

Identification of key parameters for automated assembly

Malte Jakschik^{1*}, Julian Rolf², Kian Bahri¹, Bernd Kuhlenkötter¹

¹Ruhr University Bochum, Chair of Production Systems, 44894 Bochum

²Ruhr University Bochum, Chair of Digital Engineering, 44894 Bochum

*Corresponding author. E-Mail address: jakschik@lps.ruhr-uni-bochum.de; Tel.: 02324 32 24611

Abstract:

Demographic change and the resulting shortage of skilled labor increase the need for automation in industrial production systems. Since decisions influencing automation suitability are fixed mainly in early product development phases, reliable assessment methods are required even when product and process information is incomplete. Established Design for Automation and Automated Assembly (DFA/DFAA) methods provide valuable expert knowledge but are often too information-intensive for early-stage applications. This paper presents a hybrid intelligence approach that combines expert-based DFA/DFAA evaluation methods with machine learning-based surrogate models to support early assessment of automation suitability. First, a systematic literature review is conducted to identify key product-related criteria influencing automated assembly. Based on these criteria, a synthetic dataset of standardized product descriptions is generated and labeled using a validated DFA evaluation algorithm derived from established methods. Subsequently, a graph isomorphism network is trained to predict the Automation Suitability Degree directly from graph-based product representations.

Validation results demonstrate high predictive accuracy and strong correlation with expert-based evaluations, indicating that the model reliably captures relative suitability trends even for partially specified products. While absolute errors increase for previously unseen product variants, the approach shows strong potential as a scalable decision-support tool.

Keywords:

Design for Automated Assembly, design decision support, Machine Learning Surrogates, Early Product Development, Automation Suitability Assessment

1 Introduction

Demographic change and the resulting shortage of skilled labor pose significant economic and structural challenges for industrialized high-wage countries. The declining availability of qualified workers already causes substantial economic losses and is expected to intensify with the retirement of the baby-boomer generation [1]. To remain competitive, companies increasingly rely on digitalization and automation. Beyond reducing physical workload, technological support can improve efficiency throughout product development and production [15]. Adapting product design to enhance automation suitability can significantly reduce assembly effort and production time. Since up to 70 % of total product costs are determined in early development phases, automation-related decisions should be made as early as possible [2]. However, in these phases, essential process information is often incomplete, making reliable assessment of automation potential difficult. Consequently, digital engineering tools must provide adequate decision support under limited information.

Recent advances in computing have enabled the use of Machine Learning-based Surrogate (MLS) models to complement or partially replace computationally expensive simulations in engineering design. MLS models allow efficient exploration of large design spaces and can support early decision-making with reduced computational effort. In this context, this study focuses on Design for Automation and Automated Assembly (DFA/DFAA) and investigates which product characteristics determine the suitability for automated assembly.

This work addresses two research questions (RQ):

RQ1: *Which product parameters determine automation suitability in early product development?*

RQ2: *To what extent can a graph-based ML surrogate model reliably approximate expert-based automation suitability evaluations??*

From a hybrid intelligence perspective, the proposed approach combines expert knowledge embedded in established DFA/DFAA methods with data-driven learning mechanisms. While evaluation criteria and labeling logic are derived from human expert models, MLS models generalize this knowledge across large and partially incomplete design spaces. The system is intended to support rather than replace human decision-making by providing early, consistent, and explainable feedback on the suitability of automated assembly.

This article is structured as follows: First, relevant DFA/DFAA criteria are identified through a systematic review of the state of the art. Subsequently, the generation and labeling of a synthetic dataset are described and validated. Finally, a graph isomorphism network (GIN) is used to predict automation suitability, and the results are discussed and summarized.

