PRODUCTION ENGINEERING ARCHIVES

Activity based model based on AI to support the prediction of activity durations in metalworking project management

José Silva[1]* [ID], Paulo Ávila[2,3] [ID], Luiz Faria[2] [ID], João Bastos[2,3] [ID], Luís Pinto Ferreira[2,4] [ID], Hélio Castro[2,3] [ID], João Matias[1,5] [ID]

[1] University of Aveiro, Campus Universitário de Santiago, Aveiro 3810-193, Portugal; jose.sil@ua.pt (JS); jmatias@ua.pt (JM)
[2] ISEP, Polytechnic of Porto, rua Dr. António Bernardino de Almeida, 4249-015 Porto, Portugal; psa@isep.ipp.pt (PA); lef@isep.ipp.pt (LF); jab@isep.ipp.pt (JB); lpf@isep.ipp.pt (LPF); hcc@isep.ipp.pt (HC)
[3] INESC TEC – Instituto de Engenharia de Sistemas e Computadores, 4200-465 Porto, Portugal
[4] Associate Laboratory for Energy, Transports and Aerospace (LAETA-INEGI), 4200-465 Porto, Portugal
[5] GOVCOPP – Unidade de Investigação em Governança, Competitividade e Políticas Públicas, Universidade de Aveiro, 3810-193 Aveiro, Portugal
*Correspondence: jose.sil@ua.pt

Abstract
Effective project management is crucial to the success of any industry, particularly in metalworking, where deadlines, resources, and costs play critical roles. However, accurately predicting project execution times remains a significant challenge, directly impacting companies' competitiveness and profitability. In this context, the integration of Artificial Intelligence (AI) tools emerges as a promising solution to improve the accuracy of time predictions and optimise project management in the metalworking industry.

AI, particularly through techniques such as Machine Learning (ML), has demonstrated significant potential in predicting timeframes for engineering projects. Predictive activity-based models can be trained with historical data to identify patterns and forecast future durations with high accuracy. In the metalworking sector, where projects are often complex and subject to variability, AI can provide notable advantages in terms of precision and efficiency.

This study aims to formulate an activity-based model, represented in IDEF0 (part of the Integration Definition for Function Modelling), for predicting activity durations using AI to support project management in the metalworking industry. By applying the principles of the IDEF0 tool, the objective is to develop a robust and adaptable system capable of analysing historical data, environmental factors, project characteristics, and other relevant inputs to produce more accurate time forecasts.

With this work, we aim to contribute to the advancement of Project Management (PM) in the metalworking industry, particularly by providing an activity-based model to support the creation of an innovative AI tool for predicting execution times with greater accuracy.

1. Introduction

Effective project management is essential for the success of any industry. In the metalworking sector, where deadlines, resource allocation, and cost control are particularly critical, managing project execution times accurately remains a major challenge with direct implications for competitiveness and profitability (Silva et al., 2022).

Optimising process duration in production systems is a key factor for improving efficiency and maintaining a competitive edge (Krynke, 2021). However, this task is complicated by the challenges of data collection in industrial environments. As noted by (Hasegawa et al., 2025), resistance to sharing detailed data and difficulties in sustaining improvement programmes are significant barriers.

In response to these challenges, the integration of Artificial Intelligence (AI) tools presents a promising solution to enhance time prediction accuracy and improve project management in metalworking (Egwim et al., 2021), (Silva et al., 2024). AI has already demonstrated transformative potential

in broader industrial applications, particularly within the framework of Industry 4.0 (Wachnik, 2022).

Despite these advances, no studies have been identified that specifically address the application of AI in project management within the metalworking industry. This gap in the literature highlights a valuable opportunity for future research and innovation (Silva et al., 2024). The novelty of this study lies in the integration of AI-based predictive modelling with IDEF0 process representation, creating a structured and iterative framework tailored for metalworking projects. This combination has not been explored in previous research, making our approach unique in addressing both technical and operational challenges in this domain. AI's rapid response capabilities and high generalisation power are already generating positive impacts across various sectors (Castro et al., 2024).

Techniques such as Machine Learning (ML) and Deep Learning (DL) have shown strong potential in predicting project durations in engineering. Predictive activity-based models trained on historical data can identify patterns and forecast future durations with high precision. In metalworking, where projects are often complex and variable, AI offers significant advantages in determining activity durations accurately (Silva et al., 2024), (Y. C. Chen et al., 2021). For instance, (Palakshappa et al., 2025) successfully applied a machine learning method to improve prediction accuracy in project planning.

This study proposes the development of an activity-based model, represented using IDEF0 (Integration Definition for Function Modelling), to predict activity durations with AI support in metalworking project management. By leveraging the principles of IDEF0, the model aims to analyse historical data, environmental factors, project characteristics, and other relevant inputs to generate more accurate time forecasts (Cempel & Dąbal, 2014), (Gil Ruiz et al., 2021).

The goal is to contribute to the advancement of project management in the metalworking industry by offering a robust and adaptable AI-powered tool for precise execution time prediction. In short, this paper proposes a model and provides initial empirical validation using real industrial welding data, demonstrating its applicability to metalworking project environments.

The paper is organised as follows: the next section presents a literature review on time prediction in project management and the role of AI in this context. This is followed by a detailed explanation of the proposed methodology, including the development and integration of the AI-based activity model into the IDEF0 framework. Finally, the expected results, potential challenges, and practical implications for the metalworking industry are discussed.

2. Theoretical Framework

2.1. Focused AI Applications in Project Management

Artificial Intelligence (AI) is reshaping project management, especially in Industry 4.0 environments, by enhancing forecasting, resource optimization, and decision-making (Wachnik, 2022). Among the various applications, execution time prediction stands out as a critical challenge in industrial sectors such as metalworking, where delays directly impact costs and efficiency (Krynke, 2021).

This section synthesizes the literature and critically compares three AI algorithms: LSTM, Gradient Boosting Machines (GBM), and GANs, highlighting their suitability for time prediction in project management.

2.1.1. Long Short-Term Memory (LSTM)

LSTM networks are a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. In project management, they are particularly effective for modelling sequences of operations and predicting durations based on historical patterns.

- Use Case: LSTM has been successfully applied in predictive maintenance and fault diagnosis in industrial systems, improving detection accuracy by up to 30% (Kim et al., 2024).
- Advantages: Handles time-series data well; adapts to dynamic project environments.
- Limitations: Requires substantial training data and tuning.

2.1.2. Gradient Boosting Machines (GBM)

GBM algorithms, including XGBoost and LightGBM, are powerful for tabular data with mixed features (categorical and numerical). They are widely used in industrial settings for predictive maintenance and quality control.

- Use Case: GBM models have shown high accuracy in predicting standard execution times in manufacturing environments (Çakıt & Dağdeviren, 2023) and in hybrid models with LSTM for structural health monitoring (Kesarkar et al., 2025).
- Advantages: High interpretability; effective with small datasets.
- Limitations: Less suited for sequential data unless combined with temporal models.

2.1.3. Generative Adversarial Networks (GANs)

GANs are used to generate synthetic data, which is valuable in contexts where historical data is scarce—a common issue in industrial project management.
Use Case: GANs have been integrated with LSTM and autoencoders to augment datasets for fault diagnosis in industrial pumps, improving model robustness (Kim et al., 2024).

2.1.4. Conclusion and Research Direction

Our study focuses on the application of these algorithms to predict the duration of project management activities in the metalworking sector. Preliminary findings (Silva et al., 2024) suggest that ANNs, Random Forest, GBM, CNN, and RNNs are promising candidates. However, further empirical

validation is needed to determine their effectiveness in real-world scenarios.

Recent studies also emphasize the importance of integrating AI with big data and IoT for real-time prediction (Fang et al., 2020) and highlight the potential of hybrid models combining LSTM and GBM for enhanced accuracy (Mahale et al., 2025).

2.2. Process Modelling Methods

Modelling methods are techniques used to represent, analyse, and improve systems, processes, or concepts in various fields such as business, engineering, software development, and data science. They help visualise complex systems, making them easier to understand, communicate, and optimise. Among the various methodologies for modelling a system, whether more process-centric or more data-centric, the former is the one that best fits our requirements for modelling the AI-based activity duration forecasting system to support the management of metalworking projects.

