Ref. Ares(2024)2353996 - 29/03/2024

D4.1 – Industrial Equipment Manufacturing Suite v1

WP4 – BUILD: AIDEAS 4 Industrial Equipment Manufacturing

Co-funded by the European Union

Document Information

GRANT AGREEMENT NUMBER	101057294	ACRONYM	AIDEAS
FULL TITLE	AI Driven Industrial Equipment Product Life Cycle Boosting Agility, Sustainability and Resilience		
START DATE	01-10-2022	DURATION	36 months
PROJECT URL	https://aideas-project.eu/		
DELIVERABLE	D4.1 – Industrial Equipment Manufacturing Suite v1		
WORK PACKAGE	WP4 –BUILD: AIDEAS 4 Industrial Equipment Manufacturing		
DATE OF DELIVERY	CONTRACTUAL 31-Mar-2024	ACTUAL	29-Mar-2024
NATURE	Other	DISSEMINATION LEVEL	Public
LEAD BENEFICIARY	TAU		
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TARGET AUDIENCE	1) AIDEAS Project partners; 2) industrial community; 3) other H2020/ Horizon Europe funded projects; 4) scientific community		
DELIVERABLE CONTEXT/ DEPENDENCIES	This document is the first version and is part of the series of deliverables on the “Industrial Equipment Manufacturing Suite”. Its relationship to other documents is as follows: - D4.2: Industrial Equipment Manufacturing Suite v2 (M24) - D4.3: Industrial Equipment Manufacturing Suite v3 (M36)		
EXTERNAL ANNEXES/ SUPPORTING DOCUMENTS	None		
READING NOTES	None		
ABSTRACT	D4.1 aims to present the features, technical specifications and implementation status of the toolkits developed in the Industrial Equipment Manufacturing Suite. There are three toolkits presented in this suite, namely: Procurement Optimiser (AI^{PO}), Fabrication Optimiser (AI^{FO}), and Delivery Optimiser (AI^{DO}).		

Document History

VERSION	ISSUE DATE	STAGE	DESCRIPTION	CONTRIBUTOR
0.1	09-Feb-2024	ToC	Table of Contents	TAU
0.2	06-Mar-2024	Draft	First draft of the document - Contributions from all concerned partners	TAU, ITI, UNIVPM, CERTH
0.3	12-Mar-2024	Review	Conduction of Internal Reviews and Plagiarism check	IANUS, UNIVPM, UPV
0.4	20-Mar-2024	Draft	2nd Draft addressing the comments by the reviewers	TAU
1.0	29-Mar-2024	Final Doc	Quality check and issue of final document	CERTH

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ABBREVIATIONS/ACRONYMS

AI	Artificial Intelligence
ANN	Artificial Neutral Networks
API	Application Programming Interface
AR	Augmented Reality
CNC	Computer Numerical Control
CSV	Comma Separated Values
DB	Database
DO	Delivery Optimiser
EDD	Earliest Due Date
ERP	Enterprise Resource Planning
FO	Fabrication Optimiser
GA	Grant Agreement
KPI	Key Performance Indicator
ML	Machine Learning
MP	Machine Passport
MRP	Material Requirements Planning
NSGA	Non Dominating Sorting Genetic Algorithm
PO	Procurement Optimiser
SQL	Structured Query Language
UI	User Interface
XAI	Explainable Artificial Intelligence

Executive summary

WP4 (BUILD: AIDEAS 4 Industrial Equipment Manufacturing) is concerned with the development of AI technologies to support the manufacturing phase of the Industrial equipment lifecycle. This is to enhance European machinery manufacturing companies' sustainability, agility, and resilience.

This deliverable describes the features, functionalities, technical specifications, and implementation status of the toolkits developed in the Industrial Equipment Manufacturing Suite. This includes the Procurement Optimiser (AI^{PO}), Fabrication Optimiser (AI^{FO}), and Delivery Optimiser (AI^{DO}). In this deliverable, the technical progress regarding the development of the different toolkits is presented. The main AI algorithms utilised in the toolkits are also specified. In addition, the current implementation of the AIDEAS Machine Passport in relation to the manufacturing phase of the industrial equipment lifecycle is also presented. Other information relating to the architecture and viewpoints of the different toolkits can be found in D2.2: AIDEAS Viewpoints v2 (M18). Further information about the toolkits is available via (https://viewpoints.aideas-srv.cigip.upv.es/)

This deliverable is the first version and is part of the series of deliverables on the "Industrial Equipment Manufacturing Suite". It will be updated in M24 as D4.2: Industrial Equipment Manufacturing Suite v2 and in M36 as D4.3: Industrial Equipment Manufacturing Suite v3.

