Manufacturing and AI – Industrial Machine Data Generation and Artificial Optimisation

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Abstract
The AIDEAS project targets the development of AI technologies strategically designed to improve European engineering companies' sustainability, agility, and resilience throughout the lifecycle of industrial assets, i.e., in the design, manufacturing, and repair/reuse/recycling phases. In the context of the AIDEAS project, this workshop paper focuses on the early stages of the product development process to accelerate the development process with the help of AI-supported tools. The results of some of these AI solutions will also help at a later stage to decide which machine parameters need to be considered and optimised during product development to optimise the later life cycle according to the current requirements of the repair, reuse, and recycle phases.

Keywords
Design Optimization, Artificial Intelligence, Simulation, Digital Twin, Machine Design

1. Introduction

This paper outlines the objectives and structure of Work Package 3 (WP3) in the broader context of the BUILD process for the AI-assisted lifecycle of industrial plants. WP3 focuses mainly on the initial phase of the BUILD process, the DESIGN part, with the aim of developing AI-supported optimisation modules for the construction of industrial plants.

2. Methodology

The aims of WP3 include the development of AI-based optimisation modules for industrial plant engineering. As a result, companies can improve their resilience by reducing waste and increasing their responsiveness to changing customer needs. The aims are specified in the relevant subchapters below. Each of the tasks deals with different aspects of AI-supported optimisation. The tasks cover optimal design, data synthesis, integration with standard systems, data storage and exchange, and continuous validation. Depending on the task, competencies and project phases, the companies IANUS, IKERLAN, XLAB, CERTH and ITI work together to achieve the objectives of the work package.

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The goal is to create a framework that facilitates the optimal design of industrial machinery by integrating AI into mechanisms, structures, and control components. This will be achieved through data synthetization, integration with CAD systems, appropriate data exchange mechanisms and continuous validation.

3. Machine Design Optimiser (MDO)

This task focuses on developing a toolkit to assist designers in optimally defining the key design parameters in multi-physical systems, enhancing machine performance as required for each scenario. The toolkit will be based on reduced models developed by AI from physically based model simulations that will take account of the degradation of the joints during the entire life cycle of the machine. The optimiser will need a theoretical model (physical or data-driven model) that can estimate the system's behaviour. The developments done during the first part of the project are related to the following topics:

- Definition of the Demonstration Scenarios and Monitoring KPIs Definition for the two pilot use cases (PAMA and BBM).
- Definition of the use case specifications, goals, and restrictions for the two pilot use cases.
- Definition of the user interface Mock-ups.
- Significant developments of the use case model to be used as case studies.

The PAMA use case, a dynamic model of the 5-axis machine, has been developed considering the wear development of the vertical sliding system. The optimization objective has been defined as a trade-off between the static stiffness and the number of cycles before wear creates backlash. The next figure represents a schematic representation of the objectives, and the parameter expected behaviour is represented (**Figure 1**).