Furthermore, these modelling methods help structure and organise the development of AI systems, ensuring that all aspects of the project are well planned and executed. The use of diagrams and standardised notations facilitates communication between team members and other stakeholders, reducing the likelihood of errors and increasing development efficiency.

There are several system modelling methods focused on representing processes and complex systems through activity flow diagrams, particularly applicable in AI. The main process modelling methods utilised are:

- **BPMN (Business Process Model and Notation)**: A standard notation for modelling business processes, which uses specific symbols to represent activities, events, decisions, and sequence flows. This notation is widely used due to its ability to provide a clear and detailed view of processes, facilitating communication among different stakeholders and improving operational efficiency (Heinzl et al., 2024).
- **UML (Unified Modelling Language)**: Includes a variety of diagrams to represent different aspects of systems, including activity diagrams that show the flow of control between activities. UML is a versatile modelling language that can be used to describe the structure and behaviour of complex systems, making it particularly useful in software development and systems engineering (Hupont & Gómez, 2022).
- **Flowcharts**: Simple diagrams that represent the flow of a process, showing steps as boxes of different shapes and the flow between them with arrows. Flowcharts are a basic yet powerful tool for visualising processes, identifying bottlenecks, and improving efficiency. They are widely used across various fields, from engineering to project management (Kumar Dukhiram Pal et al., 2023).
- **SIPOC Diagram (Suppliers, Inputs, Process, Outputs, Customers)**: Helps identify all relevant elements of a business process before working on it in detail. This diagram is particularly useful for mapping high-level processes and ensuring that all critical components are considered. It provides a clear view of the inputs and outputs of a process (Simion et al., 2024).
- **CRISP-DM**: is the most widely used reference model in data mining projects, structured into six phases (business understanding, data understanding, preparation, modelling, evaluation, and deployment). Despite its broad adoption, studies highlight that the method presents limitations in complex industrial environments, particularly due to its low flexibility in iterative processes and its limited emphasis on the deployment phase (Martínez-Plumed et al., 2021).
- **IDEF0 (Integration Definition for Function Modelling)**: A technique used to model and analyse system processes in a hierarchical and detailed manner. Developed by the United States Air Force in the 1970s, this methodology was designed to support the understanding and improvement of complex systems, providing a clear view of interactions between different functions (Luo et al., 2011).

Although no exhaustive comparison of the different modelling methods has not been conducted, we have chosen the IDEF0 method to represent the activity-based duration determination model. This decision is based not only on its widespread use, but also on a critical assessment of its advantages compared with alternative approaches (see the "Comparative Table: Process Models" in Appendix A). While methods such as BPMN or flowcharts are accessible and simple, they often lack the functional depth required for complex industrial environments. Similarly, while CRISP-DM is robust for data mining, it is insufficient for capturing systemic functional dependencies in project workflows. Unlike CRISP-DM, which structures data mining projects into six linear phases, IDEF0 explicitly incorporates feedback loops through its "Integration and Monitoring" activities. This enables iterative retraining and evaluation cycles, which are essential in metalworking environments where variability in welding and machining requires continuous model adjustment. While CRISP-DM offers a strong data-centric approach, its limited flexibility for iterative operational feedback makes it less suitable for dynamic industrial contexts compared to IDEF0.

By contrast, IDEF0 stands out for the following reasons (Ávila, 2004):

- **Clarity and Comprehension**: IDEF0 provides a clear visual representation of system functions and their interactions, facilitating understanding and communication among stakeholders.
- **Systematic Structuring**: The hierarchical and detailed approach of IDEF0 ensures that all functions and interactions are carefully considered and documented.
- **Proven and Well-Tested**: It has been successfully applied in the development of military, governmental, scientific, and industrial projects.

Therefore, the preference for IDEF0 is a deliberate choice, grounded not only in its historical application, but also in its capacity to provide a systemic view of complex industrial processes, thereby supporting the development of AI models for forecasting metalworking projects duration.

2.3. Phases of an AI-Supported Activity-Based Model for Time Prediction

In general, the phases of an AI-supported activity-based model, also referred to as the AI model lifecycle, are referenced in the literature by various authors, although no standardisation exists.

Several frameworks have been proposed to define the lifecycle of AI systems, differing mainly in the number and granularity of phases. Table 1 summarises the most relevant models referenced in this study, emphasising their similarities and distinctive elements.

Table 1. Summarises the most relevant models

Reference	Nº of Phases	Main Focus	Remarks
(OECD, 2019)	4	Design; Validation; Deployment; Operation.	Emphasis on governance and monitoring
(Joseph Kozhaya, 2020)	6	Business understanding; data understanding; data preparation; modelling; evaluation; deployment.	Based on CRISP-DM principles
(Sarajcev et al., 2022)	5	Data preparation; model building; training and tuning; deployment; management.	Focus on iterative improvement
(Y. Chen et al., 2023)	3	Design; Develop; Deploy.	Streamlined three-step process
(Almagrabi & Khan, 2025)	7	Problem definition; Data collection; Model selection; Evaluation; Deployment; Monitoring; Retiring.	Comprehensive lifecycle including maintenance

Despite these differences, the authors emphasise the need for organisations to adopt a well-defined and robust methodology for developing, deploying, and maintaining AI systems. Such methodologies streamline end-to-end tasks, optimise data scientists' time, facilitate collaboration, and enhance overall productivity (Joseph Kozhaya, 2020).

However, these frameworks rarely describe how such phases can be operationalised in a process-oriented modelling environment like IDEF0. In particular, none explicitly integrates activity-based representations with AI lifecycle phases, which is crucial for industrial contexts such as metalworking, where time prediction and process transparency are essential.

Therefore, the proposed model in this work integrates the conceptual structure from (OECD, 2019) and (Almagrabi & Khan, 2025) with the process modelling capability of IDEF0 to form an AI-supported activity-based model for time prediction in project management.

The proposed model comprises six interconnected phases, as follows:

- **Definition of Objectives and Requirements**: Define the project objectives and requirements, identifying measurable indicators such as time accuracy and resource efficiency expected from AI integration.
- **Initial Process Mapping IDEF0**: Identify and map existing processes using IDEF0 diagrams to capture functions, data flows, and interdependencies. This step enables visualisation of where time estimation plays a critical role in project execution within the metalworking industry.
- **Data Analysis and Preparation**: Collect, clean, and analyse historical project data on execution times. This phase defines relevant variables (e.g., task type, machine configuration, material complexity) and establishes the foundation for model training.
- **Development of the AI-Supported Activity-Based Model:** Based on the identified functions and analysed data, an AI-supported activity-based model is developed using appropriate Machine Learning (ML) and/or Deep Learning (DL) techniques. This activity-based model is trained with historical data to predict the execution times of future projects.
- **Integration and Validation**: Integrate the AI-supported model within the IDEF0 project management structure. Define the interfaces among AI components, management functions, and data inputs/outputs. Perform validation through historical backtesting and stakeholder evaluation to confirm predictive reliability.
- **Monitoring and Continuous Adjustment:** Continuously monitor model performance, track deviations, and retrain or fine-tune algorithms when necessary. This phase ensures sustained accuracy and adaptability to changing production conditions.

In the context of the IDEF0 notation, each phase of the proposed AI-supported activity-based model corresponds to a specific functional block, ensuring a clear and structured representation of the process. "Definition of Objectives and Requirements" (A1) represents the initiation function, generating the defined project goals and constraints as outputs. "Initial Process Mapping" (A2) documents the existing workflow and relationships between activities. "Data Analysis and Preparation" (A3) handles the collection, cleaning, and transformation of historical data into usable inputs. "Model Development" (A4) encapsulates the application of Machine Learning and Deep Learning methods for model training and validation. Finally, "Integration and Monitoring" (A5) closes the loop by linking predictive outputs to project management dashboards and enabling continuous feedback and re-training when deviations occur, "Monitoring and Adjustments" (A6) adjusts the model based on feedback and performance, ensuring accurate predictions over time.

This alignment between the model's conceptual phases and their IDEF0 representation ensures transparency and traceability throughout the lifecycle, which are essential for decision-making in complex industrial environments such as metalworking.

3. Development of the IDEF0 Model for AI-Supported Activity-Based Time Prediction in Projects

Building on the lifecycle phases described in Section 2.3, the proposed model was structured in IDEF0 notation to ensure a systematic and traceable representation of all processes involved in AI-supported time prediction. The IDEF0 approach allows clear visualization of functions, inputs, controls, outputs, and mechanisms (ICOMs), ensuring transparency and consistency across the model's development and deployment stages (Morariu et al., 2020).

