AI-based Solutions for Optimising Industrial Equipment Manufacturing

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Abstract
The AIDEAS project is concerned with the development of Artificial Intelligence (AI) technologies for optimising the entire phases of the industrial equipment lifecycle i.e., design, manufacturing, use and repair/reuse/recycle. This is aimed at enhancing the sustainability, agility, and resilience of European machine manufacturing companies. This paper focuses on the manufacturing phase of the industrial equipment lifecycle and thus presents the AIDEAS Industrial Equipment Manufacturing Suite, which consists of a set of AI-based solutions for optimising the procurement, fabrication, and delivery of industrial equipment. These solutions rely on powerful AI algorithms to provide optimal recommendations for component selection and procurement, enhance the process for manufacturing industrial machines and ensure smooth delivery of the equipment to the end-users. At the centre of these AI-based solutions is the AIDEAS Machine Passport, which binds the solutions together and facilitates seamless interaction and data exchange between them, thus ensuring that the output from one solution may be utilised as input in another solution. The AIDEAS Machine Passport is a critical element within the AIDEAS ecosystem as it ensures secure inter-phase data transfer and communication between the different phases of the industrial equipment lifecycle. These data flows serve as the basis for creating the industrial equipment footprint i.e., industrial equipment profile, which is an important element for achieving circularity in supply chains.

Keywords
Artificial Intelligence, Industrial Equipment Manufacturing, Procurement Optimisation, Fabrication Optimisation, Delivery Optimisation, Supply Chain Management

Introduction

The objective of the EU-funded AIDEAS project (www.aideas-project.eu) is to boost the sustainability and viability of European machinery manufacturers through the development and provision of a variety of AI tools and technologies to address different concerns across the entire phases of the industrial equipment lifecycle. Specifically, the AI technologies are applied to optimise the design, manufacturing, use and repair/reuse/recycle of industrial equipment. In the AIDEAS project, the AI technologies development methodology involves the development of four different software suites, one for each phase and with each suite containing a set of AI-based solutions for

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optimising different aspects relating to a phase of the industrial equipment lifecycle. It also involves the development of the Machine Passport, a generic solution that can be instantiated in different user companies and across the different phases of the industrial equipment lifecycle. The Machine Passport binds all the AI solutions together and manages component interactions and data exchange across the different suites. This paper focuses on the manufacturing phase of the industrial equipment lifecycle and thus presents the AIDEAS Industrial Equipment Manufacturing Suite, which consists of a set of AI-based solutions for optimising the procurement, fabrication, and delivery of industrial equipment. This ensures the utilisation of AI technologies to implement and obtain optimal strategies and approaches for machine component selection and purchase, production scheduling and resource allocation, and machine packaging, storage, and delivery, with the objective of achieving sustainability, agility, and resilience in the entire manufacturing process.

The optimisation of the procurement, fabrication, and delivery of industrial equipment is an important factor to consider in the supply chain operations in the production and manufacturing industry. Optimisation ensures that the most suitable component is selected, optimal purchasing plan is generated, and production resources are optimally allocated for the manufacture of industrial equipment in a way that guarantees smooth, efficient, and on-time delivery to the end-users and customers. This also guarantee high quality, waste reduction and enhanced logistics. Optimisation is achieved through the application of AI techniques, methodologies, and technologies across the manufacturing phase of the industrial equipment lifecycle. AI has its application across different domains, which also extends to smart manufacturing [1],[2]. According to [3], the application of AI and Machine Learning (ML) techniques has enhanced the optimisation of different manufacturing processes. In addition, the utilisation of AI technologies in smart factories has strengthened the potential of manufacturing systems [4]. The use of AI technologies in manufacturing gave rise to the concept of Industrial AI [5], which details how AI is implemented to monitor, control, and optimise industrial processes. As enumerated in [5], the main AI techniques in Industrial AI includes modelling, diagnostics, prediction, decision, optimisation, decision, and deployment. Furthermore, the study in [6] presents a comprehensive review of the applications of AI techniques across the entire industrial equipment lifecycle, with the most significant being Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), Bayesian Networks, Support Vector Machines (SVM) etc.

The rest of this paper is structured as follows: Section presents the State of the art and Section the AIDEAS Industrial Equipment Manufacturing Suite. In Section , the Machine Passport is presented, while Section concludes the document.

