Empowering Supply Chain Management with AI-Based Tools in the Inspection Machinery Industry

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***Abstract*— The manufacturing industry is increasingly adopting Artificial Intelligence (AI)-based solutions to improve production planning and operational efficiency. This article reflects the work carried out in the context of the AIDEAS project. AIDEAS aims to develop AI solutions for the lifecycle of industrial equipment, within the manufacturing phase focusing on three of the key processes within the Supply Chain Management of procurement, fabrication and delivery. The AI-Procurement Optimizer module supports purchasing decisions by considering supply constraints and cost targets, while AI-Fabrication Optimizer module improve production planning and scheduling through a combined approach of mathematical optimization and reinforcement learning. Finally, AI-Delivery Optimizer optimizes delivery logistics to reduce delays and transport costs. A holistic framework, AIDEAS Manufacturing Framework, is proposed that integrates all solutions, showing the connections between them and their workflow. The proposed framework undergoes testing in a real company from the inspection machinery industry through a structured implementation plan, highlighting both the benefits and challenges of adopting AI in small and medium enterprises. The findings underscore the role of AI in driving greater agility, sustainability, and resilience across manufacturing operations.**

***Keywords*— Artificial Intelligence, Supply Chain Optimization, Industrial Optimization, Industry 4.0**

I. Introduction

Manufacturing industry is increasingly adopting cutting-edge Industry 4.0 technologies to improve the efficiency and automation of their manufacturing processes [1]. This industrial revolution integrates advanced innovations such as cyber-physical systems, IoT devices and advanced data analytics, enabling automated and optimized manufacturing operations and seamless data connectivity between system components [2]. Within Industry 4.0, Artificial Intelligence (AI) has become a disruptive technology, which is increasingly being applied to different professional and scientific areas [3]. With its ability to analyze large datasets, identify patterns, and provide predictive insights, AI serves as the backbone for informed decision-making, efficient manufacturing operations planning, real-time optimization, and a growing range of applications [4]. Authors such as [5, 6] promise a more efficient and sustainable future in Supply Chain Management (SCM), with AI-driven improvements in areas such as procurement, supplier selection, production planning, scheduling, and delivery optimization. By leveraging these innovations, companies can reduce downtime and address inefficiencies across their supply chains (SC), ensuring smoother and more reliable operations [5].

The development and integration of AI solutions in manufacturing operations presents several opportunities and challenges, especially for Small and Medium Enterprises (SMEs). Frameworks proposed in recent studies aim to help SMEs overcome obstacles such as high costs, lack of technical expertise and employee resistance [9]. These approaches typically recommend a gradual progression, starting with basic awareness and moving towards advanced AI application.

AI techniques, such as machine learning and optimization algorithms, are being used throughout the lifecycle of industrial equipment, including design, manufacturing and recycling, offering improvements in efficiency and sustainability [10]. While AI offers significant benefits for manufacturing, including improved decision-making and process optimization, its integration still faces important challenges, particularly for SMEs [8].

Although numerous reviews and frameworks have addressed the implementation of AI systems in manufacturing, few focus specifically on supporting decision-making across the integrated SCM planning processes of procurement, production, and delivery. Most existing approaches tend to treat these stages in isolation, lacking a holistic perspective that connects them within a unified framework. This limits their practical applicability in guiding SMEs through the coordinated use of AI in real-world manufacturing planning contexts.

This paper aims to advance the AI integration in manufacturing planning by exploring the following research questions:

RQ1. Can AI improve SCM planning, specifically procurement, production, and delivery decision-making, in SME manufacturing settings through a holistic framework?

RQ2. How can such a framework be effectively implemented into the operational structure of a real manufacturing SME?

RQ3. What are the main barriers and enablers for implementing AI-based planning frameworks in resource-constrained environments?

This article exposes the research carried out in the AIDEAS project [9], which develops AI technologies to support the lifecycle of industrial equipment from design to manufacturing, use, and repair/reuse/recycle, enhancing sustainability, agility, and resilience in European machinery manufacturing. While AIDEAS addresses multiple lifecycle stages, this paper focuses exclusively on the manufacturing phase. In this phase, AIDEAS develops and validates tools to support three key planning processes: procurement, production, and delivery. These areas are essential for the daily operations of manufacturing SMEs and represent points of high impact for AI integration in terms of efficiency, responsiveness, and coordination. Other lifecycle stages are covered in other work packages within the AIDEAS project.

The paper is structured as follows. Section two provides a review of the existing literature on the use of AI in manufacturing planning, with a particular focus on procurement, production, and delivery processes. Section three presents the proposed framework, detailing the AI-driven techniques selected and their intended roles in supporting decision-making. Section three report briefly the research approach used for this study. Section four describes a real-world use case, demonstrating the practical application of the framework within a manufacturing SME. Section five outlines the implementation architecture developed to integrate the AI tools into the company's planning workflow. Finally, Section six discusses the key findings, practical implications, and future research directions.

