Artificial Intelligence in Engineering Design:

Opportunities, Limitations, and Industrial Readiness

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Executive summary

Engineering design workflows in industrial organisations continue to rely heavily on skilled, manual engineering effort, supported by mature CAD, simulation, and manufacturing planning tools. While these workflows are effective within current technological constraints, they can become difficult to scale in contexts characterised by high product variety, increasing system complexity, compressed timelines, and stringent quality requirements. This whitepaper examines whether recent advances in Artificial Intelligence (AI) offer opportunities to support, augment, and modernise selected aspects of engineering design practice, rather than replace established tools or expertise. The report focuses on five areas where AI techniques have demonstrated potential for delivering near- to medium-term industrial value:

- ***Mesh-to-CAD reverse engineering :*** where AI-assisted feature recognition and hybrid reconstruction methods may reduce manual effort when converting scan data into editable CAD models, particularly in through-life support, legacy part digitisation, and refurbishment contexts.
- ***AI-assisted predictive simulation,*** where surrogate and reduced-order models can provide rapid performance insight earlier in the design cycle, enabling faster exploration of design alternatives while full-fidelity simulation remains available for validation.
- ***Automatic assembly sequence generation and validation,*** where rule-based and geometry-driven reasoning can support early manufacturability checks, improve consistency in design-for-assembly decisions, and reduce reliance on tacit individual expertise.
- ***Automated CAD generation,*** where generative and language-driven technologies show promise for accelerating early concept creation and simple part modelling, while their application to production-grade design typically involves substantial human oversight.
- ***Facility layout optimisation,*** where AI and optimisation techniques can enhance scenario exploration and performance analysis in brownfield environments, but do not yet autonomously generate validated layouts for discrete manufacturing.

Across these domains, the review finds that AI-enabled tools are already capable of delivering measurable benefits in specific, well-bounded use-cases, particularly where workflows are repetitive, rule-constrained, or data-rich. However, current technologies vary in maturity depending on use-case. Commercial solutions are commonly applied where AI is tightly integrated with existing CAD and simulation platforms, while many academic and experimental approaches show promise but remain at earlier stages of development and evaluation. Evidence presented in this whitepaper is drawn from a combination of vendor-reported capabilities, published research, and technologies that have been independently developed and evaluated by MTC.

Importantly, engineering judgement remains an important component in existing technologies as they shift effort from routine or procedural tasks towards higher-value decision-making.

Industrial Considerations:

The information presented in this whitepaper positions AI as a design support capability rather than a disruptive replacement for engineering practice. Viable near-term value lies in targeted deployment: piloting AI tools in specific workflows, integrating them with existing CAD, simulation, and manufacturing systems, and maintaining clear accountability with engineers in the loop. Organisations that combine incremental AI adoption with strong domain knowledge, data governance, and transparent, explainable tools can achieve productivity gains while managing risk. Over time, these foundations may support future adoption of advanced AI-driven design automation as technologies mature.

1. Introduction

Engineering design in industrial organisations is under sustained pressure from increasing product complexity, expanding product variants, and the need to deliver high quality outcomes within constrained timelines. Contemporary CAD, simulation, and manufacturing planning tools are well established and highly capable; however, applying them effectively at scale continues to require significant expert effort. As a result, organisations are increasingly exploring whether emerging digital technologies, including AI, can complement existing practices by reducing manual effort in specific, well-defined parts of the design workflow.

This whitepaper does not assume that current engineering workflows are inefficient or obsolete. Instead, it examines selected design activities to understand whether AI technologies can augment existing tools and practices, particularly in situations characterised by repetition, formalised rules, large volumes of data, or time-critical decision-making. The intent is to assess where AI has reached sufficient maturity to offer practical industrial value, and where expectations should remain cautious.

1.1 Industry Challenges in Design Workflows

While core engineering tools are mature, several recurring challenges continue to arise in industrial design environments, particularly for high mix, high complexity products and through life support contexts. These challenges are not universal bottlenecks, nor do they occur with equal frequency across all organisations, but they are consistently observed in specific classes of work:

- ***Reverse engineering effort:*** Converting scan or point-cloud data into editable, parametric CAD models often requires extensive manual interpretation, particularly for legacy components, life extension programmes, or parts produced using conventional manufacturing routes. The challenge lies less in data capture than in reconstructing design intent and manufacturable geometry.
- ***Delayed simulation feedback:*** High fidelity simulation remains computationally expensive and time consuming to set up, which can limit the number of design iterations performed early in the design process. As a result, many performance insights are gained later, when design freedom is already reduced.
- ***Assembly sequence reasoning:*** Assembly planning and design for assembly evaluation rely heavily on specialist knowledge. While effective in expert hands, this knowledge is often tacit, difficult to scale, and not consistently embedded in CAD models or formal rules.
- ***CAD model generation and modification effort:*** Creating and maintaining robust, parametric CAD models requires careful management of feature trees, constraints, and geometric dependencies. Much of the time invested by engineers is spent managing detail, dependencies, and downstream robustness rather than geometric novelty.
- ***Facility layout exploration in constrained environments:*** For existing manufacturing facilities, layout modification is constrained by fixed infrastructure and operational risk. Although analysis tools exist, the creation and evaluation of multiple alternative layouts remain a largely manual, iterative activity.

These challenges are amplified in environments characterised by high product variety, stringent regulatory or quality requirements, and increasing pressure to reduce lead times without compromising engineering rigour. They provide the motivation for examining where AI technologies may offer targeted support.

1.2 The Potential of AI in Design Workflows

AI technologies have advanced rapidly in recent years, particularly in areas, such as pattern recognition, optimisation, surrogate modelling, and language-based interfaces. In engineering design, these capabilities are most relevant where tasks involve repetition, structured rules, or large datasets, rather than open ended creative judgement.

Rather than proposing wholesale automation of design activities, this whitepaper evaluates AI as a ***supporting capability*** that can:

- Accelerate specific tasks by automating well defined, repeatable steps.
- Provide earlier or faster feedback to inform engineering decisions.
- Improve consistency by embedding explicit rules and checks into workflows.
- Reduce reliance on undocumented, tacit expertise without removing human accountability.

Five domains were identified where AI shows the strongest near term potential:

- ***Reverse engineering,*** particularly for feature recognition and hybrid reconstruction.
- ***AI-assisted predictive simulation*** using surrogate and reduced order models.
- ***Automatic assembly sequence generation*** and validation using rule based and geometric reasoning.
- ***Automated CAD generation*** for early stage concepts and simple, well defined parts.
- ***Facility layout optimisation*** to enhance scenario exploration and performance evaluation.

Across these domains, AI does not replace engineering judgement. Instead, it shifts effort away from procedural or clerical activities towards interpretation, validation, and decision making, with engineers remaining responsible for outcomes.

1.3 Scope

This whitepaper presents a targeted assessment of AI technologies across five selected engineering design workflows where near to medium term industrial value is commonly plausible. The scope has been deliberately constrained to areas where AI methods either have demonstrable industrial application today or are expected to reach practical maturity within the next three to five years. Commercial tools referenced in this report are included as representative examples of broader technological approaches.

The descriptions provided are not intended as a formal benchmarking or evaluation of specific vendor solutions. The scope of this assessment focuses on AI as a capability that complements engineering design activities rather than replacing them. While AI can assist with a range of engineering tasks, human judgement, expertise, and accountability remain essential, with engineers retaining responsibility for design outcomes.

The assessment is structured as follows:

- ***Reverse engineering (Section 2)*** examines the conversion of scan and mesh data into editable, parametric CAD models, with coverage of commercial hybrid tools and emerging AI-driven feature recognition approaches. The focus is on through-life support, legacy components, and refurbishment contexts rather than routine new-product design.
- ***AI-assisted predictive simulation (Section 3)*** evaluates surrogate and reduced-order modelling techniques that provide rapid performance feedback earlier in the design cycle. Both physics-aware and physics-agnostic approaches are considered, alongside a comparative review of selected commercial software platforms.
- ***Automatic assembly sequence generation and validation (Section 4)*** investigates rule-based and geometry-driven methods for early-stage design-for-assembly assessment. The section focuses on explainable, deterministic approaches that support manufacturability reasoning during design, rather than full downstream manufacturing process planning.
- ***Automated CAD generation (Section 5)*** reviews the current state of generative and language-driven CAD technologies, assessing their suitability for concept generation and simple part modelling, while explicitly distinguishing these capabilities from production-grade parametric design.
- ***Facility layout optimisation (Section 6)*** examines AI and optimisation techniques applied to brownfield manufacturing environments, with emphasis on data preparation, scenario exploration, and performance evaluation rather than autonomous layout generation.

The report concludes with cross-domain recommendations (Section 7) that distinguish between actions organisations may consider today using commercially available tools and areas where emerging techniques should be monitored as the technology matures.

This whitepaper does not attempt to catalogue all AI applications in engineering design, nor does it provide exhaustive benchmarking or endorsement of specific products. Instead, it aims to clarify current capabilities, limitations, and industrial readiness, enabling engineering leaders and practitioners to make informed decisions about where and how AI can be integrated into existing design workflows.

2. Mesh-to-CAD Reverse Engineering

Mesh-to-CAD Reverse Engineering (RE) is a process that involves converting physical objects into digital models suitable for design, refinement and manufacturing. The procedure typically begins with the digitisation of a physical part through 3D scanning, which generates a mesh file, a collection of points in space representing the object's surface geometry (Bénière, Subsol, Gesquière, Le Breton, & Puech, 2013) As illustrated in *Figure 1*, this mesh, while detailed, is not commonly usable in CAD workflows, hence, the next step is to transform this mesh data into a parametric CAD model.

Figure 1. Conceptual problem statement for the Mesh-to-CAD Reverse Engineering process.

The conversion process often includes several stages: cleaning and refining the scanned mesh to remove noise and fill gaps, segmenting the mesh into meaningful regions, and then fitting algorithmic surfaces (such as the RANSAC algorithm) to these regions creating a Boundary Representation (B-Rep) of the scanned part. Advanced techniques, such as quad-remeshing, primitive detection, and hybrid surface fitting, may be employed to provide a more accurate representation of the point-cloud geometry. The final output is a CAD file that represents the original part as closely as possible, enabling some detailed analysis, simulation, reproduction, or enhancement within established engineering workflows. However, the accuracy of a reverse-engineered part relies heavily on a variety of factors, such as geometry simplicity, mesh conversion method, and overall input mesh quality.

Reverse Engineering is especially valuable for those organisations who typically deal with the following industrial use-cases:

1. Digitisation of legacy parts or assemblies for archive, reproduction, or enhancement.
2. Use of digitised parts for Model-Based Systems Engineering (MBSE) and model-based digital twins.
3. Performing detailed simulation and analysis of parts to assess performance and structural integrity.
4. Sourcing of alternatives for obsolete or custom components through modern manufacturing techniques.

From these use-cases above, reverse engineering tools must generate sufficiently accurate and detailed digital representations of scanned components. In contemporary workflows, the process typically starts with capturing the physical part using a 3D scanner, which produces a mesh file composed of grouped spatial points representing the surface geometry. Subsequently, this mesh data may be converted into a parametric CAD file suitable for design and manufacturing applications.

2.1 Commercial Mesh-to-CAD Conversion Methods

The current landscape of commercial Mesh-to-CAD conversion methodologies can be categorised into three primary approaches:

- Prismatic Mesh Conversion
- Quad Remeshing
- Hybrid Conversion

These methods are evaluated based on their ability to produce accurate, editable CAD models from mesh data, which is a critical capability for modern reverse engineering workflows. This section reviews their strengths, limitations, and strategic implications.

a. Prismatic Mesh Conversion

This class of conversion techniques is typically effective for geometries characterised by well-defined analytic features (e.g. planar, cylindrical).

(Bénière, Subsol, Gesquière, Le Breton, & Puech, 2013) An example of Prismatic Mesh Conversion using Fusion 360 (McGarry, 2022) is illustrated in *Figure 2*. Commercial solutions that adopt Prismatic Mesh Conversion include software, such as Dassault Systèmes' SOLIDWORKS platform (Dassault Systèmes, 2025).