State of the Art

According to [3], the application of AI in industrial processes falls under three broad categories namely, AI-based process monitoring, AI-based process optimisation, and AI-based process control. While all three categories are important, the most important with respect to this paper is AI-based process optimisation, since it focuses on the use of AI to optimise industrial processes. Common applications of AI-based process optimisation include yield management, shopfloor scheduling, capacity optimisation etc., which are all vital aspects of supply chain management. The review conducted in [7] reveals Artificial Neural Networks (ANN), fuzzy logic models, and multi-agent systems as major AI techniques utilised in supply chain management. The research in [6] further details SVM, ANN, Multilayer Perceptron (MLP), Genetic Programming (GP), K-Nearest Neighbours (KNN), and Genetic Algorithms (GA) as the most prominent AI techniques in the manufacturing phase. The relevant studies on the AI approaches applicable to procurement, fabrication and delivery are presented in the next paragraphs.

In the 1950s, companies began experimenting with production methodologies to manage purchases and to decrease stock levels, leading to the development of Material Requirements Planning (MRP) by Joseph Orlicky in 1974 [8]. MRP is a system for managing manufacturing processes by ensuring the availability of materials while minimising costs. The advanced version, MRP II is a more comprehensive system, which considers factors like capacity planning and forecasting. It provides a holistic view of production processes, aiding informed decision-making. MRP and MRP II play crucial roles in production planning. Various studies have explored MRP, including Enns in [9], which analyses production lot size effects on MRP performance. Sadeghian in [10] introduces Continuous

MRP (CMRP), contrasting it with Discrete MRP (DMRP) and proposing three algorithms for CMRP. Uncertain market demand and production costs are addressed in articles like [11]. Yimsri et al. [12] highlights MRP's impact in medical material manufacturing, reducing planning time and errors. Challenges persist due to diverse production types and data sources. Efforts like Finite Capacity MRP (FCMRP) integration with scheduling algorithms and new algorithms demonstrate ongoing attempts to address these challenges.

With the introduction of the Industry 4.0 paradigms and the Smart factory concept, modern companies are subject to an increasingly rapid and changing market. For this reason, production site efficiency is a key factor in the success of a business. The ability to be able to react quickly to any anomalies and to be able to readjust the scheduling plan according to available resources enables companies to be able to guarantee delivery times to their customers [13]. In Smart factories where the amount of production data is high, the use of AI techniques for solving decision-making problems is a vital tool. The use of AI to solve scheduling problems is a hotly debated topic in the scientific community and has attracted many researchers to study the subject. The study in [14] shows that the most widely used AI techniques are Particle Swarm Intelligence (PSO), Neural Network (NN) and, especially in recent years, Reinforcement Learning (RL). The RL algorithms show high flexibility to solve production scheduling problems in different scenarios [15] even with different objective functions. One of the reasons why RL's popularity is growing in the scientific community in recent years is based on its low computational time to solve complex scheduling problems. There are several approaches that can be used, such as the single-agent approach [16], [17] or the multi-agent approach [18], [19], in which several agents make decisions in a virtual environment and can share knowledge with other agents.

Achieving optimal delivery of machine components and industrial equipment to end-users involves ensuring optimal packaging and storage. This is to attain sustainable production. The research in [20] utilises NN for achieving a low-carbon, energy-saving packaging design that enhances production and product usage. In [21], multimodal deep learning is applied to determine the most ideal packaging type for transporting products to ensure safety and waste reduction. In factories, finished products might require temporary storage in the warehouse before they are shipped to the customers. This brings up the need for storage to be done optimally prior to delivery. Ma et al. [22] propose an ensemble multi-objective biogeography-based optimisation (EMBBO) algorithm to solve the automated warehouse scheduling problem. Ren et al. [23] design a dual-objective warehouse optimisation model that quantifies the relationship between logistic and non-logistic factors. In [24], the authors applied randomised constructive heuristics (RCH) for the arrangement of packaging boxes in a shipping container. AI techniques have also been applied to enhance product delivery. The research in [25] presents a deep reinforcement learning algorithm (routing optimisation algorithm) for optimising delivery path. The authors in [26] present machine learning framework for optimising last-mile delivery routes. In [27], the authors utilise Random Forest, Bayes classifiers and Neural networks for the design of classifiers for the estimation of travel mode for a multi-modal journal planner.