Document structure

Each section of the document contains the information of one of the solutions, with a final section for conclusions, namely:

Section 1: Procurement Optimiser

Section 2: Fabrication Optimiser

Section 3: Delivery Optimiser

Section 4: Machine Passport

Section 5: Conclusion

1. Procurement Optimiser

1.1 Overview

The AIDEAS Procurement Optimiser aims to modernize the way industry produces, acquires, and recycles products. In this context, AI^{PO} will allow a fast plan adaptation to most changes that may occur in the providers' environment, raw or semi elaborated materials procurement and production. AI^{PO} will provide optimisation algorithms to quickly calculate and maintain updated MRP (Material Requirements Planning), also considering the possibility of reusing recycled or refurbished components in production.

The Procurement Optimiser generates a list of dated necessities of materials based on an initial production plan and the minimum stock level of each material. Given these necessities and the current state of the material stocks, the application uses the suppliers and the possible offers together to obtain a solution, which consists of a list of dated purchases of materials, including selected prices, offers or discounts and providers. Procurement Optimiser obtains optimised solutions for the problem based on the KPIs or the pilot priorities. As part of the results, the procurement optimiser will deliver a list of alerts about materials that cannot be received on time, pointing out changes needed in the production plan.

1.2 Features

- **Data import from different sources**: The solution includes the capability of obtaining information from different sources like ERP API, databases, text files, excel files, etc.
- **Data validation and formatting**: Data imported from different sources is formatted using a standardized model that will be shared among all solutions. This facilitates the connection between solutions and the connection with externals tools.
- **Calculating MRP related to production plan**: The main goal here is to calculate the procurement plan to fulfil the current production plan. This production plan can be delivered from organisation sources (such as ERP, database, etc.) or from other solutions (like AI^{FO}).
- **Include recycled or refurbished materials**: The MRP considers recycled or refurbished materials as a material source as a way of extending their life cycle.
- **Selection of supplier**: As part of the procurement plan calculation, the best supplier for each material will be selected, while considering not only the delivery times but also special offers and bulk prices.
- **Fast Response to changes**: To have an adaptative procurement plan, it is necessary to have the capacity to carry out necessary calculations in a short time. This will allow the plant to be adapted and changed when unforeseen events occur, like delay in delivery times or high priority products added to the current production plan, etc.

1.3 Technical specifications

The solution is composed of different specialized services, with each service providing functionality specific to a function or feature.

The import service will connect to different data sources and obtain raw data in different formats. The service will also validate input data and format it to the standardized common format. Another service (Calculation service) will calculate the procurement plan. Finally, the export service will oversee formatting and storage of the generated information in different data containers and will communicate the information to other solutions (like AI^{FO}).

AI^{PO} will have a service to interact with users, which will provide the user interface and connect with other services as needed. The user interface service usually called frontend service will be developed using REACT, while the different backend services will be developed mostly using the .NET framework.

AI^{PO} solution will be tested in two pilots, using the standardized data model. The only difference between these pilots is the mail service that will be developed to contact suppliers and request prices in one of them. The mail service will also include a separate user interface service that will allow a user to interact with suppliers, read and receive emails from them. The backend service will be developed mostly in python and the front end in REACT. Docker containers will be used to package and execute each service.

1.4 Implementation status

1.4.1 Current implementation

The current implementation of AI^{PO} includes the following:

- Design of a common data model.
- Generation of initial datasets for testing services and algorithms.
- Specific modification of the data model to accommodate the mail negotiation service.
- User interface designs (mockups).
- User interface for procurement calculation.
- User interface for mail negotiation service.
- User interface services.
- General user interface (1st version).
- Mail negotiation user interface (1st version).
- Import services (under development).
- Export services (under development).
- Calculation service (under development).
- Calculation API ready but not connected to import services.
- Data is fed to the calculation service manually.