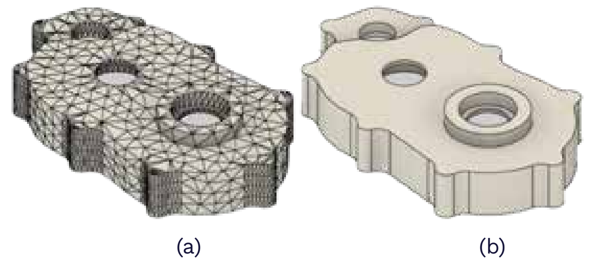


Figure 2. Prismatic Mesh (a) to CAD (b) Conversion in Fusion 360. (Autodesk, 2025).

b. Quad Remeshing

Quad Remeshing, illustrated in *Figure 3*, approximates complex or organic geometries into structured quad meshes. It is commonly applied in simulation and analysis but often requires additional processing when transitioning to parametric CAD reconstruction. Examples of commercial tools that support such approaches include Rhino 3D (Rhino3D, 2026), Mesh Inspector (Mesh Inspector, 2026), Polyworks, and others.

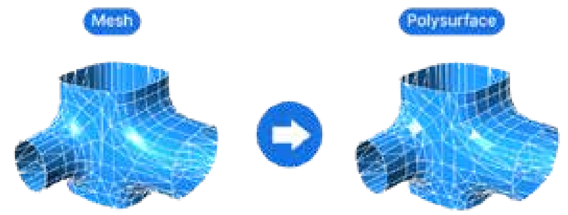


Figure 3. Example of Quad Remeshing to make a simplified mesh (Tait, 2023).

c. Hybrid Conversion

Hybrid Conversion combines prismatic and quad-remeshing techniques to reconstruct both simple and complex features. It offers highly accurate results and some automation capabilities. An example of a hybrid conversion is illustrated in *Figure 4*. Several commercial platforms now offer robust hybrid conversion capabilities. Hybrid conversion is increasingly adopted in the modern workflow of mesh conversion and can be found in software that is specifically dedicated to reverse engineering of parts, such as Geomagic Design X (Artec 3D, 2026), the Creaform Scan-to-CAD (FARO CREAFORM, 2026), and QUICKSURFACE Pro (QUICKSURFACE, 2026).

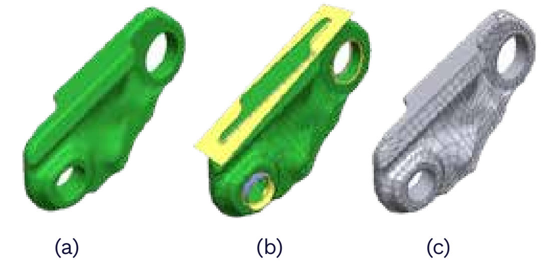


Figure 4. A demonstration of hybrid methods combining quad remeshing with prismatic Features. Step 1: Quad Mesh construction (a), Step 2: Primitive Features identification (b), and Step 3: CAD Bodies combination (c).

d. A Comparative Analysis of Commercial Mesh-to-CAD Conversion Methods

Commercial Mesh-to-CAD conversion methods offer varying degrees of accuracy and automation. While prismatic and quad-remeshing methods serve specific use-cases, hybrid approaches are increasingly adopted in reverse engineering workflows. Continued development and integration of AI-driven tools will be essential to achieving fully automated, parametric CAD model generation from mesh data. Overall, strategic implications of the three conversion methods can be summarised as follows:

- Prismatic conversion is typically applied to digitising legacy components with straightforward, simple geometries, ensuring high accuracy and integration into parametric modelling workflows.
- Quad remeshing offers significant value for simulation and analysis workflows, especially when handling complex or organic forms, albeit with reduced suitability for precise CAD reconstruction.
- Hybrid conversion combines prismatic and quad-remeshing techniques, enabling accuracy and automation in reverse engineering workflows.

A comparative analysis of the strengths and limitations of all three commercial methods are summarised in *Table 1*.

Note: The table on the next page summarises general characteristics of methodological approaches and should not be interpreted as a comparison of specific commercial software products.

Table 1. A summary of the strengths and limitations of each Mesh-to-CAD conversion method.

Mesh Method	Strengths	Limitations
Prismatic Conversion	• High accuracy for simple geometries. • Enables parametric modelling and integration.	• Manual segmentation required. • Limited to clean, simple meshes.
Quad Remeshing	• Handles complex and organic shapes. • Improves mesh quality for simulation.	• Produces approximations, not exact geometry. • Requires manual CAD reconstruction.
Hybrid Conversion	• Combines strengths of both methods. • Supports automatic sketching and feature recognition.	• Output quality depends on mesh fidelity. • Manual input is still required for sketch placement.

While the three methods demonstrate that commercial reverse engineering software is moving towards more accurate conversion techniques, the extraction and representation of geometry-defined features within CAD environments remains a key challenge. Improvements in mesh-to-CAD accuracy are particularly valuable for manufacturing workflows, such as additive manufacturing where higher-fidelity geometry can reduce downstream errors and enhance process reliability. However, for workflows that rely on explicit feature-based definitions (e.g. machining and forming processes), manual intervention is still often required to reconstruct manufacturing-relevant features. This limits the seamless integration of such models into multi-step manufacturing scenarios and broader engineering workflows.

2.2 Academic Approaches for Mesh-to-CAD Conversion Methods

The academic and research landscape has been thoroughly examined to identify innovative and emerging technologies at lower Technology Readiness Levels (TRLs) suitable for advanced Mesh-to-CAD reverse engineering. These cutting-edge approaches can be broadly categorised into three principal methods aimed at effective feature extraction and precise geometric conversion:

- Graph-based Feature Recognition Methods
- Geometry-driven Reconstruction Methods
- Segmentation-based Decomposition Methods

Collectively, these methods represent active areas of research striving to bridge the gap between raw mesh data and high-fidelity CAD models.

a. Graph-based Feature Recognition Methods

Graph Neural Networks (GNNs) are employed for advanced feature extraction by leveraging the strengths of neural networks in conjunction with the inherent complexity of graph-based data structures. Rather than simply analysing entire datasets, GNNs focus on deciphering the intricate relationships between individual data nodes. In the context of Mesh-to-CAD conversion, this approach is used to support the extraction of meaningful features by interpreting the geometric connections among faces, edges, and vertices within CAD models (Lambourne, et al., 2021). By modelling these relationships, GNNs can identify and distinguish structural and functional components with greater precision, thereby enhancing the quality of geometric conversion from Mesh-to-CAD representations. A high-level process of using a GNN model for feature and recognition is illustrated in *Figure 5*.

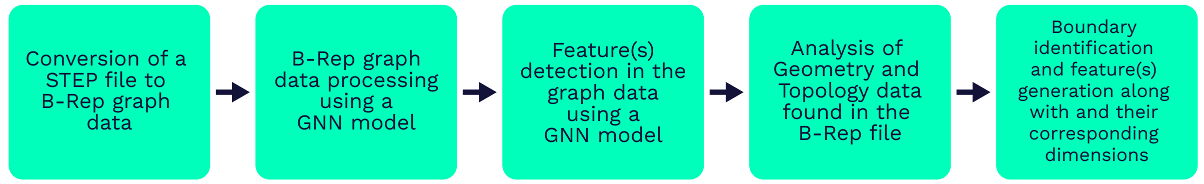


Figure 5. A high-level process flow of using a GNN model for feature and recognition.

Several research publications have utilised GNNs to advance Mesh-to-CAD conversion, demonstrating the technique's effectiveness in extracting geometric features and enhancing model fidelity. Notable examples can be found in manufacturing already as a paper from 2023 developed a new software designed to undertake feature recognition for 3D models (Betkier, Oszczypała, Pobożniak, Sobieski, & Betkier, 2023), with most academic research being focused in machining feature recognition (Khan, et al., 2024), (Colligan, Robinson, Nolan, Hua, & Cao, 2022).

b. Geometry-driven Reconstruction Methods

Geometric Reasoning refers to the application of AI models to recognise and extract shapes, which are subsequently processed to generate detailed geometries of complex parts. This method typically involves clustering similar points within a point-cloud or grouping analogous meshes of a component using primitive shapes, such as cylinders, triangles, or planar surfaces. An overview of the geometric reasoning process for extracting shapes and geometries is depicted in *Figure 6*.

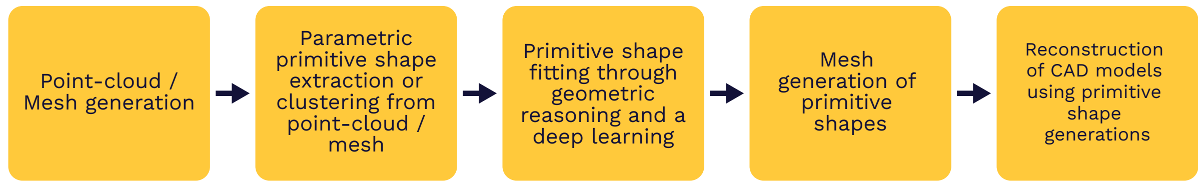


Figure 6. A high-level process flow of using geometric reasoning to extract shapes and geometries.

Several research studies have employed geometric reasoning to improve Mesh-to-CAD conversion. Most examples of this type of reverse engineering can be found in mesh reconstruction from point-cloud (Wang, Liu, & Deng, 2025), (Liu J. , 2020), (Liu, Xu, Xiao, & Wang, 2023).

c. Segmentation-based Decomposition Methods

Instance Segmentation of 3D Models involves partitioning a 3D model into Multiple Sectional Views (MSVs), which serve as inputs for a Deep Learning (DL) network. These MSVs are processed as individual 2D instances, allowing feature recognition to be performed using widely adopted Convolutional Neural Network (CNN) architectures. Once features are identified across the sectional views, the MSVs are recombined, enabling the system to accurately recognise and localise features within the original 3D model. This approach uses 2D representations to support the handling of intersecting features and geometric properties, compared with direct 3D processing or conversion to point-cloud or mesh formats. The approach leverages the strengths of 2D segmentation techniques while providing comprehensive insight into complex 3D geometries. A high-level process flow of adopting instance segmentation of 3D models is illustrated in *Figure 7*.

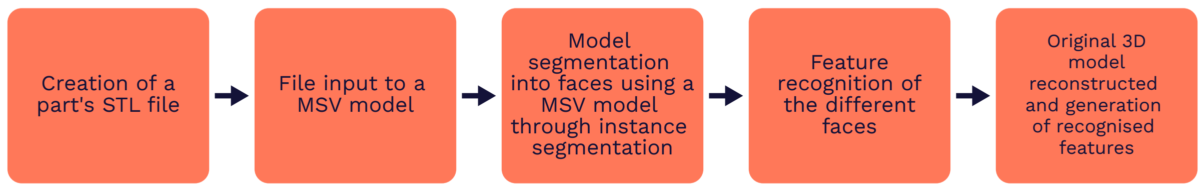


Figure 7. A high-level process flow for using Instance segmentation of 3D models.

Research studies that have employed instance segmentation of 3D models to improve Mesh-to-CAD conversion. Examples of this in research literature can be seen in feature recognition in machining (Yeo, Kim, Cheon, Lee, & Mun, 2021), (Lee, Lee, & Mun, 2022) and also in general manufacturing and Artificial Intelligence development (Shi, Qi, Qin, Scott, & Jiang, 2020).

d. A Comparative Analysis of Academic Mesh-to-CAD Conversion Methods

A comparative analysis of academic mesh-to-cad conversion methods is summarised in *Table 2* outlining three academic approaches for feature identification in CAD and 3D models: GNNs, Geometric Reasoning, and Instance Segmentation of 3D Models.