As previously described, each function in the IDEF0 hierarchy aligns with the lifecycle phases (A1–A6), ensuring that the conceptual model is operationalized through a structured and verifiable process.

The choice of IDEF0 over traditional approaches like BPMN or UML stems from its superior ability to represent hierarchical decomposition and control flow, which is essential for AI systems involving iterative learning and retraining. (Chari et al., 2023).

The resulting IDEF0 model provides a structured means of integrating machine learning into project management workflows in the metalworking sector, facilitating improved estimation of task durations and better resource planning.

As illustrated in Figure 1 (A0 diagram), the top-level activity "Estimate of Time with AI in Metalworking Projects" is decomposed into the previously described sub-activities (A1–A6). Subsequent diagrams detail the internal logic and data flow of each phase.

The proposed model addresses the limitations of static activity times by incorporating real production variability. It identifies project management needs, selects suitable AI techniques, prepares relevant data, implements the solution, and ensures continuous evaluation. This approach enhances operational efficiency, supports informed decision-making, and improves overall project performance in the metalworking sector.

3.1. General Activity-Based Model

The global representation of the activity-based model is depicted in Figure 1, allowing it to be subsequently subdivided into its six phases.
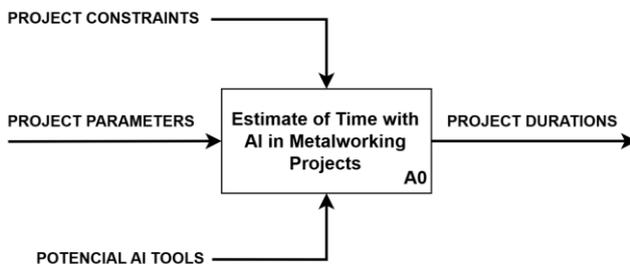

Fig. 1. IDEF0 Representation of the General Activity-Based Model for Project Duration Forecasting with AI

The main project flows for the inputs and project parameters comprise seven key flows, namely:

- **Product Types**: As discussed in (Silva et al., 2022) five product possibilities will be considered, namely: Reservoirs - Structures designed for the storage of liquids or gases, frequently used in the food, chemical, and petrochemical industries. The complexity of the design may vary depending on the size and safety requirements; Heat exchangers - Equipment that transfers heat between two or more fluids. They are essential in industrial processes for energy efficiency. The types include plate heat exchangers, shell and tube heat exchangers, among others; Condensers - Devices that convert vapour into liquid, commonly used in refrigeration systems and power plants. The efficiency of a condenser depends on both the material and the design; Reactors - Equipment where controlled chemical reactions take place. They can be of various types, such as fixed-bed reactors, fluidised-bed reactors, among others, each with its own specific design requirements; Wind towers are structures that support wind turbines for power generation. Their design must consider factors such as wind resistance, height, and material to ensure stability and efficiency.

- **Materials**: The selection of materials such as stainless steel, carbon steel, duplex, and super duplex directly impacts time estimates in the management of metalworking projects, especially in scheduling. Each material has specific characteristics that influence the time required for manufacturing. For example, materials such as super duplex, although offering high corrosion resistance, require more stringent welding and heat treatment processes, increasing production time. Carbon steel, on the other hand, being easier to work with, may reduce the project duration, although this also depends on the complexity involved (Silva et al., 2022). Additionally, the availability of materials in the market and suppliers' delivery times are critical factors for time estimation and may cause delays if not properly accounted for in project planning (Zennaro et al., 2019). Therefore, material choice affects the accuracy of time estimates, making detailed analysis essential to avoid deviations in planning and ensure deliveries within the established deadlines.

- **Dimensions**: As presented in (Silva et al., 2022), the dimensions of components directly influence the estimation of time in metalworking project management, as they affect processes such as transport, assembly, and manufacturing. Larger or more complex components may require more time for manufacturing, handling, and assembly, impacting the project schedule. Furthermore, the need for specific equipment for handling or assembly may add extra steps to the process, increasing the expected duration (Amran et al., 2019). Therefore, a realistic time estimate should consider not only the number of components but also their dimensions and the impact they have on each phase of the project.

- **Project network/sequence**: Clarity in defining the sequence of activities and identifying their dependencies is crucial for creating accurate and reliable time estimates

(Monteiro et al., 2019). With a well-defined sequence of activities, it is possible to anticipate challenges and optimise project planning. This approach not only results in more realistic schedules but also significantly increases the likelihood of completing the project within the established timeframe, minimising the risk of unforeseen events and ensuring greater control over task progress (Drobintsev et al., 2017).

- **Workload percentage over time**: In the context of project management, monitoring workload over time is crucial to project success. Accurate time forecasting allows project managers to plan resource allocations in advance, avoiding both shortages and waste of capacity (Ruschel et al., 2021). This involves not only estimating the time required to complete tasks but also considering periods of high demand, where resource needs are greater and may affect project execution. By monitoring progress in real-time, it is possible to quickly identify when the project is progressing slower than expected or when the pace of work can be increased. This continuous analysis enables real-time adjustments in resource allocation, anticipating potential bottlenecks (Wang et al., 2022). Time predictability helps managers ensure that workload overloads do not occur, which could negatively impact project deadlines.
- **Project tracking/control scale**: As identified in (Duncan Kimutai Ronoh, 2020), time estimation is essential in project management to ensure that deadlines are met. Assessing project tracking on a scale of 1 to 3 (insufficient, sufficient, and good) helps to determine the accuracy of time forecasts. When tracking is "insufficient," failures in reviewing estimates may occur, resulting in delays. In cases of "sufficient" tracking, estimates are monitored, but there is room for improving accuracy. Finally, "good" tracking ensures that the project is progressing as planned and that any issues are promptly addressed (Wang et al., 2022). Effective control ensures that time estimates are continuously adjusted, contributing to improved project management.
- **Confidence level in estimates and margin of error**: The authors (Elena Bruni et al., 2011) highlight the importance of the confidence level in estimates and the margin of error, emphasising how these elements are crucial for the accuracy of project forecasts. Additionally, the authors (Hassan et al., 2021) consider uncertainty in production rates, which can be applied to estimate the margin of error in project durations. They also develop stochastic models to optimise team scheduling, including the analysis of confidence intervals and margins of error in duration estimates. The genetic algorithms used by the authors (Szwarcfiter et al., 2023) help identify deployment plans that consider both the margin of error and confidence in estimates. By representing confidence in estimates and error as a percentage, with a confidence level of 95% and a margin of error of 10%, the accuracy of forecasts can be quantified. This is fundamental for informed decision-making and risk management within the project.

As the main project flows for the constraints, project constraints, we have five important flows, namely:
- **Non-compliance Penalty**: According to the study by (Zennaro et al., 2019) on manufacturing systems for large-scale and highly customised products, effective management of production planning and control is essential to avoid non-compliance. Furthermore, the authors in (Amran et al., 2019), when discussing the use of Lean project management in the manufacturing of storage tanks, highlight the importance of risk analysis. This approach not only enables the identification of potential non-compliance issues and their consequences but also helps to minimise delays and ensure that projects are completed within established deadlines, thereby avoiding financial penalties. Understanding these penalties is crucial for risk management and informed decision-making, ensuring that projects are completed within budget and on schedule.
- **Project Completion Deadline**: According to (Silva et al., 2024), a solid foundation is essential for estimating the total time required to complete projects in the metalworking industry. Moreover, the authors in (Zennaro et al., 2019) highlight the importance of manufacturing systems for large-scale, highly customised products, while the authors in (Amran et al., 2019) assess the importance of estimating the total time needed for project completion. The inclusion of deadlines for each project phase, from planning to execution and final delivery, is fundamental. According to the cited authors, the accuracy of these estimates is essential for efficient scheduling and to avoid delays.
- **Percentage of Compliant Products**: According to the authors in (Gonzales-Romero et al., 2022), the percentage of compliant products indicates the proportion of products that meet established quality standards and specifications. A high compliance rate is indicative of efficient and high-quality production processes, while a low rate may signal the need for improvements in quality control processes.
- **Level of Resource Optimisation**: This assessment measures how well resources (human, material, financial) are being utilised in the project, being measurable on a scale from 1 to 3 (insufficient, sufficient, and good). According to (Silva et al., 2024), the implementation of Artificial Intelligence tools, such as Artificial Neural Networks (ANN), can significantly optimise project resources. Furthermore, the research by (Zohrehvandi, 2024) demonstrates that effective resource optimisation in project management within construction and industrial companies minimises costs and ensures a smooth resource flow between projects. A high degree of optimisation indicates that resources are being used efficiently, minimising waste and maximising productivity.
- **Availability of Equipment for Operation (in %)**: This rate reflects the percentage of time that equipment is ready and fit for use in operations. A high operational availability rate indicates that the equipment is reliable and well-maintained, reducing downtime and increasing

operational efficiency. According to (Palomino-Valles et al., 2020), the implementation of a maintenance management model can significantly increase equipment availability, improve reliability and further reduce downtime.