LITERATURE REVIEW

In recent years, the application of AI in SCM has been widely studied, highlighting its advantages in many areas within the SC processes [10]. For instance, Machine Learning (ML) techniques have been utilized to handle complex datasets, improving decision-making and operational performance in procurement and fabrication [10]. Similarly, AI has been applied to improve logistics operations, including route optimization and last-mile delivery, thereby enhancing service levels and customer satisfaction [11].

SCM involves the coordination and management of suppliers, manufacturers and customers to ensure an efficient flow of goods and services. However, significant challenges arise at each stage. Suppliers face problems such as delays in delivery, lack of flexibility and limited capacity [12]. Manufacturers must balance efficiency and flexibility, reducing production bottlenecks, resource constraints and unpredictable demand [13]. Increasing customer expectations for speed, customization and sustainability add pressure to optimize logistics and last-mile delivery [14].

The Supply Chain Operations Reference (SCOR) framework offers a structured approach to addressing these issues [15], focusing on five core processes: Plan (forecasting and resource alignment), Source (procurement and supplier management), Make (production and manufacturing optimization), Deliver (logistics and order fulfillment), and Return (handling returns and recycling).

This review takes the SCOR model structure as a reference with a specific focus on Source, Make and Deliver, as these processes directly coincide with the manufacturing phase addressed by the AIDEAS project. These processes represent the operational core where AI-based planning can bring value to SMEs through improved procurement, fabrication efficiency and delivery performance.

Source: AI for Procurement Planning Process

Since the 1950s, companies began developing methodologies to organize their production, laying the foundation for what later became known as Material Requirements Planning (MRP), a term first introduced in [16].

MRP is a production planning and inventory control system used to manage manufacturing processes. It helps businesses to ensure that they have the right materials on hand to meet customer demand, while also minimizing inventory costs. MRP II, on the other hand, is a more comprehensive system that considers a wider range of factors, including capacity planning, scheduling, and forecasting. In addition to using BOMs (Bill Of Materials) and production schedules, MRP II systems often include tools for tracking and managing inventory levels, labour and machine resources, and other production-related data. The goal of MRP II is to provide a more holistic view of a business's production processes, and to help managers make more informed decisions about how to optimize those processes.

In [17] the author studies the effect that production lot size has on MRP performance, and he shows that it has direct implications on inventory size and delivery performance. This study uses simulation and a MRP programmed inside excel spreadsheet to test different lot sizes against the same production structure. This work demonstrates that adjusting lot batch sizes in production will lead to reduced work in process inventory and tardiness on delivery.

[18] proposes a new approach named CMRP or continuous material requirements planning where production is continuous and planning is updated at any time when changes occur in the input variables: production, demand, procurement, etc. This approach is contrasted versus the standard MRP, called here discrete MRP or DMRP, which is applied in industries where production is discretized and occurs at predefined time intervals.

The integration of scheduling algorithms into MRP has led to Finite Capacity MRP (FCMRP), as explored in [19] and [20]. A hybrid genetic algorithm and tabu search method is proposed in [21] for FCMRP in a flexible flowshop with assembly operations, outperforming previous solutions. In [22], a genetic algorithm is developed to solve the lot-bucket MRP problem, where the lot-bucket defines the period required to produce a full product batch.

In all these studies, it can be observed that in the Source stage there is a great variety of problem typologies present in the different industries. In addition, there are different data sources, sometimes coming from software such as excel, relational or non-relational databases, ERPs, etc., which gives rise to the need to coordinate all this information together with a changing and lively manufacturing environment.

Make: AI for Fabrication Planning Process

The Make process involves planning the resources of the manufacturing company with the objective of meeting customer demand on time and minimizing total production and inventory costs. Over time, authors have increasingly published papers on modelling and solving production planning problems, proposing robust models and solving them with optimization tools, heuristics, metaheuristics and matheuristics techniques [23] Production planning operates at three decision levels: strategic (resource allocation and facility planning), tactical (aggregate and master production plans), and operational (scheduling and sequencing for daily execution) [24].

Reinforcement Learning (RL) and ML are increasingly applied to production planning and control (PPC) to address complex decision-making challenges in modern manufacturing environments. RL techniques have shown promise in various PPC areas, including production scheduling, capacity planning, and inventory management [25]. Deep RL (DRL) algorithms, in particular, have demonstrated superior performance compared to traditional heuristics in production systems, offering real-time decision support and adaptability to changing conditions. While model-free and single-agent RL approaches are most common, recent trends show increased use of actor-critic methods. Despite the potential benefits, challenges remain, such as safety and reliability concerns, which necessitate more extensive testing in real-world applications [26].

The production scheduling problem is an NP-hard classified problem [27] and widely discussed in literature [28]. Over the years there have been several approaches to solving these problems, from mathematical models to heuristic algorithms. With the advent of Industry 4.0 and the increasing ease of access to sufficient computing power in recent years there have been several approaches using AI and ML techniques in this area. A previous study [29] found that the use of Particle Swarm Optimization (PSO), Neural Networks (NN) and RL algorithms have been the most popular in literature since the advent of Industry 4.0 in 2011. These approaches are used to solve different types of problems showing great flexibility and adaptability to the needs of companies. The authors propose different frameworks and solution to solve multi-objective problems like [30] who propose a PSO algorithm to solve a single machine scheduling problem optimizing the total energy consumption and total tardiness on a CNC machine [33]. However, in recent years several authors have presented solutions that exploit RL or DRL algorithms, obtaining results that are often better than those obtained with PSO [31].