AIDEAS Industrial Equipment Manufacturing Suite

The AIDEAS Industrial Equipment Manufacturing Suite consists of three optimisers (i.e., AI-based solutions) that aim to improve the manufacturing phase of the industrial equipment lifecycle, right from the point of component selection and procurement to parts fabrication and finally delivery to the final customer. The optimisers are listed below:

- AIDEAS Procurement Optimiser (AI-PO): An AI-based toolkit for optimising the inventory and purchase of materials and components that are required to build a machine and meet customer delivery dates.
- AIDEAS Fabrication Optimiser (AI-FO): An AI-based toolkit for optimising production scheduling and resource allocation by predicting production and setup times, operations dependencies, etc. allowing a near real-time response to environment changes like machine breakdowns, last minute customer orders and raw materials delays.

- AIDEAS Delivery Optimiser (AI-DO): An AI-based toolkit for optimising the packaging, storage, and delivery of products. This optimisation targets storage space, storage conditions, product transportation, logistics scheduling and planning.

The data flows and communication within the AIDEAS Industrial Equipment Manufacturing Suite is enhanced by the AIDEAS Machine Passport. Through the Machine Passport, the three optimisers receive data from shopfloor devices. In addition, the optimisers connect to other data sources such as Databases and ERP systems to extract data and information to be processed by the algorithms, to generate an output. In Figure 1, the interaction and communication flow between the optimisers, machine passport and shopfloor is presented.

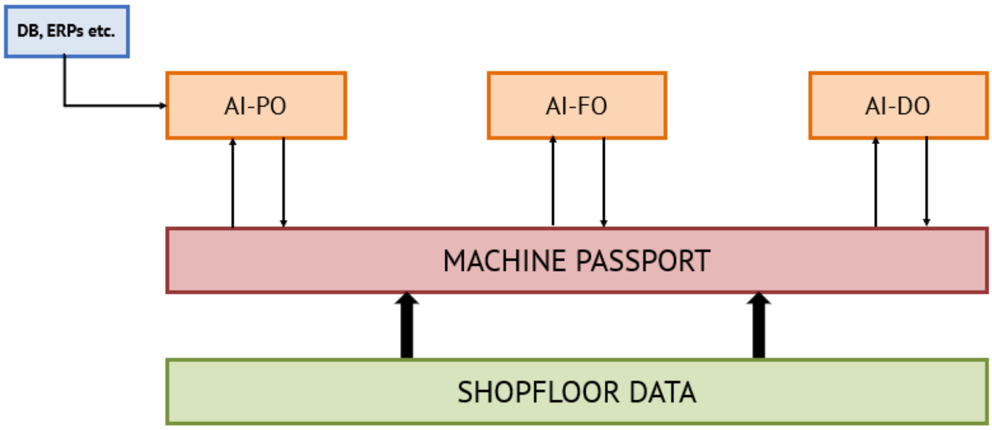

Figure 1. Communication flow within the AIDEAS Industrial Equipment Manufacturing Suite

In the next sub-sections, the AI-based solutions of the AIDEAS Industrial Equipment Manufacturing Suite are presented.

AI for Procurement Optimisation

The creation of the purchasing plan is an iterative process that depends on the status and completion of other administrative and manufacturing processes within a company, such as the production plan, demand forecasts and warehouse status. The AI-PO tool provides a link between these processes and at the same time obtains an optimised and updated procurement plan. AI-PO facilitates quick decision making by considering the purchasing process and the planned production process. This makes it possible to anticipate likely supply problems and help to improve production planning and scheduling. This is achieved through the quick provision of information, which allows the restructuring of the purchasing plan almost in real time.

AI-PO considers several data such as sources of materials (raw and intermediate), global plant production capacity, due dates, provider's delivery times, maximum lot capacity, scale prices and energy consumption, final product stocks and in-storage deposits, materials delivery times etc. This way, the MRP computed meets up with customer delivery dates and minimises raw and final product stocks. Another remarkable feature of AI-PO is the ability to perform calculations within short periods of time, to maintain the materials and update daily plan, thus allowing fast reactions and increased resilience to unexpected changes in industrial production plans.

In AI-PO, AI techniques related to metaheuristics are applied using a framework called FACOP (Framework for Applied Combinatorial Optimisation Problems). This framework provides a set of libraries that allow the composition of algorithms from independent parts or components through code injection techniques. This provides flexibility and allows the testing of different components when solving an optimisation problem. The use of AI techniques within AI-PO improves response times and maintains an up-to-date purchasing plan that responds to changes in the environment, such as late material arrivals, urgent orders, or order cancellations.