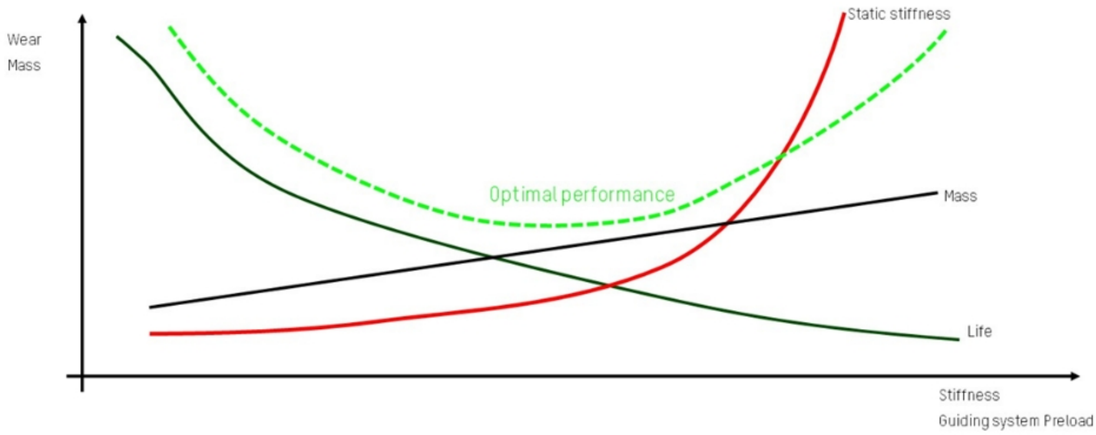

Figure 1: Schematic representation of the objectives and parameters.

A parametric modelling of the extrusion die head is built for the BBM model. This allows the generalisation of different designs of the flow channel of the die just by changing parametric values like diameter, number of spirals or total height and directly performing highly accurate 3D-CFD-Simulation with it. With this opportunity, numerous flow simulations can be performed by the MDG, which will be presented in the next chapter. With the calculated data out of the MDG, a meta-model can be created, which allows the running of AI-based optimum algorithms within a short period of time.

For the PAMA use case, the first version of the dynamic model has been developed and validated, verifying that the model is able to predict the cycles to wear. This model generates data for the next step of developing the AI optimizer. In the Case of the blow mold dies for BBM, different existing dies were simulated via the parametric model. They show a good match regarding pressure loss, flow homogeneity and overlap of the different layers. This shows that the model can be used for optimization strategies. To ensure that, a manual first optimization of one die was performed, resulting in significantly shorter residence times, a more homogenous outflow, and thus waste reduction and the capability of using a higher percentage of recycled material.

In the coming months, the AI optimizer is expected to be developed. The core concept involves utilizing AI to generate an improved reduced model for efficient iteration, optimizing the design within a reasonable timeframe. The accompanying image illustrates the proposed implementation, beginning with the dynamic model and parameter definition. Initial simulations are conducted to obtain KPIs for these designs, and the results are used to create a reduced-order model of system behaviour. This reduced model proposes "near-optimum" parameter values, evaluated through the multibody model. The process is iterated until an optimal value is achieved.

The main anticipated advantages include:

- Improved iteration efficiency.
- Valuable information about the sensitivity of each design parameter, aiding future design proposals and evaluations.

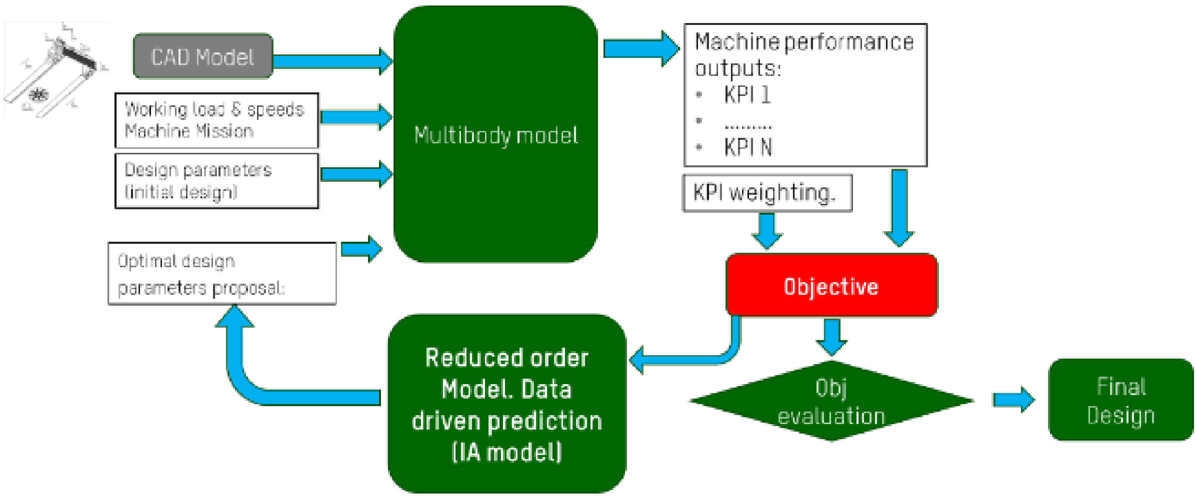

Figure 3: Representation of the flow chart of the optimization process.