GNNs excel at identifying features and their geometries, but they face challenges due to the complexity of graph data and relationships between nodes. Moreover, their application has so far been typically constrained to relatively simple geometries. Geometric Reasoning is noted for its effectiveness in determining geometric properties of complex parts, even when mesh quality is poor. Its configurability allows for recognition of specific primitive shapes, although it struggles with detecting subtle or smaller features, and its reconstruction methods typically rely on sketch-based features. Instance Segmentation of 3D Models can recognise various features, such as holes, fillets, pockets, and slots in CAD models, provided that a complete and high-quality mesh is available. However, it necessitates a powerful CNN architecture capable of handling MSVs, and its success is heavily dependent on mesh quality.

Table 2. A summary of the strengths and limitations of each academic Mesh-to-CAD conversion approach.

Academic Approach	Strengths	Limitations
Graph Neural Networks	• Highly effective at identifying features and their respective geometry.	• Complexity of Graph Data and establishing the relationship between data nodes. • Current research has only demonstrated this technology to be used on simple geometry.
Geometric Reasoning	• Effective at determining geometric properties for complex parts and shapes even if the mesh quality is poor. • High configurable for use-cases due to being able to determine specific primitive shapes to recognise.	• Difficulty in finding small and more nuanced features. • Method for feature reconstruction is typically constrained to sketch-based features.
Instance Segmentation of 3D Models	• Capable of recognising many features in CAD models, such as holes, fillets, pockets, and slots. • A complete and high-quality mesh is required to achieve accurate results from this method.	• Does require a powerful CNN model that can handle Multiple Sectional Views (MSVs). • A complete and high-quality mesh is required to achieve accurate results from this method.

From an industrial maturity perspective, hybrid commercial mesh-to-CAD tools are commonly applied in industrial workflows, albeit with continued reliance on manual intervention. Although the hybrid approach represents significant progress, it does not currently support a truly "smart" reverse engineering process capable of interpreting and quantifying CAD features.

AI-assisted academic approaches highlight method relevant to feature recognition and the reconstruction of complex geometries, addressing several limitations present in existing software. While these academic approaches demonstrate considerable potential, they remain at earlier stages of development and evaluation and may require further validation on complex, real-world industrial components. Further development will require ongoing collaboration among software developers, academic researchers, and end users to achieve a fully integrated smart reverse engineering tool.

3. AI-assisted Predictive Simulation

Simulation and virtual validation methods are often computationally intensive and time-consuming, especially when dealing with complex geometries, multi-physics interactions, or simulations with large numbers of parameters. Large simulations can take days or weeks to run using even the high-powered workstations. AI-driven predictive simulation software aims to address these limitations by leveraging Machine Learning (ML) algorithms, surrogate modelling, and data-driven approaches to accelerate complex simulations and enable real-time decision-making. This chapter explores the current landscape of AI-assisted simulation tools, and examines their underlying principles, applications, and potential for adoption within engineering design.

3.1 Technology Overview: Surrogates and Reduced Order Models (ROMs)

The use of AI in modelling and simulation is a widespread topic, and 'AI-Driven Simulation' may refer to one of many different technologies. However, AI-driven predictive simulation tools are commonly built on an ML-based surrogate modelling approach.

A surrogate model is a simplified, data-driven model which approximates the behaviour of a complex system. They are used to predict an output from a range of inputs, where the actual relationship between the two is unknown or too computationally expensive to evaluate. Surrogate models may be AI or non-AI driven, as shown in ***Table 3***. A surrogate model is an example of a Reduced Order Model (ROM). A ROM refers to any form of simplified model. For example, one which uses a simplified set or governing equations to find a solution, whereas a surrogate model derives its prediction from result data only. However, the terms are often used interchangeably in literature (Wong, 2025). Surrogate models for multi-physics prediction are typically trained using large sets of input and output data from high-fidelity simulations (like CFD or FEA). Once trained, these models can then be used to make fast predictions on new models and geometries, without solving the full set of governing equations each time.

Table 3. AI-Driven vs Non-AI-Driven Surrogate Models.

	AI-Driven Surrogate Models	Non-AI-Driven Surrogate Models
Definition	• Use ML or DL to learn complex relationships from data.	• Use traditional statistical techniques to approximate outputs from sampled data.
Examples	• Deep Neural Networks (DNNs). • Physics-Informed Neural Networks (PINNs). • Graph Neural Networks (GNNs). • Autoencoders.	• Polynomial Response Surface (PRS). • Kriging, Radial Basis Function (RBF). • Proper Orthogonal Decomposition (POD). • Polynomial Chaos Expansion (PCE).

3.2 Technology Overview: Physics-aware and Physics-agnostic Models

ML methods used in simulation tools typically fall into one of two categories: physics-aware, or physics-agnostic. Physics-aware methods incorporate governing physical equations, such as PDEs (partial differential equations) into their structure or training process, ensuring outputs remain physically consistent (Reverberi & Procario, 2024). Such models learn to satisfy both data and physics constraints during training. Examples of physics-aware ML models include Physics-Informed Neural Networks (PINNs), and Physical Equation-Embedded Machine Learning (PEeML) (Meng, Griesemer, Cao, Seo, & Liu, 2025).

Physics-agnostic methods learn a latent representation of the physics directly from the solver outputs but are agnostic to the underlying equations and solvers themselves (Reverberi & Procario, 2024). Physics-agnostic methods are purely derived from training data, and are therefore not constrained by complex PDEs, making them much faster and often more reliable. Physics-agnostic methods are supervised DL models that statistically learn the known or unknown physics of a desired phenomenon by extracting features from raw training data. Examples of physics-agnostic DL architectures include deep neural networks (DNNs), and graph neural networks (GNNs) (Meng, Griesemer, Cao, Seo, & Liu, 2025). The strengths and limitations of both model types are summarised in ***Table 4***.

Table 4. Physics-Aware vs. Physics-Agnostic models.

Category	Physics-Aware	Physics-Agnostic
Definition	• Incorporates governing physical laws into the model architecture or training process.	• Learns patterns directly from data without incorporating physical constraints.
Examples	• Physics-Informed Neural Networks (PINNs). • Physics-Encoded Neural Networks (PeNNs).	• Deep Neural Networks (DNNs). • Graph Neural Networks (GNNs).
Use-cases	• Applications where simulation data is expensive or scarce, but the governing physical laws are well understood.	• Applications requiring fast and flexible predictions, where large volumes of simulation or experimental data are available.
Strengths	• Physically consistent predictions. • Low training data requirements. • Better extrapolation from limited data.	• Faster, simpler training and deployment. • Scalable to large, diverse datasets. • Highly flexible across multi-physics systems.
Limitations	• Computationally intensive. • More complicated to train and tune. • Less flexible - must be tailored to specific, well-defined physics problems.	• Requires large, high-fidelity datasets. • Risk of overfitting to training data. • May produce physically inaccurate results. • Less accurate outside of training data.

3.3 Software Assessment

a. Methodology

The following software assessment has been conducted using publicly available information from official vendor documentation, websites, and other reputable sources as listed in the bibliography. Therefore, the findings and conclusions presented in this paper are based solely on the available information at time of writing and do not constitute an independent benchmarking activity.

The software assessment criteria used is divided across four primary groups: Usability, AI-Infrastructure, Model Training, and Accuracy & Reporting, as shown in ***Table 5***.

Table 5. Assessment criteria used in the review.

Category	Criteria	Description
Usability	**Platform Deployment**	Cloud-based or Desktop-Based Software Deployment
	User Interface	No-Code, Low-code, or Code-focussed UI
	Developer tools	Compatibility with scripting tools (such as Python)
	Expertise Required	Level of ML / simulation expertise required
	Documentation & Support	Availability of documentation and training materials
AI	**AI-Native**	Native support for end-to-end AI workflows
	AI Architecture	Underlying AI architecture (e.g. DL, GNN, etc.)
	Physics-usage	Physics-informed or physics agnostic approach
Model Training	**Training Data Source**	Permitted training data sources
	File Format (s)	Training data file format(s)
	Data Requirements	Minimum number of training data required
Accuracy & Reporting	**Data Fitting Metrics**	Reporting of training metrics (e.g. training losses)
	Confidence Metrics	Reporting of confidence metrics for predictions

b. Software Selection

A total of six software tools were assessed, as summarised in *Table 6*. Of these, four products can be considered as dedicated-AI platforms which support the full predictive modelling workflow from training data creation to model training, simulation prediction, and post-processing. These are Ansys SimAI, Altair Physics AI, Simscale, and Siml.Ai. Conversely, Siemens and COMSOL's offerings represent software tools which can build AI-driven simulation prediction workflows, but this is not their central focus.

Table 6. A summary of selected software solutions.

Provider	Product(s)	Description
Ansys	**Ansys SimAI**	A standalone, cloud-based platform for AI simulation prediction.
Siemens (formerly Altair)	**PhysicsAI**	A 'geometric deep-learning'-based software for simulation prediction, accessed from within Altair Hyperworks.
Siemens	**HEEDS Simulation Prediction + Simcenter ROM Builder**	An ML-based predictive modelling toolset for ROMs.
COMSOL	**COMSOL w/Python**	A multiphysics modelling and simulation software with a range of ML integration options using Python / MATLAB.
SimScale	**Simscale**	A cloud-native, AI-native, multiphysics simulation platform.
DimensionLab	**Siml.ai**	A cloud-native, AI-native, multiphysics simulation platform.

c. A Comparative Analysis AI-assisted Predictive Modelling Software Tools

A comparative overview of several AI-assisted predictive modelling software tools is presented in *Table 7* focusing on their features and deployment options. The table lists products including Ansys SimAI, Hyperworks with PhysicsAI, HEEDS & Simcenter ROM, COMSOL Multiphysics, Simscale, and Siml.ai. For each software, details regarding their user interface and platform deployment are provided, allowing for a straightforward assessment of their capabilities and suitability for various simulation needs. This comparison analysis was conducted based on publicly available information, and aims to help users identify the most appropriate tool for their specific multiphysics modelling and simulation requirements, particularly those seeking AI integration and cloud-native solutions. However, this comparison is illustrative and does not constitute a formal evaluation or benchmarking of vendor solutions.

Table 7. Characteristics of selected software solutions.

	Product(s)	Ansys SimAI	Hyperworks w/ PhysicsAI	HEEDS & Simcenter ROM	COMSOL Multiphysics	Simscale	Siml.ai
UI	**Platform Deployment**	Web-based (cloud-enabled)	Desktop-based (cloud-enable)	Desktop/ cloud-integrated	Desktop-based	Web-based	Web-based
	Programming Interface	No-code (GUI-based)	Low-code (workflow-driven GUI with scripting options)	Low-code (GUI with scripting)	Low-code (GUI with MATLAB scripting)	No-code (GUI-based)	Low-code (node-based)
	Developer Tools / SDK	Direct via PyANSYS	No	Python + MATLAB	Python + MATLAB	No	No
	Technical Expertise	Minimal	Intermediate	Advanced	Advanced	Minimal	Minimal
	Documentation & Support	In depth user guide, API documentation, and example files	In depth user guide, API documentation, and a selection of example files	In depth user guide with a selection of example files for AI	In depth documentation for external Python integration with a selection of examples	In depth user guide, API documentation, and example files	Documentation availability is currently constrained
AI	**AI-Native**	Yes	Yes	Yes (via HEEDS)	No	Yes	Yes
	AI Architecture	Generative AI (GenAI)	'Geometric Deep Learning' Type Graph-Neural-Network (GNN)	Traditional surrogate modelling + NN and ML	No native AI support. Various ML methods supported via Python	Graph-Neural-Network (GNN)	Deep learning (DL)
	Physics-Informed or Agnostic	Physics-agnostic	Physics-agnostic	Physics-agnostic	Physics-informed (with Python integration)	Physics-informed (w/ NVIDIA PhysicsNeMo)	Physics-informed (w/ NVIDIA PhysicsNeMo)
Training	**Training Data Source**	Native & 3rd Party	Native & 3rd Party	Native & 3rd Party	Native & 3rd Party	Native Only	3rd Party
	File Format(s)	VTK Format (.vtp, .vtu)	Multiple (Full list here)	Tabular (.txt, .csv, excel)	Tabular (.txt, .csv, excel)	N/a	Tabular (.csv)
	Data Requirements	Typically, 30 to 100 simulation results	Minimum 10 recommended	Varies / no minimum	Varies / no minimum	Minimum 20 simulation runs (from one or models)	Varies / no minimum
Accuracy	**Confidence Metrics**	Confidence score	Confidence score	Built-in accuracy awareness	Varies via ML-method	Accuracy metrics	Unknown

In this section, state-of-the-art AI driven simulation prediction tools were reviewed, focusing on the use of surrogate and reduced order models to significantly accelerate computationally expensive engineering simulations. The review outlines the key distinctions between physics-aware and physics-agnostic approaches, and assesses six leading commercial software platforms against criteria including usability, AI infrastructure, model training, and accuracy reporting.