AI-PO provides the ability to obtain and update the procurement plan in a short execution time, which in turn speeds up production scheduling. The procurement plan links planning and production, as the latter depends not only on what is to be produced, but also on the status of material storage. AI-PO functions as a link between planning and production, allowing the delivery of materials to be controlled, while considering supplier capacity, prices, bulk purchase offers and delivery times. To ensure flexibility and scalability, AI-PO provides a REST API encapsulated in a docker container, making it cross-platform, and allowing communication with other applications using a widely known standard.

AI for Fabrication Optimisation

The AIDEAS Fabrication Optimiser (AI-FO) aims to optimise production scheduling and resource allocation by enabling near real-time response to changes in the environment, such as last-minute customer orders and raw materials delay, using AI technology. The advantage of machine learning models for solving complex optimisation problems such as production scheduling, classified NP-hard problems, lies in the quality of results and short computation time. There is also a need to retrain the model when the environmental conditions changes. From the production plan, information is extracted concerning the products to be manufactured in a predefined time frame. The input data include the processing cycles, where the processes and the related times for manufacturing a product are reported, and the availability and type of human resources involved in production. Other essential information for defining the scheduling problem is related to the constraint between the various activities, but also production constraints related to the production site such as machinery availability etc.

To optimise the production scheduling plan, it is important to know the information about the availability of raw material necessary for each manufacturing stage. This information is the key to the connection with the AI-PO solution. In particular, the AI-PO solution provides the delivery date of the materials, which enables the start of the various production processes required to complete the production order. Based on the input data, a Reinforcement Learning (RL) model is trained to solve the scheduling problem with the aim of minimising the production delays and makespan value. The output of the model is several scheduling plans with corresponding Gantt charts that allow the company's production manager to choose the most appropriate plan. From the production schedule that is generated, it is possible to extract data on the production end date, which is an input for the AI-DO solution to predict the delivery date of the order to the customer.

AI for Delivery Optimisation

The main objective of the AI-DO is to optimise the packaging, storage, and delivery of products to the end-users and final customers. The optimal delivery of products can be associated with optimal packaging and storage. Using AI technology, AI-DO aims to ensure waste reduction, reduction of packaging time, reduction of carbon footprints, cost-effective logistics, on-time delivery, reusability, and ease of recycling, which are all geared towards achieving sustainability in manufacturing operations. Optimal packaging, storage, and delivery impacts product planning, supplier’s capacity, plant capacity, scheduling, and shopfloor operations. To achieve optimisation of packaging, storage, and delivery, AI-DO collects and utilises several types of data. Packaging data includes packaging material, size, dimensions, capacity, product size and images. Storage data includes storage size, storage capacity, production frequency, material handling, and storage environmental conditions (such as temperature, pressure, humidity etc.). Delivery data includes production schedules, product orders, delivery schedules, and transport costs. It is important to mention that some of these data come from AI-PO and AI-FO.

These set of input data are used to train three different AI models to address packaging, storage, and delivery problems. The packaging model utilises data processing libraries such as NumPy and Pandas to preprocess and feed the data to the AI algorithm. The algorithms use the ensemble learning techniques to predict packaging results. The output prediction is of categorical classification type based on random forest regressors. The packaging model predicts optimal packaging designs, packaging material type and need for extra protection. The storage model is based on Genetic algorithms (belonging to a class of AI algorithms called Evolutionary Algorithms), which draws inspiration from biological evolution. The storage model facilitates the prediction and recommendation of optimal warehouse layout and optimal arrangement of products in packaging boxes and shipping containers. In addition, Augmented Reality (AR) functionalities is integrated into AI-DO to support the human worker in arranging machine components in packaging boxes and loading package boxes in the shipping container. Finally, the delivery model based on metaheuristics predicts the shortest delivery route with respect to different constraints such as carbon footprint, fuel consumption or delivery time etc. AI-DO addresses single product-single customer and multiple products-multiple customers deliveries.

AIDEAS Machine Passport

In the realm of modern manufacturing, the flow of data is akin to the lifeblood of efficient decision-making. As a critical component in the AIDEAS framework, the AIDEAS Machine Passport addresses the intricacies of data exchange across multiple dimensions of the manufacturing landscape. It explores how data formats, communication protocols, and the nature of data delivery are meticulously curated to enhance data compatibility, interoperability, consistency, and quality. It centres on the exchange of manufacturing data, spanning various manufacturing stages, involving key players in the supply chain (i.e., suppliers, manufacturers, and customers), and encompassing critical product life phases. The intricacies of data formats, communication protocols, and data delivery mechanisms are painstakingly crafted to facilitate seamless data exchange. The Machine Passport introduces a mechanism for keeping track of the machine conditions and the overall operations across the manufacturing phase of the industrial equipment lifecycle. The data and knowledge gathered during this process is essential for improving the procedures at specific stages of the manufacturing phase, foreseeing possible issues and eradicating bottlenecks and inefficiencies. This makes it possible to use the data and knowledge obtained in one stage of the manufacturing phase to enhance another next stage.