Link to the GITLAB repository of the solution: https://gitlab-cigip.alc.upv.es/aideas/industrial-equipment-manufacturing/po-procurement-optimiser

1.4.2 Next developments

The future development and implementation of AI^{PO} will include the following:

- Finalize import service (to facilitate the testing of the calculation service in pilots).
- Finalize export service (to connect results to other solutions and to store results in pilots).
- Test algorithms with data from pilots and modify algorithms if necessary.

- Parametrize algorithms for each pilot, using data read from each pilot to run parametrization and training experimentation.
- Connect user interfaces with services.
- Test user interfaces in pilots and modify the UI if necessary.
- Perform integration tests for all services.
- Package services with docker.

2. Fabrication Optimiser

2.1 Overview

The AIDEAS Fabrication Optimiser (AI^{FO}) is a toolkit that ensures the optimisation of production scheduling and resource allocation using AI technologies to predict production and setup times, operation dependencies etc., that guarantees near real time response to changes such as machine breakdown, last minute customer orders, raw material delays etc. In the context of the AIDEAS project, AI^{FO} aims to realize two different solutions for optimizing production processes.

The first solution uses PAMA S.p.A. as a pilot (**Solution1**) and aims to optimise the machining of large components, which takes a long time and often leads to delays in delivery dates. The developed solution aims to optimise material removal parameters on a 3-axis CNC machine to reduce the number of re-machining operations. Two Artificial Neural Networks (ANN) were trained to predict the amount of material to be removed from two critical areas of the component. The solution considers several factors as input (length, weight, temperature, etc.) to return the correction to be made every 500mm in height.

The second solution uses MULTISCAN and BBM as pilots (**Solution2**). Here, the tool takes various manufacturing data from different sources to generate an intelligent scheduling plan that optimises the use of resources internally during the various machine production phases. The solution will also generate the master production plan using a mathematical programming model.

2.2 Features

Solution1

The main features and functionalities of AI^{FO} (Solution1) are:

- **Input Data**: An easy and intuitive user interface where the operator can enter measurement values and avoid making mistakes.
- **Data Validation and Preprocessing**: The data before being processed by the model will be validated and pre-processed to confirm the parameters of the pre-trained models.
- **Generation of the corrective parameters**: This feature allows the company to evaluate the material quantity to be removed to avoid subsequent reworking of the component.
- **Data Export**: The results of the AI models are saved in a cloud repository as Excel file according to the template provided by the company.

Within large machinery manufacturing companies, it can happen that one or more processes slow down production due to non-conforming parts. Specifically, in the machining of metallic materials, processes may fail to guarantee the technical requirements due to various internal and external factors (e.g. wear and tear, deformation due to temperature, weight, etc.). The proposed solution aims to take several factors into account and based on historical data, predict the correction to be made to the component to reduce the number of re-manufacturing steps. This will ensure greater control over production and help the company to meet delivery dates. The tool also provides for a report (excel file) to be generated for each machining process. It contains all the information on the component's measurements and other useful data for the company. These reports are saved on a drive shared with the company and, in addition, at each iteration, the datasets used for training are updated with new machining operations. This last aspect is important because it allows the models to be re-trained periodically to improve the solution.

Solution2

The main features and functionalities of the AI^FO (Solution2) are:

- **Import data**: Import data from different sources (Microsoft SQL database, Excel, CSV etc.)
- **Data validation and preprocessing**: This allows the input data to be validated to ensure that it is in the correct format. It also pre-processes the data to make it ready for the AI model input.
- **Generation of a new production plan**: This allows a production scheduling plan to be generated based on the results of the main production plan and the results of the AI^PO solution. It constitutes the production/assembly plan for the machines, allocates the necessary resources for implementation and sets the theoretical end date of production.
- **Generation of a new scheduling plan**: This allows the generation of a master production plan based on production orders, production forecasts and resource availability.
- **Data Export**: Saving the result on Machine Passport and in the company database.

