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ORIGINAL

The fusion of Lean Manufacturing with Industry 4.0 technologies towards a new pillar for improving supply chain performance, the case of the automotive industry in Morocco

La fusión del Lean Manufacturing con las tecnologías de la Industria 4.0 hacia un nuevo pilar para mejorar el rendimiento de la cadena de suministro, el caso de la industria del automóvil en Marruecos

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ABSTRACT

In response to the COVID-19 pandemic, a Moroccan automotive glass company embarked on a strategic overhaul to improve its supply chain performance and resilience. Faced with excessive working capital tied up in inventory (Working Capital = $200M), the company chose to integrate advanced artificial intelligence (AI) technologies with Lean Manufacturing principles, including Just-In-Time (JIT) production and workload balancing. The goal was to lower inventory levels while maintaining a high service rate to meet customer demands. AI tools have played a crucial role in predicting quality defects and forecasting equipment availability, facilitating streamlined operations and cost reduction. This initiative also aims to enhance the supply chain's ability to withstand and adapt to future disruptions.
The paper explores the successful integration of Lean Manufacturing and AI technologies, highlighting their significant impact on operational efficiency, cost savings, and adaptability. By detailing the implementation and outcomes of these innovations, this study demonstrates how combining lean practices with AI technologies can drive substantial improvements in supply chain performance and resilience.

Keywords: Supply Chain Resilience; Lean Manufacturing; JIT; Artificial Intelligence; Industry 4.0.

RESUMEN

En respuesta a la pandemia de COVID-19, una empresa marroquí de fabricación de vidrio para el sector automotriz emprendió una reestructuración estratégica para mejorar el rendimiento y la resiliencia de su cadena de suministro. Con un capital de trabajo excesivo inmovilizado en inventarios (Capital de Trabajo = $200M), la empresa optó por integrar tecnologías avanzadas de inteligencia artificial (IA) con los principios de Manufactura Esbelta, incluyendo la producción Justo a Tiempo (JIT) y el equilibrio de la carga de trabajo. El objetivo era reducir los niveles de inventario manteniendo un alto nivel de servicio para satisfacer la demanda de los clientes. Las herramientas de IA han desempeñado un papel crucial en la predicción de defectos de calidad y la previsión de la disponibilidad de equipos, facilitando operaciones optimizadas y la reducción de costos. Esta iniciativa también tiene como objetivo mejorar la capacidad de la cadena de suministro para resistir y adaptarse a futuras disrupciones.
El documento explora la exitosa integración de la Manufactura Esbelta y las tecnologías de IA, destacando su impacto significativo en la eficiencia operativa, el ahorro de costos y la adaptabilidad. Al detallar la implementación y los resultados de estas innovaciones, este estudio demuestra cómo la combinación de prácticas esbeltas con tecnologías de IA puede impulsar mejoras sustanciales en el rendimiento y la resiliencia de la cadena de suministro.

Palabras clave: Resiliencia de la Cadena de Suministro; Manufactura Esbelta; JIT; Inteligencia Artificial; Industria 4.0.

INTRODUCTON

In the wake of the COVID-19 pandemic, an automotive glass company based in Morocco has embarked on a strategic transformation to enhance its supply chain performance and resilience. The initiative was driven by the recognition that the company is working capital, particularly the value tied up in inventory (Working Capital= 200 M$), was excessively high. To address this challenge, the company decided to deploy new technologies in artificial intelligence (AI) alongside Lean Manufacturing concepts, such as Just-In-Time (JIT) production and workload balancing.