This comparative evaluation indicates that solutions like Ansys, SimAI, and Altair PhysicsAI demonstrate higher levels of maturity and accessible AI-based simulation workflows, particularly due to their strong documentation, support for legacy data, and minimal expertise requirements. While expert focused tools, such as Siemens and COMSOL, offer high flexibility, ongoing developments suggest a shift towards fully pretrained, physics-aware AI simulation tools that enable real-time prediction with little or no user experience required.

4. Automatic Assembly Sequence

Assembly sequence planning remains one of the more labour-intensive aspects of engineering design (Boothroyd, Dewhurst, & Knight, 2010). Even in organisations with mature CAD practices, engineers typically define assembly logic manually, validate it through visual inspection, and rely on specialist knowledge to detect inconsistencies or violations of design-for-assembly (DfA) principles (Hölttä-Otto & Otto, 2005). These processes can be time-consuming and prone to variation, particularly when assemblies grow in scale or complexity (Wilson & Latombe, 1994).

This section explores whether these challenges can be addressed through rule-based automation supported by geometric reasoning (de Mello & Sanderson, 1990; Wilson & Latombe, 1994). The objective is not to replicate the full capabilities of enterprise digital manufacturing platforms, but to demonstrate how lightweight, transparent algorithms can accelerate early-stage assembly planning and ensure consistent adherence to DfA guidelines (Boothroyd, Dewhurst, & Knight, 2010).

To this end, the Manufacturing Technology Centre (MTC) has developed a modular Python-based toolchain built on FreeCAD (FreeCAD, n.d.). The toolchain integrates geometry interrogation, disassembly-based reasoning, and structured rule validation to provide deterministic assessments of assembly feasibility, potential clashes, fixture requirements, and part consolidation opportunities. Although still a prototype, the work shows that significant elements of the assembly workflow can be automated reliably using deterministic, rule-based methods.

4.1 Problem Statement

Across the consortium of participant MTC members, several recurring pain points were identified (Boothroyd, Dewhurst, & Knight, 2010):

- ***Time-intensive workflows:*** Assembly sequences are typically developed through repeated manual iterations, slowing down concept evaluation (Hölttä-Otto & Otto, 2005).
- ***Inconsistent guideline adherence:*** MTC's internally developed design-for-assembly guidelines (i.e., Design for One-Way or Zero Turnover (DOZO) Fastener Reduction Assessment Guidelines (FRAG)) are not systematically enforced, leading to deviations that only surface during manufacturing planning (Boothroyd, Dewhurst, & Knight, 2010).
- ***Reliance on tacit expertise:*** Assembly and fixturing knowledge remains siloed, making it difficult to scale best practice across teams (Nee, Ong, & Kumar, 2004).
- ***Limited design governance:*** CAD models often lack embedded rules, meaning manufacturability issues are detected late in the process (Wilson & Latombe, 1994).

These challenges are amplified for high-complexity or high-mix products, where early-stage design decisions have disproportionate downstream impact (Siemens PLC, 2026; Dassault Systèmes, 2026).

4.2 MTC's Modular, Rule-Driven Toolchain

a. Assembly by Disassembly Reasoning

To enable assembly-by-disassembly reasoning, the MTC team have developed a novel module, referred to as the AssemblyByDisassemblySolver module. The solver module evaluates whether components can be removed along candidate directions without obstruction, as shown in *Figure 8* (Wilson & Latombe, 1994). This approach, simulating disassembly to infer assembly feasibility, provides a deterministic method for detecting access constraints and ordering dependencies. It is explainable, computationally efficient, and well-suited for early design iterations.

A few test models were used to assess the effectiveness of the algorithm, as shown in *Figure 9*. The algorithm disassembled all parts successfully (Wilson & Latombe, 1994). The solver performs tests that allow it to infer which components must be removed first, which depend on others, and where access constraints exist. *Figure 10* shows the steps followed by the algorithm to disassemble a simple assembly that is held together by a pin.

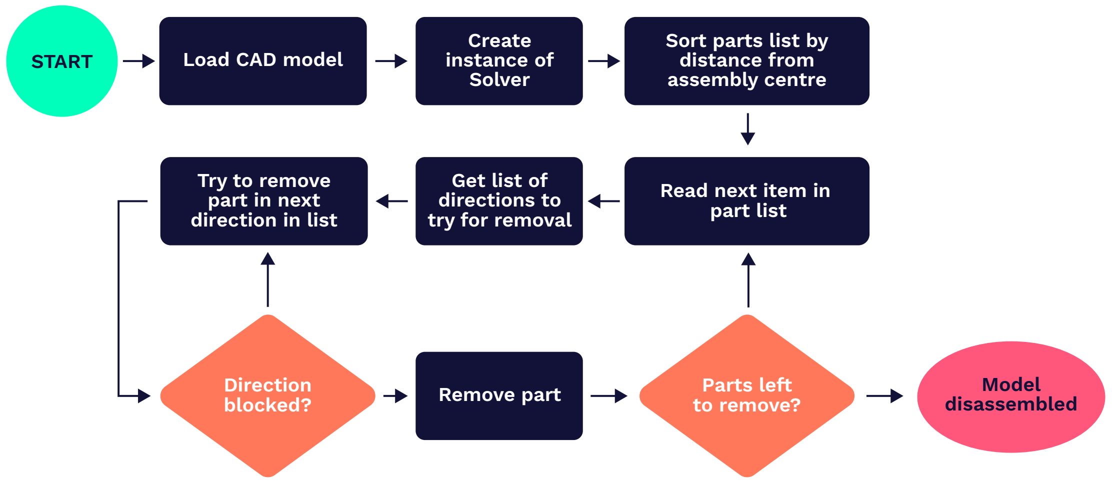


Figure 8. High level logic flow of the 'Assembly-by-Disassembly' algorithm.

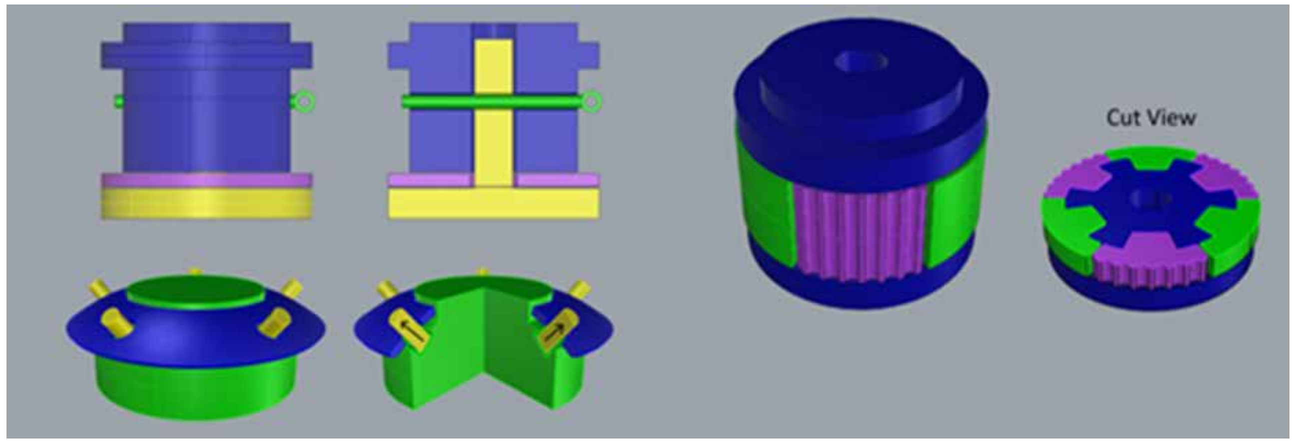


Figure 9. Models used to test the disassembly algorithm.

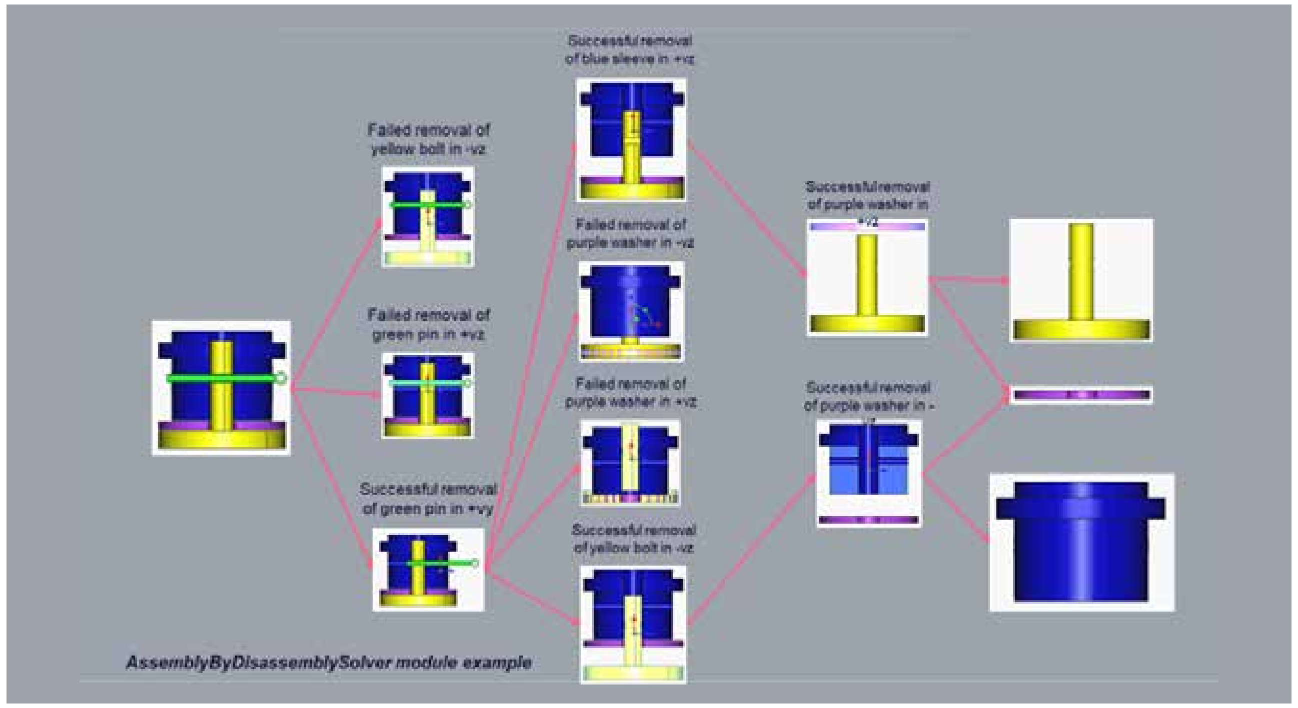


Figure 10. Diagram showing the steps followed by the algorithm to find possible disassembly vectors for each part.

b. DfA Rule Codification

MTC's internal Design for One-Way or Zero Turnover (DOZO) Fastener Reduction Assessment Guidelines (FRAG), or DOZO/FRAG guidelines, were codified into a structured ruleset. The rules cover:

- Turnover minimisation and stable orientations (DOZO).
- Reduction of fasteners and part variation (FRAG).
- Unobstructed assembly paths.
- Fixturing and accessibility considerations.
- Basic component consolidation logic.

