classical scheduling techniques are increasingly complemented by advanced computational models.

Despite these advancements, a notable gaps remains in the integration of Just-In-Time (JIT) scheduling with human factors, particularly regarding worker fatigue. Most existing studies and models focus primarily on optimizing machine and process efficiency, often overlooking the critical aspect of human well-being. Given the recognized impact of fatigue on worker performance, judgment, and overall productivity, why have not more studies combined JIT principles with considerations for human fatigue in pull flow lines?

This gap is significant because effective scheduling should not only aim to minimize production costs and times but also consider the physical and cognitive load on workers. Integrating human fatigue into JIT scheduling models can potentially improve both productivity and worker well-being. For example, fatigue impacts worker performance by increasing error rates and reducing efficiency, highlighting the need for optimized schedules that include adequate rest breaks and workload distribution to minimize fatigue. This integration is crucial to develop more sustainable and human-centered manufacturing systems, aligning with the principles of Industry 5.0, which emphasize human well-being alongside technological advancement.

Furthermore, the scope of our domain is broad, encompassing various facets of manufacturing. Within this scope, we have concentrated our literature review on five essential aspects that most comprehensively address our project, thus enabling us to situate our work appropriately within the field (see Figure II.1). These aspects are: (1) Digitalisation in Lean manufacturing and industry 4.0, (2) Meta-Heuristics and Scheduling, (3) Integration of AI in Lean manufacturing, (4) Machine learning in scheduling, and (5) the incorporation of human factors into scheduling models.

## II.4 Work direction

Regarding the literature review conducted above, there are so many directions we could have taken after a long comparison between work directions that we will cite in chapter IV.4.2. Regarding to the gap cited in II.3 we located our focus on bridging the two major domains as we can visualize in II.1, the scheduling cluster and the human-centric fields.

Moreover, taking in consideration The success of JIT in optimizing various aspects such as inventory management, cost reduction, waste minimization, and ensuring high-level time efficiency in production planning aligns well with the goals of contemporary manufacturing environments. Through this work we aimed to develop a just in time scheduling model and also expose the other side of the story which is the human-factors.

We plan to implement this innovative strategy within our learning factory described in chapter III. Despite the challenges we anticipate, such as inventory capacity constraints, non-automated stations, and varying skill levels among workers, we are committed to leveraging our expertise to address these issues and achieve our primary goal: generating practical and valuable results for the manufacturing sector.

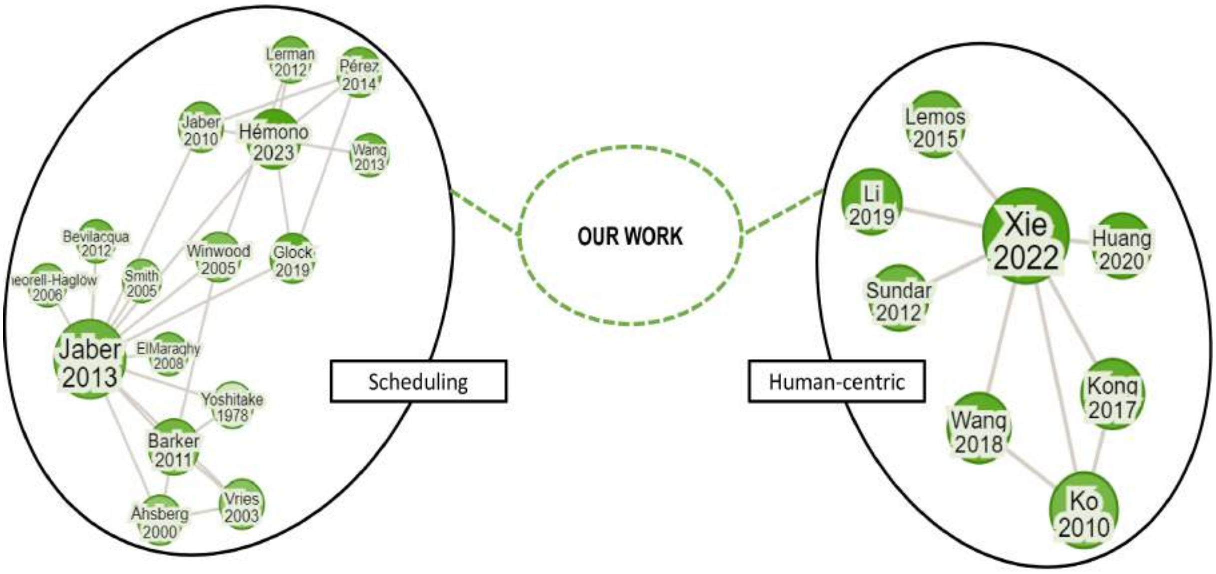


Figure II.1: Contextualizing Our Work within the Literature Review

# Conclusion

In this chapter , we have tried to expose the major gapes that we found in our literature, ensuring by that the work direction and its aspects.

# Chapter III

# ErmaLean Learning Factory Bridging Theory and Practice in Modern Manufacturing

## Introduction

Learning factories are specialized educational environments that have been meticulously designed to offer students a unique and immersive learning experience in the field of manufacturing and production processes. These cutting-edge facilities not only enhance technical skills but also foster critical thinking and problem-solving abilities, empowering learners to innovate and improve processes continuously.

At the core of a learning factory lies the replication of real-world industrial settings, creating by that a warm engaging environment for student to enhance their skills and professional refection. Equipped with basic tools, and different softwares, these facilities enable learners to directly apply the principles and methodologies they have studied, such as Lean manufacturing, Six Sigma, and Industry 4.0 concepts. This hands-on approach fosters a deeper understanding of operational excellence, process optimization, and digital transformation, crucial elements for success in the modern manufacturing firms.

By providing a controlled space, yet realistic, setting, learning factories empower students to experiment, troubleshoot, and problem-solve in a safe and supportive environment. Instructors and industry experts work closely with learners, offering guidance and feedback to ensure that the knowledge gained is directly applicable to real-world scenarios. This iterative process not only enhances technical proficiency but also cultivates critical thinking, decision-making, and collaboration skills – attributes highly sought after by employers in the manufacturing sector.

Learning factories present a vibrant connection between educational institutions and industries, enabling valuable partnerships and joint efforts. Businesses and universities work together to address complex challenges. Industry professionals and topic specialists are making programs, ensuring that learning side keeps pace with the changing demands and advancements in manufacturing. This dynamic collaboration empowers learners to stay at the forefront, developing the essential skills and expertise to succeed in the rapidly evolving technological realm.

Figure III.1: ErmaLean

## III.1 Definition of the ErmaLean

ErmaLean is a cutting-edge learning factory that combines Lean Six Sigma principles with Industry 4.0 digital technologies. It provides a comprehensive learning experience in a realistic industrial setting where learners can engage in continuous improvement activities.

At the core of ErmaLean is a carefully designed manufacturing system that mimics real industrial workflows, processes, and challenges. Learners apply their knowledge and skills in a hands-on, dynamic environment, gaining practical experience that connects the gap between theory and real-world application.The goal from this learning factory, is how to teach students the Lean manufacturing and its insights using this novel method of learning.

The facility is equipped with advanced digital technologies, such as IoT sensors, automated data collection systems, and analytics platforms. These tools allow learners to use Industry 4.0 technologies to gather, analyze, and interpret data in real-time, identifying opportunities for optimization and continuous improvement.

This learning factory, incorporates classroom instruction, interactive simulations, and hands-on workshops to teach Lean Six Sigma and Lean manufacturing principles. Learners explore process mapping, root cause analysis, mistake-proofing techniques, and data-driven decision-making while navigating a dynamic manufacturing environment.

Industry experts and industry professionals mentor learners, offering guidance and insights. This collaborative approach fosters knowledge-sharing and continuous learning, preparing participants for the demands of modern manufacturing.

By integrating Lean Six Sigma and Industry 4.0 technologies, ErmaLean sets a new standard for industrial learning, it equips future manufacturing leaders with the skills, knowledge, and practical experience needed to drive innovation, enhance efficiency, and stay competitive in the global market and the most important thing ErmaLean is one of the few learning factories that teaches the learners the importance of taking the good decision especially with the integration of the Lean manufacturing discipline, learner will gain a crucial skill in every industry different hierarchical levels which is the decision making .

## III.2 Components and Structure of ErmaLean

ErmaLean is composed of 5 evolutionary manual assembly stations, parts storage warehouse and a supervision post,the didactic line comprises other elements, as well, such as a supervision station shown in Figure III.3 , and trolleys for transportation of raw materials, work-in-progress, and finished products as illustrated in Figure III.2. The line supports digital management as it is fitted with Tulip software that is integrated with ease at every assembly station and very key in enhancing information flow by providing detailed steps to human operators on assembly, placement of tools, and organization of the workstation. This is very key to efficiency optimization in operations. regarding to its flexibility, this line can take different shapes as we can see in III.5 referring to the L-shaped layout and in III.3 referring to the U-shaped layout. These implementations mode gives us more cases to adopt, we can compare between the two modes we can create several practical spans scenarios.

Figure III.2: trolleys

Figure III.3: Supervision post

### III.2.1 Assembly stations

The assembly station is built to ensure efficient and adaptable operations. There are 5 workstations, each equipped with wheels for easy reconfiguration of the layout. Each workstation includes the following elements:

1. A reversible work surface with a smooth side and a side equipped with pallet retention slots and grooves for positioning component box supports at an ergonomic angle, enhancing label visibility and small component handling ( Ergonomics scenario).
2. Ergonomic LED lighting with anti-glare covers for operator comfort.
3. Under each work surface, an RFID reader detects pallet presence at the workstation. Each entry and exit at a workstation is recorded in the "Time at Stations". RFID reader information is transmitted via the IO-Link master to the Tulip Edge unit.
4. A lower area for component box supply and empty box disposal, equipped with label holders ( Visual Management scenario).
5. A storage drawer for small tools under the work surface (5S scenario).
6. A reject bin (red box) to isolate non-conforming parts, equipped with an opening detector. Opening the box triggers a reject declaration window display if screens connected to TULIP are in use (=¿ Quality scenario).
7. A removable Andon. Control of the 3 cylinders is done via the selector button when not using the operator's digital assistance environment (Tulip). When using the Tulip interface, display control (green; orange; red) is based on the operator's manipulations on the workstation screen display (Visual Management scenario).
8. Each workstation is equipped with 3 document holders (process sheets; instructions...). These holders are removable and can be replaced with a PC screen connected to the TULIP software, positioned in place of the document holders ( Visual Management scenario).

9. A groan-box board for KANBAN labels can be positioned on the left post uprights. It is used for Kanban supply management, dividing operations into two subprocesses. Removable tabs (green; yellow; red) are used to visually indicate replenishment needs. A label printing file is available.

10. Ergonomic chairs, with various designs to match each operator's morphology, are provided for testing ( Ergonomics scenario).

11. A label printer is also included to equip one of the workstations. It allows for product identification with serial numbers. These labels are affixed to each product for identification purposes. The serial number is generated by the TULIP software each time a pallet passes through workstation 1. For printer usage, refer to the usage document.