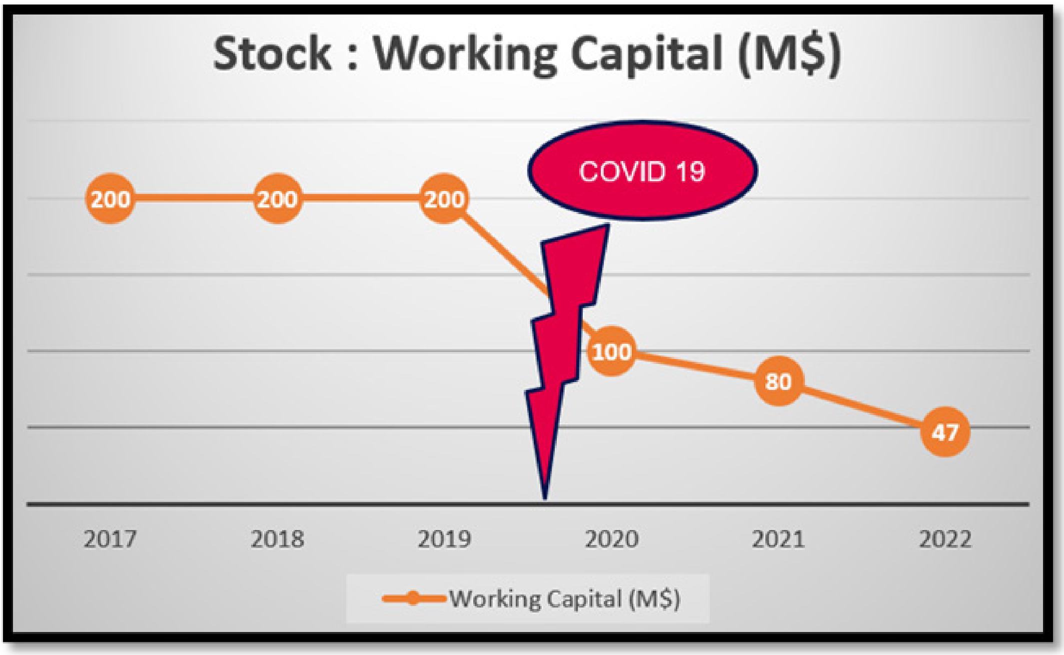

Figure 1. Working Capital value per years

The primary objective was to reduce inventory levels while maintaining a high service rate that satisfies end customers. The AI tools have been particularly instrumental in predicting quality defects and forecasting the availability of manufacturing equipment. This proactive approach not only aims to streamline operations and reduce costs but also to build a more resilient and responsive supply chain capable of adapting to future disruptions. This introduction sets the stage for an in-depth exploration of how these technological and methodological innovations have been implemented and their impact on the company's supply chain performance.

We all remember the example of a ship on water used to illustrate the relationship between inventory levels (water level) and various disruptions (rocks). These disruptions include quality defects, data uncertainty, machine breakdowns, intermediate stocks, and more. To effectively manage inventory, it is essential to combine lean initiatives with a robust technological arsenal. This approach ensures a commitment to reduce stock levels while maintaining operational efficiency. In this sense, the Japanese company decided to start its supply chain performance improvement project through the following pillars:

In order to ensure these guidelines, the company was obliged to launch improvement projects based on Industry 4.0 (including artificial intelligence) and lean manufacturing as two strategic pillars on which to build a strong and resilient supply chain. This choice confirms the importance of these two axes to achieve the improvement of resilience.

This article is primarily divided into two main sections. The first section sheds light on Lean Manufacturing initiatives that have been launched to enhance supply chain performance. The second section delves into the new concepts of artificial intelligence, which are proposed to predict various aspects that we will explore further.

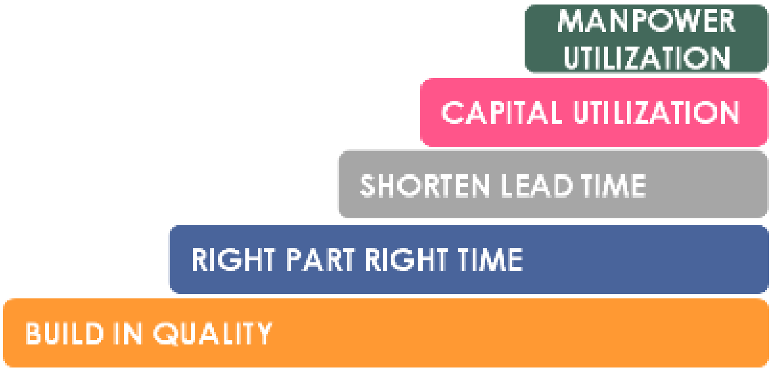

Figure 2. Chosen pillars to reduce the stock level

Impact of lean practices on the supply chain performance

Lean manufacturing, originating from the Toyota Production System, has gained widespread adoption due to its emphasis on waste elimination and efficiency improvement. Its integration into supply chain management has shown to significantly enhance performance metrics across various dimensions. The adoption of Lean Manufacturing principles has facilitated a more agile and responsive production system. The Just-In-Time approach minimizes inventory-holding costs and aligns production schedules closely with actual demand, thereby reducing waste and increasing efficiency. Workload balancing has addressed bottlenecks in the production process, leading to smoother operations and higher productivity.(1)

Operational Efficiency

- Reduced Lead Times: lean practices shorten production cycles, leading to faster delivery times.
- Inventory Reduction: JIT and other lean methods significantly cut down on inventory costs and reduce the need for large storage spaces.

Quality Improvement

- Defect Reduction: lean's focus on quality at the source helps decrease the defect rates and improves overall product quality.
- Higher Customer Satisfaction: enhanced product quality and timely deliveries result in improved customer satisfaction.

Cost Savings

- Lower Operational Costs: elimination of waste and reduced inventory levels contribute to significant cost reductions.
- Energy and Resource Efficiency: lean practices promote efficient use of resources, leading to cost savings in energy and materials.

Enhanced Flexibility and Responsiveness

- Agility in Supply Chain: lean supply chains can better adapt to changes in market demand and customer preferences.
- Improved Supply Chain Coordination: enhanced communication and collaboration among supply chain partners result in better coordination and responsiveness.

Sustainability

- Environmental Benefits: reduced waste and optimized resource use contribute to lower environmental impact and promote sustainability.