Where possible, abstract guidelines were translated into concrete, machine-interpretable checks. Abstract rules were grouped into higher-level categories suitable for future extension, as shown in ***Table 8***.

Table 8. A list of the DOZO/FRAG guidelines, selected as suitable for development.

Rule Category	Rule Description
Assembly Sequence & Process Flow	Design products with one-way/axial assembly sequences.
	Use linear assembly sequences (top-down, bottom-up, or horizontal).
	Define CAD assembly start points based on product orientation and future maintenance.
	Prefer single-action fastener insertion.
	Minimise tool changes during fastening operations.
Part Merging & Component Reduction	Merge parts to eliminate extra fasteners, plates, or covers.
	Combine parts that can be merged with their mating components.
	Consider accessibility and maintenance requirements when merging components.
	Minimise the number of fasteners when merging components.
	Consider assembly/disassembly requirements when merging parts.
	Reduce supporting features, such as bosses and ribs.
	Remove the need for fasteners wherever possible.
Fastening Strategy & Simplification	Use standard fasteners wherever possible.
	Ensure appropriate spacing and distribution when multiple fasteners are required.

c. Automated Fixture Concept Generation

For automated fixture concept generation, the MTC team have developed another module, referred to as the FixtureDesigner module. It demonstrates automated creation of simplified 3-2-1 fixturing concepts (Rong, 1999). Although currently limited to planar and prismatic geometries, it illustrates how fixturing intent can be generated programmatically and evaluated for compatibility with assembly paths. An example of the output of the base implementation on a rectangular part is shown in ***Figure 11***.

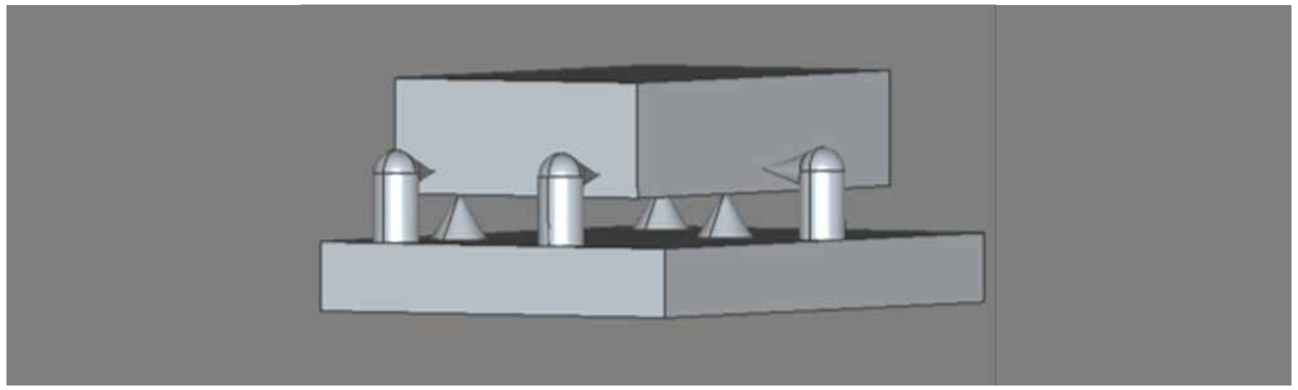


Figure 11. Fixture with contact points automatically generated by the FixtureDesigner algorithm.

d. Part Consolidation Assessment Tool

Early decision rules identify where multiple components could be combined into a single part, subject to functional, motion, and serviceability constraints. This supports FRAG principles by reducing unnecessary part count. Basic rules for identifying opportunities for component consolidation were implemented in line with DfA guidance, supporting early decisions that reduce part count, handling steps and assembly time (Boothroyd, Dewhurst, & Knight, 2010).

A lightweight user interface was developed to support visualisation of imported assemblies, solver results, and rule feedback, providing designers with immediate interpretability.

e. Demonstrated Capabilities

Across representative test assemblies, including pin-sleeve parts, segmented hubs, and fastener-constrained components, the demonstrator successfully identified:

- Feasible and infeasible removal directions.
- Ordering dependencies between parts.
- Clash or clearance violations.
- Basic fixture support positions.

These results confirm the feasibility of embedding DfA logic directly into early-stage design workflows. The current user interface for interacting with the solver is shown in ***Figure 12***.

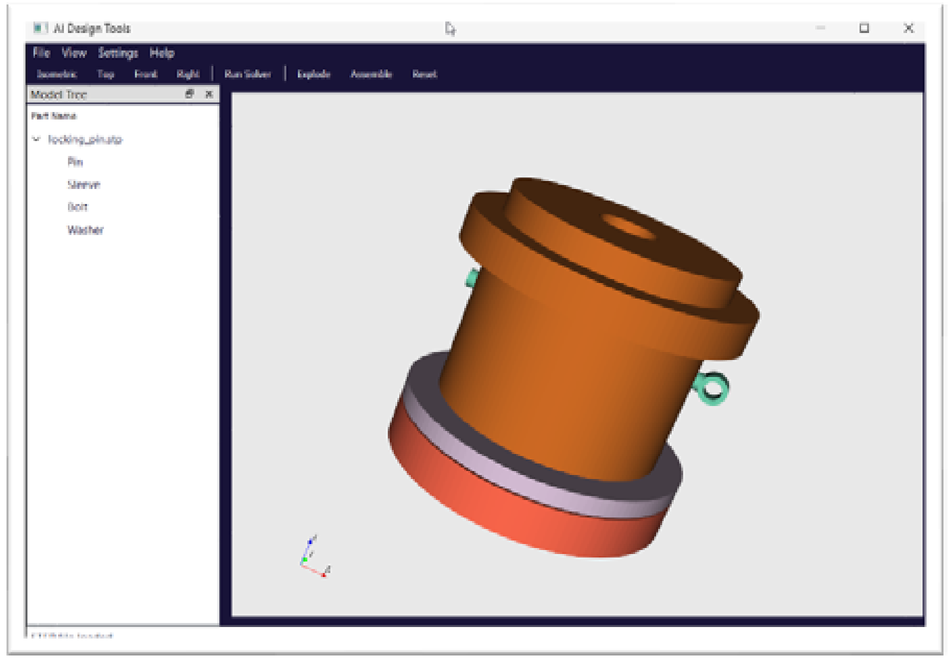


Figure 12. User Interface of the prototype Python application.

4.3 Commercial Context Positioning

Enterprise digital manufacturing platforms provide trajectory planning, collision checks, and full integration with manufacturing processes (Siemens PLC, 2026; Dassault Systèmes, 2026). A comparison of current enterprise platforms with MTC's developed toolchain is shown in *Table 9*.

The MTC-developed toolchain is not intended to replace or compete with enterprise digital manufacturing platforms. Instead, it complements them by addressing early-stage design-for-assembly considerations that are often not well supported in downstream planning tools. The results suggest that value can be realised in openness, explainability, and early feedback, enabling manufacturability considerations to be embedded while design decisions are still fluid.

Capabilities, presented in *Table 9*, may vary depending on software configuration, version, and specific use-case. This comparison is illustrative and does not constitute a formal evaluation or benchmarking of vendor solutions.

Table 9. Summary of selected capabilities for assembly sequence generation and validation.

Feature / Capability	Enterprise Platforms	Python Toolchain (FreeCAD-based)
Automatic sequence generation	Collision-free trajectories	Partial - removability checks only
Collision & clearance validation	Built-in	Implemented via B-Rep intersection
Integration with process planning	Full manufacturing bill of materials and resource integration	Standalone prototype
Fixturing concept generation	Manual/semi-automated	Proof-of-concept 3-2-1 fixture generator
Rule-based DfA validation	Typically constrained	Explicit DOZO/FRAG rule mapping
Openness / extensibility	Proprietary	Open-source, modular

However, enterprise platforms have notable limitations:

- They primarily support downstream planning, not early-stage DfA.
- Their rule engines are typically constrained and rarely open to user extension.
- They require significant licensing investment and operate within proprietary ecosystems.

In contrast, ***MTC's developed toolchain*** provides:

- ***Openness:*** full access to geometry, logic, and data structures.
- ***Explainability:*** deterministic reasoning with auditability of results.
- ***Low adoption friction:*** modular Python components without enterprise overhead.
- ***Design-phase value:*** immediate feedback while the CAD model is still evolving.

4.4 Technology Readiness and Current Limitations

The toolchain remains in an early stage of maturity. It has been validated on controlled assemblies, yet still requires development to accommodate complex geometries, more sophisticated fixturing logic, and a broader set of design rules. These limitations echo long-standing challenges highlighted in earlier research on assembly automation (de Mello & Sanderson, 1990; Wilson & Latombe, 1994):

- Handling of non-manifold and highly complex geometries remains constrained.
- Simplified removal direction search.
- Improved efficiency for large assemblies.
- Surface normal–based placement is not currently included within the fixturing logic.
- Partial rule coverage.
- Early-stage user interface.

These limitations define a clear roadmap for maturing the system into a deployable industrial tool. The developed toolchain demonstrates that significant portions of assembly sequence planning, fixturing logic and DfA validation can be automated using deterministic, transparent, rule-driven methods (Wilson & Latombe, 1994). By embedding guidelines directly into the design environment, the toolchain reduces reliance on tacit expertise, improves consistency and accelerates early-stage decision-making (Boothroyd, Dewhurst, & Knight, 2010). While further development is required, the work provides a credible foundation for integrating lightweight automation into modern engineering workflows (Siemens PLC, 2026; Dassault Systèmes, 2026).

5. Automated CAD Generation

A CAD model is defined by a sequence of parametric commands, commonly known as a CAD program or "Feature Tree," which can then be compiled into an exact 3D solid model known as a Boundary Representation model (B-Rep) (Yu, Alam, Hart, & Ahmed, Sep, 2025). While the final output is the B-Rep model, it is the CAD program representation that provides engineers with the precise, parametric control over geometric manipulation that is not offered by other 3D modalities. CAD programs are integral to engineering design due to their editability and integration with other steps of the design process (Yu, Alam, Hart, & Ahmed, Sep, 2025). However, creating manufacturable and editable 3D geometry in CAD remains:

- ***A largely manual and time-intensive process,*** as engineers must carefully define and manipulate parametric commands to achieve the desired design outcomes. This often involves extensive iteration and attention to detail, particularly when ensuring that the geometry meets manufacturing requirements and can be easily modified in future design cycles.
- ***Constrained by the complex topology of boundary-representation (B-rep) solids,*** which require a thorough understanding of geometric relationships and dependencies. The intricacies of B-rep modelling, such as managing faces, edges, and vertices, can make the process challenging, especially when dealing with intricate or highly detailed components that demand precise control over every feature.
- ***A complex sequential process that requires human expertise and intuition at each stage,*** from initial concept through to final refinement. Engineers are responsible for interpreting design objectives, anticipating manufacturing constraints, navigating software tool limitations, and ensuring adherence to relevant industry standards and guidelines. This expertise is critical for translating abstract ideas into robust, manufacturable CAD models that integrate seamlessly with downstream engineering workflows.

5.1 The Potential of Generative AI for Automated CAD Generation

Automated CAD generation refers to the process of creating CAD models through software-driven methods that reduce or eliminate the need for manual intervention by engineers. Traditionally, engineers construct CAD models by carefully defining a sequence of parametric commands, known as a CAD program or "Feature Tree," which are then compiled into precise B-Rep solid models. This manual approach is both time-consuming and requires significant expertise to manage complex geometries and ensure manufacturability.

Non-parametric 3D shape-generation methods and commercial tools often generate meshes, voxels, or point-clouds, however, engineering workflows need ***modifiable, manufacturable*** CAD models and techniques that can generate CAD geometry from ***diverse inputs, such as text or images.***

Recent studies have demonstrated the capability of Generative AI techniques to automate CAD creation by enabling easy-to-use interfaces like natural language or image-based commands. The importance of AI-assisted CAD generation lies in its ability to:

- ***Extract new value from existing data,*** streamlining reverse engineering of 3D scans (e.g., meshes, point-clouds) into editable CAD models. This process enables engineers to quickly remake discontinued parts by scanning and converting them into CAD, though current tools still require significant manual intervention and time.
- ***Accelerate design workflows,*** allowing faster modelling and ideation.
- ***Lower software-specific experience requirements*** through AI-driven systems and natural language interfaces.