The AIDEAS Machine Passport is a groundbreaking concept that heralds a new era of data management. In particular, the Machine Passport operates as an intelligent platform, designed to oversee multi-source, large-scale data acquisition, management, and sharing. The Machine Passport operates not merely as a tool but as the very essence that binds all the different AI-based solutions together. As different solutions contribute their unique insights, the Machine Passport assumes the responsibility of summarising, and presenting the most relevant information. Its sphere of influence extends to different devices and tasks, particularly those related to the manufacturing phase of the industrial equipment lifecycle. Unified standard service modelling techniques underpin its architecture, ensuring that data remains compatible, interoperable, consistent, and of the highest quality. Within the manufacturing phase, the Machine Passport manages large-scale data flows using artificial intelligence algorithms. This is crucial for decision-making, which may also influence other phases of the industrial equipment lifecycle. At the centre of the Machine Passport are powerful databases such as MongoDB and PostgreSQL, which communicates with the Machine Passport via RESTful APIs and guarantees scalability, security, and interoperability. The use of RESTful APIs makes it easier to store and retrieve requests, allowing for smooth data flow and integration in the Machine Passport. An important mention is the concept of digital trusted datasets; a major contribution to the AIDEAS framework, which is significant for creating the Machine Passport and ensures seamless inter-phase data exchanges within the industrial equipment lifecycle. The Machine Passport guarantees trust by ensuring data traceability and exchange throughout the phases of industrial equipment lifecycle.

Conclusions

In this paper, the AIDEAS Industrial Equipment Manufacturing Suite has been presented. It consists of three main AI-based solutions referred to as optimisers, which utilises AI techniques and technologies to enhance component procurement, parts fabrication, and delivery of industrial equipment to end-users and final customers. Thanks to the utilisation of AI technology, the optimisers provide recommendations and predict optimal results to boost the manufacturing of industrial equipment and ensure on-time delivery to the customers. The prediction of optimal results relies on efficient and quality data, which is generated and exchanged between different actors (manufacturers, suppliers, customers etc.) in the manufacturing supply chain. This is where the AIDEAS Machine Passport comes into play as the data flows serve as the basis for creating the industrial equipment footprint i.e., industrial equipment profile, which is an important element for achieving circularity in supply chains.

The future work within the manufacturing phase of the industrial equipment lifecycle is the testing and validation of the different optimisers in different real-world industrial scenarios defined in different pilots. This is to ascertain the functionalities of the developed AI-based solutions. This also involves the specification of different evaluation metrics for assessing the performance of the algorithms within the pilot cases. Another interesting aspect of this activity is the integration of the algorithms with legacy systems, which involves the investigation of novel mechanisms for achieving the integration. In conclusion, the industrial equipment lifecycle data gathered over time enhances decision-making regarding recycling or remanufacturing. Through this, the AIDEAS project supports European machine manufacturers to achieve sustainability, agility, and resilience in their operations.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

References

[1] Rautaray, S. S., & Agrawal, A. (2015). Vision based hand gesture recognition for human computer interaction: a survey. *Artificial intelligence review*, *43*(1), 1-54.

[2] Cambria, E., & White, B. (2014). Jumping NLP curves: A review of natural language processing research. *IEEE Computational intelligence magazine*, *9*(2), 48-57.

[3] Teerasoponpong, S., & Sugunnasil, P. (2022, January). Review on Artificial Intelligence Applications in Manufacturing Industrial Supply Chain–Industry 4.0's Perspective. In *2022 Joint International Conference on Digital Arts, Media, and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT & NCON)* (pp. 406-411). IEEE.

[4] Chen, M., Zhou, P., & Fortino, G. (2016). Emotion communication system. *IEEE Access*, *5*, 326-337.

[5] Ding, H., Gao, R. X., Isaksson, A. J., Landers, R. G., Parisini, T., & Yuan, Y. (2020). State of AI-based monitoring in smart manufacturing and introduction to focused section. *IEEE/ASME Transactions on Mechatronics*, *25*(5), 2143-2154.