Material and information Flow analysis

Material and information Flow Analysis or Value Stream Map (VSM) is a fundamental tool used to understand activities occurring in the supply chain.(2) It identifies three types of activities: value added activities (VA), Necessary but non-value-added activities (NNVA) and non-value added (NVA). For non-value added, it is considered waste to be reduced or eliminated to increase the efficiency of supply chain operations.

The following steps have been taken to map flows:

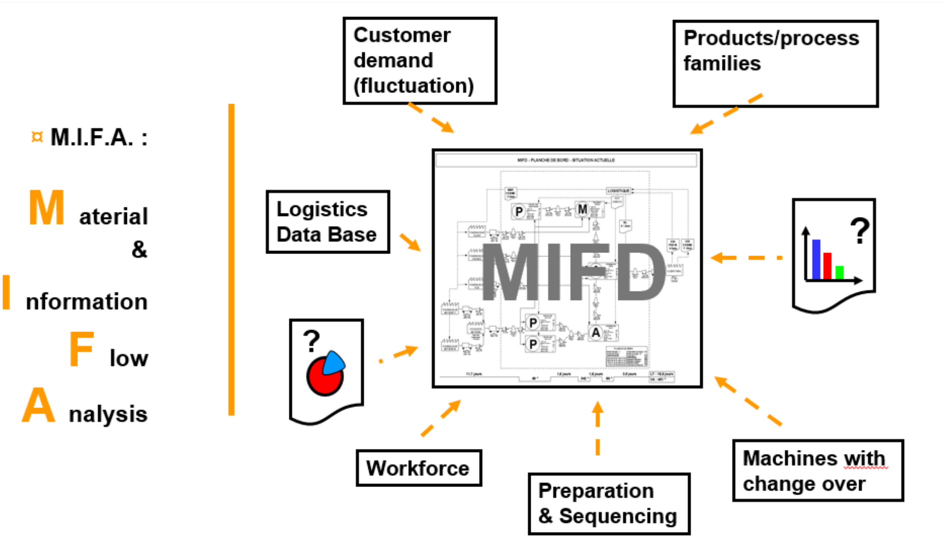

Figure 3. Material and information flow diagram

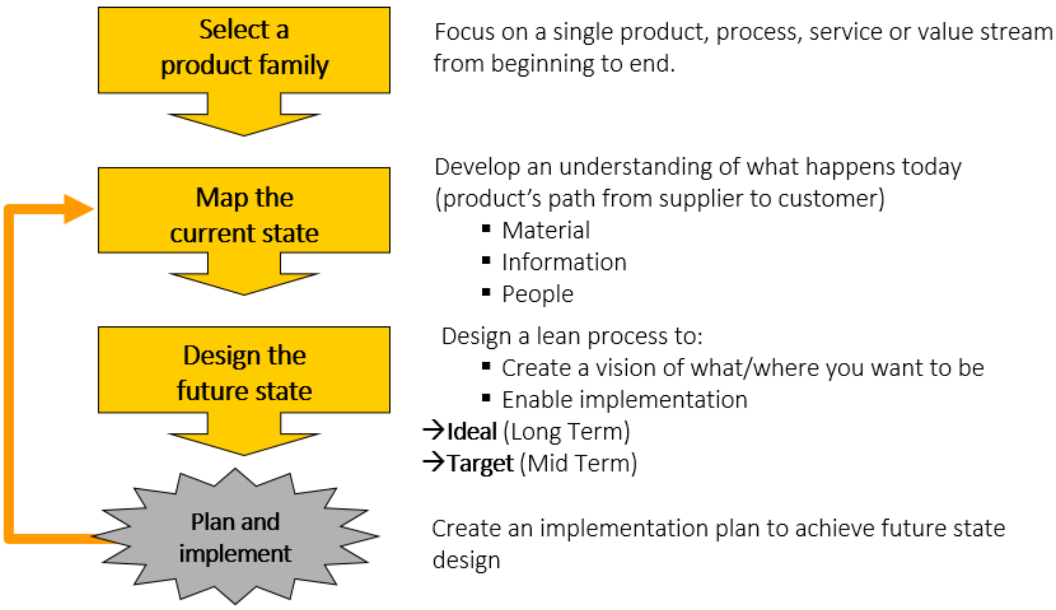

Figure 4. MIFA's Methodology

Shop floor takt time: Adaptation of production load to production line capacity (Jishuken)

Jishuken is a form of problem-solving technique[3] which uses Kaizen combined with a Kaizen blitz, it is shop-floor action that leads to production line progress through a succession of improvements. This action starts with a rapid change and then continues indefinitely. JISHUKEN is never finished and goes with a KAIZEN state of mind (progress one small step at a time).

The objective is to make the production rhythm equal to that of the customer consumption (Takt Time). In reality, cycle time (the operator's instant production time) is less than Takt Time, in order to allow for all malfunctions.