Although these technologies are still developing, they promise easier access and reduced manual effort for CAD users. This section provides an in-depth overview of methods for automated CAD creation using inputs like text or images. It covers both research papers and commercial products, as well as experimental or beta solutions that are available for demonstration.

5.2 Commercial solutions for automated CAD generation

Emerging AI-enabled tools adopt the capability of generating 3D CAD parts from text descriptions and 2D images or sketches. These commercial solutions typically produce platform independent outputs, such as B-Reps, parametric CAD code, or native CAD files, instead of mere meshes or point-clouds. *Table 10* summarises key solutions, detailing their input methods and whether they produce parametric CAD models. The summary, presented in *Table 10*, was conducted based on publicly available information. It is illustrative and does not constitute a formal evaluation or benchmarking of vendor solutions.

Table 10. Summary of key commercial solutions for automated CAD generation.

Commercial solution	Description	Input types (FreeCAD-based)	Produces parametric CAD models
Zoo Design Studio (Zoo)	An AI-native Text-to-CAD platform that builds on proprietary geometry engine and combines graphical modelling with fully programmable design through code. Includes Zookeeper, a conversational CAD agent, adding research and reasoning capabilities.	Text prompts.	Yes, it generates parametric CAD programming language called KittyCAD (Dimitrijević, 2025) (Zoo).
CadXStudio (CadXStudio)	An AI-native platform that unifies Text-to-CAD, advanced parametric modelling, and Text-to-CAM (Computer-Aided Manufacturing) (CadXStudio).	Text prompts	Yes, it generates parametric CAD code, where parameters can be finetuned / tweaked live with immediate visual feedback (CadXStudio).
CADWIN by Desperado Labs (CADWIN)	An AI-native platform that generates industry-grade, watertight CAD models from text or sketches.	Text prompts, sketches.	Yes, specific parameters can be adjusted through text prompts, and the model will be regenerated again while keeping the rest of the design intact (CADWIN).
Makistry (Makistry)	An AI-powered 3D design platform that converts text prompts into parametric CAD models.	Text prompts.	Yes, specific parameters can be adjusted through text prompts, and the model will be edited again with built-in version history (Makistry).
AdamCAD (AdamCAD)	An AI-powered 3D design platform that converts text prompts and images into parametric CAD models.	Text prompts, images, 2D technical drawings.	Yes, parameters can be finetuned / tweaked live with immediate visual feedback and built-in version history (Dimitrijević, 2025).

While changing the geometry (e.g., STEP editing) modifies the shape that already exists, these solutions introduce modifiable, parametric CAD generation by changing the parameters, i.e., modifying the rules or logic, that create the shape, then rebuilding it.

These solutions are often powered by Large Language Models (LLMs) for CAD code generation. For example, Zoo uses KCL (KittyCAD Language), a Zoo Design Studio's domain-specific, parametric CAD programming language, to programmatically create 3D geometry using primitives, sketches, transforms, Booleans, and parameters (Discover Zookeeper).

a. Considerations for text and image-based, parametric CAD generation tools

Some current parametric CAD generation solutions based on text and image inputs are in early development or beta phases, with ongoing progress towards wider industrial maturity. These tools are primarily used for simple mechanical parts and operate most effectively with clear, well-defined prompts. For more complex geometries or less structured inputs, outputs may involve additional user interaction or refinement. Key considerations include:

- ***Early-stage maturity:*** Some solutions are in beta or early development phases, with ongoing evaluation and refinement of performance in real-world applications.
- ***Complexity handling characteristics:*** Rapid prototyping and the creation of simple components (e.g. gears, brackets, and enclosures) are commonly supported, particularly when based on well-defined instructions. For highly complex or non-standard designs, outputs may require additional refinement or user input.
- ***Need for manual refinement:*** Generated outputs may require further refinement within a CAD programme for applications involving high precision or intricate detail.
- ***Prompt sensitivity:*** Output quality depends on the clarity and specificity of input prompts. Where prompts are ambiguous, results may require adjustment to align with intended specifications.
- ***Training data considerations:*** Performance is influenced by the scope and structure of training data and associated knowledge sources, and clarification may be requested where inputs are not sufficiently defined.

While text- and image-based CAD generation tools demonstrate ongoing progress, they are not typically applied as a replacement for conventional CAD modelling in production environments. Their use is currently associated with rapid concept generation, early ideation, and support for well-defined parts. Human oversight and post-processing are generally required for manufacturing-grade designs. The field continues to evolve, with increasing interest in AI-assisted CAD workflows to support design generation and iterative development.

5.3 Research methods for automated CAD generation

Methods for AI-driven generation of parametric CAD models from natural language and/or images have been presented in the literature. These methods can be generally categorised into two groups: (a). image conditioned CAD program generation, and (b). vision and language-based CAD code generation. The scope of this section excludes mesh and point-cloud inputs, since those are addressed in Section 2 (Mesh-to-CAD Reverse Engineering).

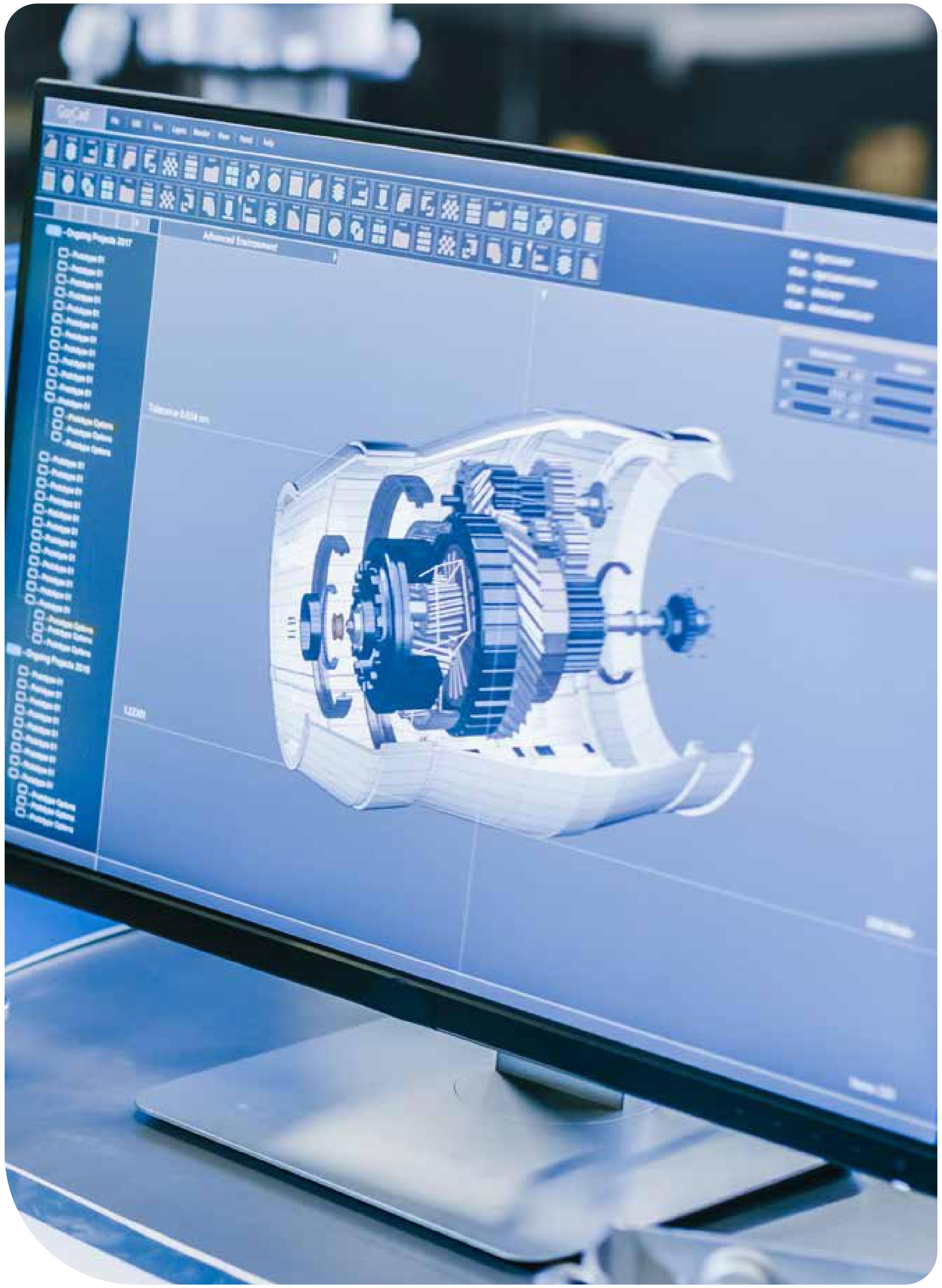
a. Image conditioned CAD program generation

This method (Alam & Ahmed, Sep, 2024) is parametric, sequential, and transformer based. It converts CAD images into parametric CAD command sequences, retaining design history and enabling full editability. It avoids directly producing B-Reps, since B-Reps lack parametric intent. The approach utilises autoregressive transformers, contrastive learning, and latent diffusion to model CAD sequences from images. CAD models are treated as a language modelling problem, where each CAD command acts like a token in Natural Language Processing (NLP). Editable CAD programs are then produced to be compiled into B-Rep, mesh, voxel, or point-cloud representations. The approach also supports image-based retrieval of CAD models due to its contrastive learning framework. An example of this approach is GenCAD (Alam & Ahmed, Sep, 2024), which is trained on DeepCAD (Wu, Xiao, & Zheng, May, 2021), a large design-history-aware dataset derived from ABC via Onshape parsing.

b. Vision and language-based CAD code generation

This method uses fine-tuned multimodal models, such as Vision Language Models (VLMs) and LLMs, that take an input image or textual description of the CAD model and produce directly executable script-level Python CAD modelling code. When the generated code is executed, an editable solid model is produced. Open-source language models are well-suited to this task because they can be customised and fine-tuned on domain-specific datasets. Such datasets contain pairs of input images or text descriptions matched to their corresponding output CAD code. For example, CADCoder (Doris, Alam, Nobari, & Ahmed, May, 2025) uses a fine-tuned VLM (LLaVA-derived) that takes an image and outputs CadQuery Python code. Moreover, CAD-Coder (Doris, Alam, Nobari, & Ahmed, May, 2025) finetunes Qwen2.5-7B-Instruct that takes an input text and generates CadQuery Python code.

In summary, AI-driven generation of parametric CAD models from natural language and/or images supports the definition of geometry and the capture of design intent at the point of creation. However, a significant proportion of CAD effort continues to be associated with the refinement of existing models. Although these aspects are not the primary focus of this section, further research will explore AI-assisted capabilities for geometry repair and optimisation of existing models.



6. Facility Layout Optimisation

This section focuses on facility layout optimisation in discrete manufacturing environments, where production is organised around distinct parts, assemblies, and material flows between defined process steps.

Manufacturing facilities often evolve over long periods of time, resulting in permanent building features, such as walls, columns and structural boundaries that cannot be changed, along with immovable equipment, mandatory safety and exclusion zones, and embedded services, such as power, air and drainage that restrict options for reconfiguration. These constraints make layout optimisation complex and effort intensive. Fragmented data stored across different systems, formats and units add further preparation effort before analysis can begin. In addition, the decision to initiate layout optimisation is often ambiguous. Performance degradation in existing facilities is typically incremental rather than abrupt, and the operational risk associated with reconfiguration can outweigh clearly attributed short-term benefits. As a result, organisations may favour local workarounds or incremental process changes over broader layout redesign. Over time, this can lead to facilities that are known to be sub-optimal but have never crossed a clear threshold that mandates reconfiguration.