[6] Elahi, M., Afolaranmi, S. O., Martinez Lastra, J. L., & Perez Garcia, J. A. (2023). A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment. *Discover Artificial Intelligence*, *3*(1), 43.

[7] Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, *122*, 502-517.

[8] Orlicky, J. A., 1974. *Material Requirements Planning: The New Way of Life in Production and Inventory Management.* s.l.:McGraw-Hill, Inc..

[9] Enns, S. T., 1999. The effect of batch size selection on MRP performance. *Computers & Industrial Engineering,* 37(1-2), pp. 15-19.

[10] Sadeghian, R., 2011. Continuous materials requirements planning (CMRP) approach when order type. *Applied Soft Computing,* 11(8), pp. 5621-5629.

[11] Paraskevopoulos, D., Karakitsos, E. & Rustem, B., 1991. Robust capacity planning under uncertainty. *Management Science,* 37(7), pp. 787-800.

[12] Yimsri, B., Watanapa, A. & Wiyaratn, W., 2022. *Flexible applications of MRP based prototyping software for production planning and diversified raw material inventory management.* s.l., s.n.

[13] Serrano-Ruiz, J. C., Mula, J., & Poler, R. 2021. "Smart manufacturing scheduling: A literature review." *In Journal of Manufacturing Systems* (Vol. 61, pp. 265–287). Elsevier B.V.

[14] Del Gallo, M., Mazzuto, G., Ciarapica, F. E., & Bevilacqua, M. 2023. "Artificial Intelligence to Solve Production Scheduling Problems in Real Industrial Settings: Systematic Literature Review." *Electronics*, 12(23), 4732.

[15] Kayahnm, B.M., Yildiz G. 2021. "Reinforcement learning applications to machine scheduling problems: a comprehensive literature review". *Journal of Intelligent Manufacturing, pp 905–929.*

[16] Vijayan, S.; Parameshwaran Pillai, T. 2022. "Application of Machine Learning algorithm in a multi-stage production system." *Transactions of Famena*, 46, 91–102.

[17] Elsayed, E.K.; Elsayed, A.K.; Eldahshan, K.A. 2022. "Deep Reinforcement Learning-Based Job Shop Scheduling of smart manufacturing". *Computers, Materials & Continua.* 73, 5103–5120.

[18] Yu, T.; Huang, J.; Chang, Q. 2021. "Optimizing task scheduling in human-robot collaboration with deep multi-agent reinforcement learning." *Journal of Manufacturing Systems.* 60, 487–499.

[19] Wang, X., Zhang, L., Lin, T., Zhao, C., Wang, K., & Chen, Z. 2022. "Solving job scheduling problems in a resource pre-emption environment with multi-agent reinforcement learning." Robotics and Computer-Integrated Manufacturing, 77.

[20] Zhang, S. (2022). Research on energy-saving packaging design based on artificial intelligence. *Energy Reports*, *8*, 480-489.

[21] Meiyappan, P., & Bales, M. (2021). Position paper: Reducing Amazon's packaging waste using multimodal deep learning.

[22] Ma, H., Su, S., Simon, D., & Fei, M. (2015). Ensemble multi-objective biogeography-based optimization with application to automated warehouse scheduling. *Engineering Applications of Artificial Intelligence*, *44*, 79–90.

[23] Ren, Q., Ku, Y., Wang, Y., & Wu, P. (2023). Research on design and optimization of green warehouse system based on case analysis. *Journal of Cleaner Production*, *388*, 135998.

[24] Gajda, M., Trivella, A., Mansini, R., & Pisinger, D. (2022). An optimization approach for a complex real-life container loading problem. *Omega*, *107*, 102559.

[25] Xing, E., & Cai, B. (2020, October). Delivery Route Optimization Based on Deep Reinforcement Learning. In *2020 2nd International Conference on Machine Learning, Big Data and Business Intelligence (MLBDBI)* (pp. 334-338). IEEE.

[26] Florio, A. M., Özarık, S. S., & da Costa, P. R. O. (2021). A machine learning framework for last-mile delivery optimization. *Technical Proceedings of the 2021 Last Mile Routing Research Challenge (pp. XII. 1–XII. 19). MIT Libraries.*

[27] Mäenpää, H., Lobov, A., & Lastra, J. L. M. (2017). Travel mode estimation for multi-modal journey planner. *Transportation Research Part C: Emerging Technologies*, *82*, 273-289.