An evolutionary AI approach designs spiral distributors with different parameters for the BBM model, generating thousands of variants for efficient production process simulation. The meta-model significantly reduces simulation time compared to real 3D-CFD simulations. The MDO identifies designs that best match the desired KPIs, selects and examines the top 30% for regularities, and creates new digital twins until an optimal distributor within a confidence interval is identified or the maximum iteration time (TBD) is reached [1].

Parametric machine designs based on physics models are commonly used in the design stage for performance verification, reducing development time. Despite the good agreement with real behaviour, these simulations can be time-consuming, limiting exploration during the design phase. Optimization is often neglected due to a lack of knowledge and required simulation time. To address this, the tool simplifies the process by requiring the user to provide:

- A parametric simulation model (physical or data-driven) to calculate the desired KPI.
- Parameter range values.
- Defined total iterations, with initial trials recommending a reduced number for faster results.

After simulation, the tool provides optimal parameter proposals and sensitivity analysis, assisting the designer in understanding each parameter's relative effect on the objective. This information is crucial for defining the design concept.

1. Machine Synthetic Data Generator (MDG)

This task focuses on the synthesis of data for the training of optimisation modules. Preparatory work has already been carried out on this based on the FeatFlow simulation code used [2]. It involves the creation of AI solutions for shorter time series and production volumes through the artificial generation of data using digital twins [3] and simulations. Real and historical data is also used for training without data synthesis. The front-end components (figure 4) required to implement the given machine designs and provide operational constraints have been successfully created. These components have been tested with dummy data sets to ensure their functionality and reliability.

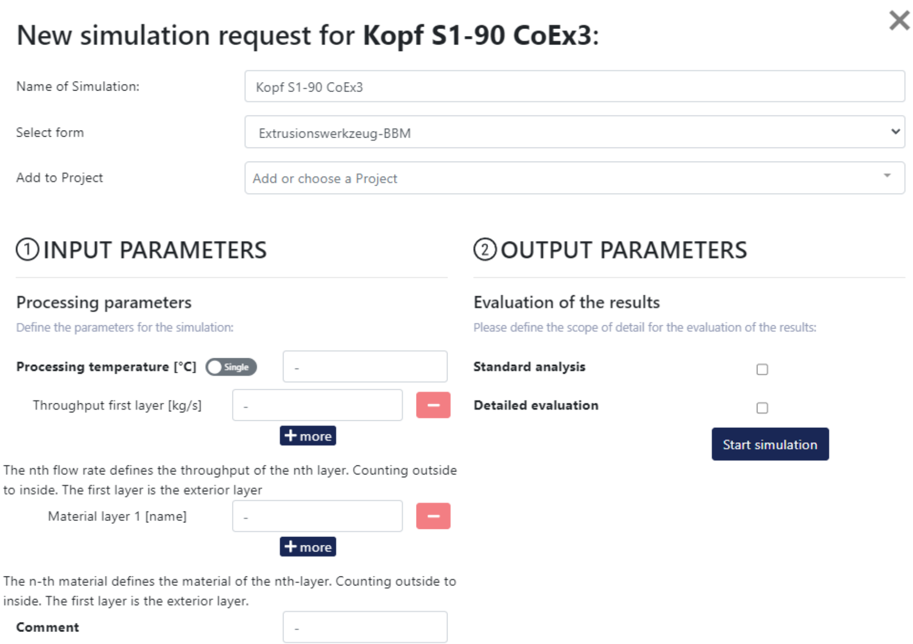

Figure 4: Frontend for Start-Up-Parameters.