Today's production environments are subject to various events that generate delays in production or otherwise a deviation between the state of production and what was planned. The solution allows the generation of a production scheduling plan that optimises production sequences, resources, space, and operators. An AI model will generate the sequence of production/assembly activities guaranteeing a good solution in terms of resource utilisation, adherence to delivery dates and calculation times. It will thus allow rescheduling of activities if there are unforeseen abnormal events during the manufacturing phase. In the case of the MULTISCAN pilot, the tool also provides the option of generating the master production plan. For this functionality, a mathematical programming model was developed that interacts with the AI model for scheduling by providing input data.

The results of the solutions will include the production and scheduling plan, the relevant Gantt chart and resource utilisation diagrams, which will allow the company to assess the efficiency of the production site more effectively and with a data-driven approach. Finally, the results will be saved on the company database.

2.3 Technical specifications

The backend of the AI^FO solutions is implemented using Python 3.8.10 and are both new developments with no background.

Solution1

The purpose of this solution is to guarantee the tolerance levels required by design for large components. To do this, all available historical machining data was collected to create two datasets. The data is imported into Python using the Pandas and Openpyxl libraries. Given the different orders of magnitude between one input parameter and another, the input data to the models are standardized using the “StandardScaler” function of the sklearn library. The two datasets were used for training the AI models. Two regression models were created using MPLRegressor (also from the sklearn library), which predicts the amount of material to be removed to avoid subsequent rework of the component. The data is then saved in Excel format (i.e., Excel reports) containing all the parameters used by the model and others. The reports comply with the template provided by the company and are also saved on a common driver platform so that developers and users can access them.

Since the solution is to be used by non-expert operators, the tool provides a single endpoint built with the Flask library. The operator will feed the component measurement data to the REACT interface, which will communicate with the listening endpoint and return the values predicted by the model. As the containerisation solution used most frequently, Docker is used for packaging and testing code. The packed program's deployment in the runtime environment is also made easier by Docker, which is supported by a broad variety of deployment tools and technologies.

Solution2

This solution generates scheduling plans that ensure adherence to delivery dates and utilisation of available resources, materials, and space. The solution considers different parameters such as list of machines in catalogue, operation activities, operation constraints, material constraints, operators available for each shift, type of operators, production plant constraint. All this data is stored in a Microsoft SQL database in the case of MULTISCAN pilot. Input and output data comply with the standard proposed in Andres et al. (2021), to ensure information exchange with AI^{PO} and AI^{DO} solutions. The tool will also provide the possibility to realize the master production plan. For the realisation of this functionality, a mathematical programming model using the Pyomo library was created. It will also consider several parameters such as customer orders, planned orders, resource availability, etc.

A heuristic algorithm has been developed for the generation of the scheduling plan. This algorithm schedules tasks based on EDD (Earliest Due Date) logic, i.e. it prioritizes tasks that have the earliest delivery date. For its realisation, the Pandas and NumPy libraries were used, and for the graphical representation of the results, Matplotlib was used. The scheduling plans generated by the heuristic algorithm are not optimised but will be used to train the AI model in the next months. This model will use Reinforcement Learning technology and will be implemented in Python with the help of the Gym and TensorFlow libraries. For this solution, more than one endpoint must be realized that communicates with the REACT front end. Docker is also used for code packaging.

2.4 Implementation status

2.4.1 Current implementation

The current implementation of AI^{FO} for Solution1 and Solution2 includes the following:

Solution1

- Creation of the training and testing datasets.
- Import data function.
- Preprocessing data function.
- Data elaboration using the two AI models.
- Data export and storage.
- Endpoint and API communication.
- UI realized with REACT.

- Packaging of code with Docker.

Link to the GITLAB repository of the solution: https://gitlab-cigip.alc.upv.es/aideas/industrial-equipment-manufacturing/fo-fabrication-optimiser

Solution2

- Heuristic algorithm to generate a non-optimal scheduling plan.
- Production plan model.
- Microsoft SQL Database realisation according to standard proposed in Andres et al. (2021).