Regarding the DRL approach, during the last year, several contributions were published using these techniques in different ways. [32] employ a Proximal Policy Optimization (PPO) to train a new policy to solve the job-shop scheduling problem optimizing the makespan value. A PPO agent with an Actor-Critic architecture to solve the flexible job-shop scheduling problem was proposed by [33]. In this paper the authors propose a DRL approach using PPO as agent to solve a hybrid flow-shop scheduling problem with an Open-shop block in the production steps. The algorithm solves the problem assigned the tasks and the operators to the different workstations presented in the production plant optimizing makespan, resource allocation and the delays during the manufacturing phase.

Deliver: AI for Delivering Planning Process

The main objective of the Delivery planning process is to ensure that the final product is delivered to the end customer in an optimal manner, while satisfying packaging, storage and transportation and time constraints. The achievement of these activities is crucial in ensuring the completion of the manufacturing phase of the industrial equipment lifecycle as well as guaranteeing maximum customer satisfaction. The advent and application of AI has further enhanced these operations through the utilization of powerful algorithms aimed at enhancing the decision-making process based on real-time data analysis for the optimization of different manufacturing processes such as delivery planning.

According to the extensive review carried out in [7], AI plays a significant role in the optimization of industrial equipment lifecycle, with the most prominent AI techniques in the manufacturing phase being Support Vector Machines (SVM) and Artificial Neural Networks (ANN) as they both accounted for about 40% of all the studies reviewed. In relation to delivery planning, the review also shows that RL was greatly utilized for inventory management, while heuristics took centre stage for logistics operations.

Sequel to the procurement of components and fabrication of the equipment, the main aspects of the delivery planning process are packaging, storage and delivery. In packaging, the machine components and the equipment are packed or arranged in a secure manner to ensure their safety upon delivery. This usually involves the use of protective packaging materials such as corrugated boards, wood, plastic films etc. [34]. These materials ensure protection against environmental and storage conditions (like temperature and humidity) as well as ensure safety and durability during handling and transportation. The main objective here is to achieve sustainable packaging supported by initiatives like the European Commission's Directive 94/62/EC [35] and others like the European Union's Circular economy action plan [36]. AI techniques have optimized packaging design and material selection, with Neural Networks (NN) reducing carbon emissions [37], multimodal deep learning models predicting optimal packaging types [38], and machine learning models achieving high classification accuracy [39].

Storage operations focus on two main areas: products-in-waiting, stored in warehouses, and products-in-transit, placed in containers for delivery. This gives rise to warehouse optimization and container loading optimization, both increasingly supported by AI techniques. Warehouse optimization aims to improve resource and space utilization [40]. The authors in [41] proffered solution to an automated warehouse scheduling problem by proposing an ensemble multi-objective biogeography-based optimization algorithm. In [42], a dual-objective warehouse optimization model is designed to estimate the connections and interdependencies between logistics and non-logistics factors. On the other hand, and as it relates to container loading optimization, the goal is to ensure that the container space is maximally optimized for the delivery process. This is mostly formulated as Container Loading Problem (CLP) in the logistics sector.

Finally, regarding delivery optimization, the main objective is to ensure efficient, on-time and cost-effective product delivery. It specifically points to measures applied for route optimization and involves efficient resource management and prevention of service disruptions, which may lead to delays in product delivery to the customer. Authors in [43] presented an approach for determining the optimal delivery route using deep reinforcement learning algorithm. In [44], a DRL4Route (Deep Reinforcement Learning for Route Optimization) model is presented to solve problems relating to complex route planning, leading to reduction in transportation cost and time. Lastly, an approach for optimizing last-mile delivery services based on data-driven optimization and machine learning is proposed in [45].

However, even though the application of the foregoing AI algorithms, methods, techniques in manufacturing operations have brought about commendable results, several challenges still exist, such as compliance, ethical consideration of AI and data privacy concerns [46], high costs and need for robust technical infrastructure [47]. It is important to address these challenges to maximize the benefits of AI application in delivery planning and logistics operations.

Frameworks for SCM in the literature

The following frameworks align with different stages of the SCOR model, each enhancing specific SCM functions through advanced methods. [48] take a more cross-cutting approach, leveraging AI for production planning, predictive maintenance, logistics, and quality control within lean and intelligent SCs. [49] propose a Return and Source-centric framework that optimizes closed-loop manufacturing-remanufacturing systems using a hybrid decision approach. [50] focus on Plan, Make and Deliver, using deep learning to jointly forecast demand, plan production, maintenance and collaborative distribution through multi-site networks. [51] also work on Make and Deliver, introducing a synchronized model for production and routing in mobile facilities to minimize costs and improve service levels. Finally, [52] work on Plan and Make, integrating capacity expansion and production planning in pharmaceutical supply chains to optimize manufacturing goals under uncertainty. In general, each framework enhances a specific SCOR phase with advanced decision-making or forecasting tools.