Takt Time represents, in units of time, the number of parts the customer expects us to deliver:

$$TAKT\ Time : \frac{Available\ Time\ (Opening\ Time - Planned\ brakes)}{Customer\ Demand}$$

Based on TAKT Time and equipment capacity, calculate the number of operators needed. This can be done using the following formula:

$$Number\ of\ Operators\ :\ \frac{Work\ Content}{TAKT\ Time}$$

$$Work\ Content = \sum Cycle\ Time\ = Cycle\ Time\ Op\ 1 + Cycle\ Time\ Op\ 2 + \cdots + Cycle\ Time\ Op\ n$$

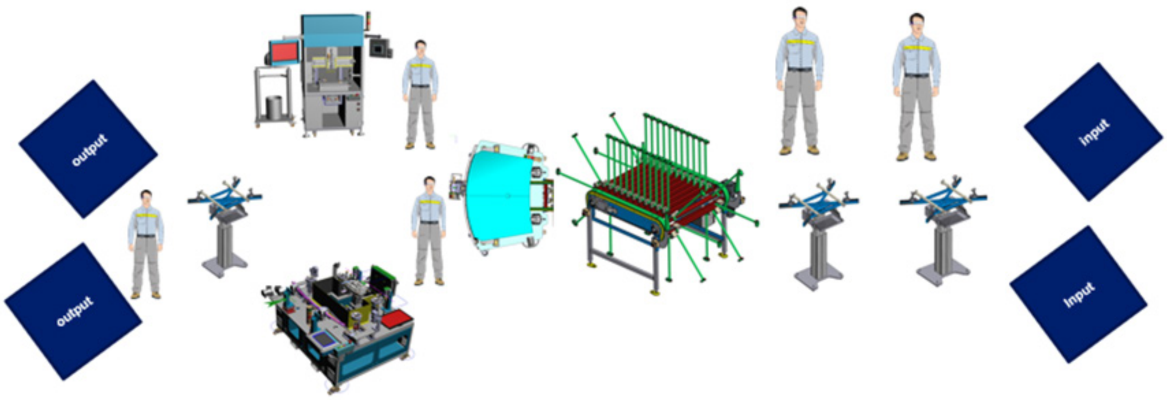

Figure 5. The line's Lay-out

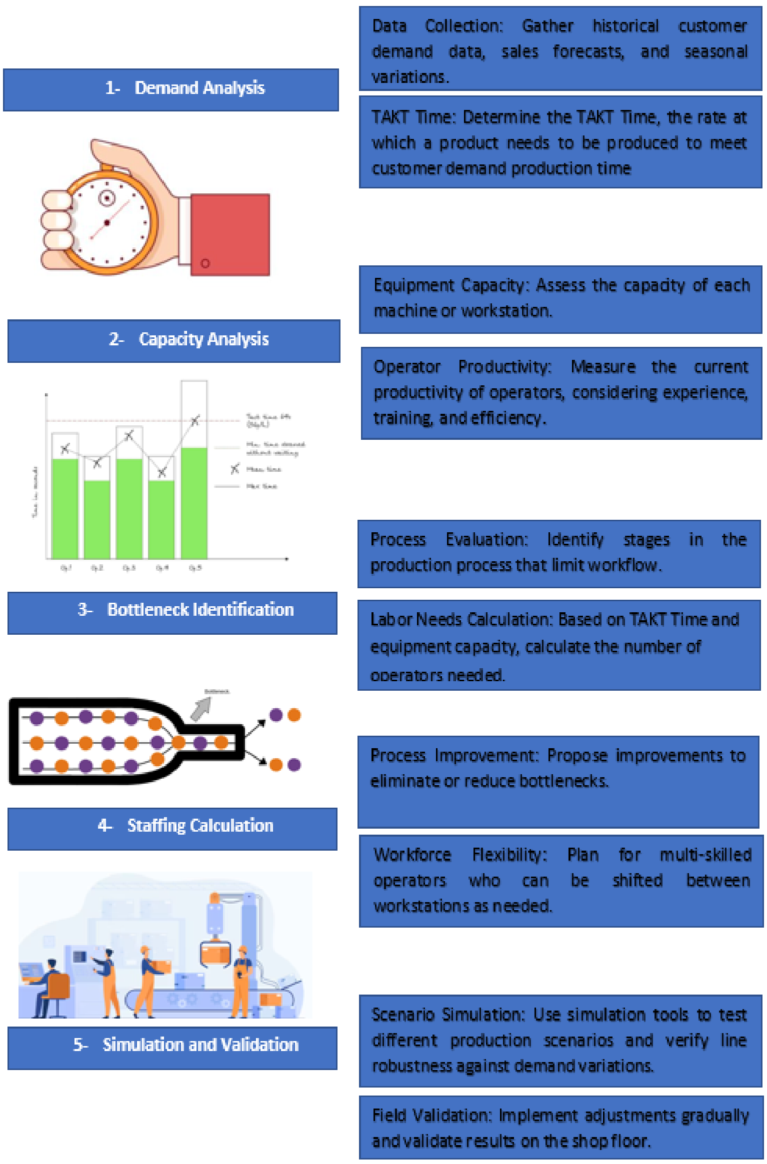

Figure 6. Client's workload

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One Peace Flow

Flexibility and agility are crucial for supply chain resilience, especially to adapt to customer demand variations and TAKT Time. To effectively staff production lines, the case we are going to study involves an assembly line of a Japanese glass manufacturer established in Morocco since 2018. Its client, an automobile manufacturer, is located right next door. The layout of its assembly lines has the following shape: Our objective will be to reduce the number of operators if there is a decrease in the client's workload (Takt time). In other words, it will be necessary to adapt the capacity to the manufacturer's workload. To achieve this, we followed the following approach:

Today, mass production has shattered, and strategic segmentation has become a formidable weapon. The notion of a diversity economy has replaced the economy of scale. With this in mind,the reduction of lot sizes has become a key success factor and clearly displayed as a major goal of managers since the reflections and initiatives led by Taiichi Ohno.[1] Maximal elimination of waste implies working with zero intermediary stock between operators. This means that every operator must pass on a good part to the operator at the next workstation. Nevertheless, a maximum of one part between each work station can be allowed to deal with synchronization problems that can arise between operators. One-piece flow (i.e. working "part by part") is the best way to reveal cycle time differences among operators. In fact, whenever several parts appear between workstations, imbalances are covered up.[9]

Master Planning Schedule Vs Material Resources Planning

When companies first began using MRP, they relied on sales forecasts and/or customer orders (demands). In other words, to calculate material requirements, the computer multiplied the latest demand numbers by the quantities required in the Bill of Materials (BOM). The problem with this approach was that it blindly assumed the resources would be available to manufacture products in sufficient quantities as they were sold.

Furthermore, as demand numbers inevitably changed over time, material requirements changed with them. With emerging software tools, it became very possible to generate overwhelming changes to schedules that plants and suppliers could not handle. This meant that the information in the software system was often chaotic, and therefore, so was the production line. The frequent result was an overloaded schedule, underutilized resources, or both.

Some of the MRP pioneers quickly realized that their software was of little value if it failed to predict and control the resources needed to support actual production schedules. They also realized that they had given the computer too much decision-making power. Nowhere in the process was there a human being ensuring a true balance between demand (customers) and supply (manufacturing and supplier resources). These insights led to the development of a Master Production Schedule (MPS).[5]

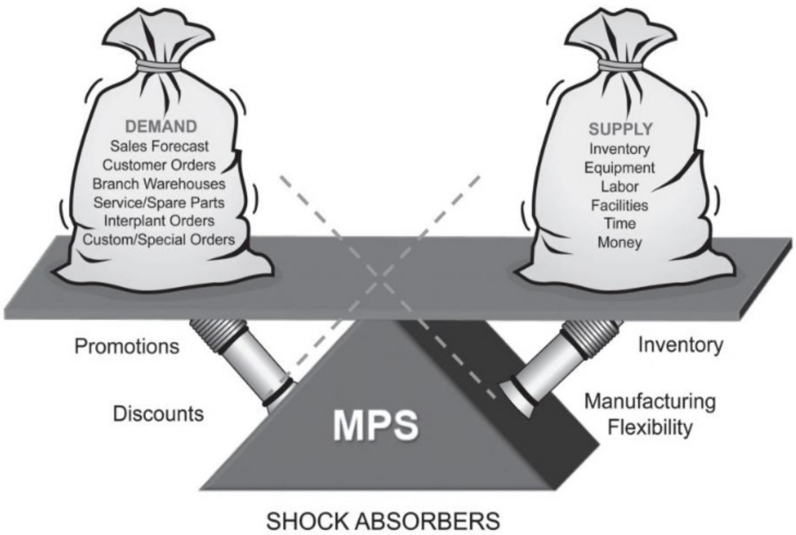

Figure 7. Workload Vs Work force

The Master Production Schedule is a pivotal point in manufacturing where market demand is balanced with the real-time capacities of the company and its suppliers. As the modern manufacturing environment has grown more complex in terms of products and product options, and more demanding in terms of quality, fast delivery, low prices, quality service, and technological enhancements, this balancing mechanism has become a vital tool for management at many levels. In our case, the Japanese company based in Morocco opted for a fixed agenda for the MPS to adjust the workforce each time in relation to client needs. To this end, we have implemented dedicated follow-up processes to absorb changes in customer demand.