As we can see in III.6 the difference between a simple configuration of the station and the configuration 4.0 using Tulip software

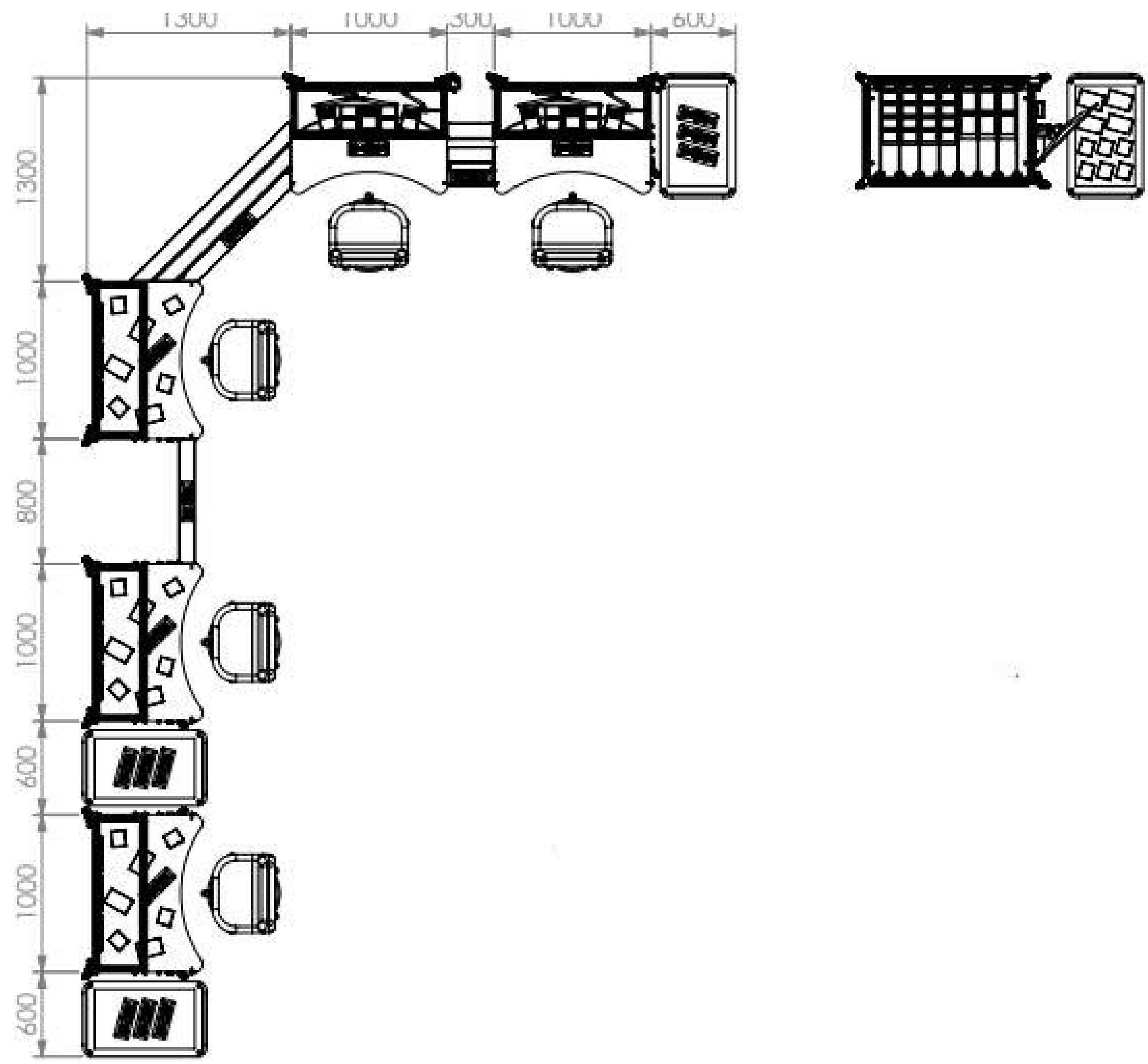


Figure III.4: Spatial Layout in L-shaped Learning Factory

Remark: L'Andon is an alarm system that allows an operator to signal when encountering an anomaly at their workstation.

Figure III.5: Spatial Layout in U-shaped Learning Factory

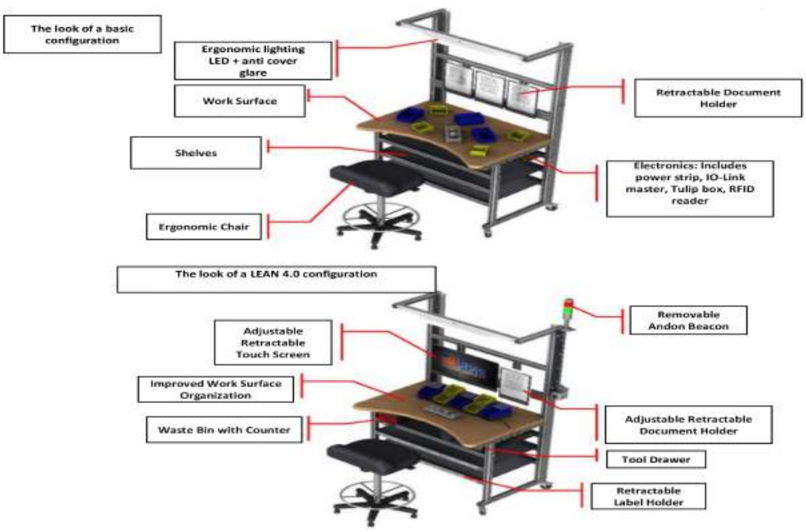


Figure III.6: Basic configuration vs Lean 4.0 configuration

#### III.2.1.1 Control quality post

In addition to the necessary equipment at every production workstation, one specific station can be set up as a "networked quality control station" as referred in III.7. This specialized station can include the following elements: a networked power supply, which can be managed through the "Tulip" software to test the assembled gear motor under different scenarios and confirm its proper operation on the "Electrical Measurement Bench for Gear Motor"; a networked caliper to complete the mechanical assembly compliance check; an industrial vision control module with AI (not part of this setup) for automated inspection tasks; a set of augmented reality glasses (not part of this setup) to assist operators and support maintenance activities; and a collaborative robot (not part of this setup).

Figure III.7: networked quality control station

### III.2.2 The Warehouse

The warehouse, as its name suggests, is designed to store parts by reference (manufactured parts and standard components) that will be used for assembling the different variants of the gear motor (0.197, 0.213, and 0.218).

As shown in III.8 it features four gravity-fed shelves to ensure FIFO (First In, First Out) consumption of components and a top shelf for the return of empty containers and finished products. This storage unit can accommodate two types of bins:

- 1-liter blue bins (3 per row)
- 0.3-liter yellow bins (6 per row)

**Entry Side Identification:**

- Labels are in place with the assigned codes, product reference, designation, and supplier.

**Exit Side Identification:**

- Labels are in place with the assigned codes, product reference, and designation.

The storage unit is equipped with a pick-to-light system for efficiently managing the entry and exit of components. Component transactions are recorded using a QR code scanner on the labels of the bins.

Implementing QR code scanning technology at this station highlights the advantages and drawbacks of QR code technology compared to the RFID technology used at other stations, providing a comprehensive understanding of both systems' effectiveness in a learning factory environment.

#### III.2.2.1 Basic Version of the Warehouse

It is the basic version of the warehouse, the warehouse includes the following elements to allow the operator to stock and destock component bins:

- A power socket block for the electrical supply of the warehouse
- A shelf for the quick return of empty bins and finished products
- Four gravity-fed shelves for storing component bins
- Label holders on the entry side of the warehouse
- Label holders on the exit side of the warehouse
- Labels with assigned codes: product reference and designation on both the entry and exit sides
- Two supports for hanging paper documents (inventory, instructions, part references, etc.)
- A Tulip Gateway (not used in this version of the warehouse)
- A light kit box (not used in this version of the warehouse)


Figure III.8: Illustration of a digitally-enabled Warehouse 4.0 featuring RFID technology

- LED strips on both the entry and exit sides (not used in this version of the warehouse)
- Two sensors: a temperature sensor and a humidity sensor (not used in this version of the warehouse)
- A barcode scanner (not used in this version of the warehouse)
- A Wi-Fi repeater to connect the Tulip Gateway to an internet connection (not used in this version of the warehouse)

This warehouse layout is designed to efficiently manage the flow of goods, making it easy for operators to handle stocking and unstocking tasks. The straightforward and user-friendly design ensures that all necessary components are readily accessible, minimizing downtime and disruptions during the work process. Moreover, this setup is not just a solution for today's needs; it is strategically planned to adapt to future requirements. The modular nature of the configuration allows for seamless integration of new technologies, such as automated guided vehicles, advanced inventory management systems, and real-time data analytics. This flexibility ensures that the warehouse can evolve alongside the advancements in manufacturing and logistics, maintaining its efficiency and effectiveness over the long term. In summary, this warehouse layout combines simplicity and sophistication, providing a robust foundation for current operations while being prepared to incorporate cutting-edge innovations as they become available.

The production process is flexible, able to adjust to the ever-changing requirements of a contemporary educational setting. It can effectively respond to the diverse and evolving needs of a modern learning facility.

#### III.2.2.2 Warehouse in LEAN 4.0 Version

In the LEAN 4.0 version, several elements are added to facilitate the operator's stocking and destocking of component bins. Below are the features included in the LEAN version of the warehouse:

- A power socket block for the electrical supply of the warehouse
- A shelf for the quick return of empty bins and finished products
- Four gravity-fed shelves for storing component bins
- Label holders on the entry side of the warehouse
- Label holders on the exit side of the warehouse
- Labels with assigned codes: product reference and designation on both the entry and exit sides
- A removable, height-adjustable touch screen PC
- A Tulip Gateway
- A light kit box to illuminate LEDs upon reading a QR code
- LED strips on both the entry and exit sides to guide the operator to the relevant row as shown in III.9
- Two sensors: a temperature sensor and a humidity sensor
- A barcode scanner for scanning the QR codes of components to be processed
- A Wi-Fi repeater to connect the Tulip Gateway to an internet connection

This cutting-edge configuration significantly boosts the operator's productivity by seamlessly blending state-of-the-art digital tools and advanced automation technologies. By optimizing the stocking and unstocking procedures, it ensures smooth operations with minimal manual intervention, embracing the principles of a LEAN 4.0 environment. The integration of these advanced technologies transforms the warehouse into a highly responsive and adaptable space. Real-time data collection and analysis enable precise inventory management, reducing waste and ensuring the availability of components exactly when needed. This level of efficiency not only accelerates the workflow but also diminishes the likelihood of errors, contributing to higher quality outcomes. User-friendly digital interfaces, such as the touch screen PC and the Tulip Gateway, provide operators with intuitive platforms to manage their tasks. These tools offer immediate access to essential information, instructions, and real-time updates, streamlining decision-making processes and enhancing overall productivity. Furthermore, the incorporation of automation elements, like the pick-to-light system and QR code scanning, reduces the physical and cognitive burden on operators. These technologies guide operators through their tasks with precision, ensuring each step is carried out accurately and efficiently. Moreover, the integrating LEAN 4.0 into warehouse operations doesn't just improve efficiency, but also plays a crucial role in the comprehensive digital transformation of manufacturing. By adopting digital technologies like IoT sensors, RFID systems, and automated analytics, the warehouse becomes a vital component of Industry 4.0. Real-time data insights from the warehouse floor enable predictive maintenance, optimize inventory, and support agile decision-making across the production line. This digital integration enhances responsiveness to market demands and fosters a more interconnected and adaptable manufacturing ecosystem. Embracing LEAN 4.0 principles firmly positions the warehouse as a foundational element in the transition to Industry 4.0, driving continuous improvement and innovation within the modern learning factory.

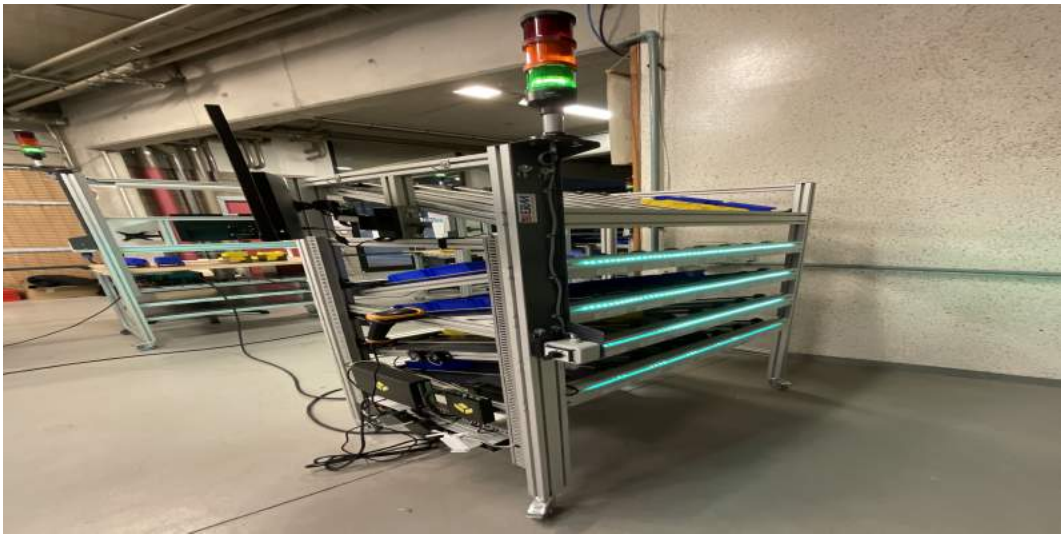

Figure III.9: Visualization of LED strip guidance system in a Warehouse 4.0

## III.2.3 Peripheral Stations

### III.2.3.1 Handling with Trolleys

A three-tier trolley is utilized for supplying workstations III.10, featuring perimeter-equipped trays for positioning identification labels on component boxes or recipient stations. Labels for these trays are provided in the technical file annexes for printing purposes, contributing to Visual Management (VM) and 5S principles.