Link to the GITLAB repository of the solution: https://gitlab-cigip.alc.upv.es/aideas/industrial-equipment-manufacturing/fo-fabrication-optimiser

2.4.2 Next developments

The future development and implementation of AI^{FO} for Solution1 and Solution2 will include the following:

Solution1

- Collect the feedback from the pilot.
- Use the tool to collect data to re-train the models. In this way, it will be possible to improve the overall performance of the solution.

Solution2

- Realisation of the AI model to solve the scheduling problem.
- Export data function.
- Communication with AI^{PO}, AI^{DO} and Machine Passport solutions.
- UI realisation.
- Packaging of code with Docker.

3. Delivery Optimiser

3.1 Overview

The AIDEAS Delivery Optimiser (AI^{DO}) is a toolkit that ensures the optimisation of the storage and delivery of products. It provides AI-based solutions for optimizing the packaging, storage, and delivery of industrial equipment. AI^{DO} provides AI applications that support users with optimised plans and strategies on logistics for the delivery of products to customers. AI^{DO}'s optimisation targets storage space, storage conditions, product packaging, product transportation, warehouse optimisation, container loading and unloading, logistics scheduling and planning. The goal is to maximise the agility in the manufacturer-customer supply chain. This will bring about cost savings, waste reduction and maximisation of energy consumption.

3.2 Features

The main features and functionalities offered by the AIDEAS Delivery Optimiser includes the following:

- **Import Data**: This facilitates the reading of data from different sources such as databases, ERPs, files etc.
- **Data Validation and Preprocessing**: This validates the training data and ensures that the input data is in the correct format before it is fed into the AI model.
- **Create and Export Respective ML Models**: This provides different ML models, which train on the available pre-processed data to make predictions for optimising product packaging, storage, and delivery.
- **Create Predictions and Display Results**: This facilitates the prediction of optimal storage, delivery and packaging with new data using the trained models.

The main problem that can be solved with the AIDEAS Delivery Optimiser is the provision of optimal recommendations for packaging the product, maximizing the utilisation of the shipping container volume, and achieving a cost-effective product delivery. Specifically, the user of the solution can:

- Optimise cargo space (i.e., maximise container volume utilisation).
- Ensure security and integrity of product using the most suitable packaging materials.
- Achieve environmentally friendly product delivery.
- Reduce wastes and energy costs.

The optimal packaging of the product, using the most suitable packaging materials, ensures that the security and integrity of the product can be guaranteed, either during the process of storage or transportation of the product. The consideration around security and integrity is to ensure that the product is packaged in a manner that supports the weight of the products when stacked on top of one another during transport and to also ensure protection from light and moisture. In addition, the use of the most suitable packaging materials limits the movement of products inside packaging boxes, while in transit, to prevent product damage. This is very important for fragile products. Following optimal product packaging, the AIDEAS delivery optimiser provides recommendations for arranging the products in within the shipping container in a manner that helps the user to maximise the container volume (i.e., cargo space), such that user can make the most of the available space, thereby reducing freight and logistics costs. The recommendations provided by the delivery optimiser consider different constraints such as customer priority (i.e., the order of delivering the products to different customers), cargo stability, load-bearing capacity, weight limits, stackability etc. To enhance the features of the AIDEAS delivery optimiser and by utilising AR, it is planned to include functionalities that aid the human worker to skilfully load and unload the products to/from the shipping container. The primary objective remains the optimisation of the total volume of the shipping container (i.e., cargo).

3.3 Technical specifications

The data for packaging recommendation consists of multiple dimensions which include product dimensions, weight, fragility (binary value), atmospheric seal (binary value), storage time, packaging material, extra protection, and environmental impact. This data has been used to train AI models, which predict the most suitable packaging material, the extra protective material (in case extra protection is required), and the environmental impact of the packaging solution. Other data includes box size, stackability (binary), and rotatability. Rotatability defines the level of freedom to which the product package can be rotated before being placed. For instance, a product with the limitation 'this side up' can only be rotated around one axis (z-axis). The AI models for packaging recommendations have been selected from the sklearn library. The class of algorithms are selected from ensemble learning, namely the random forest classifier. This works by using a collection of decision trees where each tree is trained on a subset of the data, and the final prediction is an average of that of all the trees. The model configurations were then saved and deployed to the backend of the AI^{DO} to provide recommendations according to the user inputs. The outputs of the predictions, along with other historical data will then be stored in the database for bookkeeping purposes.