Based on the literature review in (Silva et al., 2024), the most commonly used AI tools in project management have been identified and will be considered here. Given the above, the main project flows for the mechanisms and potential AI tools include two important flows, namely:

1st Deep Learning

- **Convolutional Neural Networks (CNNs)**: CNNs are a class of neural networks specifically designed to work with structured data in matrix form or images, such as photos or videos. They are widely used in computer vision, such as in object recognition (e.g., identifying a car or a person in an image) and image classification (e.g., determining whether an image depicts a dog or a cat). CNNs use convolutional layers to detect patterns at different levels, making them highly effective for tasks related to static images or video streams.
- **Recurrent Neural Networks (RNNs)**: Recurrent Neural Networks (RNNs) are developed to handle sequential data, where the order of information is essential. They have a memory mechanism that captures temporal dependencies, making them particularly suitable for applications such as Natural Language Processing (NLP), including text translation, sentiment analysis, and time-series forecasting, such as estimating stock prices or predicting weather conditions on a specific day. Unlike traditional neural networks, RNNs feature a structure where the output of one neuron can be reused as input for the next, allowing the network to retain information from previous steps.
- **Generative Adversarial Networks (GANs)**: GANs are an innovative technique for generating synthetic data. They involve two models: the generator, which attempts to create fake data (such as images or text), and the discriminator, which tries to distinguish between real and fake data. These models compete against each other, leading the generator to improve continuously until it can produce data almost indistinguishable from real ones. GANs are widely used for generating realistic images, augmenting datasets (creating new samples from existing data), and even producing artwork or generating text.
- **Long Short-Term Memory Networks (LSTM)**: LSTMs are networks specialised in capturing long-term dependencies in sequential data. These networks feature an internal memory structure that enables them to retain information over extended periods. They are used in tasks such as automatic translation and time-series forecasting, where prolonged context plays a crucial role.
- **Gated Recurrent Units (GRU)**: GRUs are recurrent neural networks designed to capture temporal dependencies in sequential data. Their structure includes mechanisms that help mitigate the vanishing gradient problem, allowing better utilisation of information over time. GRUs are well-suited for various applications, such as Natural Language Processing (NLP) and time-series analysis, offering a good balance between performance and training time.
- **Region-based CNN (R-CNN)**: R-CNNs are an extension of CNNs, designed for object detection in images. They divide an image into regions of interest and apply a convolutional neural network to classify each region. This is particularly useful for tasks such as object recognition (e.g., detecting cars or people in a scene) and video surveillance (where identifying and tracking objects over time is important).

2nd Machine Learning

- **Artificial Neural Networks**: ANNs are artificial neural networks inspired by the structure and functioning of the human brain. ANNs consist of multiple layers of artificial neurons that learn patterns and information from data. They are used in a wide range of supervised learning tasks, such as classification, prediction, and anomaly detection. ANNs are particularly useful in sectors like construction, where they can be applied to predict project costs, assess risks, and optimise construction schedules.
- **Ensemble Algorithms** (Random Forest and Gradient Boosting Machines)
  Random Forest: This algorithm is an ensemble of decision trees trained on randomly selected subsets of data. It is highly effective for problems involving complex data and variables. Random Forest creates a "forest" of decision trees and makes predictions based on the average or vote of these trees' decisions. It is widely used in classification and regression tasks and is particularly effective in the construction sector for predicting budgets and project timelines.
  Gradient Boosting Machines (GBM): Gradient Boosting builds a robust model by combining multiple weak models (usually decision trees) sequentially. In each iteration, the model attempts to correct the errors of the previous model. It is highly effective in improving model accuracy and is widely used in various types of projects, from sales forecasting to medical diagnosis.
- **Logistic Regression**: Logistic regression is a binary classification model that predicts the probability of a dependent variable taking one of two possible values (yes or no). It is widely used in medical fields, such as disease diagnosis, where doctors may need to predict the likelihood of a patient having a specific condition based on symptoms and test results.
- **Support Vector Machines (SVM)**: SVMs are powerful algorithms for classification and regression, particularly useful when working with high-dimensional data (i.e., data with many features or variables). They aim to find a hyperplane that separates data classes with the largest possible margin, making them effective even when classes are not linearly separable. SVMs are applied in areas such as medical research for image classification or in technical sectors like electrical engineering to predict failures or optimise processes.

As the main project flows for the outputs and project durations, three important flows are expected, namely:

- **Project Duration**: By using AI algorithms, the system can analyse data from the history of similar projects, taking into account previous variables. Based on this analysis, the algorithm can predict the most likely duration of the project (critical path). Additionally, AI can dynamically adjust the schedule as new data and circumstances arise during project execution. The AI algorithm can analyse the dependencies between project activities and automatically identify the critical path. By considering the interrelation of tasks and available resources, AI can help project management focus efforts on the most crucial activities, ensuring that any delay in these activities directly impacts the project's final deadline (Dahmani et al., 2021).
- **Processing time for each activity**: Artificial intelligence can analyse historical data and execution patterns to accurately predict the duration of each project activity. The algorithm can take into account the variables from the previous chapters to generate more precise estimates. Thus, activity duration predictions are adjusted based on the project's specific conditions in real-time (Shoushtari et al., 2024).
- **Work Duration for Each Activity**: The AI algorithm can automate the calculation of the work required for each activity, considering factors such as the amount of human effort and necessary resources. By analysing past performance patterns and real-time data, AI can distribute work among team members, ensuring a more efficient allocation of resources to maximise productivity (Kumar Dukhiram Pal et al., 2023).

3.2. Detailed Activity-Based Model

The graphical and hierarchical representation of IDEF0 provides a clear visualisation of the interdependencies between activities, facilitating the identification and definition of improvement strategies. Below, the IDEF0 (activities) diagrams developed for each phase of our activity-based model will be presented, detailing the process steps along with their respective inputs, outputs, tools, and controls.

Activity A1, "Definition of Objectives and Requirements," represented in Figure 2, is crucial to the project's success, as it establishes the foundation upon which all other activities will be built. A clear definition of objectives and requirements ensures that all stakeholders share a common understanding of the project's goals and specific needs. This helps to avoid ambiguities and misunderstandings throughout the development process.

The inputs of this activity provide the necessary information on what will be produced, how it will be produced, and the project's technical specifications. The constraints ensure that the project complies with metalworking industry standards and that deadlines and costs remain viable. The valuable expertise of specialists is essential in defining realistic and achievable objectives and requirements, based on their

knowledge and historical data. The output serves as a clear and detailed guide for all subsequent phases of the project.
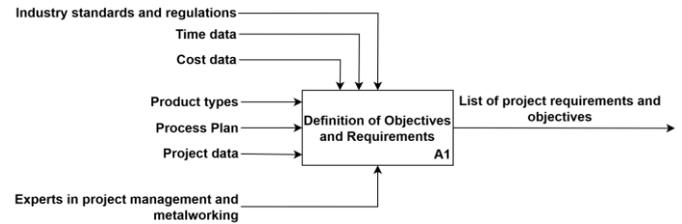