From the best of the authors knowledge there is a gap in literature regarding frameworks which propose an integrated framework that connects the Source, Make, and Deliver processes within the SCOR model. For this reason, the authors propose a holistic framework that exploits AI-based solutions that interact dynamically, using business data as both input and output to continuously improve decision-making across procurement, fabrication, and delivery.

RESEARCH APPROACH

This research adopts a structured methodology to explore AI-based solutions for optimizing Source, Make and Deliver processes in SCM manufacturing. The approach focuses on reviewing existing solutions, conceptualizing tools and integrated framework, defining key challenges, and proposing an implementation plan for a real case.

1. Literature Review of AI Solutions in SCM: This section analyzes AI methods applied in Source, Make, and Deliver within SCOR model. Identify key pain points and evaluate the effectiveness of these solutions in addressing operational challenges. Furthermore, the review identifies a gap in the integration and coordination of AI applications across Source, Make and Deliver.
2. Framework Proposal and Technological Integration: Based on the identified gap, a conceptual framework is proposed that integrates key AI-based tools and technologies. Each tool is described in terms of its functionality, emphasizing how they contribute to a cohesive, AI-driven system. The results from the development and testing of the core algorithms are also presented and analyzed.
3. Testing and Validation Plan in a Real-World Environment: A practical testing and validation plan is outlined to test and validate the proposed framework and tools in a realistic scenario. This plan outlines an architecture that establishes a workflow for using AI-based solutions, tests improvements in plan coordination and reinforcement in decision-making processes throughout the SC.

AI MANUFACTURING SOLUTIONS

AIDEAS Procurement Optimization

The Procurement Optimization (AI-PO) module aims to optimize the procurement decisions for materials and resources needed for production, based on the needs of the system and the production plan. The important points of its operation are:

1. Starting point: Input data Before the execution of the AI-PO module, the data of the problem to be solved is prepared. The Master Production Plan and the current stock situation need to be analyzed. At this stage, the materials needed to achieve the production objectives are identified, considering the inventory status and pending purchases in

delivery. It is determined which resources are already available and which must be acquired. All information regarding suppliers, offers, etc. is prepared, thus preparing the input data that will be used later by the problem-solving module.

2. Optimization considering restrictions: Once the initial data has been processed, the module uses AI techniques to evaluate the procurement options, considering multiple restrictions and characteristics of the problem. Constraints include production starting times, supplier availability, supplier stock, different offers with their delivery times, minimum purchase times, offer stocks, etc. The characteristics considered are priority suppliers and supplier reliability. This approach ensures that purchasing decisions are feasible and effective within the framework of operational constraints.

3. Definition of optimization objectives: The AI-PO module is designed to maximize various key objectives: cost and time optimization, improved stability and continuity in the supply chain. These objectives are aimed at ensuring operational efficiency, minimizing risks associated with supply interruptions, and meeting the specific requirements of each production process.

4. Generation of optimized proposals: After analyzing constraints and objectives, the module generates optimized proposals that identify the best possible combinations of suppliers, quantities, and acquisition times. These proposals are presented as optimized solutions that offer clear purchasing and deadline recommendations, allowing informed decisions to be made on the necessary purchases.

5. Dynamic recalculation: The AI-PO module is designed t be used on a recurring basis, allowing procurement decisions to be recalculated and adjusted as conditions change. So, after making some relevant purchases and adjusting the production plan, the module can be called iteratively to adjust the result again, obtaining improvements or adjusting the result dynamically. This capability ensures agile and flexible planning in a dynamic production environment.

Overall, the AI-PO module constitutes a comprehensive solution for procurement optimization, playing a fundamental role in the AIDEAS ecosystem and contributing significantly to the efficiency and sustainability of the manufacturing process.

AIDEAS Fabrication Optimization

Fabrication Optimizer comprises two integrated algorithms to optimize production planning and scheduling, each focused on providing medium- and short-term decisions: AI-FO^{MPP} for master production planning (MPP) and AI-FO^{PS} for production scheduling (PS).

AI-FO^{MPP} focuses on optimizing master production planning by addressing challenges such as material and labour resource allocation and demand fulfilment delays. It uses a metaheuristic approach that encompasses combination of mixed-integer linear programming for accurate optimization, simulated annealing to explore complex solution spaces and heuristic methods to solve the allocation problem. Together, these techniques ensure efficient resource allocation by considering factors such as company demand, demand forecasts, operator availability and inventory levels.