A dedicated front-end for presenting results has been developed in the realm of new material data generation. Pilot BBM studies have identified material parameter ranges to refine simulations, as depicted in Figure 5. Initial automated simulations have been rigorously tested with dummy datasets. This collaborative effort signifies the successful establishment and validation of key components, laying the groundwork for further project progress.

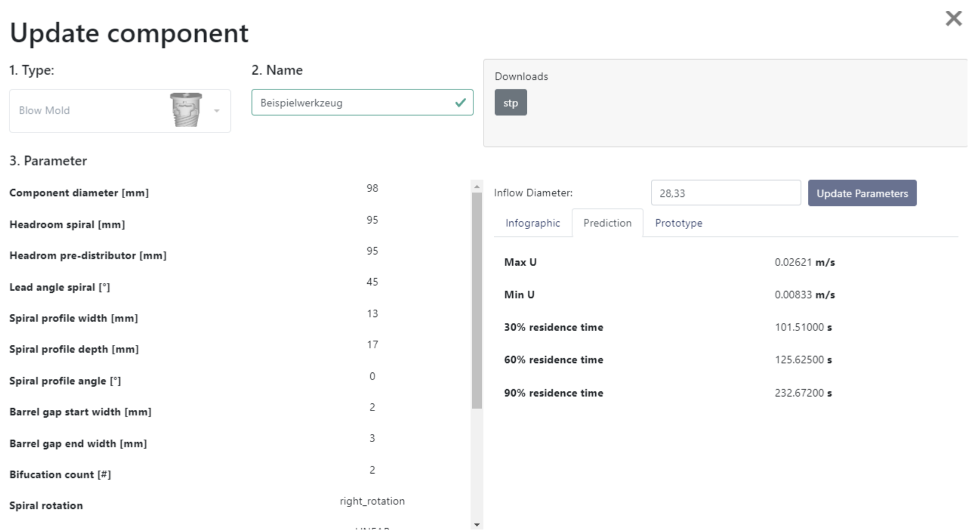

Figure 5: Front End for generating spiral distributors for different materials.

This collaborative effort signifies the successful establishment and validation of key components, laying the groundwork for further project progress. Regarding start-up parameters, pilot BBM studies will define possible data ranges, followed by the creation of an extensive simulation dataset to train the AI. Subsequently, the AI will be integrated into the front-end, significantly advancing overall project functionality.

Upcoming tasks include developing a valid approximation for various materials to generate new material data. Simulation results will be validated using diverse materials and real-life data for accuracy. A substantial set of simulation data, akin to start-up parameters, will be generated for AI training, and the AI will be integrated into the front-end to streamline the material data generation process. These planned steps represent the next phase towards achieving the project's overarching goals. The market gap analysis identifies challenges such as a lack of simulation expertise, insufficient customer awareness in selecting data analysis tools, and redundant execution of real experiments. To address expertise gaps, the MDG solution will provide an easy way for any employee to generate data and initiate simulations effortlessly.

Future developments aim to introduce an automated AI solution to combat insufficient customer awareness in selecting and using AI for data evaluation and experimental design construction. This MDG solution ensures optimal data analysis while mitigating the risk of biased sample data. Customers facing capacity constraints in running real experiments require AI-supported simulations to generate training data. The project aims to seamlessly integrate into the market, offering accessible and automated solutions to close existing gaps and enhance the overall user experience [4].

4. CAx Addon (CAx)

Task T3.3 transfers the AI-supported optimisation modules developed in T3.1 and T3.2 to production. This includes the compatibility of the modules with standard CAD/CAM/CAE systems, the integration of APIs and the user interface, and testing and performance optimisation.

For the common CAD Software Autodesk Fusion, which is a low entry in terms of pricing and therefore used by many small businesses, a plugin was written that connects directly to the IANUS StrömungsRaum(c), which performs the Machine Data Generator (figure 6). Therefore, a bank security API and Login were written, enabling direct access via Fusion to perform simulations without using additional software. Due to the cloud computing approach of StrömungsRaum(c), the user can perform the simulations from any computer, which allows them to run Fusion 360. Fusion was selected as the first adaptor CAD software; besides the low-end pricing, it is also cloud-based and, therefore, usable from many different devices [5].