Fig. 2. Activity A1: Definition of objectives and requirements

The A2 activity "Initial Process Mapping," represented in Figure 3, is crucial for visualising and understanding the interrelationships between the project's activities. Through process mapping methodologies and industry best practices, we create diagrams that clearly and thoroughly represent the processes involved. This graphical representation aids in identifying opportunities for improvement and optimisation. The inputs provide a comprehensive view of the project's needs and the current state of the processes. The constraints ensure that the mapping follows recognised standards and aligns with industry norms. The combination of specialised tools and the team's expertise is essential for creating an accurate and useful diagram. The resulting diagrams offer a clear visual representation of the processes, facilitating the analysis and optimisation of the activities within this project in the field of metalworking.
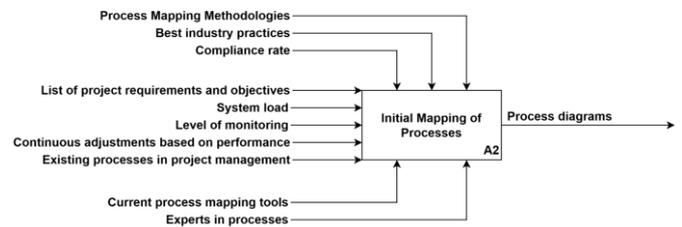

Fig. 3. Activity A2: Initial Process Mapping

The activity A3 "Data Analysis", represented in Figure 4, is a crucial process for transforming raw information into valuable knowledge. In this activity, advanced data analysis techniques are used, combined with the expertise of specialists, to identify patterns and trends in historical data. The quality of the data and compliance with project requirements are essential to ensure the accuracy and reliability of the results. The inputs provide the necessary dataset to conduct detailed analyses and identify relevant statistical patterns. The constraints ensure that the analysis is aligned with the project objectives and adheres to the established quality standards. The data analysis tools used are essential for performing complex calculations and generating informative visualisations. The outputs of this activity provide valuable insights that can be used to enhance the accuracy of project duration predictions in the field of metalworking, optimising the management of time and resources.
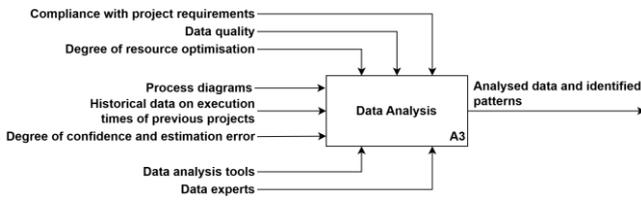
Fig. 4. Activity A3: Data Analysis

The activity A4, "development of the model based on AI activities," represented in Figure 5, is the core of this project. Using advanced ML and/or DL techniques, this activity enables the creation of an activity-based model capable of predicting project duration with high accuracy. The rigorous validation of the activity-based model and its compliance with the established development criteria ensure that the activity-based model meets the project requirements. The inputs provide the data and information necessary to train and validate the AI activity-based model. The collected data will be transformed into a suitable format to train the neural network, including data normalisation and the creation of training, validation, and test sets. The constraints ensure that the development of the activity-based model follows quality standards and best practices in the field. As mechanisms, Artificial Neural Networks (ANNs) are a good choice for predicting project duration, as mentioned earlier (Egwim et al., 2021). However, Generative Adversarial Networks (GANs) may also be suitable for predicting project duration in the metalworking industry. GANs are a type of neural network consisting of two parts: a generator and a discriminator. The generator creates synthetic samples that resemble the training data, while the discriminator evaluates whether the samples are real or fake. The goal of training is to make the generator produce increasingly realistic samples, while the discriminator becomes better at distinguishing between real and fake samples. GANs have been successfully used in various applications, including time series forecasting (Kumar Dukhiram Pal et al., 2023). However, it is important to consider that the choice of the ANN methodology depends on the availability and volume of data. To test the neural network, test data must be used to assess its accuracy in predicting project duration. If the neural network is not functioning correctly, it may be necessary to adjust the architecture or the initial training parameters (Dahmani et al., 2021), (Shoushtari et al., 2024). In our case, the data is not abundant. It may be necessary to use another methodology alongside the ANN to ensure the success of our proposed work. Additionally, it is important to compare two different types, such as ML (ANN) and DL (GAN), depending on the complexity of the data and forecasting requirements. Tests will be carried out to evaluate the performance of both approaches before selecting the best option for project management in the metalworking industry (Kumar Dukhiram Pal et al., 2023). The combination of cutting-edge techniques and the expertise of the team is crucial in building a robust and effective AI activity-based model. The output of this activity is the trained AI activity-based model, ready to be used in predicting the duration of new projects in the metalworking field.
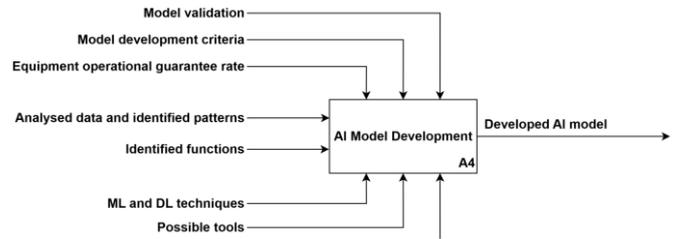

Fig. 5. Activity A4: Development of the AI activity-based model

The activity A5 "Integration and Validation", represented in Figure 6, ensures that the activity-based AI model can be effectively integrated into existing project management platforms. In this activity, we conduct a rigorous evaluation of the performance of the activity-based model, validating it based on key performance indicators and predefined assessment criteria. Successful integration results in a robust AI solution capable of providing accurate and reliable predictions regarding project durations in the field of mechanical engineering. The constraints ensure that integration and validation are carried out in compliance with quality and safety standards. The tools and expertise of the team are essential to ensure the compatibility of the activity-based model with existing platforms and to optimise its performance. The output of this activity is a fully integrated and validated AI solution, ready to be used for generating detailed predictions and making strategic decisions in the field of mechanical engineering.
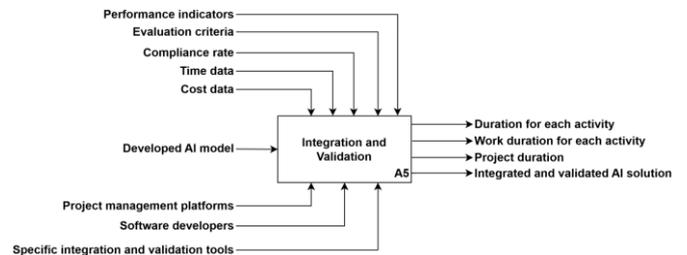

Fig. 6. Activity A5: Integration and Validation

The activity A6, "Monitoring and Adjustments," depicted in Figure 7, is crucial to ensuring the longevity and accuracy of the model based on AI-driven activities. In this activity, we use user feedback and performance indicators to identify areas for improvement and make adjustments to the algorithms and parameters of the activity-based model. This iterative approach ensures that the activity-based model continues to deliver accurate and relevant predictions, adapting to changes in project conditions. The inputs provide the necessary data to assess the performance of the activity-based model and identify deviations from the expected outcomes. The constraints ensure that adjustments are made in a controlled manner and do not compromise the integrity of the model. The tools and expertise of the team are essential to implement the necessary changes and monitor their impact. The output of this activity is a continually refined AI-based activity model, capable of providing accurate and reliable predictions over time.
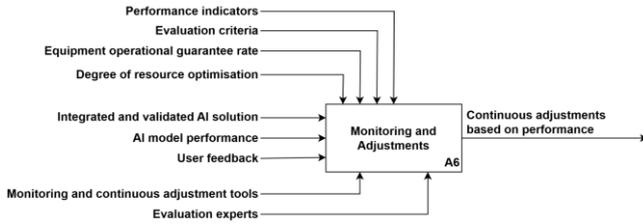
Fig. 7. Activity A6: Monitoring and Adjustments

To conclude the representation of the activity-based model, Figure 8 represents the six activities integrated into a single representation, enabling the visualisation of the integration of all activities in relation to one another. After the successful training and testing of the model, it will then be ready to be implemented in a project management system, contributing to the prediction of the duration of future projects (Alexandru Zamfirache et al., 2023).

Fig. 8. Detailed IDEF0 Activity-Based Model

4. Inicial Empirical validation of the Model

To assess the effectiveness of the proposed predictive models, an initial empirical validation was conducted using real-world data. This section outlines the data preparation process, model training, evaluation metrics, and comparative analysis of the results.

4.1. Analysis of the main flows of the model

The development of Artificial Intelligence models in this project followed a structured methodology based on the IDEF0 model, ensuring that each phase was guided by well-defined constraints, relevant inputs, appropriate tools, and measurable outcomes. This approach enabled the creation of predictive solutions aligned with an industrial process in the metalworking sector (Welding Activities).

Inputs provided the context and necessary data for each activity. Examples include:

- Time and cost data, product types, and process plans used in A1 to define modelling objectives.