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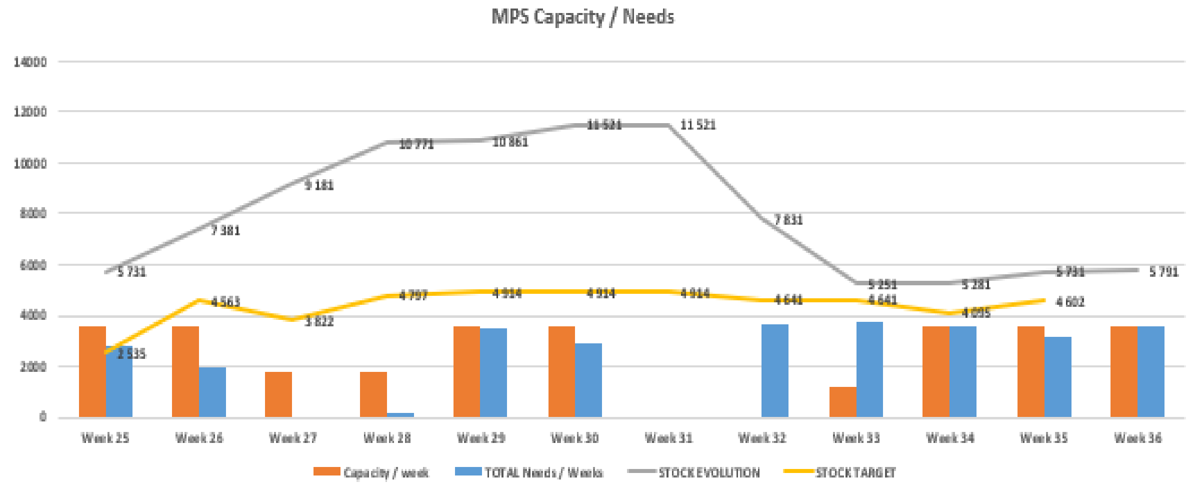

Figure 8. MPS Follow Up

Industry 4.0

Industry 4.0 represents the fourth industrial revolution defining the 21st century. The term “Industry 4.0” was coined in Germany in 2011 by a working group of academics and industry professionals to study the impact of innovative digital technology systems on manufacturing. Core Industry 4.0 technologies include the Internet of Things (IoT), Cyber-Physical Systems (CPS), Big Data Analytics (BDA), Artificial Intelligence (AI), and Additive Manufacturing (AM). Many other digital technologies are also considered key enablers for Industry 4.0.(6)

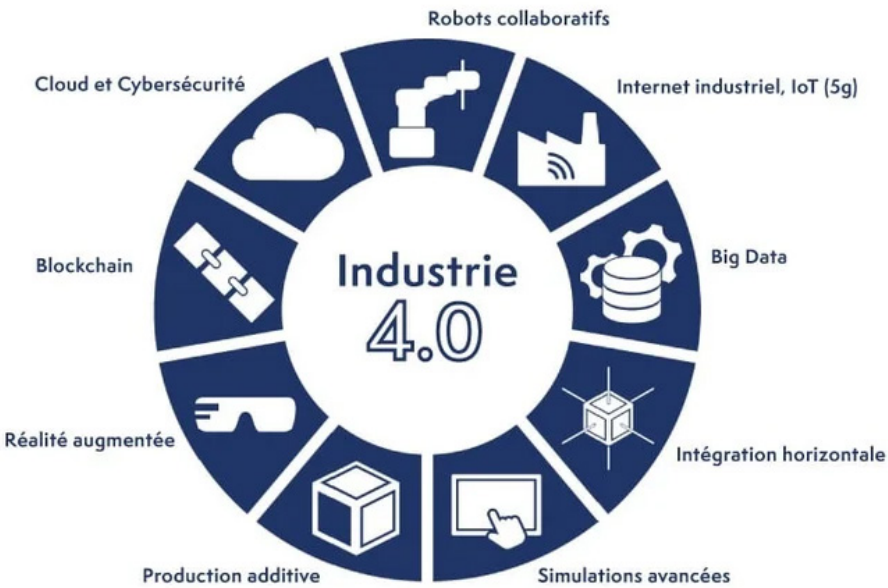

Figure 9. Industry 4.0 technologies

Artificial intelligence (AI) is a cornerstone of Industry 4.0, driving transformative changes across the manufacturing sector. By enabling machines to learn from data and make autonomous decisions, AI enhances efficiency, productivity, and flexibility. It powers predictive maintenance, reducing downtime and extending equipment lifespan. AI also optimizes production schedules, improves quality control, and facilitates real-time monitoring and decision-making. Integrating AI with other Industry 4.0 technologies, such as IoT and big data analytics, creates smart factories that can adapt to changing demands and conditions swiftly. Ultimately, AI propels the manufacturing industry towards greater innovation and competitiveness.

Artificial intelligence (AI), plays a crucial role in enhancing the resilience of modern supply chains. Faced with challenges such as global disruptions, demand variability, and logistical constraints, advanced technologies provide innovative solutions to anticipate, respond to, and adapt quickly to changes. AI enables precise predictive analysis, real-time optimization of processes, and proactive risk management, transforming traditional supply chains into adaptive and robust networks. Through these advancements, companies can not only improve operational efficiency but also ensure business continuity in the face of uncertainties.

It is important to note that these improvement projects were published in indexed journals. The factory's Industry 4.0 manager, who was simultaneously pursuing doctoral studies, led them. Consequently, we will utilize his articles to detail the deployed technical solutions.