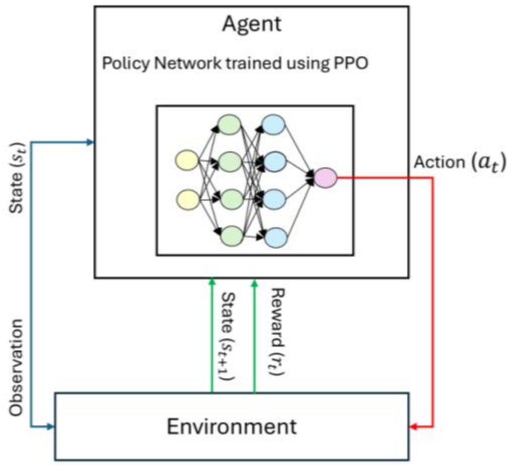

Figure 1. Markov Decision Process scheme

Regarding solving the scheduling problem using a DRL approach, first, the problem must be expressed as a Markov Decision Process (MDP) (Fig. 1). A MDP is a mathematical model that describes how to make decisions sequentially in a stochastic environment. The basic idea is that, at each instant, the agent is in a state s (summarizing all relevant information), chooses an action a and receives a reward from the system:

- A reward r which quantifies the goodness of the choice.
- A new state s'which it will be in after performing the action.

A MDP is characterized by the following tuple (S, A, P, R). At each step, the environment shows its state s_t ($s_t \in S$)to the agent, which selects an action a_t from the action space A according to a trained policy π(S, A). After the agent takes this action, the environment transitions from state s_t to the state s_{t+1} and sends the reward value r_t ($r_t \in$ R) corresponding to the action made. The goal of DRL is to develop a policy that maximizes the cumulative reward over time.

Going into the specifics of the problem addressed, the environment contains information from several sources of business data. The algorithm presented considers the delivery dates of the products to be manufactured, the availability of raw materials, the availability and expertise of the operators, and the constraints present at the manufacturing site. All this information is needed to build the environment using OpenAI's Gymnasium library. In this way, it is possible to define the space of actions that an agent can perform and the space of observations that represents the state of the production system at each step t. In addition, the reward function through which the agent understands the goodness or otherwise of the action taken must be defined; this function should reflect the goal to be achieved by the scheduling plan.

For solving the scheduling problem, the authors propose a multi-objective function that optimizes the values of makespan, delivery delays, waiting time and operator utilization rate.

A new policy obtained by training a policy network through PPO was developed for the optimization of the objective function.

Thus, by collecting data from the company's data sources and from the other solutions in the AIDEAS project (AI-FO^{MPP} and AI-PO), it allows an optimized schedule to be obtained in reduced computation time (<10 seconds). The model was tested on 40 different configurations, guaranteeing excellent results in terms of percentage of operator utilization (>82.3%), reduced delivery delays (maximum 1 in less than 10 configurations, 0 in the remainder) and makespan comparable with results obtained by FIFO algorithm.

The proposed tool, combining AI-FO^{MPP} and AI-FO^{PS}, addresses these gaps through a holistic approach. AI-FO^{MPP} leverages a metaheuristic framework to optimize medium-term master production planning. This ensures efficient allocation of material. AI-FO^{PS} complements this by employing machine learning-driven production scheduling, dynamically adjusting task sequencing and resource allocation to adapt to real-time conditions. The integration of these two solutions within a single tool represents a novel approach to bridging medium- and short-term decision-making in production planning and scheduling.

AIDEAS Delivery Optimization

Delivery optimization is aimed at optimizing the packaging, storage, and delivery of products. The objective here is to ensure that the customers can receive their order in the most optimal fashion, that guarantees package safety, on-time delivery, recyclability, cost efficiency etc. This is mainly to achieve sustainable and environment-friendly product delivery. Delivery optimization is achieved through the utilization of AI algorithms. Specifically, the Delivery optimizer (AI-DO) utilises AI algorithms to optimize the entire delivery process. It provides 3 main algorithms (AI models) to optimize product packaging, storage and final delivery to the customer. The delivery optimization applies to storage spaces, environmental conditions, container space utilization, product transportation, logistics scheduling and planning etc. In this paper, our focus will be on packaging optimization, storage optimization (container loading and unloading) and delivery plan optimization (route optimization).

Packaging optimization plays a significant role in the delivery planning process as it is the first stage, on which all other stages are implemented. In this use case, the datasets for the training of the algorithms were synthetically generated keeping in mind the operating conditions at the site of the industrial pilot. The dataset was then divided into a training-set and a test-set. The AI models were trained on the training set to predict the most suitable packaging material for each item, as well as the most suitable protective material, in the case that extra protection was required. The packaging optimization AI model leverages "NumPy" and "Pandas" libraries for data preprocessing. The AI algorithms were selected from the "sklearn" library and utilizes ensemble learning techniques for the prediction of packaging recommendations. Random Forests regressors have been utilized for categorical classifications due to their high accuracy (About 97-99% accuracy has been achieved, when the trained algorithms were tested against the test-set). The utilization of AI algorithm for predicting packaging starts with the collection of relevant data, which serves as the input fed into the prediction algorithm. These input data types include product size & dimensions, packaging material and storage capacity. According to the type and characteristics of the machine component or equipment to be packed, AI-DO provides recommendations for the most suitable packaging material type, the need for extra protection (internal protection in the case of fragile parts) and the estimation of total CO_2 emissions of the entire package, hence enhancing sustainable packaging. It is important to mention that the emission calculations are estimated by providing an "emission factor" based on the type of packaging material used. The inspiration for this approach was established based on Lifecycle Assessment (LCA) methodologies.