Current optimisation workflows depend on manual effort and specialist expertise. Existing software can evaluate layout alternatives but cannot generate them automatically. As a result, the range of scenarios explored is often constrained.

Layout optimisation in brownfield manufacturing facilities requires engineers to assess design options within environments that are often difficult to change. AI-assisted methods have the potential to reduce the effort involved in this process by supporting data preparation, scenario exploration and performance evaluation.

This section assesses how these methods can contribute to the optimisation of existing layouts. It reviews the parameters and performance indicators used to evaluate layout performance and examines both commercial tools and research approaches that aim to streamline layout analysis. The goal is to provide a clear and evidence-based understanding of the current capabilities that are relevant to brownfield facility layout optimisation.

6.1 Parameters and KPI Prioritisation

Layout optimisation in brownfield facilities, meaning existing sites with established buildings, fixed equipment and legacy infrastructure, is constrained by fixed geometry, immovable assets, safety zones and embedded services that limit the range of feasible design changes. Beyond physical constraints, re-layout activities are inherently disruptive to ongoing operations and introduce significant operational risk. In many cases, the primary challenge is not the suitability of the proposed future layout, but the transition from the existing state to the new configuration. Managing temporary workarounds, interrupted material flows, safety implications, and degraded performance during this transition period can be complex and costly. These risks often discourage organisations from pursuing layout changes, even where performance improvements are well understood. Detailed simulation is then required to understand how layout options affect material flow, throughput, space use and operator movement, which is time consuming to configure and run. Current tools primarily support the evaluation of layouts rather than their automatic generation. As a result, engineers typically build and test alternatives manually, which can influence the number of scenarios explored.

6.2 Parameters and KPI Prioritisation

A range of parameters influence layout performance, including material flow, use of space, workforce activity, visibility, scalability and operational performance. Their combined effect explains why layout optimisation in existing facilities requires careful preparation and engineering judgement. These parameters and their associated metrics are summarised in *Table 11*. A high-level prioritisation can also be developed based on how frequently each parameter appears in the academic literature and how strongly it influences operational outcomes. This prioritisation is also shown in *Table 11*. Material Flow, Cost Impact, and Quality Impact score highest in this analysis, and therefore, form the three Key Performance Indicators (KPIs) used to evaluate tools and research methods in the following sections.

Table 11. A list of parameters, their definitions, and prioritisation scores.

Parameter	Definition of Associated Metric	Frequency	KPI Impact	Total
Cost Impact	Cost of implementation and operational cost.	5	5	25
Quality Impact	Influence on reliability and product quality.	4	4	16
Material Flow	Distance and time of movement and information flow.	3	5	15
Workforce Efficiency	Labour travel time and takt time.	2	4	8
Space Utilisation	Footprint reduction and flexibility of equipment.	1	4	4
Scalability	Ability to scale operations.	1	3	3
Visual Accessibility	Sightlines and ease of supervision.	1	2	2

Material Flow is directly supported through Discrete Event Simulation (DES) because it captures dynamic behaviour, such as queuing, routing and throughput. Cost and Quality related impacts are usually inferred from scenario-based or logic driven models unless dedicated representations are included. These KPIs form the basis for assessing tools and methods as follows.

6.3 Commercial Tools Landscape

A range of commercial tools support analysis of existing facility layouts. These tools help engineers understand material flow, equipment interaction and operational performance within constrained environments. The reviewed material identified three groups of tools that are commonly used for this purpose. These include DES platforms, movement analysis tools and AI-assisted generative tools for process environments. Each category provides different forms of support when evaluating layout changes.

DES tools, such as Tecnomatix Plant Simulation (Siemens PLC, 2026), FlexSim (Autodesk PLC, 2026) and AnyLogic (AnyLogic, 2026), provide detailed modelling of dynamic material flow. Tecnomatix refers to a broader suite of factory modelling tools, while Siemens NX Line Designer supports layout creation and configuration. They can represent queues, routing behaviour, congestion and throughput. They also provide scenario-based costing although the level of financial modelling varies between platforms. Quality related impacts are inferred from indicators like bottleneck behaviour and flow stability rather than from explicit quality models.

Movement analysis tools, such as Layout-iQ (Layout-iQ, 2026), focus on travel distances, congestion patterns and operator movement. These tools provide insight into workflow and space use, but do not model dynamic production behaviour, so they offer a different perspective compared to simulation platforms.

Generative tools, such as Aspen OptiPlant (AspenTech, 2026), can automatically create alternative layout configurations for process industry settings, including equipment placement and routing paths. These tools may not be typically applied to discrete manufacturing and therefore do not directly prioritise the optimisation tasks described in this paper. They are included here, within the scope of this section, as examples of how generative AI is already being applied to layout creation in process industries, highlighting capabilities that are not yet available for discrete manufacturing. Some emerging AI branded tools claim to automate discrete manufacturing layout optimisation although no independent validation was identified for these capabilities.

Across all reviewed tools, layout creation remains a manual engineering activity. DES tools are widely adopted for modelling dynamic flow behaviour for candidate layouts, but do not generate layouts themselves and instead support layout optimisation through iterative, engineer-led evaluation. Movement analysis tools provide insight into movement and congestion patterns but do not evaluate system behaviour over time. AI-assisted generative capability appears only in process industries. None of the reviewed platforms demonstrate automated generation of validated discrete manufacturing layouts.

6.4 State-of-the-art Research Methods

A range of methods were identified in the reviewed research papers, as summarised in *Figure 13*. The reviewed research papers used several methods to support layout planning in existing manufacturing environments. Each method addresses specific elements of the layout challenge and provides partial evidence of how optimisation or AI techniques can reduce manual effort.

a. Simulation Based Optimisation

Several studies combined optimisation with DES to explore predefined layout variants. These approaches reduced manual scenario creation, although engineers were still required to define layout structures, constraints and input data. Material flow was evaluated directly through simulation, while cost and quality effects were inferred from model logic.

b. Metaheuristic Search

Some papers used metaheuristic techniques, including genetic algorithms, simulated annealing, and other stochastic search methods, to explore large numbers of candidate layout configurations. These approaches intentionally operate on simplified or abstract layout representations and typically optimise static or aggregate objective functions, such as material handling distance, adjacency cost, or space utilisation. DES is not typically applied within the optimisation loop, as the computational cost would limit scalability. This is not inherently a limitation, but a design trade-off: metaheuristic methods enable broad exploration of the solution space at the expense of modelling dynamic behaviours, such as queuing, congestion, and throughput. As a result, engineers remain responsible for interpreting the abstract optimisation output and validating promising layouts using higher-fidelity analysis.

c. Constraint Based Approaches

Constraint based models generated feasible layouts by encoding adjacency rules and space requirements. These approaches reduced feasibility checking but did not assess operational performance. Material flow, cost and quality impacts were not directly evaluated.

d. Learning Based Approaches

Several studies applied reinforcement learning or ML to support decision making in restricted layout problems. When reinforcement learning was combined with simulation, material flow could be evaluated directly. Cost and quality remained inferred from simulation logic. The interaction between reinforcement learning and simulation has been described in previous work, which shows how a reinforcement learning agent evaluates layout decisions using feedback from a DES model (Klar, et al., 2024).

e. Hybrid Approaches

Hybrid methods combine constraints with optimisation or learning. Constraints are used to guide the search towards feasible options, while simulation is applied to evaluate dynamic behaviour. These methods reduced infeasible layouts but still required engineers to define constraints and simulation models.

f. KPI Support Observed Across the Reviewed Methods

Support for the selected KPIs varied across method types. Simulation based optimisation, learning based approaches and hybrid methods provided direct support for material flow because their performance is evaluated through DES. Metaheuristic and constraint-based methods provided indirect or unsupported KPI coverage, as they rely on simplified or proxy measures rather than explicit performance modelling. This alignment is summarised in *Table 12*.

Across both the reviewed commercial tools and research methods, DES remains widely used for evaluating dynamic material flow within existing facilities. Simulation captures queuing, routing behaviour, throughput and congestion, and these features are not available in simplified methods. AI and optimisation techniques depend on simulation to assess performance, so simulation continues to act as the central evaluator for layout evaluation.

Current evidence also shows that AI-driven layout optimisation for DES remains typically constrained in scope. Existing approaches can support data preparation, scenario exploration and constraint checking, but they do not yet generate complete, validated layouts without significant engineering input. AI techniques therefore act as accelerators within established workflows rather than autonomous layout designers.

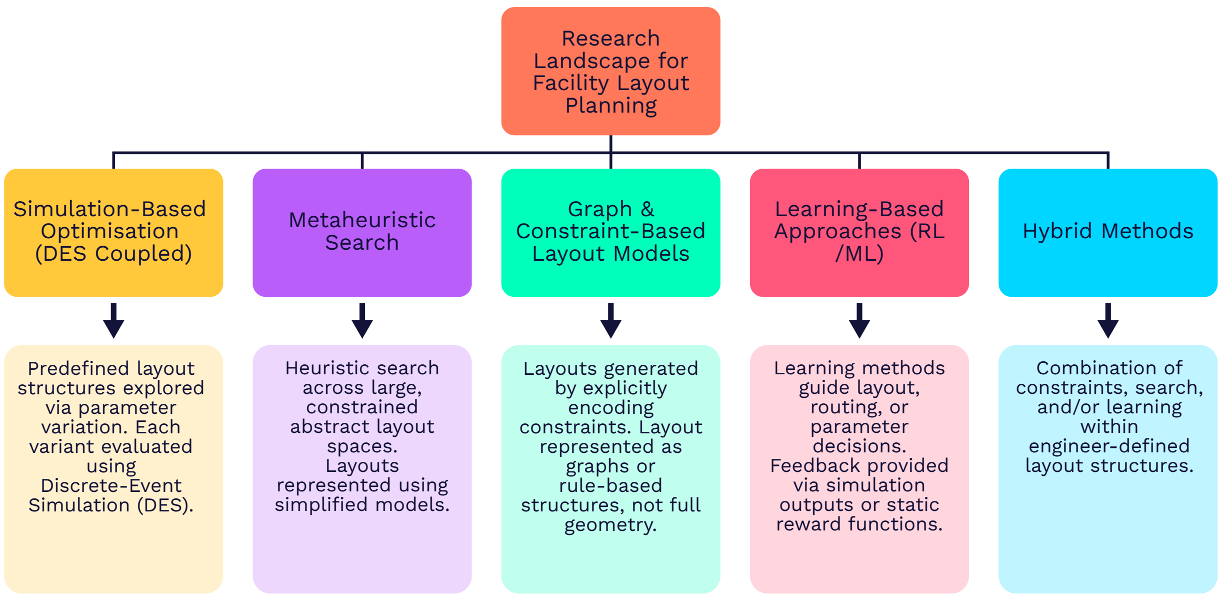


Figure 13. Overview of reviewed approaches for automated facility layout planning.

Table 12. KPI alignment across reviewed method categories.

Method Category	Material Flow	Cost Impact	Quality Impact
Simulation Based Optimisation	Direct when DES is used	Indirect	Indirect
Metaheuristic Search	Indirect	Indirect	Unsupported
Graph and Constraint Based Models	Unsupported	Unsupported	Unsupported
Learning Based Approaches	Direct when DES is used	Indirect	Indirect or Unsupported
Hybrid Methods	Direct when DES is used	Indirect	Indirect or Unsupported

7. Recommendations

The following recommendations distinguish between actions organisations may consider now using commercially available tools and areas where emerging technologies may offer future value.