2 Identification of key parameters in literature

Various methods exist to evaluate the design for automated assembly. In literature, the most established methods are the Boothroyd-Dewhurst (B&D) method, the Lucas method, and the Hitachi-Assembly Evaluation Method (Hitachi-AEM) [3–7]. All these methods were developed in the 1990s; therefore, it is appropriate to review the factors and key criteria to ensure they remain as relevant today as they were then and to address RQ1. A literature review was conducted to identify the key drivers by analyzing the criteria used for the DFA and DFAA approaches. The non-sharp separation of the focal points in mind, the relevant contributions can be categorized into three groups: those focusing on manual assembly [8–22], those focusing on automated assembly [5,23–30], and those that do not explicitly differentiate between the two [7,31–36]. The established methods mentioned above each have a different focus: For example, the B&D method distinguishes between manual, automated, and robot-assisted assembly. The Lucas method also distinguishes between manual and automated assembly. The Hitachi AEM does not explicitly differentiate between the assembly approaches, but it sees manual assembly as a fundamental prerequisite for automated assembly [6]. Since the criteria for the DFA and DFAA assessments overlap considerably and there is no clear distinction between the two design methods in the literature, both approaches were considered in this research [37]. Figure 1 shows the distribution of all relevant criteria, where the primary y-axis shows the overall number of uses, and the secondary y-axis shows the quantitative distribution of the criteria relative to the established method. A total of 48 distinct criteria were identified in the contributions, although it was often not possible to distinguish among them clearly. For example, the evaluation of the working space was addressed separately in some contributions, whereas in others it was covered under the criterion of accessibility. However, it should be noted that, due to the clear correspondence between the established methods' criteria and the state of the art, the criteria of the existing established methods remain the most relevant.

Given the need for early feedback on the suitability of automated assembly, it makes sense to analyze the distribution of criteria relative to the methodical application period. The development process is

typically divided into four stages: task clarification, conceptualization, design, and elaboration [38]. The approaches presented in [10,21,23–27,32,33,36,39] are applied in the conceptual phase of product development and require relatively low information content regarding the product to be developed. The methods used in the design phase are described in [18–20,35,40,41]. In [8,9,30], the product is already on the market, resulting in the highest information density. In contrast, the methods in [5,28,29] are designed for application across all phases of product development. To evaluate the product in the elaboration stage, the authors in [7,11–17,28,31,34,42,43] present applicable approaches. The established methods can also be assigned to these categories, with the Lucas method to the concept phase, the Hitachi AEM to the design phase, and the B&D method to the elaboration phase [5]. This distribution is also shown in Figure 1. Furthermore, the 18 most frequently used criteria are applied across all stages of the development process. These, in turn, are also consistent with established methods, thus once again demonstrating the relevance of these methods and criteria.