Storage optimization ensures optimal placement of the packaged machine components and equipment into the container for onward delivery to the customer. This is generally represented as a container loading problem (CLP). In our case, it is a multi-objective problem aiming to maximize the utilization of the container space and to optimize container unloading by reducing unwanted movements. This also extends to the sorting and ranking of the packaged boxes to determine the placement order and priority, which is influenced by other constraints such as delivery mode (single or multi-drop), customer delivery sequence, weight, box dimensions and geometry, orientation, fragility, stackability etc. The storage optimization AI model utilizes a hybrid Genetic Algorithm (GA) approach for solving CLPs based on Non-dominated Sorting Genetic Algorithm (NSGA-II) [53], which is very effective in solving complex and real-world multi-objective problems, leading to the generation of different solutions and the recommendation of the most optimal solution based on the previously specified sets of constraints. Specifically, the primary GA operators (crossover and mutation) are responsible for the management of the constraints associated with the multiple customer orders with heterogenous boxes. Box heterogeneity introduces an additional layer of constraint which is duly handled by the storage optimization AI model.

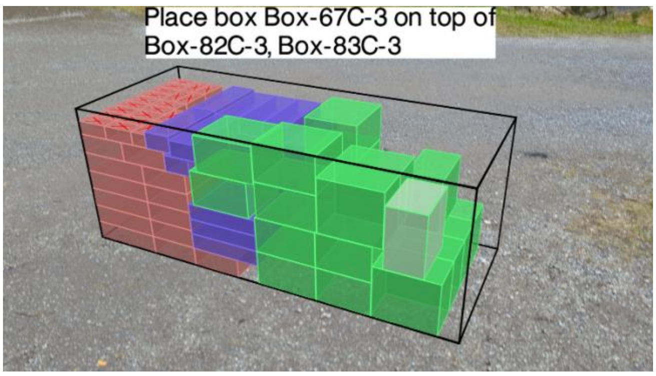

Figure 2. AR View for Container loading optimization (Box placements visualization)

The storage optimization AI model also utilizes point placement heuristics for the optimization of box placement within the container. The has ensured the reduction in computation time during the GA generation. The efficiency here is based on the removal of duplicate points from the placement point list. In cases where multiple corners of a new box elongate beyond the box under it, the placement heuristics reduces wasted spaces in the container by adjusting the positions of these points, ensuring space is available for incoming boxes. To enhance the visualization of the box placements within the container, Augmented Reality (AR) functionalities are utilized. This is also to support the human operator in the container loading and unloading operations. An illustration of a typical AR view visualization from the AI-DO is presented in Fig 2, which highlights the placement of boxes in a container for three different customers (denoted by 3 different colours), together with the instructions for placing the boxes in an order that guarantees the most optimal arrangement of the boxes within the container. The input data for the storage optimization AI model includes box dimensions, weight, geometry, fragility index, container size, customer priority etc., which are processed by the AI algorithm to provide the

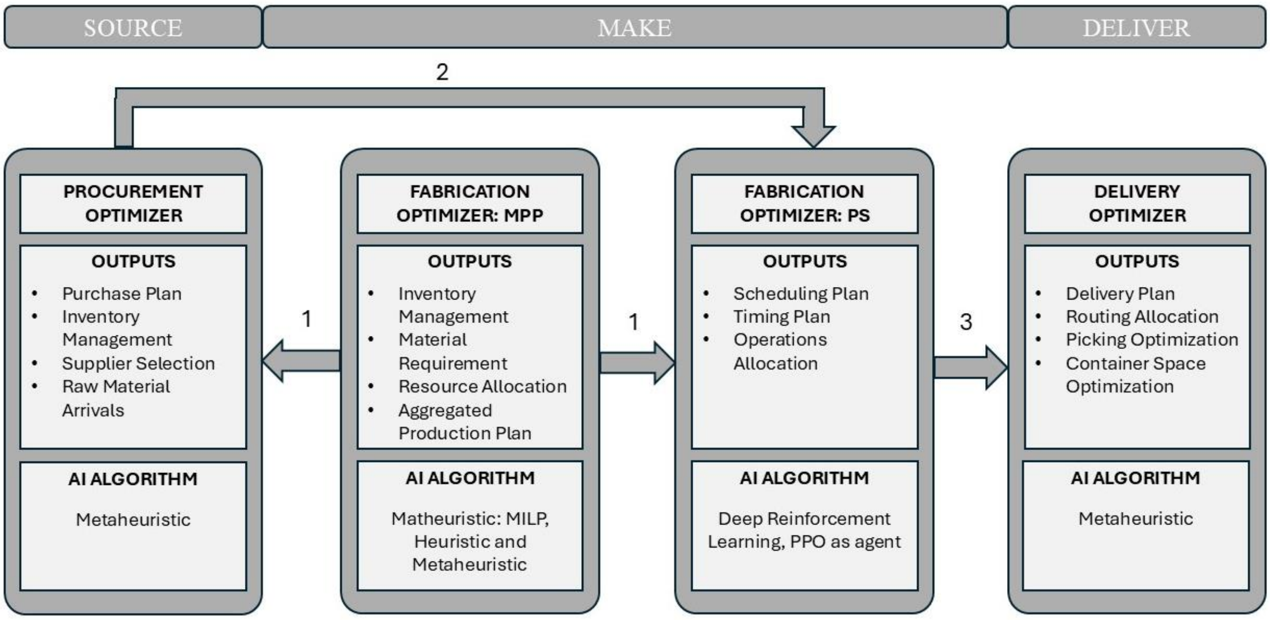

Figure 3. AIDEAS Manufacturing Framework.