7.1 Mesh-to-CAD Reverse Engineering

Commercial reverse engineering tools have made notable progress in automating mesh-to-CAD conversion, particularly through prismatic mesh conversion and hybrid approaches. However, they still require significant manual input for complex, fully parametric CAD models and to reconstruct feature trees and design intent. The automation capabilities are typically constrained to basic geometries, and do not prioritise intelligent feature recognition for scalable industrial use. Meanwhile, academic research has introduced promising AI-driven methods, though these remain at an early stage and are yet to prove robust on real-world industrial components.

a. Areas of Development within Commercial Solutions

- Integration of AI and ML techniques for geometry interpretation, feature recognition and design intent reconstruction.
- Increased emphasis on interoperability, collaboration and traceability through standardised workflows and data exchange approaches.
- Continued exploration of hybrid conversion methods that combine rule-based and data-driven feature extraction techniques, including approaches that communicate confidence and uncertainty to users.

b. Areas of Ongoing Research

- Development of AI approaches, including graph-based and segmentation-based methods, for the handling of complex geometries and assemblies.
- Investigation of industrial-scale datasets and validation methodologies to assess performance across a broader range of applications.
- Exploration of CAD-specific AI architectures that incorporate domain knowledge, manufacturability considerations and integration with existing CAD environments.

7.2 AI-assisted Simulation Prediction

Commercial activity in AI-assisted simulation prediction is evolving rapidly, with several organisations exploring the use of pre-trained models for engineering applications. Simscale currently offers a commercially available pre-trained AI-driven simulation prediction capability for centrifugal pump applications, while additional foundation-model-based approaches are being developed across the sector.

Pre-trained simulation models represent one approach to reducing the reliance on organisation-specific training datasets and bespoke model development. Such approaches may broaden access to AI-enabled simulation capabilities by allowing users to apply pre-trained models within established engineering workflows. Simscale, Siemens, PhysicsX and other technology providers are exploring the use of pre-trained and foundation-model-based approaches for engineering applications. These developments reflect broader industry interest in AI models designed to support recurring engineering workflows and extend access to simulation capabilities across a wider range of users. However, AI-assisted simulation prediction is intended to complement, rather than replace, physics-based modelling and engineering judgement, as responsibility for the validity, interpretation, and verification of simulation results remains with the user and cannot be fully delegated to the AI model. As commercial offerings continue to evolve, these approaches may contribute to reduced model development effort and increased accessibility of AI-enabled engineering tool.

7.3 Automatic Assembly Sequence Generation and Validation

The developed toolchain demonstrates that rule-based, geometry-driven toolchains can provide practical early-stage support for assembly planning, particularly by embedding DfA logic directly into the design workflow. However, to move beyond prototype capability, further development can prioritise strengthening core modules, including improved robustness of the assembly-by-disassembly solver and more realistic fixture generation through surface-aware placement and orientation. In parallel, high-priority DOZO/FRAG rules represent a viable approach to be formalised into a structured and extensible knowledge base to ensure consistent and scalable design governance.

From a deployment perspective, maintaining the modular Python and FreeCAD-based architecture can preserve flexibility, transparency, and ease of extension. Usability can be enhanced through clearer visualisation and feedback mechanisms, such as sequence viewers, rule-failure indicators, and standardised output formats, enabling more effective integration into engineering workflows and reducing reliance on specialist expertise.

Looking ahead, further value can be realised by expanding rule coverage, improving algorithm robustness for complex assemblies and large part counts, and optimising performance through spatial acceleration techniques. Additional capabilities, such as part consolidation assessment and integration with downstream CAD, CAM, and Product Lifecycle Management (PLM) workflows, represent areas for further exploration. While optional ML enhancements may improve sequence prioritisation and fixture placement, the primary focus should remain on developing robust, explainable, and scalable rule-driven toolchains that augment engineering decision-making.

7.4 Automated CAD Generation

AI-enabled CAD tools are increasingly being applied alongside existing design workflows, particularly for early-stage concept generation and rapid prototyping. Commercial text- and image-driven approaches for parametric CAD generation are available and support the definition of geometry and design intent from natural language or visual inputs. Published evaluations have primarily focused on concept development and relatively simple components, while evidence relating to complex manufacturing CAD models remains limited. Current applications include concept generation, simple component design and selected reverse-engineering workflows, with ongoing development and evaluation across a broader range of industrial use-cases.

At a strategic level, organisations may invest in capability development and data readiness to maximise long-term value for manufacturing use-cases. This includes building internal expertise in integrating AI tools with existing CAD workflows and curating high-quality, manufacturing, parametric CAD datasets to support research and improve AI model outputs. At the same time, human oversight and validation processes represent a necessary step to ensure manufacturability and compliance, particularly for complex or production-critical designs, positioning themselves to scale adoption as the technology matures.

As the technology matures, its application is expanding beyond initial prototyping and geometry generation towards supporting iterative design and model refinement. This reflects a broader shift towards more integrated, AI-assisted CAD workflows. Current research is increasingly focused on addressing the areas where engineering effort is commonly concentrated, particularly the refinement of existing models and the debugging of complex geometry. Ongoing development includes enhancing AI capabilities for automated detail-level repair, optimisation, preservation of parametric intent, and effective management of change propagation across feature trees. By tackling these low-level, labour-intensive challenges, emerging approaches aim to reduce reliance on manual intervention, which is often repetitive, error-prone, and technically demanding, allowing engineers to focus on higher-value design activities.

7.5 Facility Layout Optimisation

The reviewed evidence demonstrates that AI-assisted layout optimisation currently serves as a support mechanism rather than a replacement for engineering-led layout development. These methods can reduce the effort involved in data preparation, scenario exploration and constraint checking, but they cannot yet produce complete or validated layout configurations for brownfield facilities without substantial engineering input.

For industrial organisations, a practical near-term approach is to integrate AI techniques into existing simulation-based workflows. This may include using optimisation algorithms to suggest candidate arrangements, applying movement-analysis tools to screen alternatives more rapidly, or using ML models to structure layout data more efficiently. These applications can widen the range of scenarios evaluated and improve the consistency of early-stage decisions, particularly in facilities constrained by legacy assets and fixed infrastructure.

Current research methods, including reinforcement learning, graph-based models and hybrid optimisation techniques, show promising potential for future automation but have not yet demonstrated the robustness or reliability required for autonomous layout generation in discrete manufacturing environments. Developments in these areas, together with the availability of reliable layout data, modular simulation models and consistent flow-mapping practices, are likely to influence the adoption of more advanced AI-enabled layout tools as they mature.

Conclusion

Mesh-to-CAD reverse engineering remains an increasingly relevant but technically challenging process in modern design workflows. Commercial mesh-to-CAD tools have advanced significantly, especially through hybrid conversion methods, but still rely heavily on manual input. Academic research offers promising AI-driven approaches for feature recognition and geometry reconstruction, though these remain at low maturity levels. To realise scalable, intelligent reverse engineering, future progress must focus on integrating AI into commercial platforms, advancing academic models for industrial use, and fostering collaboration across sectors. This convergence has the potential to support automated, accurate, and interoperable CAD generation from mesh data, transforming reverse engineering from a manual bottleneck into a streamlined design asset.

A total of six ***AI-assisted predictive simulation*** platforms were reviewed in depth, including offerings from both large industry-leading technology corporations and small software startups. The review, concluded using a range of publicly available information, indicates that platforms, such as Ansys SimAI and Altair PhysicsAI currently provide some of the widely accessible end-to-end workflows for AI-assisted simulation prediction, particularly for organisations seeking rapid adoption with minimal AI expertise. Other platforms, including Siemens and COMSOL, offer high flexibility and depth but typically require higher levels of specialist knowledge. The market is evolving rapidly, with increasing emphasis on pre-trained, physics-aware models designed for specific engineering problem classes.

It was demonstrated that early-stage ***assembly sequence planning,*** traditionally reliant on tacit expertise and manual visual inspection, can be meaningfully enhanced through deterministic, rule-based automation. The MTC's FreeCAD-based toolchain integrates geometric reasoning with codified DOZO/FRAG design-for-assembly guidelines to evaluate removal paths, ordering dependencies, clashes, fastening strategies, and opportunities for part consolidation directly within the CAD environment. Its assembly-by-disassembly approach provides transparent and repeatable assessments of insertion feasibility, while supplementary modules generate basic 3-2-1 fixturing concepts and highlight manufacturability issues at a stage when corrective design changes are still practical. Although enterprise digital manufacturing platforms support more comprehensive downstream process planning, the MTC toolchain plays a complementary upstream role by embedding explainable, early-stage DfA validation without the overhead of proprietary ecosystems. Current constraints in geometry handling, fixturing logic, and rule breadth place the capability at TRL 2-4, yet the demonstrator establishes a compelling foundation for integrating design governance, manufacturability intelligence, and consistent assembly reasoning directly into everyday engineering workflows.

AI-enabled tools for ***automated CAD generation*** are rapidly emerging, enabling the creation of parametric 3D models from text descriptions, images, and sketches, typically producing editable outputs, such as B-Rep solids or CAD code rather than static meshes. Leading commercial solutions increasingly leverage LLMs to generate and modify parametric design logic, allowing users to adjust geometry through parameter changes rather than direct editing. However, there is currently typically constrained evidence of systematic benchmarking or validation of these tools within manufacturing-grade production environments, the generated outputs may require manual refinement to achieve acceptable design fidelity. Although these tools show strong potential for rapid prototyping, early-stage ideation, and supporting less experienced users, they are not currently considered as an alternative to manual CAD modelling in production contexts. In parallel, emerging research approaches, such as image-conditioned CAD program generation and vision or language-based code generation, demonstrate the feasibility of producing fully editable parametric models from images or text by treating CAD construction as a sequence modelling or language generation task. However, enabling manufacturing-grade parametric CAD generation for complex use-cases involving long command sequences remains an open challenge. Addressing this will require accumulative efforts in the curation of high-quality, parametric CAD data sets that represent complex, manufacturing-relevant use-cases to support robust model training and improve output reliability. On the other hand, experienced designers continue to spend significant effort on tedious and error-prone low-level tasks, particularly in debugging and repairing geometric inconsistencies. This highlights a complementary opportunity for AI, represented in the development of tools focused on the automated repair, validation, and optimisation of existing CAD models.

Across the commercial tools examined for ***facility layout design,*** layout creation remains a manual engineering activity. Simulation tools assess how a defined layout performs. Movement analysis tools provide useful information on travel distances and congestion, while generative tools are typically constrained to process industries. No reviewed platforms were identified as demonstrating automated generation of validated layouts for discrete manufacturing. The research methods identified in the literature show how optimisation, learning and constraint-based techniques can reduce specific forms of manual effort. Simulation-based optimisation supports scenario exploration, metaheuristics expand search coverage, and constraint-based approaches prevent unfeasible layouts. Learning-based and hybrid methods improve decision making when used with simulation, although they still require engineers to define constraints and prepare models. None of these approaches demonstrate fully automated layout creation for existing manufacturing environments. Material flow is a well-represented feature as it can be evaluated directly using simulation. On the other hand, cost and quality impacts are commonly inferred through proxies. Current tools and methods provide direct support for these KPIs, although this support is often constrained.

In summary, the findings of this whitepaper show that AI is beginning to reshape engineering design in practical and measurable ways, particularly in domains where tasks are repetitive, data-rich or rule-constrained. Across Mesh-to-CAD workflows, AI is accelerating digitisation but still requires human oversight to reconstruct design intent. In predictive simulation, emerging platforms demonstrate that pretrained, physics-aware models can provide real-time insight without specialist expertise. MTC's work on assembly sequence generation shows that explainable, rule-driven automation can embed manufacturability checks directly within CAD, improving consistency long before digital manufacturing systems are engaged. Early-stage CAD generation tools are advancing rapidly, although their use remains most appropriate for concept development rather than production-grade modelling. Facility layout optimisation, meanwhile, shows that AI currently acts as an enabler rather than an autonomous planner, expanding scenario exploration, but not yet generating validated layouts for complex brownfield environments.

Incremental adoption of AI within existing workflows is increasingly being explored across industry, particularly in areas where opportunities for productivity improvement have been identified. Emerging approaches commonly combine domain expertise, AI-enabled technologies and engineering data to support decision-making and engineering processes. Ongoing developments are contributing to increasing levels of integration between design, simulation and manufacturing workflows through interoperable and data-driven systems.

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