- System load, monitoring level, and existing processes used in A2 to identify relevant variables.
- Historical execution time data and resource optimisation metrics used in A3 to detect patterns.
- The analysed dataset and selected ML/DL techniques used in A4 to train the Gradient Boosting and LSTM models.
- Project management platforms and performance indicators used in A5 to validate model integration.
- Real-time performance data and user feedback used in A6 to guide continuous adjustments.

Constraints were applied to ensure compliance, consistency, and quality throughout all phases. For example:
- In the definition of objectives (A1), welding industry standards and data formatting rules were considered to ensure that the requirements were technically feasible.
- In process mapping (A2), methodologies such as IDEF0 and industrial engineering best practices were used to accurately represent workflows.
- In data analysis (A3), integrity tests using "pandas" were conducted to validate the dataset prior to modelling.
- In model development (A4), criteria such as equipment reliability and acceptable error margins guided the choice of algorithms and model complexity.
- In integration and validation (A5), metrics such as MAE, RMSE, and R^2 were used to ensure the model met performance requirements.
- In monitoring (A6), uptime rates and feedback mechanisms helped maintain the model's relevance over time.

Tools enabled each phase to be executed with precision. Examples include:
- Diagramming tools for IDEF0 modelling in A1 and A2.
- Libraries such as "pandas", "numpy", and "matplotlib" for data analysis in A3.
- "scikit-learn" for the Gradient Boosting model and "Keras" with "TensorFlow" for the LSTM model in A4.
- Application Programming Interfaces (APIs) and dashboards for integration in A5.
- Monitoring platforms and alert systems in A6.
- The involvement of metalworking domain experts in all phases ensured that technical decisions were grounded in domain knowledge.

Outcomes were generated at each stage to support the next phase and validate progress. These included:
- A structured list of project requirements and objectives from A1.
- Process diagrams from A2 that guided variable selection.
- A cleaned and analysed dataset with identified patterns from A3.
- A trained and validated AI model from A4.
- An integrated AI solution with duration predictions from A5.
- A performance-based continuous adjustment mechanism from A6 that maintained model effectiveness over time.

This structured approach ensured that the AI models were technically robust and operationally relevant, supporting accurate predictions and continuous improvements in industrial environments within the metalworking sector.

4.2. Analysis of the results of the model implementation

Data Loading and Preprocessing: The dataset used for this study was loaded from a CSV file (Welding data.csv) using the pandas library in a Google Colab environment. The target variable selected for prediction was duration, while all other columns were treated as input features (X_real). The dataset was split into training and testing sets using an 80/20 ratio via the train_test_split function from scikit-learn, with a fixed random seed (random_state=42) to ensure reproducibility.

Gradient Boosting Model: A Gradient Boosting Regressor was implemented using the scikit-learn library. The model was trained on the training set and evaluated on the test set. The following performance metrics were used:

- **Mean Absolute Error (MAE)**: Measures the average magnitude of errors in predictions.
- **Mean Squared Error (MSE)**: Emphasizes larger errors by squaring the differences.
- **Root Mean Squared Error (RMSE)**: Provides an interpretable error metric in the same units as the target variable.
- **Coefficient of Determination (R^2)**: Indicates the proportion of variance in the dependent variable explained by the model.

The Gradient Boosting model achieved an R^2 score of 0.9818, demonstrating a strong fit to the real data.

LSTM Model: A Long Short-Term Memory (LSTM) neural network was also developed using the Keras library. Although the dataset is not inherently sequential, the LSTM architecture was employed to capture potential complex temporal dependencies. Prior to training, the data was normalized using MinMaxScaler, and reshaped to match the expected input format for LSTM layers.

The model architecture consisted of a single LSTM layer followed by a dense output layer. The model was compiled with the Adam optimizer and mean squared error as the loss function. After training, predictions were generated on the test set and evaluated using the same metrics as the Gradient Boosting model.

The LSTM model achieved an R^2 score of 0.9814, indicating a similarly high level of predictive performance.

Comparative Analysis: The Table 2 below summarizes the performance of both models:

Table 2. Models performance.

Model	MAE	MSE	RMSE	R^2
Gradient Boosting	1.6367	4.2849	2.0700	0.9818
LSTM	1.6539	4.3855	2.0942	0.9814

Both models achieved R^2 values above the baseline of 0.79, demonstrating a strong ability to capture the underlying patterns in the data. This conclusion is visually supported by the scatter plots presented in Figures 9 and 10, which illustrate the distribution of predicted versus actual values for each model.

Quantitative Analysis of Results: The performance evaluation of the models was complemented by a quantitative analysis of the relationship between the predicted and actual values of the duration variable. A scatter plot was used for this purpose (see Figures 9 and 10), where each point represents an individual prediction against its corresponding observed value.
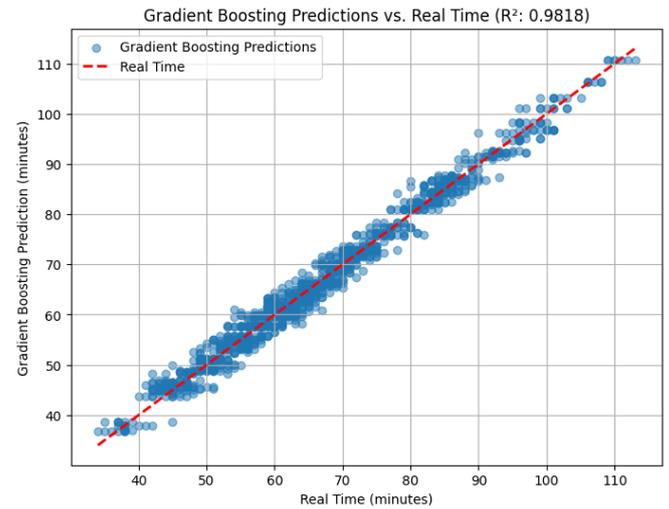
Fig. 9. Gradient Boosting distribution of predicted values against actual values
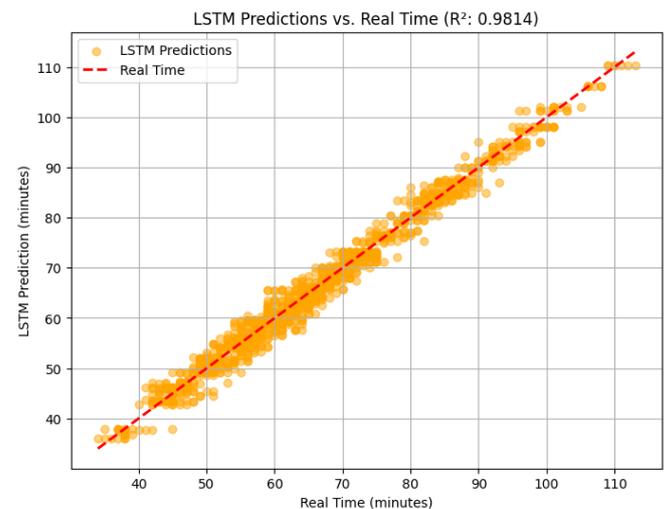
Fig. 10. LSTM distribution of predicted values against actual values

The distribution of points along the identity line (diagonal) highlights the closeness between predicted and actual values. Both the Gradient Boosting and LSTM models exhibited a high concentration of points near this line, confirming the accuracy of their predictions. This observation aligns with the R^2 values obtained, which exceeded 0.98, and reinforces the robustness of the models in capturing the underlying patterns in the data.

5. Conclusion

The proposed activity-based model supported by Artificial Intelligence (AI) represents an innovative and practical contribution to project management in the metalworking industry. By integrating machine learning techniques, specifically Gradient Boosting and Long Short-Term Memory (LSTM) neural networks, into activity-based planning, the model addresses key limitations of traditional estimation methods, particularly in dynamic and resource-constrained environments.

The scientific contribution of this work lies in the structured operationalisation of AI within the IDEF0 framework. This integration enables traceable, adaptable, and data-driven decision-making, enhances project visibility, and supports predictive analytics. Additionally, the approach promotes interdisciplinary collaboration between AI specialists and metalworking professionals, bridging the gap between data science and industrial practice.