Four 2-tier trolleys are employed for transferring products between stations in a push-flow configuration. The ample surface area of these trolleys allows for the storage of multiple pallets, reducing errors and ensuring adherence to FIFO (First In, First Out) principles.

Additionally, two two-tier trolleys III.11 serve as entry and exit points for line pallet transfers. In a KANBAN setup, these trolleys facilitate product transfer between sub-processes.

Figure III.10: 3-tier trolley

Figure III.11: 2-tier trolley

### III.2.3.2 Option - Industrial Vision Kit (not included in this proposal)

The Industrial Vision Kit can be integrated into connected stations to perform automated inspection tasks. It includes specific supports, necessary connectivity for integration (on the connected station), an intelligent industrial camera, and a 3D camera. Two industrial software programs accompany this hardware for camera programming.

This kit enables various operations, including part presence detection, object detection, counting, assembly verification, shape/profile detection, and more. It can also operate independently for vision-based activities. We provide several educational activities on vision applications, such as shape detection, part measurement, BLOB analysis, and more.

## III.2.4 Management Station

The management station, also referred to as the "supervisory PC," serves as the operational hub of the ErmaLean learning factory. It consists of a dedicated PC that allows configuration, visualization, and efficient management of all operations on the production line through the Tulip software environment. This station plays a crucial role by providing a comprehensive and interactive dashboard essential for optimal management and continuous monitoring of manufacturing activities.

Key functionalities of the management station include:

- Real-time monitoring of the status of each Work Order (WO), providing visibility into the progress and status of each production batch.
- Monitoring critical events throughout the production process, facilitating early detection of issues and immediate corrective actions.
- Analysis of production times to assess operational performance and identify opportunities for efficiency improvement.
- Continuous quality control to ensure product compliance with required standards and specifications, using real-time data.
- Detailed tracking of the specific assembly stage where each operator is working, enabling fine-grained resource management and efficient task allocation.
- Proactive management of stock levels to optimize inventory levels and prevent potential stockouts.
- Comprehensive monitoring of defect history and blocking states, supporting retrospective analysis and continuous process improvement.

In addition to these operational functionalities, the management station is equipped with a set of displayed documents to materialize the "factory cockpit." These documents include examples of dashboards and KPI (Key Performance Indicator) tracking reports, essential for evaluating the overall performance of the factory and guiding strategic decisions.

This centralized station represents not only an advanced control interface but also a powerful tool for proactive management and effective direction of the ErmaLean factory, thereby supporting continued commitment to operational excellence and innovation in the modern manufacturing sector.

### III.2.5 Production Line Layouts

The ErmaLean line allows for diverse manufacturing processes, referred to as flows. Each flow has unique specifications and materials that vary from one production run to the next. A critical parameter that greatly affects these flows is the layout of the line before initiating the planned production. This parameter greatly influences the movement of information, materials, and personnel. Therefore, the decision-making process will consider the identified developments and their associated impacts. The following subsection will outline the various layout options available on this line. But before that we have to cite briefly the production ranges proposed by the ERM team

#### III.2.5.1 Flow Type A: Push Flow Organization

The Flow Type A is designed for a push flow organization. - Scheduling by Manufacturing Order

The production run using this flow type aims to create significant work-in-progress (WIP) inventory. This approach intentionally generates imbalances between workstations to highlight inefficiencies and bottlenecks in the production process. By doing so, it allows for the identification and analysis of areas that require improvement, enabling a better understanding of how to streamline operations and reduce waste.

#### III.2.5.2 Workshop Organization for Flow Type B

The Flow Type B approach is tailored for organizations prioritizing a flexible, responsive supply chain. By incorporating insights gained from the initial Flow Type A evaluation, this method strives to enhance customer service by minimizing order fulfillment times. For optimal outcomes, it's advised to implement this flow under the guidance of TULIP supervision. The production line's U-shaped layout promotes seamless workflow and open communication among team members.

#### III.2.5.3 Workshop Organization for Flow Type C

The Flow Type C approach is tailored for a pull-based workflow, leveraging a KANBAN system to manage the materials moving between workstations 2 and 3. This design incorporates the enhancements identified during the initial analysis of Flow Type A. The goal of this production flow is to minimize the time it takes to fulfill customer orders, ultimately enhancing the service rate. For the best outcomes, it is advised to implement this flow under the guidance of TULIP supervision. The production line is structured in a U-shape, with a designated distance maintained between workstations 2 and 3 to accommodate the KANBAN system effectively.

#### III.2.5.4 Workshop Organization for Flow Type D

For a pull-based manufacturing approach, Flow Type D is designed to integrate product customization as late as feasible in the production process. By delaying standardization, this flow builds upon insights gained from the initial Flow Type A evaluation, aiming to minimize work-in-progress stocks. For optimal outcomes, TULIP oversight is advised. The production line can be configured linearly or in a U-shaped layout, tailored to the specific needs and constraints of the manufacturing setting.

As we have seen in the previous texts, the learning line a very flexible in the layout domain we can have many line configurations ( L-shaped, U-shaped, parallel...). To explore more the possible layout of this line. we will see more details this in the following paragraphs.

#### III.2.5.5 Implementation in Line

The Implementation in Line, also known as an I-line, refers to a straight-line arrangement of the production system as shown in III.12 which refers to the different I-shaped implementations possible using trolleys and conveyors. This is one of the most standard and commonly used layouts for assembly lines. In this configuration, workstations and equipment are arranged in a direct, linear sequence. This setup offers several advantages and considerations:

- **Workflow Efficiency:** The I-line layout ensures a smooth and sequential flow of materials and components from one workstation to the next. This linear progression minimizes the distance that materials need to travel, reducing handling time and increasing overall efficiency.
- **Simplified Logistics:** With all stations aligned in a single line, the logistics of moving materials and components are simplified. It is easier to track the progress of the product as it moves through each stage of assembly.
- **Clear Visibility:** The straight-line arrangement provides clear visibility across the entire production process. Supervisors and managers can easily oversee the workflow and identify any bottlenecks or issues that arise.
- **Scalability:** An I-line layout is highly scalable. Additional workstations can be added along the line as production needs increase, allowing for easy expansion of the production capacity.
- **Flexibility in Automation:** The linear nature of the I-line makes it well-suited for automation. Automated Guided Vehicles (AGVs) or conveyor belts can be used to move materials and products along the line, further enhancing efficiency and reducing manual labor.
- **Standardization:** This layout supports standardization of processes and workstations. Each station can be designed to perform a specific task with standardized tools and procedures, ensuring consistency and quality in the final product.
- **Ergonomics:** The linear arrangement allows for ergonomic design of workstations. Operators can be positioned at appropriate intervals to minimize physical strain and optimize productivity.
- **Challenges:**
  - **Limited Flexibility:** While the I-line is efficient, it can be less flexible compared to other layouts. Changes in product design or production processes may require significant reconfiguration of the line.
  - **Space Requirements:** A straight-line layout requires a long, narrow space, which might not be feasible in all production environments.
  - **Bottleneck Risk:** If one workstation in the line experiences a delay or malfunction, it can create a bottleneck that impacts the entire production process. Effective management and maintenance are crucial to mitigate this risk.

#### III.2.5.6 Implementation in U-Shape

The U-shaped design strategically organizes the workspace to boost productivity and make the most of available space during manufacturing. This setup enables a smooth workflow, making it simple for workers to transition between the beginning and end of the production chain. Additionally, this arrangement often enhances communication and teamwork among employees. The U-shaped layout presents various benefits and factors to consider:

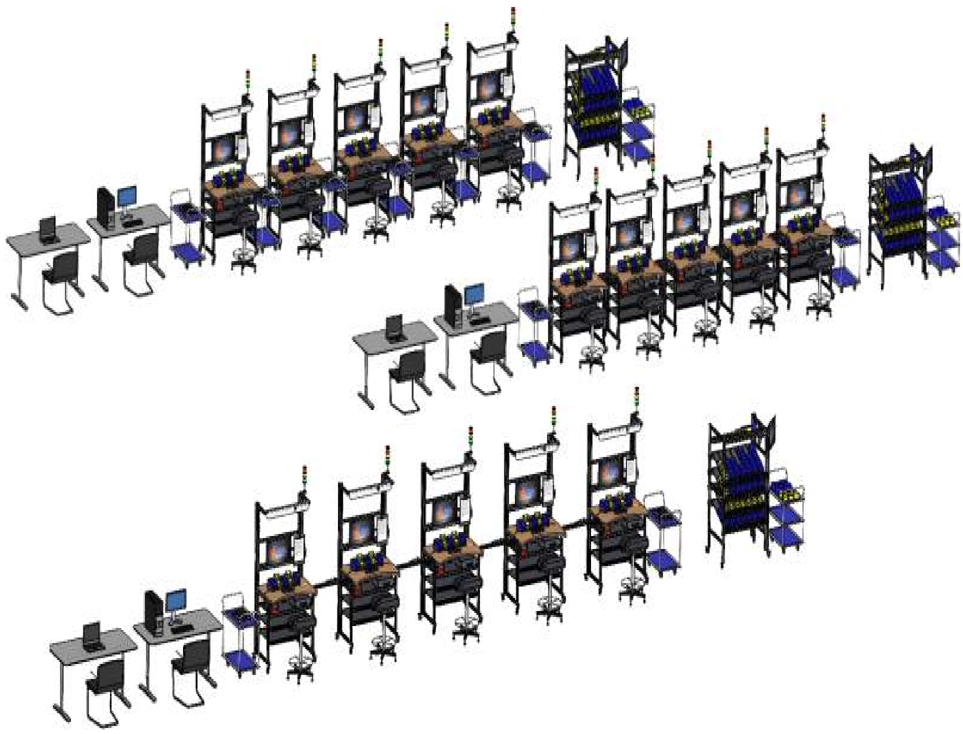

Figure III.12: Variants of Linear Implementations in Production Systems

- **Enhanced Communication and Collaboration:** The U-shaped layout brings employees closer, enabling more open communication and teamwork. Co-workers can readily observe and engage with one another, leading to faster issue resolution and coordination. III.13 refers to the different U-shaped implementations possible using trolleys and conveyors.
- **Improved Space Utilization:** By arranging the workstations in a U-shape, the layout makes efficient use of available floor space. This configuration often requires less floor area compared to straight-line layouts, making it suitable for smaller production environments.
- **Efficient Workflow:** The U-shaped layout allows for a continuous and seamless flow of materials and components. The end point of the production line is close to the starting point, reducing the time and effort needed to move materials back to the beginning of the process.
- **Flexibility and Scalability:** This layout is flexible and can be easily adapted to accommodate changes in production volume or product design. Additional workstations can be added to the U-shaped line to scale up production as needed.
- **Reduced Material Handling:** The proximity of workstations in a U-shaped layout minimizes the distance that materials and components need to travel. This reduces material handling time and the risk of damage or loss during transit.
- **Ergonomics:** The U-shaped layout can be designed to optimize ergonomic conditions for workers. Workstations can be arranged to minimize physical strain and maximize productivity, contributing to a safer and more comfortable work environment.

- **Versatility in Production:** This layout supports both manual and automated processes. Automated Guided Vehicles (AGVs) or conveyor systems can be integrated into the U-shaped line to enhance efficiency and reduce manual labor.
- **Challenges:**
  - **Complex Layout Design:** Designing a U-shaped layout can be more complex compared to a straight-line layout. It requires careful planning to ensure that all workstations are easily accessible and that the workflow is smooth.
  - **Potential Congestion:** With workers and materials moving within a more confined space, there is a potential risk of congestion. Proper management and organization are essential to avoid bottlenecks and ensure a smooth flow of production.
  - **Initial Setup Costs:** The initial setup costs for a U-shaped layout can be higher due to the need for specialized equipment and layout planning. However, these costs are often offset by the long-term benefits of improved efficiency and productivity.