As it concerns storage optimisation, the data is accepted separately for the container and the product. The data for the container includes dimensions and weights limits, while that of the product consists of dimensions, weight, stackability, rotatability, loading priority and customer orders. The stackability and rotatability information about each product is very important. The rotatability specifies the effective length, width, and height of a product. The AI model for cargo space optimisation is based on Non-dominated Sorting Genetic Algorithm (NSGA-II). For python-based evolutionary algorithms, there are open-source libraries like pymoo. However, pymoo couldn't be utilised for the cargo space optimisation problem because it does not provide the freedom to handle constraints such as rotation constraints. To address this, it was necessary to come up with an in-house implementation of Genetic Algorithm. In this self-implemented algorithm, a diploid representation of chromosomes is utilised, considering both the order and rotation of the package boxes. A modified version of the "deepest bottom-left with fill packing algorithm" is crafted to transform individuals into a 3D solution. According to the solution statics, they are tabulated as decreasing order of volume utilisation on the Frontend, and the user can then select the best solution as desired. The loading layout provided based on the solution selected can be visualised on the browser.

The data for delivery recommendations includes production schedules, delivery schedules, product orders, and transport costs, some of which will be made available by the AI^{DO} and AI^{FO} solutions. This data is fed into the AI model for delivery recommendations, for the provision of optimal delivery routes based on customer requirements and several constraints. The delivery model works based on metaheuristics (Genetic Algorithm) to predict the shortest and optimal delivery route, considering different constraints such as carbon footprints, fuel consumption, delivery times etc.

The backend of the AI^{DO} is developed using Django framework. The backend provides the endpoints with which the frontend can communicate and send requests and obtain the results. The frontend for AI^{DO} was created with the REACT Framework, since it is extremely versatile and easy to use. For packaging and testing purposes, docker is used since it is the most widely used containerisation solution. Docker also makes it easy to deploy the packaged application into the runtime environment and is widely supported by deployment tools and technologies.

3.4 Implementation status

3.4.1 Current implementation

The current implementation of AI^{DO} includes the following:

- Generation of synthetic training datasets for AI model training.
- Implementation of data acquisition and data preprocessing functions.
- Upload and data visualisation from CSV.
- UI development for receiving user inputs and visualising AI model outputs.
- Development of AI models for providing packaging recommendations (materials: Paperbox, Corrugated box, Cardboard box, Polyethylene package, Plastic box, Plastic wrap etc., and extra protection: Bubble wrap, Foam beans, Paper fill, Instapak solution, Air pillow).
- Development of AI models for cargo space optimisation. This provides the solutions for the product layout and arrangement within the cargo space.
- Development of AI models for product delivery recommendations.

Link to the GITLAB repository of the solution: https://gitlab-cigip.alc.upv.es/aideas/industrial-equipment-manufacturing/do-delivery-optimiser

3.4.2 Next developments

The future development and implementation of AI^{DO} will include the following:

- Finalisation of User AI^{DO} User Interface
- Communication with other solutions such as AI^{PO}, AI^{FO}, and the Machine Passport. Communication with the Machine Passport will form the basis for creating the product footprint, which can then be used to make decisions regarding maintenance, product recycling, reuse or decommissioning at the end-of-life of the product.
- Enhancement of packaging recommendations to include an analysis of environmental impact assessment. This will ensure that the user can choose from multiple packaging options based on the need to have a reduced environmental impact or to have the most optimal packaging.
- Integration of AR functionalities to support the human worker with instructions on how to load and unload the products into/from the shipping container.
- Testing and validation of AI^{DO} in the pilots, and modification/refactoring of AI^{DO} solution based on pilot feedback.

4. Machine Passport

4.1 Overview

The Machine Passport's manufacturing task is a specialized module designed to streamline data flow across all manufacturing stages. It's a user-friendly platform that enhances collaboration among suppliers, manufacturers, and customers by providing clear, actionable insights. Its primary goal is to facilitate a transparent exchange of data throughout the product's life phases, from conception to delivery, ensuring that every stakeholder has the necessary information for informed decision-making, you can find more detailed information on D5.1 – Industrial Equipment Use Suite v1.