Artificial Intelligence for Product Quality Inspection

This innovation project explores the application of machine learning techniques for real-time prediction of automotive tempered glass quality. The team emphasizes the importance of high-quality tempered glass for automotive safety and aesthetics, necessitating reliable quality inspection methods. Traditional quality control processes are often manual and prone to errors, prompting the need for automated solutions. The project presents a machine learning-based approach that utilizes various algorithms to predict glass quality based on input data from manufacturing processes.

By analyzing patterns and anomalies in the data, the system can provide real-time quality predictions, enabling immediate corrective actions. This initiative includes a comprehensive analysis of different machine learning models, highlighting their accuracy and efficiency in quality prediction. Experimental results demonstrate that the proposed approach significantly improves prediction accuracy and operational efficiency compared to conventional methods. The implementation of this system can lead to enhanced product reliability, reduced waste, and optimized manufacturing processes in the automotive industry.

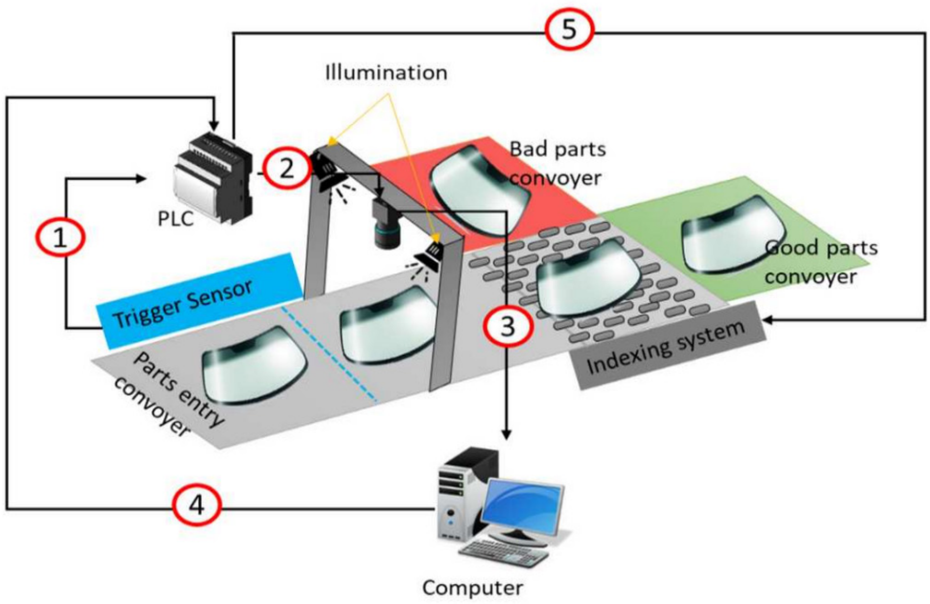

Figure 10. Assembly glass's line

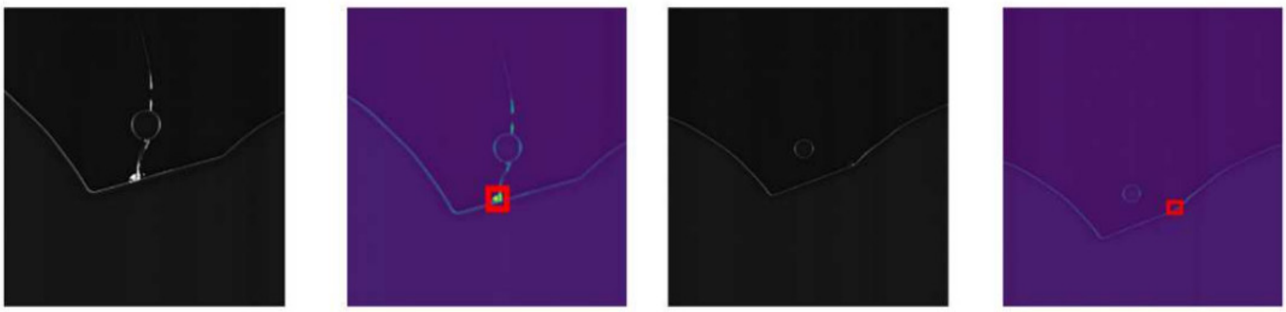

Figure 11. Glass's edge defects

Online Prediction of Automotive Tempered Glass Quality using Machine Learning

This improvement project focuses on enhancing the prediction of automotive tempered glass quality in real-time using machine learning techniques. The project highlights the critical role of high-quality tempered glass in automotive safety and aesthetics, underlining the need for reliable quality inspection methods. Traditional quality control processes are often manual and prone to errors, creating a demand for automated solutions. This initiative presents a machine learning-based approach that employs various algorithms to predict glass quality from manufacturing process data. By analyzing patterns and anomalies in the data, the system aims to provide real-time quality predictions, allowing for immediate corrective actions. The project involves a detailed evaluation of different machine learning models, emphasizing their accuracy and efficiency in quality prediction. Results show that this approach significantly enhances prediction accuracy and operational efficiency compared to traditional methods. Implementing this system is expected to improve product reliability, reduce waste, and optimize manufacturing processes in the automotive industry.