optimal layout for the arrangement of boxes in the container. AI-DO provides a set of optimal solutions from which the user selects their choice based on their preference. It is important to mention for each of the generated solutions, the associated visualization of the layout is also provided by AI-DO to enhance user experience.

Finally, Delivery optimization involves the efficient delivery of the product to the final customer following its fabrication and packaging. It deals with all the methods utilized to ensure that the product is delivered safely and on time to the customer. It covers aspects such as product transportation and logistics scheduling and planning (be it “single product-single customer” or “multiple products-multiple customers” deliveries). Specifically, it relates to route optimization, which specifies the most optimal route (i.e., delivery plan) to get the product from the factory to the final customer. The delivery optimization model utilizes metaheuristics (Genetic Algorithm) for the recommendation of the shortest delivery route considering different set of constraints such as time, fuel consumption, carbon footprints etc. The delivery process relies on data such as production schedules, delivery schedules, product orders, and transport costs etc. (some of which are outputs of the AI-PO and AI-FO solutions) to run the optimization model. Specifically, the user provides information about the origin and destination points. The user is able to provide this information by either entering the place names or coordinates, or by directly clicking the points on an interactive map available in the AI-DO solution. The algorithm utilises the data provided by the user to recommend the optimal routes to connect both points. These routes are also visualized on the map to aid the users to easily identify and select the most efficient routes.

AIDEAS Manufacturing Solutions

The AIDEAS manufacturing solutions have been developed independently but with the possibility of receiving information from different sources, which also allows them to receive information from other solutions. Figure 3 shows where each tool is applied in the production planning process and how information is transferred between them.

The production planning process begins with the production necessity triggered by customer requests, which initiates the execution of the first solution, AI-FO^{MPP}, capable of generating a master production plan. This master plan indicates future production needs considering current production capacity, material availability and material to arrival. The master production plan involves the consumption of materials that may or may not be present in the plant when needed for production. This list of needs, along with the dates when these materials are required, is sent to the second stage of the production process, which is the purchasing plan, or procurement plan. The AI-PO solution is responsible for receiving the list of needs obtained through the master production plan and, together with the necessary supplier data (obtained from the company's data source), calculates a purchasing plan that meets the material requirements. This purchasing plan considers not only material needs but also supplier capacities, delivery times, bulk purchase offers, etc. With this purchasing plan, the arrival dates of materials are updated, which, although theoretical, allow the production schedule to be calculated. The information about the arrival of materials is sent back to the AI-FO^{PS} tool, which now has more precise information and material arrival dates. With this information and information about the company's production capacity, AI-FO^{PS} calculates a more accurate and updated production plan.

The final stage of the supply chain is the delivery of manufactured products. AI-DO guarantees optimal product packaging and arrangement in the container to maximize the container volume. Based on an optimized production schedule tailored to the needs and production capacities, a delivery plan is developed. This optimized delivery plan, calculated by the AI-DO solution, starts from the precise delivery dates obtained in the production schedule generated by AI-FO. This information is supplemented with information regarding distribution capacities and needs, and with all this information, a delivery plan is calculated.

The solutions applied in the use case can obtain information from different data sources, including other AIDEAS solutions or even external software.

TESTING AND VALIDATION PLAN FOR THE INTEGRATION IN A REAL CASE

Multiscan Technologies is a Spanish SME which provides food tooling manufacturing equipment with intelligent machine vision technologies, along with innovative product transport systems to achieve optimum sorting. Multiscan provides unique computer vision and X-ray solutions for the fresh fruit and vegetables market, mainly quality inspection machines for grading and sorting processes, as well as for safety and conformity applications.

Multiscan forms one of the four pilots where the solutions are incorporatedIt plans to adopt AI-PO, AI-FO and AI-DO within a unified architecture designed to test the solutions without interrupting the company's operations. Leveraging this architecture, the factory will use AIDEAS manufacturing solutions to streamline manufacturing methodologies with advanced real-time planning, sequencing and resource allocation capabilities. This approach is expected to improve the efficient use of human and technical resources, reduce production lead times and streamline purchasing and delivery operations.

Some of the limitations observed during the implementation of previous AIDEAS solutions have been:

- The difficulty in generating cross-platform databases for the application of AI.
- The complexity of AI technologies for implementation.
- The difficulty in measuring results.
- The difficulties of integration in the working methodology.