4.2 Features

The manufacturing task of the Machine Passport introduces a robust set of features:

- **Data Exchange Harmonisation**: Standardizes the exchange of data, ensuring that all parties speak a common language.
- **Unified Communication Protocols**: Implements industry-standard protocols to ensure seamless interoperability between systems.
- **Data Quality Assurance**: Maintains high standards of data integrity and consistency throughout the manufacturing process.
- **Collaborative Platform**: Encourages active collaboration between all supply chain participants, enhancing overall productivity.
- **Enhanced Decision-Making**: Employs Explainable AI (XAI) to provide clarity on data-driven decisions, fostering a trusted environment.

4.3 Technical specifications

The Machine Passport's manufacturing task is built on a technical infrastructure that ensures efficiency and reliability:

- **Multi-Source Data Integration**: Gathers data from various manufacturing stages and parties, offering a comprehensive view.
- **Service Modelling Techniques**: Utilizes advanced modelling to maintain data compatibility and quality across systems.
- **Explainable AI (XAI) Application**: Leverages XAI for greater transparency in the decision-making process, making complex data understandable.

4.4 Implementation status

4.4.1 Current implementation

Currently, the Machine Passport's manufacturing task has laid down the groundwork for multi-source data integration and started to develop applications that align with the predefined outcomes of WP2.

Link to the GITLAB repository of the solution: https://gitlab-cigip.alc.upv.es/aideas/machine-passport

4.4.2 Next developments

The future developments of the Machine Passport will include:

- Expansion of data exchange protocols to encompass a broader range of manufacturing scenarios.
- Further advancements in XAI to deepen the interpretability of complex manufacturing data.
- Strengthening data quality checks to ensure absolute reliability and accuracy.
- Developing user-centric applications that simplify interactions with the Machine Passport for non-technical users.
- Introducing advanced security measures to protect sensitive manufacturing data.

These strategic enhancements are aimed at cementing the Machine Passport as an essential component in manufacturing, ensuring smooth data transitions and informed decision-making across the supply chain.

5. Conclusion

In this deliverable, the AIDEAS Industrial Equipment Manufacturing Suite has been presented. It consists of different AI-powered solutions for the enhancement of materials procurement, machine fabrication and final delivery to the end customers. The solutions provide optimal recommendations to enhance the manufacturing phase of the industrial equipment lifecycle. The deliverable details the features, technical specifications, and implementation status of all the solutions (i.e., toolkits) in the AIDEAS Industrial Equipment Manufacturing Suite. For each solution, a description of the main AI algorithms utilised is presented. The AIDEAS Industrial Equipment Manufacturing Suite consists of the following solutions:

Procurement Optimiser: The AI^{PO} utilises AI to optimise inventory and purchase of materials and components required for building a machine.

Fabrication Optimiser: The AI^{FO} uses AI Algorithms optimise production scheduling and resource allocation.

Delivery Optimiser: The AI^{DO} leverages the AI technologies to optimise the storage and delivery of products to enhance logistics scheduling and planning.

In addition, a detailed information about the **Machine Passport** has been presented. The **Machine Passport** ensures a seamless data exchange between the different solutions, and thus aids in the creation of the industrial equipment footprint, which is essential for achieving circularity in supply chains. The data gathered is also forms the basis for decision-making regarding recycling and remanufacturing. This is to ensure that sustainability and agility can be achieved in the operations of European machine manufacturers.

This deliverable represents the first version of the AIDEAS Industrial Equipment Manufacturing Suite (M18). The first release of the AIDEAS Industrial Equipment Manufacturing Suite is available on the AIDEAS project Gitlab repository and will be tested and validated by the industrial pilots in the AIDEAS project, to assess the features and functionalities and gather necessary feedback for improving the solutions. The next release of the AIDEAS Industrial Equipment Manufacturing Suite will be in M24 and M36 and will cover the feedback provided by the pilot.

6. References

Andres, B., Poler, R., & Sanchis, R. (2021). A data model for collaborative manufacturing environments. *Computers in Industry*, *126*. https://doi.org/10.1016/j.compind.2021.103398