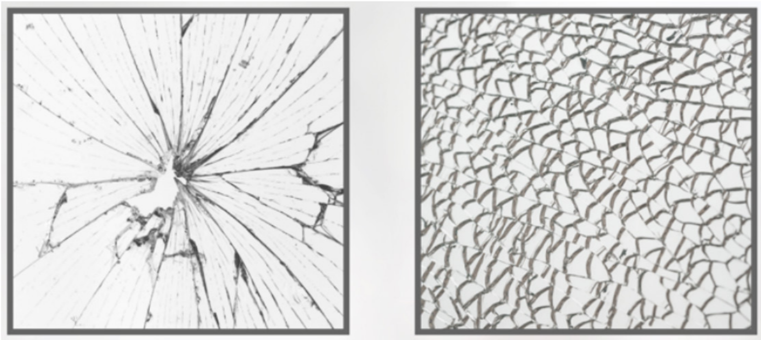

Figure 12. Tempered glass defects

Machine learning for OEE prediction

This project aims to develop a machine learning model for accurate OEE prediction to enhance production efficiency and support proactive decision-making. Extensive historical data from automotive manufacturing processes were collected and preprocessed. Various machine learning algorithms, including Random Forest, Support Vector Machine (SVM), and Neural Networks, were evaluated for their prediction capabilities. The models were assessed using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2). Results indicate that machine learning models can effectively predict OEE, uncovering patterns that traditional methods might miss. The practical benefits include improved maintenance scheduling, reduced downtime, and optimized production. The machine learning is a valuable tool for KPI prediction in the automotive industry and recommend further research to refine the models and explore their broader industrial application.

Using Machine Learning for Predicting Efficiency in Manufacturing Industry

This project explores the application of machine learning techniques to predict efficiency in the manufacturing industry. It examines how data-driven approaches can enhance production processes by providing accurate predictions of efficiency metrics. The challenges faced by manufacturers, such as equipment maintenance, production scheduling, and quality control, and how machine learning models can address these issues are addressed.

Key machine learning algorithms, such as regression analysis, decision trees, and neural networks, are evaluated for their effectiveness in predicting various efficiency parameters. The importance of data preprocessing, feature selection, and model training to ensure accurate and reliable predictions is highlighted. Case studies and examples where machine learning has been successfully implemented are presented, demonstrating improvements in production efficiency and cost savings. Additionally, the project discusses the integration of machine learning models with existing manufacturing systems, emphasizing the need for seamless data integration and real-time analysis. The potential benefits of predictive maintenance, reduced downtime, and optimized resource allocation are outlined, showcasing the transformative impact of machine learning on the manufacturing industry.

DISCUSSION

The gains realized from the initiatives launched, whether in the Lean domain or artificial intelligence, are substantial, amounting to $620K. This demonstrates that, in terms of cost, we have achieved significant results that will further enhance the company's competitiveness. However, the goal was not only financial gain but also the strengthening of supply chain resilience. The implementation of the strategies discussed earlier has enabled the company to develop greater agility and visibility, which will contribute to improved decision-making processes. Strategically, supply chain resilience has become a necessity, especially in an increasingly uncertain world.(24) Therefore, our upcoming research project will focus on measuring resilience to evaluate the maturity of our supply chain resilience.(7)

CONCLUSIONS

This study underscores the transformative impact of integrating Lean Manufacturing principles with advanced Artificial Intelligence (AI) technologies in enhancing supply chain performance and resilience. The

Moroccan automotive glass company's strategic overhaul, prompted by the COVID-19 pandemic, highlights the effectiveness of this dual approach in addressing high working capital and optimizing inventory management. The substantial financial gains of $620K reflect the significant cost reductions and operational efficiencies achieved. However, the true value of this initiative lies in its contribution to strengthening supply chain resilience.

By combining Lean Manufacturing techniques, such as Just-In-Time production and workload balancing, with AI tools for predictive maintenance and quality control, the company has not only reduced inventory levels but also improved agility and decision-making capabilities. These innovations have enabled the company to better anticipate and respond to disruptions, thereby reinforcing its supply chain's ability to adapt to an unpredictable global environment.

The findings of this study emphasize that while financial benefits are crucial, the enhancement of supply chain resilience is equally important in ensuring long-term competitiveness. The company's future research efforts will focus on measuring and evaluating supply chain resilience maturity, underscoring the ongoing commitment to adapting and thriving amidst an increasingly volatile and uncertain landscape.

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Formal analysis: Hatim Lakhouil.
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Research: Hatim Lakhouil.
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Project management: Hatim Lakhouil.
Resources: Hatim Lakhouil.
Software: Hatim Lakhouil.
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