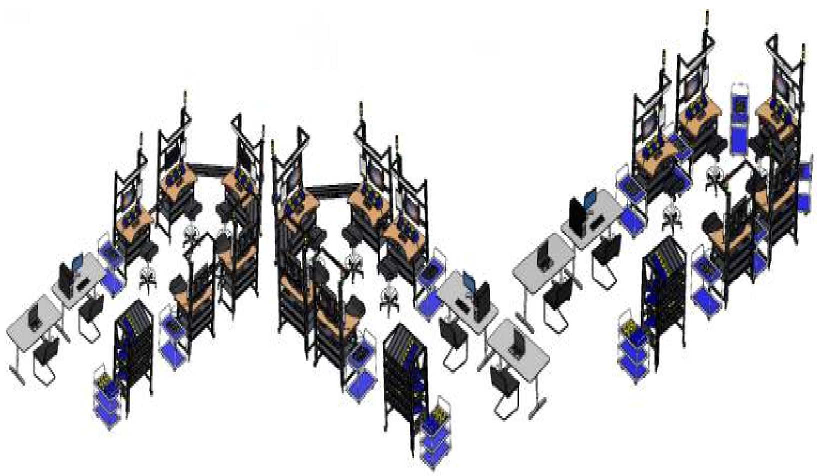

Figure III.13: Variants of U-shaped Implementations in Production Systems

### III.2.6 Tulip Software in the Learning Factory

Tulip software serves as the cornerstone across all stations within the learning factory setup. This MES and Operator Assistance solution integrates seamlessly into various workflows, enhancing operational efficiency and flexibility. It facilitates visual work instructions, replacing traditional paper-based procedures with interactive and visually guided instructions. This approach simplifies operator training and supports continuous improvement of procedures.III.14

**Key Use Cases**

- **Visual Work Instructions:** Guides operators through visual procedures rather than paper-based instructions.
- **Training:** implifying and continuously improving training procedures through digital tools enhances learning effectiveness and operational agility in industrial environments.
- **Audit & Quality:** Replacing paper forms with IoT-enabled applications (cameras, scales, etc.) enhances quality control processes, fostering accuracy and efficiency in data collection and analysis.
- **Machine Monitoring and Maintenance:** Real-time acquisition of machine data during production ensures timely insights for optimizing operational efficiency and performance monitoring.
- **Task Tracking and Visibility:** Imports Work Orders from ERP systems (e.g., Odoo), programs production indicators (OEE, MTBF, Productivity Rate), and displays them on dashboards.
- **Digital Lean:** Embracing Digital Lean harnesses cutting-edge technologies and personalized performance dashboards to elevate productivity and transparency across manufacturing operations. By seamlessly capturing real-time data and integrating smart devices, it streamlines workflows and empowers ongoing optimization, aligning with lean principles.

**Strengths**

- Elimination of paper-based documents entirely.
- Easy and rapid application development with a straightforward learning curve.
- Ability to perform mathematical calculations for determining production metrics.
- Visualization of all production-related data on tablets or computers.
- Customization of dashboards by machine, production line, or product.
- Remote communication with machines through the Kepware communication server.
- Ability to use connected devices with workstations (scales, calipers, cameras, etc.).

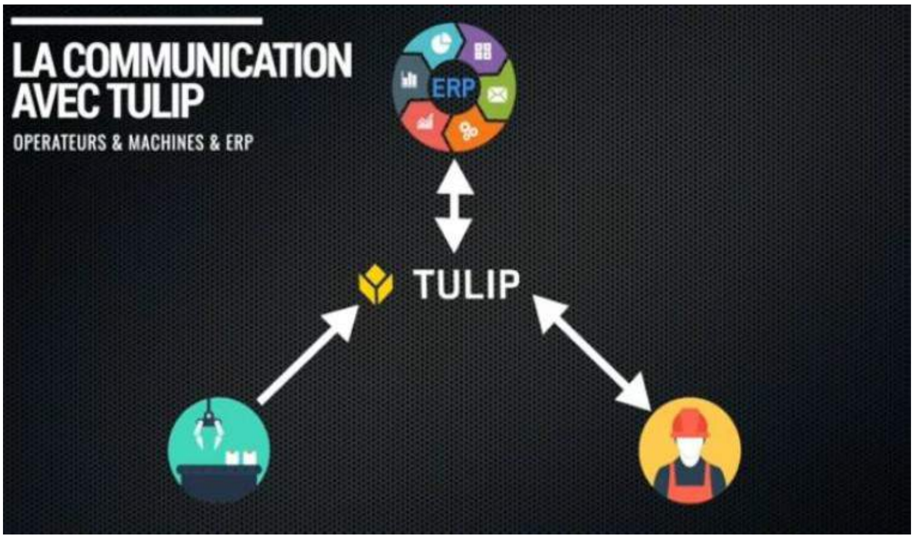


Figure III.14: Tulip software

## III.3 Conclusion

In this chapter, we explored the modalities of the ERMA lean framework, with a particular focus on learning factories. This aspect represents one of the major contributions of our work.

# Chapter IV

# Integrating JIT Scheduling with Human Factors for Optimized Production

## IV.1 Problem description

In our learning factory, we have established a production line with multiple assembly stations, each posing unique challenges. Particularly, the second assembly range operates on a pull flow system, driven by customer demand rather than a predetermined schedule. While this approach offers benefits in terms of flexibility and responsiveness, it also introduces significant challenges in maximizing efficiency.

One of the primary issues is synchronizing the completion of various jobs with the proposed schedule, which can lead to two distinct problems: earliness and tardiness. Earliness occurs when jobs are completed earlier than planned, leading to the need for storage and incurring carrying charges and additional material costs, as they cannot be immediately utilized for subsequent jobs. Tardiness, on the other hand, happens when jobs are not completed on time, resulting in long wait times for the production line. This causes high downtime and overall inefficiency, disrupting the workflow and adversely affecting the entire production process.

These idle tasks, caused by both earliness and tardiness, create a complex cost function that incorporates the penalties associated with early and late job completions. Without a properly optimized scheduling solution, these timing issues can have a significant financial impact, costing the organization a substantial amount of money and causing considerable disruption to the workflow.

First, we will consider a multi-machine problem, aiming to optimize the Just-in-Time (JIT) schedule to determine the best starting time of each job at each machine. We will begin by using standard scheduling approaches on our multi-machine production line and examine the resulting cost function. Traditional scheduling methods typically involve creating a rigid timetable for each task and production stage, aiming to meet predetermined deadlines and throughput targets. By analyzing the cost function associated with this approach, we can gain insights into potential inefficiencies and areas for improvement in our current manufacturing process.

Next, we will adopt the JIT scheduling strategy. JIT focuses on minimizing the cost function by ensuring each task is completed just when needed for the next stage of production, thereby reducing early and late completions. This lean manufacturing principle emphasizes producing only what is needed, when it is needed, and in the exact quantities required. Implementing JIT aims to eliminate waste, reduce inventory costs, and improve overall process flow, ultimately leading to a more efficient and responsive production system.

By contrasting the outcomes of traditional scheduling and JIT scheduling, we aim to assess the effectiveness of JIT in enhancing the efficiency of our production line. We will compare metrics such as earliness, tardiness, and work-in-process (WIP) inventory levels to quantify the improvements achieved through JIT.

In the second phase, we will introduce the concept of workforces, assigning a skill parameter to each worker. Each worker's assignment to a machine will have an associated cost, reflecting the impact of their skills on the production process. This addition aims to further optimize our scheduling model by not only determining the best starting times for jobs but also by ensuring that the most suitably skilled workers are assigned to each task, minimizing overall costs and enhancing efficiency.

Through this comprehensive analysis, we aim to demonstrate the significant advantages of the JIT scheduling strategy over traditional methods. By optimizing our production processes and aligning task completion with downstream requirements, we can reduce costs, enhance overall productivity, and better meet the evolving demands of our customers. This knowledge will be invaluable as we continue to refine and improve the efficiency of our manufacturing operations within the learning factory environment.

The inspiration for this (JIT) scheduling philosophy was drawn from [69].

## IV.2 Developing JIT Scheduling Models without Human Fatigue Considerations

### IV.2.1 Mathematical modeling

The Just-In-Time (JIT) precast production scheduling problem can be modeled as multi-machine single type of products and early/tardy scheduling model, which is detailed below. Assume that there are $n$ jobs with distinct due dates $d_1, d_2, \ldots, d_n$, where $j = 1, 2, \ldots, n$ and there are $m$ machines where $i = 1, 2, \ldots, m$ . Without loss of generality, let's assume that $d_1 < d_2 < d_3 < \ldots < d_n$. Let $s_i$ be the starting time of job $j$, $p_ij$ be the processing time of job $j$ in the, machine $i$, and $c_ij$ be the completion time of job $j$ in the, machine $i$. The earliness and tardiness of job $j$, denoted by $E_j$ and $T_j$, respectively, are defined as:

$$E_j = \max(0, d_j - c_mj)$$

$$T_j = \max(0, c_mj - d_j)$$

Here, $\alpha_j$ and $\beta_j$ represent the earliness and tardiness penalty weights for job $j$, respectively.

Given these definitions, the starting time $s_ij$ influences both the earliness and tardiness costs in opposite ways: starting too early or too late can both incur penalties, making JIT scheduling potentially optimal. The objective is to determine the optimal starting time $s_ij$ for each job to minimize the total earliness and tardiness costs. Consequently, the JIT precast production scheduling problem (referred to as Problem P1) is formulated as follows:

| **Symbol** | **Description** |
|---|---|
| $n$ | Number of jobs |
| $m$ | Number of machines |
| $j$ | Index for jobs ( $j = 1, 2, \ldots, n$ ) |
| $i$ | Index for machines ( $i = 1, 2, \ldots, m$ ) |
| $d_j$ | Due date of job $j$ |
| $p_ij$ | Processing time of job $j$ on the machine $i$ |
| $\alpha_j$ | Earliness penalty weight of job $j$ |
| $\beta_j$ | Tardiness penalty weight of job $j$ |
| $s_ij$ | Start time of job $j$ on the machine $i$ |
| $c_ij$ | Completion time of job $j$ on the machine $i$ |
| $E_j$ | Earliness of job $j$ |
| $T_j$ | Tardiness of job $j$ |

Table IV.1: Indexes and Parameters

## Mathematical model explanation

In the automatic mode, the scheduling problem is solved using a just-in-time (JIT) philosophy, focusing purely on minimizing earliness, and tardiness without considering human factors. The model allocates jobs to machines in a way that minimizes the overall cost, defined as a function of earliness, tardiness, and ensuring that all constraints related to processing times, due dates, and machine capabilities are satisfied.

**Objective:** Minimize the total earliness and tardiness costs:

$$\min \sum_{j=1}^{n} (\alpha_j \cdot E_j + \beta_j \cdot T_j)$$

**Subject to:**
1. Completion time constraints:

$$C_{ij} = s_{ij} + p_{ij} \quad \forall i \in \{1, 2, \ldots, m\}, \forall j \in \{1, 2, \ldots, n\}$$

2. Earliness and Tardiness constraints:

$$E_j = \max(0, d_j - C_{mj}) \quad \forall j \in \{1, 2, \ldots, n\}$$

$$T_j = \max(0, C_{mj} - d_j) \quad \forall j \in \{1, 2, \ldots, n\}$$

3. Non-negative start times:

$$s_{ij} \geq 0 \quad \forall i \in \{1, 2, \ldots, m\}, \forall j \in \{1, 2, \ldots, n\}$$

4. Ensure proper sequencing of job start times:

$$s_{ij} \geq C_{i,j-1} \quad \forall i \in \{1, 2, \ldots, m\}, \forall j \in \{2, \ldots, n\}$$

$$s_{ij} \geq C_{i-1,j} \quad \forall i \in \{2, \ldots, m\}, \forall j \in \{1, \ldots, n\}$$

The model is executed to determine the optimal starting times $s_i j$ for each job $j$ in each machine$i$ to minimize the total earliness/tardiness costs.

## Data

Here are the data values used in the model:

- Number of jobs ($n$): 10
- Number of machines ($m$): 3
- Processing times ($p$):

$$\begin{bmatrix} 14 & 11 & 17 & 20 & 20 & 21 & 14 & 16 & 14 & 13 \\ 15 & 13 & 18 & 22 & 23 & 21 & 16 & 18 & 16 & 15 \\ 13 & 12 & 17 & 21 & 22 & 20 & 15 & 17 & 15 & 14 \end{bmatrix}$$

- Due dates ($d$): [40, 60, 80, 100, 120, 140, 160, 180, 200, 220]
- Earliness penalty weights ($\alpha$): [1, 2, 3, 5 ,7 ,6 ,4, 3, 1 ,2]
- Tardiness penalty weights ($\beta$): [2, 9 ,8 ,4 ,1 ,5 ,8 ,9, 2, 1]

### IV.2.2 Results

This document presents the analysis of the scheduling results, which include the start times, completion times, earliness, and tardiness for each job across three machines. Additionally, it compares these results with a hypothetical Just-In-Time (JIT) scheduling scenario and provides suggestions for improvement.