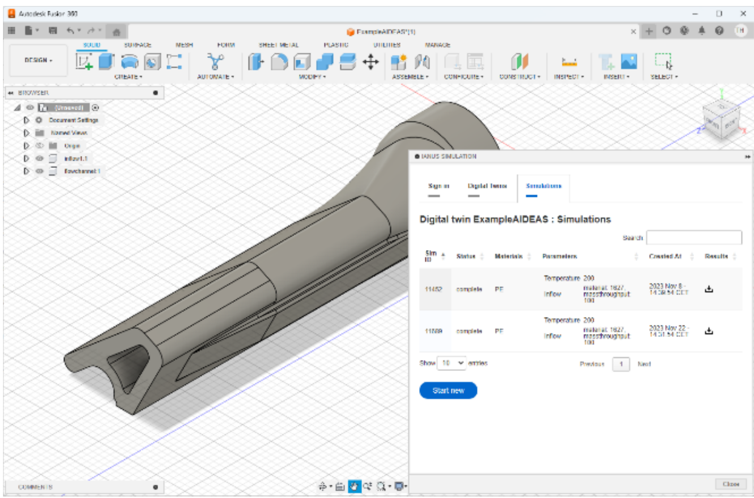

Figure 6: Example of the PlugIn interface

The main advantage of the plugin is that no additional steps need to be taken to start 3D-CFD Simulations out of an existing construction. The user doesn’t have to export CAD-Files to a common standard, import them to the simulations software, check the results and get back to the CAD Software to implement modifications if needed. All these steps will be fully integrated into Fusion and the CAx-Addon to support seamless access to 3D-Simulations and the results.

The API and Plugin for Fusion 360 also enable continuous development to implement additional features. Also, the Plugin itself is easily adaptable to different CAD Software, like SolidWorks. This is extremely important for bringing AIDEAS Suites to a wide variety of customers.

Many different simulations were directly started out of Fusion and were successfully run to StrömungsRaum(c) to generate virtual machine data, capable of building an AI. The Simulation has shown no errors or deviations, depending on running directly to the CAx Addon or directly to StrömungsRaum(c). Therefore, the overall simulation concept is validated and ready to be added with additional features.

To fully optimise geometries before building them in real life, the CAx-Addon is adapted to the Machine Data Generator. Therefore, more complex APIs will be integrated. This will result in the capability, to directly generate Geometries via Parameters in Fusion 360 and optimize them automatically via the Machine Data Generator. The idea is to start with a parametric Geometry defined by the customer. The MDG will then perform an optimization via the Meta-Model out of the MDG and bring back the parametrization and the step-file to Fusion 360. By using the fully integrated plugin, the Customer will be able to substantially decrease the construction and optimization time since nearly everything is done automatically out of the common software. These steps will be included in the second stage of the project.

The Plugin can be used for different approaches. The first is a 3D-CFD Simulation for generating synthetic data, which can be used for an AI-Module or for the customer itself to optimize geometry in a classic way. The second approach is much more powerful. With the newly developed API and the respective Plugin, the customer will be able to highly improve the iterative processes in the construction of spiral distributors in the plastic industry, by saving significant time and money for construction. Also, this API directly connects to the Meta-Model, bringing in optimizations of such a construction in less than one hour – saving more than 90% of time and money regarding the classic way. Since the API is easily adaptable to new challenges, newly generated meta-models for other industries could be implemented soon – saving resources in time, money, and material all over the world.

5. Conclusion

The approach outlined in WP3 includes a comprehensive methodology for integrating AI into the design phase of industrial plants. The focus is on developing optimisation modules, synthesising training data, ensuring compatibility with standard systems, and continuously validating to contribute to a holistic framework for AI-supported design.

6. Acknowledgements

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Declaration on Generative AI

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

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