To address these limitations, a dedicated testing and validation plan is proposed.

Testing and Validation Plan

The following workflow outlines the structured process for testing and validating AI-based solutions within the Multiscan pilot phase.

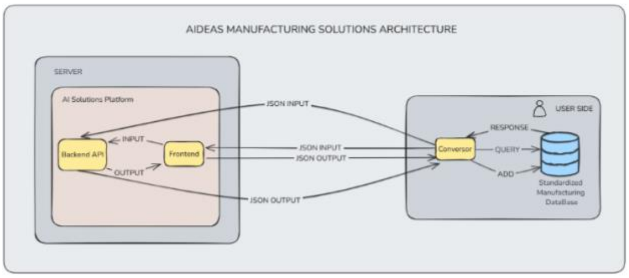

Figure 4. AIDEAS Manufacturing Solutions Architecture

The objective of this plan is to test the solutions in a way that allows the company to operate using an external database based on a standardized data model based on [54]. This approach enables the integration of company data without the need to directly access or rely on the centralized ERP system.

The AIDEAS Manufacturing Solutions Architecture (Figure 4) ensures a seamless data connection between the pilot and the algorithms server. By leveraging a standardized data model and seamless communication between components, this workflow enables the accurate assessment of AI results performance, reliability, and integration within real-world manufacturing scenarios.

The workflow for testing AI-based solutions within the Multiscan pilot phase begins with data preparation, where the Conversor retrieves relevant manufacturing data from the Standardized Manufacturing Database and converts it into a JSON input file tailored to the AI modules in the Backend API. During the pilot phase, these JSON files can be provided either through the Frontend, where users upload and manage data via an intuitive interface, or directly via the Backend API for automated integration testing. Once received, the Backend API processes the JSON input using embedded AI algorithms, generating output in JSON format for solution validation. If submitted through the Frontend, the output is displayed for user analysis and can be downloaded for further testing. If processed via the Backend API, the output is returned to the Conversor for integration into the database. Next, the Conversor converts the JSON output into SQL format, updating the Standardized Manufacturing Database to securely store validated solutions for future benchmarking. Finally, the pilot phase concludes with a review of the outputs, identifying areas for improvement and refining AI algorithms, workflows, or data formats to enhance performance in subsequent iterations.

This plan proposes testing AIDEAS solutions through an external, standardized database. This approach brings multiple advantages. Firstly, it enables the company to work independently from its central ERP system, thereby minimizing the risk of disrupting daily operations. It also simplifies data handling, enables controlled validation of results and supports integration with other tools or systems. Furthermore, it enhances scalability, as the same approach can be replicated across different plants or departments. It also accelerates the improvement cycle by facilitating more agile and transparent data access and analysis.

CONCLUSIONS

The AIDEAS project focuses on the comprehensive integration of AI within the manufacturing industry, with the aim of enhancing and optimizing various processes involved in production. This article outlines the steps undertaken to incorporate different AI models into distinct planning processes of the production process.

The main objective of this work was to investigate whether the integration of AI-based tools could improve SCM in manufacturing SMEs, in particular in the procurement, production and delivery processes, through a holistic framework (RQ1). The results obtained confirm that the AIDEAS framework enables improved decision-making throughout the entire production planning cycle. The AI-PO, AI-FO^{MPP}, AI-FO^{PS}, and AI-DO modules effectively address specific problems in the Source, Make and Deliver phases of the SCOR model, increasing efficiency, responsiveness and sustainability. Regarding the actual implementation in a real-world context (RQ2), the case study at Multiscan Technologies demonstrated that the AIDEAS framework can be successfully integrated into the day-to-day operations of an SME. The modular design and interoperability between the different tools made it possible to adapt the framework to existing business processes, while requiring some effort in data standardization and information flow management. Finally, with respect to the barriers and enabling factors identified (RQ3), the experience highlighted some difficulties, including: the complexity of AI technologies, the difficulty of building cross-platform compatible databases and resistance to operational change. At the same time, the main enablers were found to be the presence of a corporate culture oriented towards continuous improvement, the availability of well-organised production data and the strategic willingness to invest in digital solutions.

In conclusion, the proposed framework answers the three research questions positively, offering a concrete and replicable model for the integration of AI into SME manufacturing environment. Future lines of research will aim to further improve the framework's flexibility, adaptability and continuous learning capacity, in line with the principles of the circular economy and Industry 5.0.

MATCH AND CONTRIBUTION

This contribution directly contributes to the Special Session on "AI Driven Industrial Equipment Product Life Cycle Boosting Agility, Sustainability and Resilience" by presenting AI-based solutions developed within the AIDEAS project to optimize key manufacturing processes: procurement, fabrication, and delivery. Through a holistic framework that integrates mathematical optimization and AI algorithms, the work demonstrates how AI can enhance agility, sustainability, and resilience across the equipment lifecycle, with a focus on the manufacturing phase. A testing plan is proposed to validate the solutions in a real industrial setting, highlighting their practical impact and relevance, especially for small and medium-sized enterprises.

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