### IV.2.3 Objective Function Value

The value of the objective function, which aims to minimize the total operator cost, is 357.

### IV.2.4 Scheduling Results

## Earliness and Tardiness

- **Earliness:** The earliness values for all jobs are zero, indicating that none of the jobs were completed before their due dates.
- **Tardiness:** The tardiness values vary, with jobs 1, 4, 5, 6, 7, and 8 having non-zero tardiness. This suggests that these jobs were completed after their due dates, leading to potential penalties or dissatisfaction in a real-world setting.

## Start Times

| Job | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Machine 1** | 0 | 14 | 25 | 42 | 62 | 82 | 103 | 117 | 133 | 165 |
| **Machine 2** | 14 | 29 | 42 | 62 | 84 | 107 | 128 | 144 | 162 | 178 |
| **Machine 3** | 29 | 48 | 63 | 84 | 107 | 129 | 149 | 164 | 185 | 206 |

Table IV.2: Start times of each job on each machine

## Completion Times

| Job | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Machine 1** | 14 | 25 | 42 | 62 | 82 | 103 | 117 | 133 | 147 | 178 |
| **Machine 2** | 29 | 42 | 60 | 84 | 107 | 128 | 144 | 162 | 178 | 193 |
| **Machine 3** | 42 | 60 | 80 | 105 | 129 | 149 | 164 | 181 | 200 | 220 |

Table IV.3: Completion times of each job on each machine

## Earliness

| Job | Earliness |
|---|---|
| 1 | 0 |
| 2 | 0 |
| 3 | 0 |
| 4 | 0 |
| 5 | 0 |
| 6 | 0 |
| 7 | 0 |
| 8 | 0 |
| 9 | 0 |
| 10 | 0 |
| **Total** | 0 |

Table IV.4: Earliness of each job

## Tardiness

| Job | Tardiness |
|---|---|
| 1 | 2 |
| 2 | 0 |
| 3 | 0 |
| 4 | 5 |
| 5 | 9 |
| 6 | 9 |
| 7 | 4 |
| 8 | 1 |
| 9 | 0 |
| 10 | 0 |
| **Total** | 30 |

Table IV.5: Tardiness of each job

### IV.2.5 Results Discussion

The current scheduling method prioritizes Just-In-Time (JIT) scheduling without considering the human factor, such as operator costs and worker fatigue. As a result, some jobs (1, 4, 5, 6, 7, and 8) could not be finished by their due dates, potentially leading to penalties or customer dissatisfaction. This approach allows us to observe how the inclusion of human factors in the next model will affect the makespan and overall efficiency.

In contrast, a traditional scheduling approach solely focused on minimizing the overall completion time (makespan) would create a more compressed schedule by reducing idle time and maximizing machine usage. However, this approach disregards operator well-being and could lead to excessive fatigue, which could undermine productivity over time.

Our model strikes a balance by accounting for both job completion times and operator efficiency. While it may not achieve the shortest possible makespan.

Moreover, the model aimed to complete jobs in machines 1 and 2 as soon as possible, while in machine 3, it focused on minimizing earliness and tardiness. As shown in Figure IV.2, some jobs were finished just in time, while others were completed after their due dates, resulting in tardiness. The cumulative tardiness is 30 and earliness is 0, which is significant as a results. This indicates that while we succeeded in implementing the first step of this comparative analysis—Just-In-Time (JIT) scheduling—we did not yet take the human factor into consideration.

**Short explanation about the figure IV.2**: D refers to the due dates designed in the model, T refers to tardiness of jobs (1st and 4th ),J refers to jobs , there is 3 dotted lines that separate the machines and there jobs sequencing.

The current model demonstrates the potential of JIT scheduling but highlights the need for further refinement to incorporate human factors. By addressing these aspects, we can develop a more holistic and sustainable scheduling approach.

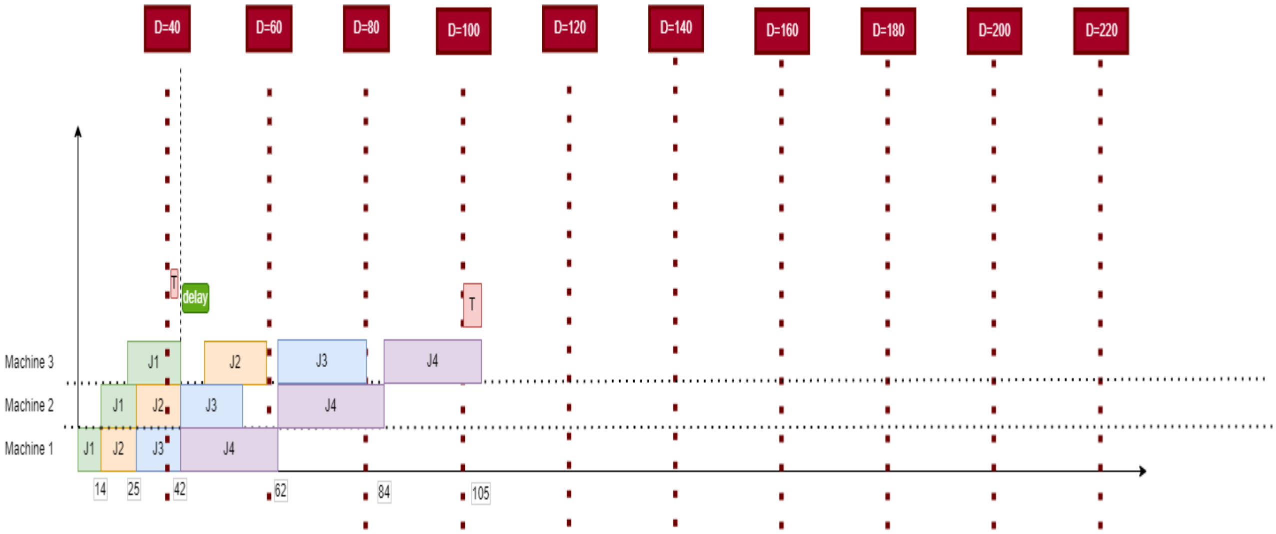


Figure IV.1: Gant chart of the first 4 jobs

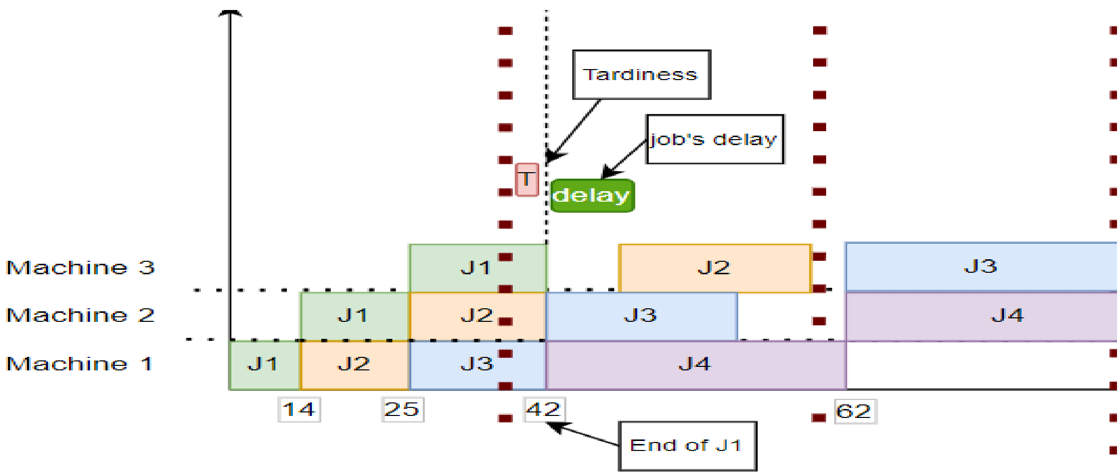


Figure IV.2: Gant chart with more details

# IV.3 Developing JIT Scheduling Models with Human Fatigue Considerations

The Just-In-Time (JIT) production scheduling problem can be modeled as a multi-machine, single-type product, early/tardy scheduling model, which is detailed below. Assume that there are $n$ jobs with distinct due dates $d_1, d_2, \ldots, d_n$, where $j = 1, 2, \ldots, n$, and there are $m$ machines where $i = 1, 2, \ldots, m$. Without loss of generality, let's assume that $d_1 < d_2 < d_3 < \ldots < d_n$. Let $s_j$ be the starting time of job $j$, $p_{ij}$ be the processing time of job $j$ on machine $i$, and $c_{ij}$ be the completion time of job $j$ on machine $i$. The earliness and tardiness of job $j$, denoted by $E_j$ and $T_j$, are important factors to consider.

In this model, we introduce the involvement of human operators. Specifically, we consider the inclusion of 10 workers, indexed as $k = 1, \ldots, o$. This is crucial because in many factories, especially those requiring human intelligence and intervention, it is not feasible to rely entirely on automated machines. Human aspects must be incorporated into the scheduling process, despite the inherent challenges. These challenges, which include operator fatigue, skill levels, and availability, need to be carefully managed to ensure an efficient and sustainable production schedule. In the following sections, we will explore these human factors and the impact they have on the scheduling model.

## IV.3.1 Mathematical modeling

### Sets and Indices

$J$ : Set of jobs, indexed by $j$

$M$ : Set of machines, indexed by $i$

$O$ : Set of operators, indexed by $k$

### Parameters

$d_j$ : Due date for job ( i kept the same due dates as the first model) $j$

$\alpha_j$ : Earliness penalty cost for job $j$

$\beta_j$ : Tardiness penalty cost for job $j$

$p_{ij}$ : Processing time for job $j$ on machine $i$

$Ca_{ki}$ : Cost of assignment for operator $k$ to machine $i$

$\text{skill}_{ki}$ : Skill level of operator $k$ for machine $i$

$\lambda_k$ : Fatigue parameter of operator $k$

$\mu_j$ : Job difficulty for job $j$

## Decision Variables

$s_{ij}$ : Start time of job $j$ on machine $i$
$C_{ij}$ : Completion time of job $j$ on machine $i$
$E_j$ : Earliness of job $j$
$T_j$ : Tardiness of job $j$
$\text{assign}_{ki}$ : Binary variable indicating if operator $k$ is assigned to machine $i$
$\text{fa}_{kij}$ : Fatigue accumulation for operator $k$ on machine $i$ for job $j$

## Objective Function

Minimize the total earliness, tardiness, and assignment costs:

$$\min \sum_{j \in J} (\alpha_j E_j + \beta_j T_j) + \sum_{k \in O, i \in M} Ca_{ki} \cdot \text{assign}_{ki} \tag{IV.1}$$

## Constraints

### Fatigue Accumulation

$$\text{fa}_{kij} = \begin{cases} 1 - \exp(-\lambda_k \cdot \mu_j \cdot p_{ij}) & \text{if } j = 1 \\ \text{fa}_{k,i,j-1} + 1 - \exp(-\lambda_k \cdot \mu_j \cdot p_{ij}) & \text{if } j > 1 \end{cases} \tag{IV.2}$$

This fatigue formula was extracted from the article [30]

### Completion Time Constraints

$$C_{ij} = s_{ij} + p_{ij} \left( 1 + \sum_{k \in O} \text{fa}_{kij} \cdot \text{assign}_{ki} \right) \quad \forall i \in M, j \in J \tag{IV.3}$$

### Earliness and Tardiness

$$E_j \geq d_j - C_{3j} \quad \forall j \in J \tag{IV.4}$$

$$T_j \geq C_{3j} - d_j \quad \forall j \in J \tag{IV.5}$$

### Non-Negative Start Times

$$s_{ij} \geq 0 \quad \forall i \in M, j \in J \tag{IV.6}$$

$$C_{ij} \geq 0 \quad \forall i \in M, j \in J \tag{IV.7}$$

### Assignment Constraints

$$\sum_{k \in O} \text{assign}_{ki} = 1 \quad \forall i \in M \tag{IV.8}$$

$$\text{assign}_{ki} \leq \text{skill}_{ki} \quad \forall k \in O, i \in M \tag{IV.9}$$

$$\sum_{i \in M} \text{assign}_{ki} \leq 1 \quad \forall k \in O \tag{IV.10}$$

**Job Sequencing**

$$s_{ij} \geq C_{i,j-1} \quad \forall i \in M, j > 1 \tag{IV.11}$$

$$s_{ij} \geq C[i-1, j] \quad \forall i > 1, j \in J \tag{IV.12}$$

**Variable Domains**

$$E_j, T_j, s_{ij} \in \mathbb{R}^+ \quad \forall i \in M, j \in J \tag{IV.13}$$

$$\text{assign}_{ki} \in \{0, 1\} \quad \forall k \in O, i \in M \tag{IV.14}$$

## Mathematical model explanation

When human factors are considered without breaks, the model incorporates fatigue accumulation for each operator. The fatigue is modeled as an exponential function of job difficulty and processing time, affecting the processing speed and, consequently, the completion times. The objective is to minimize the total cost while accounting for the increased processing times due to operator fatigue, ensuring that operators are assigned to jobs they are skilled for and that fatigue is appropriately managed.