The model's architecture is grounded in real-world operational parameters such as welding speed, material complexity, and preparation time, which reinforces its applicability to industrial contexts. The initial empirical validation demonstrated that both models achieved high predictive accuracy. The Gradient Boosting model achieved an R^2 of 0.9818, while the LSTM model achieved an R^2 of 0.9814, confirming the potential of the models for reliable prediction of task durations. Beyond these results, our approach differs significantly from existing solutions that focus solely on AI algorithms or generic lifecycle models. By integrating the AI lifecycle with IDEF0 functional modelling, we ensure traceability and iterative improvement. To our knowledge, no previous studies have applied this combined approach in the metalworking sector, representing a major advancement in bridging process modelling and predictive analytics for industrial project management.

6. Future Work

Future work will focus on the implementation and expansion of the AI-supported activity-based model, with particular emphasis on the metalworking and metalomechanical industries. The next phase of the project will involve the application of Artificial Neural Networks (ANNs) to forecast project durations, identify critical paths, and optimise resource allocation within real-world production environments.

In parallel, the potential of Generative Adversarial Networks (GANs) will be explored to enhance the model's ability to simulate complex production scenarios and generate synthetic datasets, especially in contexts where data availability is limited. This will be particularly relevant for capturing variability in welding operations, machining sequences, and assembly processes.

Comparative studies between ANN and GAN-based approaches will be conducted, taking into account the complexity of industrial data and the specific forecasting requirements of metalomechanical projects. The analysis will include performance metrics, generalisation capacity, and adaptability to evolving production conditions.

Further research will address challenges related to data volume, model architecture optimisation, and integration with existing project management systems. Collaboration with industry partners will be essential to validate the model's effectiveness and ensure its alignment with operational needs and strategic objectives within the metalworking sector.

Bibliography

Almagrabi, A. O., & Khan, R. A., 2025. Optimizing Secure AI Lifecycle Model Management With Innovative Generative AI Strategies. IEEE Access, 13, 12889–12920. DOI: 10.1109/ACCESS.2024.3491373

Amran, T. G., Saraswati, D., & Harahap, E. F., 2019. Evaluating Storage Tank Cap 10000L Manufacturer by Using Lean Project Management. IOP Conference Series: Materials Science and Engineering, 528(1), 012052. DOI: 10.1088/1757-899X/528/1/012052

Ávila, P., 2004. Rigorous Resource System Selection Model for Agile/Virtual Enterprise Design for Complex Products. PhD Thesis.

Çakıt, E., & Dağdeviren, M., 2023. Comparative analysis of machine learning algorithms for predicting standard time in a manufacturing environment. Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 37, e2. DOI: 10.1017/S0890060422000245

Castro, H., Câmara, E., Ávila, P., Cruz-Cunha, M., & Ferreira, L., 2024. Artificial Intelligence Models: A literature review addressing Industry 4.0 approach. Procedia Computer Science, 239, 2369–2376. DOI: 10.1016/j.procs.2024.06.430

Cempel, W., & Dąbal, D., 2014. IDEF0 as a Project Management Tool in the Simulation Modeling and Analysis Process in Emergency Evacuation from Hospital Facility: A Case Study. DOI: 10.1007/978-3-319-07347-7_11

Chari, A., Stahre, J., Bärring, M., Despeisse, M., Li, D., Friis, M., Mörstam, M., & Johansson, B., 2023. Analysing the antecedents to digital platform implementation for resilient and sustainable manufacturing supply chains - An IDEF0 modelling approach. Journal of Cleaner Production, 429, 139598. DOI: 10.1016/j.jclepro.2023.139598

Chen, Y. C., He, B. H., Lin, S. S., Soeseno, J. H., Tan, D. S., Chen, T. P. C., & Chen, W. C., 2021. Demystifying data and AI for manufacturing: Case studies from a major computer maker. APSIPA Transactions on Signal and Information Processing. DOI: 10.1017/ATSIP.2021.3

Chen, Y., Clayton, E. W., Novak, L. L., Anders, S., & Malin, B., 2023. Human-Centered Design to Address Biases in Artificial Intelligence. Journal of Medical Internet Research, 25. DOI: DOI: 10.2196/43251

Dahmani, S., Ben-Ammar, O., & Jebali, A., 2021. Resilient Project Scheduling Using Artificial Intelligence: A Conceptual Framework. In A. Dolgui, A. Bernard, D. Lemoine, G. von Cieminski, & D. Romero (Eds.), Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems, 311–320. Springer International Publishing.

Drobintsev, P. D., Kotlyarov, V. P., Chernorutsky, I. G., Kotlyarova, L. P., & Aleksandrova, O. V., 2017. Approach to adaptive control of technological manufacturing processes of IoT metalworking workshop. 2017 XX IEEE International Conference on Soft Computing and Measurements (SCM), 174–176. DOI: 10.1109/SCM.2017.7970530

Duncan Kimutai Ronoh, D. C. C. K., 2020. Influence of Resource Scheduling On the Performance of Residential Construction Projects in Nairobi City County, Kenya. International Journal of Research and Innovation in Social Science, 4.

Egwim, C., Alaka, H., Toriola-Coker, O., Balogun, H., & Sunmola, F., 2021. Applied Artificial Intelligence for Predicting Construction Projects Delay. Machine Learning, 6. DOI: 10.1016/j.mlwa.2021.100166

Elena Bruni, M., Beraldi, P., Guerriero, F., & Pinto, E., 2011. A scheduling methodology for dealing with uncertainty in construction projects. Engineering Computations, 28(8), 1064–1078. DOI: 10.1108/02644401111179036

Fang, W., Guo, Y., Liao, W., Ramani, K., & Huang, S., 2020. Big data driven jobs remaining time prediction in discrete manufacturing system: a deep learning-based approach. International Journal of Production Research, 58(9), 2751–2766. DOI: 10.1080/00207543.2019.1602744

Gil Ruiz, J., Martínez, J., & Gonzalez Crespo, R., 2021. The Application of Artificial Intelligence in Project Management Research: A Review. International Journal of Interactive Multimedia and Artificial Intelligence, 6. DOI: 10.9781/ijimai.2020.12.003

Gonzales-Romero, A., Huamani-Martinez, I. J., Quiroz-Flores, J. C., & Diaz-Garay, B. H., 2022. Production Management Model Based on Lean and DDMRP Tools to Increase the Rate of Project Compliance in Manufacturing SMEs in the Metalworking Sector. 2022 8th International Engineering, Sciences and Technology Conference (IESTEC), 38–45. DOI: 10.1109/IESTEC54539.2022.00015

Hasegawa, H., Lima, R., Mota Junior, V., & Teixeira, R., 2025. Challenges in data collection for enhancing productivity in Brazilian industrial processes. Brazilian Journal of Operations & Production Management, 22, e20252445. DOI: 10.14488/BJOPM.2445.2025

Hassan, A., El-Rayes, K., & Attalla, M., 2021. Optimizing the scheduling of crew deployments in repetitive construction projects under uncertainty. Engineering, Construction and Architectural Management, 28(6), 1615–1634. DOI: 10.1108/ECAM-05-2020-0304

Heinzl, B., Silvina, A., Krause, F., Schwarz, N., Kurniawan, K., Kiesling, E., Pichler, M., & Moser, B., 2024. Towards Integrating Knowledge Graphs into Process-Oriented Human-AI Collaboration in Industry. In P. Bludau, R. Ramler, D. Winkler, & J. Bergsmann (Eds.), Software Quality as a Foundation for Security (pp. 76–87). Springer Nature Switzerland.

Hupont, I., & Gómez, E., 2022. Documenting use cases in the affective computing domain using Unified Modeling Language. 2022 10th International Conference on Affective Computing and Intelligent Interaction (ACII), 1–8. DOI: 10.1109/ACII55700.2022.9953809

Joseph Kozhaya, 2020., November 16). As enterprises move from experimenting with artificial intelligence (AI) to adopting it in production, AI model lifecycle management is quickly becoming the next frontier in development and research. Https://Www.Ibm.Com/Blog/Ai-Model-Lifecycle-Management-Build-Phase/.

Kesarkar, A., Dabre, C., Agarwal, R., Chavan, Y., & Ruhina Karani, P., 2025. Enhanced Structural Health Monitoring Through LSTM-Enhanced Gradient Boosting Regressor. Computer Engineering, DJ Sanghvi College of Engineering, 8(9).