## Data Matrices

- Number of jobs: 10
- Number of machines: 3
- Number of operators: 10
- Due dates ($d_j$):

$$d = \{40, 60, 80, 100, 120, 140, 160, 180, 200, 220\}$$

- Earliness penalty weights ($\alpha$): [1, 2, 3, 5 ,7 ,6 ,4, 3, 1 ,2]
- Tardiness penalty weights ($\beta$): [2, 9 ,8 ,4 ,1 ,5 ,8 ,9, 2, 1]
- Processing times ($p_{ij}$):

$$p = \begin{bmatrix} 14 & 11 & 17 & 20 & 20 & 21 & 14 & 16 & 14 & 13 \\ 15 & 13 & 18 & 22 & 23 & 21 & 16 & 18 & 18 & 15 \\ 13 & 12 & 17 & 21 & 22 & 20 & 15 & 17 & 15 & 14 \end{bmatrix}$$

- Cost of assignment ($Ca_{ki}$):

$$Ca = \begin{bmatrix} 5 & 7 & 6 \\ 4 & 5 & 6 \\ 7 & 4 & 5 \\ 6 & 6 & 6 \\ 5 & 7 & 6 \\ 6 & 5 & 6 \\ 7 & 5 & 5 \\ 6 & 7 & 6 \\ 5 & 6 & 5 \\ 7 & 5 & 6 \end{bmatrix}$$

- Skill matrix ($skill_{ki}$):

$$skill = \begin{bmatrix} 1 & 0 & 1 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \\ 1 & 0 & 1 \end{bmatrix}$$

- Fatigue rates ($\lambda_k$):

$$\lambda = \{0.1, 0.15, 0.2, 0.1, 0.15, 0.2, 0.1, 0.15, 0.2, 0.1\}$$

- Job difficulties ($\mu_j$):

$$\mu = \{1, 1, 1, 1, 3, 3, 3, 3, 5, 5\}$$

## Results

After exporting the results to an excel spreadsheet we can see the results:

## Objective function results

The value of the objective function is 5953.

## Earliness and Tardiness

| **Job** | **Earliness** | **Tardiness** |
|---|---|---|
| J1 | 0 | 35 |
| J2 | 0 | 55 |
| J3 | 0 | 145 |
| J4 | 0 | 272 |
| J5 | 0 | 408 |
| J6 | 0 | 537 |
| J7 | 0 | 624 |
| J8 | 0 | 776 |
| J9 | 0 | 921 |
| J10 | 0 | 1060 |
| **Total** | 0 | 4833 |

Table IV.6: Earliness and Tardiness of each job

## Starting Time

| **Job** | **M1** | **M2** | **M3** | **Due dates** |
|---|---|---|---|---|
| J1 | 0 | 25 | 52 | 40 |
| J2 | 108 | 191 | 294 | 60 |
| J3 | 423 | 523 | 653 | 80 |
| J4 | 781 | 25 | 52 | 100 |
| J5 | 108 | 191 | 294 | 120 |
| J6 | 423 | 554 | 670 | 140 |
| J7 | 818 | 984 | 52 | 160 |
| J8 | 85 | 169 | 285 | 180 |
| J9 | 415 | 554 | 677 | 200 |
| J10 | 818 | 984 | 1138 | 220 |

Table IV.7: Starting time of each job at each machine

## Completion Time

| Job | M1 | M2 | M3 |
|---|---|---|---|
| J1 | 24.5476 | 51.6259 | 107.0434 |
| J2 | 190.0503 | 293.0007 | 422.0622 |
| J3 | 522.1648 | 652.1996 | 780.0369 |
| J4 | 911.9432 | 51.6530 | 84.5564 |
| J5 | 168.1027 | 284.0212 | 414.2262 |
| J6 | 553.7332 | 669.4746 | 817.8276 |
| J7 | 983.8254 | 1137.1795 | 74.4571 |
| J8 | 114.1153 | 224.1410 | 371.5438 |
| J9 | 527.6350 | 676.3459 | 783.5928 |
| J10 | 955.7015 | 1120.4930 | 1279.3807 |

Table IV.8: Completion time of each job at each machine

## Fatigue Accumulation

| | J1 | J2 | J3 | J4 | J5 | J6 | J7 | J8 | J9 | J10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **O1, M1** | 0.7534 | 1.4205 | 2.2378 | 3.1025 | 4.1000 | 5.0982 | 6.0832 | 7.0750 | 8.0741 | 9.0726 |
| **O4, M3** | 0.7275 | 1.4263 | 2.2436 | 3.1211 | 4.1198 | 5.1173 | 6.1062 | 7.1001 | 8.0995 | 9.0986 |
| **O7, M2** | 0.7769 | 1.5043 | 2.3390 | 3.2282 | 4.2272 | 5.2254 | 6.2172 | 7.2126 | 8.2125 | 9.2120 |

Table IV.9: Fatigue accumulation of each operator at each machine for each job

### IV.3.2 Discussion and Comparison with JIT Scheduling

As illustrated in Figures IV.3, IV.4, and IV.5, we used completion time as the key performance indicator to compare two modes: traditional Just-in-Time (JIT) scheduling and JIT scheduling with human considerations. The completion time in the first mode is significantly lower than in the second mode. This outcome is logical, as the workforce accumulates fatigue with each job they complete, which is accounted for in the second mode. if we talk more about the about tardiness and earliness we noticed that the 2nd mode has a more significant impact on the tardiness of jobs as we can visualize in the figure IV.6, the tardiness in 1 st scheduling model is negligible compared to the tardiness accumulated in the 2 nd mode.

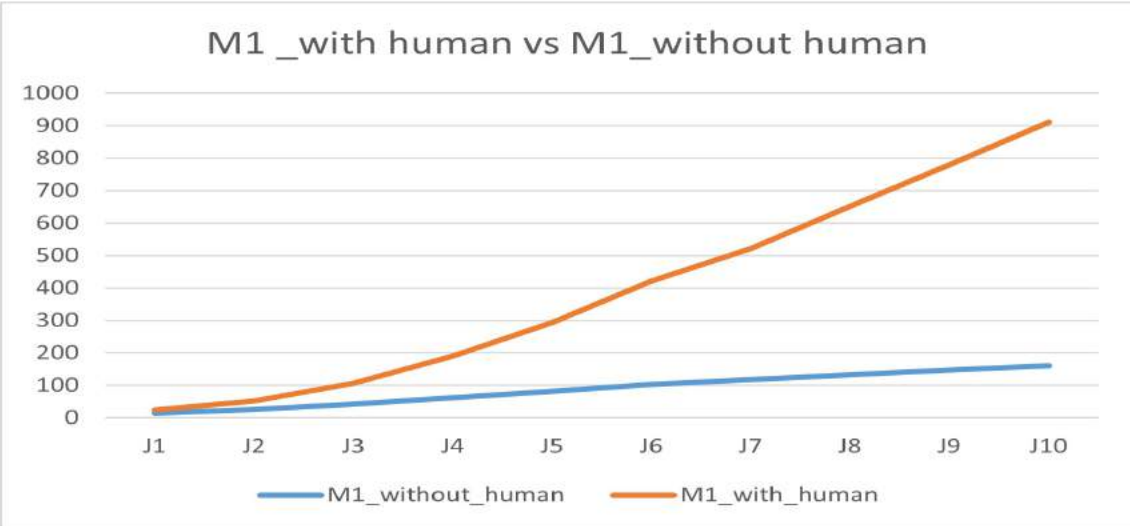


Figure IV.3: Completion time in machine 1 evolution between the two modes

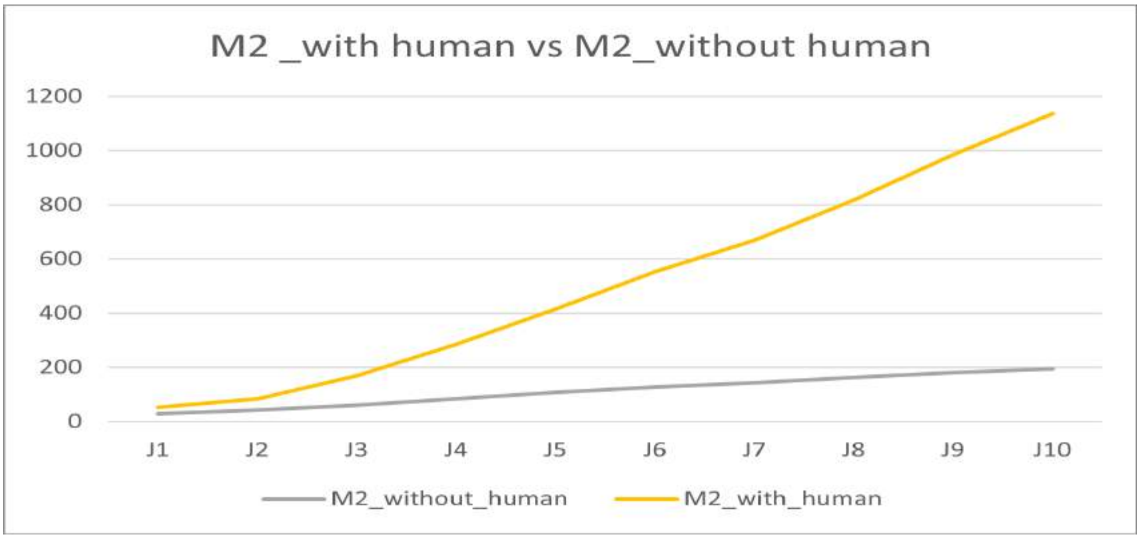


Figure IV.4: Completion time in machine 2 evolution between the two modes

The results show that the current scheduling strategy has resulted in some jobs being tardy, with non-zero tardiness values for jobs 1, 4, 5, 6, 7, and 8. This indicates that these jobs were not completed by their respective due dates, which can lead to potential penalties or customer dissatisfaction.

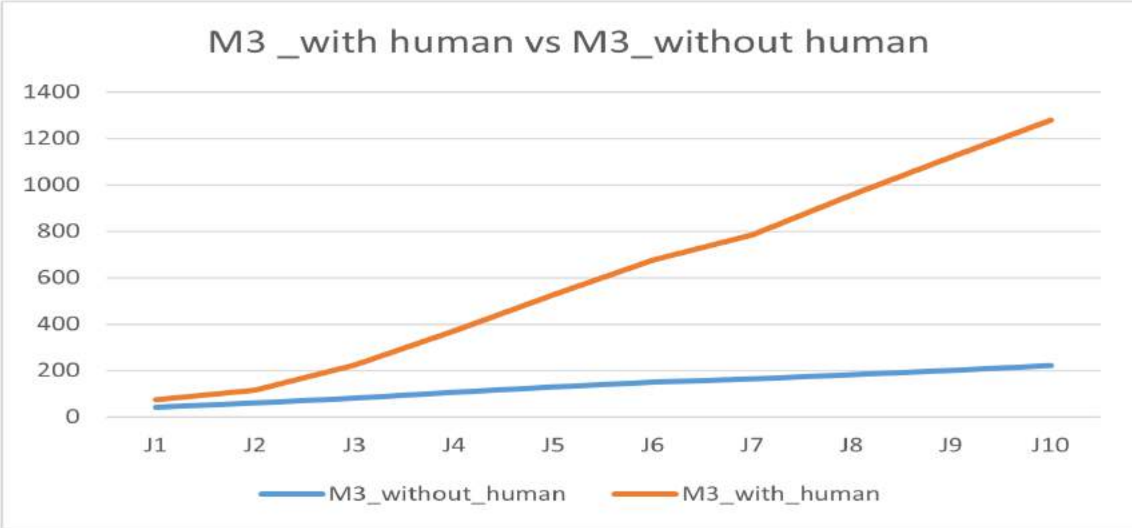


Figure IV.5: Completion time in machine 3 evolution between the two modes

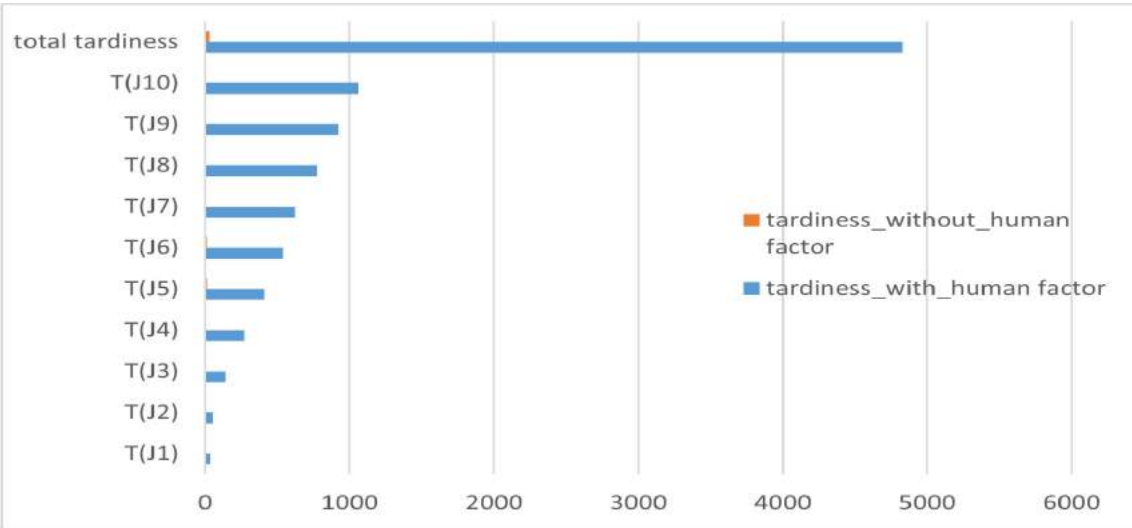


Figure IV.6: Diffrence between the tardiness of the two modes

Comparing this with a Just-In-Time (JIT) scheduling approach where all jobs are scheduled adjacently to minimize lead times, the current strategy may be less efficient. In a JIT approach, each job would start immediately after the preceding job finishes, reducing idle times and potentially minimizing tardiness.

However, the current model also considers operator costs and fatigue, aiming to balance job completion times with operator efficiency and well-being. The fatigue parameter, while not leading to an optimal JIT scheduling, helps ensure that operators do not experience excessive fatigue, which could otherwise lead to errors or decreased productivity.

# IV.4 Proposed solution: Developing JIT scheduling with human factors Considerations

## Introduction

The Just-In-Time (JIT) production scheduling problem can be modeled as a multi-machine, single-type product, early/tardy scheduling model. Assume that there are $n$ jobs with distinct due dates $d_1, d_2, \ldots, d_n$, where $j = 1, 2, \ldots, n$, and there are $m$ machines where $i = 1, 2, \ldots, m$. Without loss of generality, let's assume that $d_1 < d_2 < d_3 < \ldots < d_n$. Let $s_j$ be the starting time of job $j$, $p_{ij}$ be the processing time of job $j$ on machine $i$, and $c_{ij}$ be the completion time of job $j$ on machine $i$. The earliness and tardiness of job $j$, denoted by $E_j$ and $T_j$, are important factors to consider.

In this model, we introduce the involvement of human operators but with breaks. Specifically, we consider the inclusion of 10 workers, indexed as $k = 1, \ldots, o$. This is crucial because in many factories, especially those requiring human intelligence and intervention, it is not feasible to rely entirely on automated machines. Human aspects must be incorporated into the scheduling process, despite the inherent challenges. These challenges, which include operator fatigue, skill levels, and availability, need to be carefully managed to ensure an efficient and sustainable production schedule.

To address these challenges, we introduce the parameter of scheduled breaks into our model. In this section, we propose a novel solution aimed at mitigating operator fatigue through the strategic scheduling of breaks. Fatigue accumulation is a significant factor affecting both the completion time of jobs and overall productivity. By integrating scheduled breaks, we aim to reinitialize fatigue levels, thereby improving operator efficiency and reducing the total time required to complete each job. This approach not only impacts the earliness and tardiness penalties associated with job completion but also influences the overall cost, as refreshed operators are likely to perform tasks more effectively. We propose the implementation of coffee breaks to minimize tardiness specifically. We will compare the effects of incorporating breaks on job completion times, tardiness, and fatigue accumulation. Additionally, we will consider the cost implications of implementing this strategy, demonstrating its potential benefits in optimizing scheduling and reducing operational expenses.

In the following sections, we will explore these human factors and the impact they have on the scheduling model. We will provide a comparative analysis of the proposed solution against traditional scheduling approaches, highlighting the improvements in job completion times, reduction in tardiness, and overall operational efficiency.

### IV.4.1 Mathematical Model

#### Sets

$$
\begin{aligned}
&J : \text{Set of jobs, } J = \{1, 2, \ldots, 10\} \\
&M : \text{Set of machines, } M = \{1, 2, \ldots, 3\} \\
&O : \text{Set of operators, } O = \{1, 2, \ldots, 10\}
\end{aligned}
$$

## Parameters

$d_j$ : Due date of job $j$
$\alpha_j$ : Earliness penalty cost for job $j$
$\beta_j$ : Tardiness penalty cost for job $j$
$p_{ij}$ : Processing time of job $j$ on machine $i$
$Ca_{ki}$ : Cost of assignment of operator $k$ to machine $i$
$\text{skill}_{ki}$ : Skill indicator of operator $k$ for machine $i$
$\lambda_k$ : Fatigue parameter for operator $k$
$\mu_j$ : Job difficulty for job $j$
BREAK_TIME : Duration of coffee break

## Variables

$E_j$ : Earliness of job $j$
$T_j$ : Tardiness of job $j$
$s_{ij}$ : Start time of job $j$ on machine $i$
$C_{ij}$ : Completion time of job $j$ on machine $i$
$\text{assign}_{ki}$ : Binary variable indicating if operator $k$ is assigned to machine $i$
$\text{fa}_{kij}$ : Fatigue accumulation for operator $k$ on machine $i$ for job $j$

## Objective Function

$$\min \sum_{j \in J} (\alpha_j E_j + \beta_j T_j) + \sum_{k \in O} \sum_{i \in M} (Ca_{ki} \cdot \text{assign}_{ki})$$

## Constraints

### Fatigue Accumulation

$$\text{fa}_{kij} = \begin{cases} 1 - \exp(-\lambda_k \cdot \mu_j \cdot p_{ij}) & \text{if } j = 1 \\ \begin{cases} 0.5 & \text{if } \text{fa}_{kij-1} > 1.5 \\ \text{fa}_{kij-1} + 1 - \exp(-\lambda_k \cdot \mu_j \cdot p_{ij}) & \text{if } \text{fa}_{kij-1} \leq 1.5 \end{cases} & \text{if } j > 1 \end{cases}$$

Inspired from [30].

### Completion Time with Fatigue

$$C_{ij} = s_{ij} + p_{ij} \left( 1 + \sum_{k \in O} (\text{fa}_{kij} \cdot \text{assign}_{ki}) \right)$$

**Earliness and Tardiness**

$$\begin{aligned}
&E_j \geq 0, \quad \forall j \in J \\
&T_j \geq 0, \quad \forall j \in J \\
&E_j \geq d_j - C_{3j}, \quad \forall j \in J \\
&T_j \geq C_{3j} - d_j, \quad \forall j \in J
\end{aligned}$$

**Non-negative Start Times**

$$\begin{aligned}
&s_{ij} \geq 0, \quad \forall i \in M, \forall j \in J \\
&C_{ij} \geq 0, \quad \forall i \in M, \forall j \in J
\end{aligned}$$

**Assignment Constraints**

$$\begin{aligned}
&\sum_{k \in O} \text{assign}_{ki} = 1, \quad \forall i \in M \\
&\text{assign}_{ki} \leq \text{skill}_{ki}, \quad \forall i \in M, \forall k \in O \\
&\sum_{i \in M} \text{assign}_{ki} \leq 1, \quad \forall k \in O
\end{aligned}$$

**Sequencing Constraints**

$$\begin{aligned}
&s_{ij} \geq C_{ij-1} + \text{BREAK_TIME}, \quad \text{if } \text{fa}_{kij-1} > 1.5, \quad \forall i \in M, \forall j > 1 \\
&s_{ij} \geq C_{i-1j} + \text{BREAK_TIME}, \quad \text{if } \text{fa}_{ki-1j} > 1.5, \quad \forall i > 1, \forall j \in J
\end{aligned}$$

**Variable Types**

$$\begin{aligned}
&T_j \in \mathbb{N}, \quad \forall j \in J \\
&s_{ij} \in \mathbb{N}, \quad \forall i \in M, \forall j \in J \\
&\text{assign}_{ki} \in \{0, 1\}, \quad \forall i \in M, \forall k \in O
\end{aligned}$$

## Mathematical model explanation

In this mode, the model extends the previous one by introducing coffee breaks to manage operator fatigue. When the fatigue parameter surpasses a certain threshold 1.5 or 2, a break is scheduled to reset the fatigue to a lower level 0.5 . This inclusion helps to balance the workload and maintain operator efficiency over time. The model aims to minimize total costs while scheduling breaks as needed to ensure that operators do not exceed their fatigue limits, maintaining productivity and worker well-being.

# Results

## Earliness and Tardiness

| **Job** | **Earliness** | **Tardiness** |
|---|---|---|
| J1 | 0 | 35 |
| J2 | 0 | 45 |
| J3 | 0 | 67 |
| J4 | 0 | 109 |
| J5 | 0 | 130 |
| J6 | 0 | 160 |
| J7 | 0 | 163 |
| J8 | 0 | 186 |
| J9 | 0 | 189 |
| J10 | 0 | 204 |
| **Total** | 0 | 1288 |

Table IV.10: Earliness and Tardiness of each job

**Analysis:** The table shows that all jobs experience tardiness without any earliness. The total tardiness across all jobs is 1288 time units. This indicates a significant delay in job completions, which would result in higher penalty costs.

## Assignment of Operators to Machines

| Operator | M1 | M2 | M3 |
|---|---|---|---|
| O1 | 1 | 0 | 0 |
| O2 | 0 | 0 | 0 |
| O3 | 0 | 0 | 0 |
| O4 | 0 | 0 | 0 |
| O5 | 0 | 0 | 0 |
| O6 | 0 | 0 | 0 |
| O7 | 0 | 1 | 0 |
| O8 | 0 | 0 | 0 |
| O9 | 0 | 0 | 0 |
| O10 | 0 | 0 | 1 |

Table IV.11: Assignment of operators to machines

**Analysis:** Operators O1, O7, and O10 are assigned to machines M1, M2, and M3, respectively. This assignment ensures that each machine is operated by one operator. The remaining operators are not assigned to any machines, potentially indicating a limitation in skill matching or an optimal assignment strategy.

## Starting Time

| Job | J1 | J2 | J3 | J4 | J5 | J6 | J7 | J8 | J9 | J10 |
|---|---|---|---|---|---|---|---|---|---|---|
| M1 | 0 | 25 | 52 | 108 | 191 | 294 | 423 | 523 | 653 | 781 |
| M2 | 25 | 52 | 108 | 191 | 294 | 423 | 554 | 670 | 818 | 984 |
| M3 | 52 | 85 | 169 | 285 | 415 | 554 | 677 | 818 | 984 | 1138 |

Table IV.12: Starting time of each job at each machine

**Analysis:** The starting times for jobs on each machine show that jobs are processed sequentially on each machine with gaps indicating breaks or transition times. The starting times increase significantly for jobs assigned later in the sequence, which impacts the overall completion time and tardiness.