Kim, D.-Y., Kareem, A. B., Domingo, D., Shin, B.-C., & Hur, J.-W., 2024. Advanced Data Augmentation Techniques for Enhanced Fault Diagnosis in Industrial Centrifugal Pumps. Journal of Sensor and Actuator Networks, 13(5). DOI: 10.3390/jsan13050060

Krynke, M., 2021. Management optimizing the costs and duration time of the process in the production system. Production Engineering Archives, 27, 163–170. DOI: 10.30657/pea.2021.27.21

Kumar Dukhiram Pal, D., Chitta, S., Sri Manoj Bonam, V., Katari, P., & Thota, S., 2023. AI-Assisted Project Management: Enhancing Decision-Making and Forecasting. Journal of Artificial Intelligence Research, 3(2), 146–171. https://www.thesciencebrigade.com/JAIR/article/view/ 333

Luo, J., Wong, S. F., Yang, Z. X., & Wong, P. K., 2011. An integrated modeling framework design to support product process in manufacturing enterprises. Proceedings 2011 International Conference on System Science and Engineering, 455–460. DOI: 10.1109/ICSSE.2011.5961946

Mahale, Y., Kolhar, S., & More, A. S., 2025. A comprehensive review on artificial intelligence driven predictive maintenance in vehicles: technologies, challenges and future research directions. Discover Applied Sciences, 7(4), 243. DOI: 10.1007/s42452-025-06681-3

Martínez-Plumed, F., Contreras-Ochando, L., Ferri, C., Hernández-Orallo, J., Kull, M., Lachiche, N., Ramírez-Quintana, M. J., & Flach, P., 2021. CRISP-DM Twenty Years Later: From Data Mining Processes to Data Science Trajectories. IEEE Transactions on Knowledge and Data Engineering, 33(8), 3048–3061. DOI: 10.1109/TKDE.2019.2962680

Monteiro, C., Ferreira, L. P., Fernandes, N. O., Silva, F. J. G., & Amaral, I., 2019. Improving the machining process of the metalwork industry by upgrading operative sequences, standard manufacturing times and production procedure changes. Procedia Manufacturing, 38, 1713–1722.

Morariu, C., Morariu, O., Răileanu, S., & Borangiu, T., 2020. Machine learning for predictive scheduling and resource allocation in large scale manufacturing systems. Computers in Industry, 120, 103244. DOI: 10.1016/j.compind.2020.103244

OECD, 2019. Artificial Intelligence in Society. OECD Publishing. DOI: 10.1787/eedfee77-en

Palakshappa, A., Maradithaya, S., & V, C., 2025. A Machine Learning Method to improve Supplier Delivery Appointments in Supply Chain

Industries: A Case Study. Brazilian Journal of Operations & Production Management, 22, 2040. DOI: 10.14488/BJOPM.2040.2025

Palomino-Valles, A., Tokumori-Wong, M., Castro-Rangel, P., Raymundo-Ibañez, C., & Dominguez, F., 2020. TPM Maintenance Management Model Focused on Reliability that Enables the Increase of the Availability of Heavy Equipment in the Construction Sector. IOP Conference Series: Materials Science and Engineering, 796(1), 012008. DOI: 10.1088/1757-899X/796/1/012008

Park, H., Ji, B., Lee, M., Choi, J., Lee, J., Bang, S. H., & Cho, H., 2017. Conceptual Development Process of Mass-customizable Data Analytics Services for Manufacturing SMEs. In H. Lödding, R. Riedel, K.-D. Thoben, G. von Cieminski, & D. Kiritsis (Eds.), Advances in Production Management Systems. The Path to Intelligent, Collaborative and Sustainable Manufacturing (pp. 194–201). Springer International Publishing.

Ruschel, E., Rocha Loures, E. de F., & Santos, E. A. P., 2021. Performance analysis and time prediction in manufacturing systems. Computers & Industrial Engineering, 151, 106972. DOI: DOI: 10.1016/j.cie.2020. 106972

Sarajcev, P., Kunac, A., Petrović, G., & Despalatovic, M., 2022. Artificial Intelligence Techniques for Power System Transient Stability Assessment. Energies, 15, 507. DOI: 10.3390/en15020507

Serifi, V., Dašić, P., Ječmenica, R., & D.Labović, 2013. Functional and information modeling of production using IDEF methods. Strojniski Vestnik, 55, 131–140.

Shoushtari, F., Daghighi, A., & Ghafourian, E., 2024. Application of Artificial Intelligence in Project Management. International Journal of Industrial Engineering and Operational Research, 6(2), 49–63.

Silva, J., Ávila, P., Matias, J., Faria, L., Bastos, J., Ferreira, L., & Castro, H., 2024. Bibliographic review of AI applied to project management and its analysis in the context of the metalworking industry. Procedia CIRP, 130, 177–187. DOI: DOI: 10.1016/j.procir.2024.10.073

Silva, J., Ávila, P., Patrício, L., Sá, J. C., Ferreira, L. P., Bastos, J., & Castro, H., 2022. Improvement of planning and time control in the project management of a metalworking industry - case study. Procedia Computer Science, 196, 288–295. DOI: 10.1016/j.procs.2021.12.016

Simion, D., Postolache, F., Fleacă, B., & Fleacă, E., 2024. AI-Driven Predictive Maintenance in Modern Maritime Transport—Enhancing Operational Efficiency and Reliability. Applied Sciences, 14, 9439. DOI: 10.3390/app14209439

Szwarcfiter, C., Herer, Y. T., & Shtub, A., 2023. Balancing Project Schedule, Cost, and Value under Uncertainty: A Reinforcement Learning Approach. Algorithms, 16(8). DOI: 10.3390/a16080395

Wachnik, B., 2022. Analysis of the use of artificial intelligence in the management of Industry 4.0 projects. The perspective of Polish industry. Production Engineering Archives, 28, 56–63. DOI: 10.30657/pea.2022.28.07

Wang, W., Zhang, Y., Gu, J., & Wang, J., 2022. A Proactive Manufacturing Resources Assignment Method Based on Production Performance Prediction for the Smart Factory. IEEE Transactions on Industrial Informatics, 18(1), 46–55. DOI: 10.1109/TII.2021.3073404

Zennaro, I., Finco, S., Battini, D., & Persona, A., 2019. Big size highly customised product manufacturing systems: a literature review and future research agenda. International Journal of Production Research, 57(15–16), 5362–5385. DOI: 10.1080/00207543.2019.1582819

Zohrehvandi, S., 2024. A Fuzzy Overlapping Project Resource Optimization Model in the Project Construction Industry with a Fractal Approach. Mobile Networks and Applications, 29(2), 545–556. DOI: 10.1007/s11036-023-02254-z

Appendix

Appendix A

Table 3 - Comparative Table: Process Models and AI in Metalworking Projects

Method / Notation	Main Focus	Strengths	Limitations	Suitability for AI in Metalworking Projects
BPMN	Business process modelling.	Standardised notation; Facilitates communication across departments.	Limited functional depth; Business-oriented rather than engineering-focused.	Useful for a macro view of processes but does not detail functions and mechanisms.
UML	Software and systems modelling.	Multiple perspectives (use case, class, sequence diagrams, etc.); Consolidated in software engineering.	High complexity; Less intuitive for industrial processes.	More suitable for software development than for production processes.
CRISP-DM	Data mining process.	Structured in six distinct phases; Widely recognized as the standard in data mining.	Limited flexibility in complex environments; Restricted focus on data.	Useful for the AI lifecycle in data projects but does not integrate well with industrial functions (Martínez-Plumed et al., 2021).
FLOWCHARTS	Sequential representation of activities.	Simple, visual, widely understood.	Poor at representing controls and resources; Does not scale well in complex processes.	Suitable for simple routines but limited for integrated industrial processes.
SIPOC	High-level process mapping (Suppliers, Inputs, Process, Outputs, Customers).	Quick overview of process scope; Useful in continuous improvement (Lean/Six Sigma).	Very generic; Lacks detail on functions and resources.	Useful only for an initial overview, not appropriate for in-depth AI modelling.
IDEF0	Functional process modelling.	Represents functions, inputs, outputs, controls and mechanisms hierarchically; Applicable in engineering and industry (Ávila, 2004), (Serifi et al., 2013).	Requires discipline in modelling and technical expertise.	Most suitable, as it integrates a systemic view of complex industrial processes, providing better support for AI development to forecast project duration in metalworking (Park et al., 2017).

Appendix B

Fig. 11. Detailed IDEF0 Activity-Based Model.