## Completion Time

| Job | J1 | J2 | J3 | J4 | J5 | J6 | J7 | J8 | J9 | J10 |
|---|---|---|---|---|---|---|---|---|---|---|
| M1 | 24.55 | 51.63 | 77.50 | 125.29 | 156.00 | 208.46 | 230.00 | 271.87 | 293.00 | 365.48 |
| M2 | 51.65 | 74.50 | 120.02 | 159.00 | 216.48 | 249.50 | 293.87 | 321.00 | 365.99 | 388.50 |
| M3 | 74.46 | 104.12 | 146.50 | 208.93 | 250.00 | 299.95 | 322.50 | 365.40 | 388.50 | 423.99 |

Table IV.13: Completion time of each job at each machine

**Analysis:** The completion times for jobs at each machine indicate that jobs are completed at different times depending on their processing time and the start time. The sequential processing results in increased completion times for later jobs, contributing to the overall tardiness observed.

| | J1 | J2 | J3 | J4 | J5 |
|---|---|---|---|---|---|
| O1, M1 | 0.753403036 | 1.420531952 | 0.5 | 1.364664717 | 0.5 |
| O7, M2 | 0.77686984 | 0.5 | 1.334701112 | 0.5 | 1.498992215 |
| O10, M3 | 0.727468207 | 1.426273995 | 0.5 | 1.377543572 | 0.5 |

Table IV.14: Completion times of jobs on different machines by various operators (Part 1)

| | J6 | J7 | J8 | J9 | J10 |
|---|---|---|---|---|---|
| O1, M1 | 1.498163695 | 0.5 | 1.491770253 | 0.5 | 1.498496561 |
| O7, M2 | 1.491770253 | 0.5 | 1.49987659 | 0.5 | 0.5 |
| O10, M3 | 1.497521248 | 0.5 | 1.493903253 | 0.5 | 1.499088118 |

Table IV.15: Completion times of jobs on different machines by various operators (Part 2)

### IV.4.2 Comparative analysis between the JIT without breaks and the JIT with breaks and also with the basic JIT

In this section, we compare three distinct scheduling modes: Just-In-Time (JIT) without human considerations, JIT with human considerations but without breaks, and the proposed solution incorporating breaks to manage fatigue. The comparison focuses on the completion time of jobs, tardiness, and overall efficiency.

#### JIT without Human Considerations

In this mode as shown in figure IV.7, the scheduling is purely machine-centric, optimizing job completion without accounting for human factors such as operator fatigue. Key observations are:

- **Completion Time:** Jobs are scheduled sequentially with minimal Tardiness and earliness, resulting in the lowest completion times without taking human in consideration.
- **Tardiness:** Tardiness is minimized due to the focus on machine utilization and job completion efficiency.

#### JIT with Human Considerations but without Breaks

in this mode as shown in IV.8 and IV.7 When human factors are considered without allowing for breaks, the performance changes significantly:

- **Completion Time:** There is a substantial increase in completion time compared to the JIT without human considerations. This increase is due to the inclusion of human factors such as operator availability, skill matching, and potential delays due to fatigue accumulation.
- **Tardiness:** Tardiness increases noticeably as operator fatigue impacts their performance, delaying job completion.

## JIT with Human Considerations and Breaks

in this mode reside our solution proposal and as it is figured in IV.9 in the machine 3 case. Introducing breaks to account for operator fatigue leads to improved performance:

- **Completion Time Reduction:** Despite the inclusion of breaks, the completion time for the last job decreases by approximately 500 time units on Machine 1, around 800 time units on Machine 2, and over 800 time units on Machine 3. Breaks effectively mitigate fatigue, allowing operators to perform more efficiently.

- **Tardiness Reduction:** Tardiness is also reduced compared to the mode without breaks, as breaks help maintain consistent performance levels, minimizing delays and improving job completion timelines.

## Insights

The comparison also was conducted basing on the tardiness rate as we can see in figure IV.10 highlights several critical insights:

- **Efficiency vs. Human Considerations:** The JIT mode without human considerations shows the lowest completion times but is unsustainable due to potential operator burnout and inefficiencies in the long run.

- **Human-Centric Scheduling:** Incorporating human considerations without breaks leads to significant increases in completion time and tardiness, emphasizing the need to balance efficiency with operator well-being.

- **Breaks as a Mitigating Factor:** Introducing breaks substantially improves scheduling performance by reducing completion times and tardiness, demonstrating the importance of factoring in operator fatigue management.

Overall, the proposed solution with breaks offers a balanced approach, optimizing job completion while ensuring operator well-being. The reduced completion times and tardiness underscore the effectiveness of integrating breaks into the scheduling process, leading to a more sustainable and efficient operational model.


Figure IV.7: Machine 1 completion time

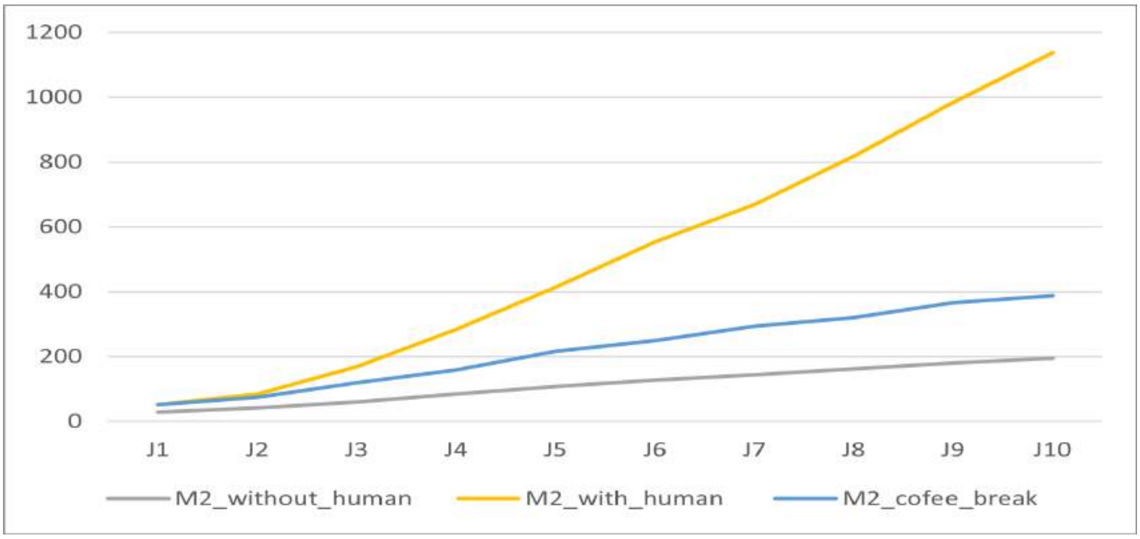


Figure IV.8: Machine 2 completion time

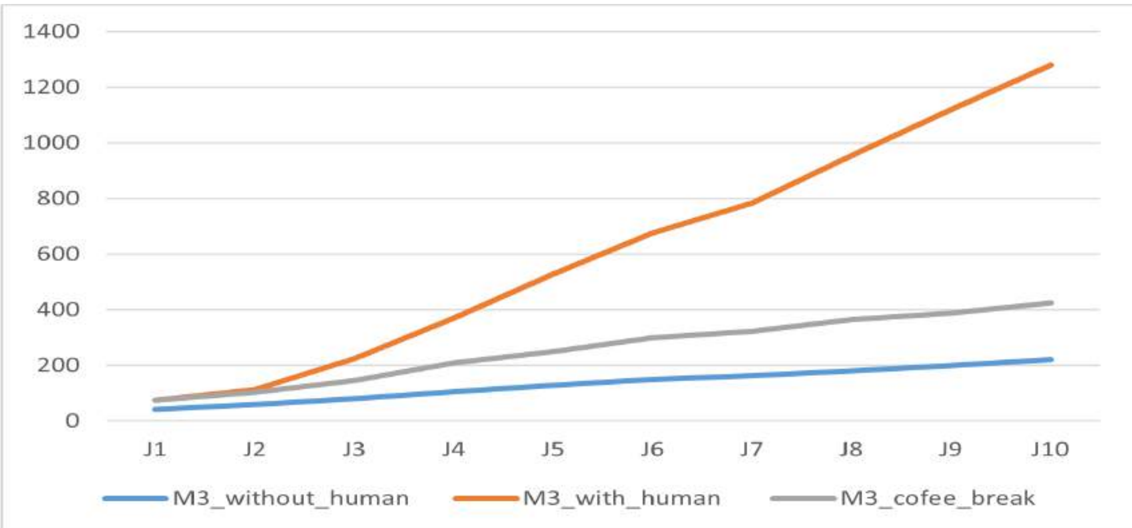


Figure IV.9: Machine 3 completion time

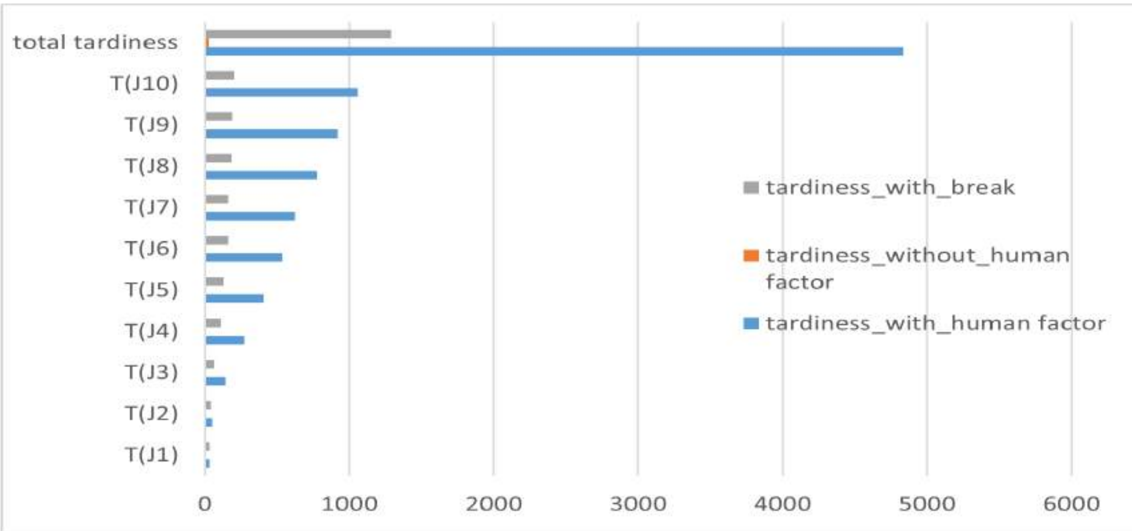


Figure IV.10: Tardiness comparison between the 3 modes

# Conclusion

The results obtained from our comprehensive scheduling model, which meticulously considers the critical factors of earliness and tardiness, demonstrate a more balanced and holistic approach to job completion compared to traditional scheduling methods that solely focus on minimizing the makespan. In traditional scheduling practices, jobs are typically scheduled in an adjacent manner to minimize the total completion time, often leading to the undesirable consequences of idle times and potential overloading of operators.

In contrast, our innovative model explicitly accounts for the earliness and tardiness of each job, allowing for a more realistic and nuanced representation of operational constraints and deadlines. While this approach may result in a slightly higher makespan, it ensures that jobs are completed much closer to their respective due dates, effectively reducing the risk of late deliveries and the associated penalties that can have a detrimental impact on customer satisfaction and overall business performance.

Furthermore, our model incorporates a deep understanding of operator costs and the critical factor of operator fatigue, aiming to strike a delicate balance between job completion times and the efficiency and well-being of the workforce. This consideration is pivotal in maintaining long-term productivity and minimizing the likelihood of errors and accidents due to operator fatigue, which can have far-reaching consequences on quality, safety, and overall operational resilience.

By using more realistic data and implementing the model in real manufacturing systems, we can further enhance its accuracy and applicability. This practical implementation will provide valuable insights and enable fine-tuning of the model to better suit the dynamic nature of real-world manufacturing environments.

In essence, while traditional scheduling methods may achieve lower makespan figures, our comprehensive approach provides a more holistic and realistic scheduling solution that aligns seamlessly with the principles of lean manufacturing and sustainable operations. By considering a multitude of factors, such as earliness, tardiness, operator costs, and fatigue, we can achieve a more efficient, resilient, and optimized manufacturing process that not only delivers superior results but also fosters a healthier and more engaged workforce, ultimately contributing to the long-term success and competitiveness of the organization.

## Perspectives

To further enhance the model's practicality and relevance, the following perspectives are proposed. Firstly, instead of arbitrarily setting the recovery rate for operator fatigue to

0.5, a more realistic recovery rate should be implemented. This approach would better reflect actual recovery patterns and improve the accuracy of the model.

Additionally, incorporating empirical data on job processing times, due dates, and penalty weights will enhance the model's applicability and ensure it reflects actual manufacturing conditions. By using real-world data, the model's performance can be more accurately assessed and improved.

Lastly, deploying the model in a real manufacturing environment is crucial for validating its effectiveness. Collaborating with industry partners for pilot studies will provide practical insights and help in fine-tuning the model for real-world applications. This hands-on approach will allow for adjustments based on feedback and ensure the model's robustness and reliability in diverse manufacturing settings.

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