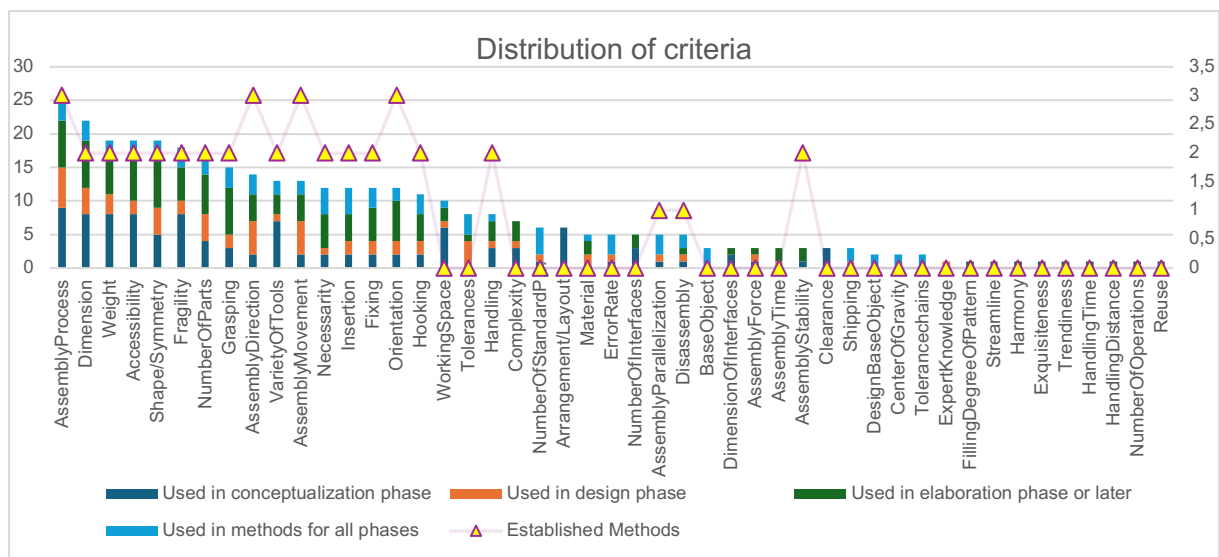


Figure 1: Quantitative distribution of DFA & DFAA evaluation criteria

In addition to the criteria used, the RQ2 should also be examined in the literature to investigate the use of ML in these articles. Similar to the research in [3], this review also concludes that there is a research gap in AI-supported DFA assessment, as only a few recent contributions in this area could be identified. Krahe streamlines the product development process by integrating a knowledge base of comparable products. Using this foundation, an AI analyzes a semi-finished product and predicts the next construction step, drawing on past products that have proven highly suitable for manufacturing. [44] The article by Suszynski et al. describes an artificial neural network (ANN) that predicts assembly times for different sequences based on selected DFA metrics. The system serves as an intelligent predictor in an automated assembly planning environment, and its results demonstrate that DFA methods can be effectively combined with ML models. The DFA key factors used here are based on the B&D evaluation method. However, the goal of the optimization presented in this paper is not to evaluate the design, but rather to optimize and predict the time of a given assembly sequence. [15] Jing et al. use a graph neural network (GNN) to generate explainable recommendations for manufacturing knowledge that can be used in early development phases. The aim is to reduce iterative optimization loops in the engineering process and expand cognitive capabilities regarding manufacturability and assembly constraints. They conclude that integrating GNNs into manufacturing knowledge provides a scalable and robust basis for knowledge-based support systems. [42] Jakschik et al. present a product evaluation algorithm based on fuzzy logic and a product description in an AutomationML (AML) file structure, which enables the evaluation of various uncertain or subjective

metrics. The contribution describes a conceptual approach to generating a comprehensive dataset using this algorithm to predict the suitability of future automatic assembly. The approach has not yet been definitively validated, but has already undergone various plausibility tests and is delivering promising results. The article serves as the basis for the approach described here and details the textual product description using AML and the evaluation algorithm. [28]

In their approach, Ereemeev et al. develop a framework for performance and assembly optimization in product development. This is based on a fully parameterized CAD model, which is subjected to various CAE simulations for the optimization approach. In addition, a DFA evaluation of the design instance is performed based on the number of standard parts used, and the assembly space for the tool is evaluated. In the framework presented, an ANN and a Gaussian process are used to abstract from and efficiently perform computationally expensive simulations, thereby enabling multidisciplinary optimization. Although this article also presents promising results, the assessment of automated assembly's suitability with respect to the identified key factors remains underrepresented and should be enriched with additional criteria. [11]

In conclusion, the literature review shows that established methods still capture the key factors for high suitability for automated assembly, given the high degree of overlap with the state of the art, and that ML delivers promising results for predicting suitability but requires further investigation.

3 Problem solving approach

The proposed workflow follows a hybrid intelligence paradigm: expert-based evaluation methods generate high-quality labels, while a graph-based machine learning model learns to efficiently approximate these evaluations. This allows expert knowledge to be reused and applied in early development phases, where manual DFA assessments would be infeasible due to limited information or time constraints. The concept was implemented using an instrument panel to control process engineering processes. Synthetically reproduced product descriptions are used to generate a data set of 500 product descriptions, which is then evaluated using a DFA evaluation algorithm. This was implemented in a setup comparable to that described in [28] and evaluates products using the established methods of B&D, Lucas, and Hitachi AEM. Due to the application period described (application in all phases of product development) and the high degree of compatibility, the evaluation method according to [29] was also taken into account. In his approach, Eskilander has already attempted to combine the established methods and develop a method that can be adapted across all development phases. The focus of the developed method is on the objectification of the evaluation criteria. Before labeling the data set, the evaluation algorithm was validated using these methods. Using the fuzzy sets underlying the evaluation algorithm, the membership functions were adjusted so that the evaluation algorithm's output corresponded to that of the established methods. The labeled data set is used to train a GNN. Validation of the ML approach confirms the relevance of the selected evaluation criteria. Below is a detailed description of each topic.

3.1 Dataset generation

To ensure a dataset of sufficient size for effective training of machine learning models, a synthetic data generation approach was used. The synthetic dataset does not represent arbitrary abstract assemblies; rather, it is derived from a realistic product class: modular instrument panels used in process engineering plants, as shown on the right side of Figure 2. The component library was created from typical industrial panel layouts and standardized connection principles (e.g., pipes, valves, sensors, mounting plates). Synthetic samples, therefore, represent structurally mountable but not company-specific product variants. The method involves rule-based combinations of components to generate a

wide range of assembly scenarios, and algorithmic replication of product descriptions to systematically expand the dataset.

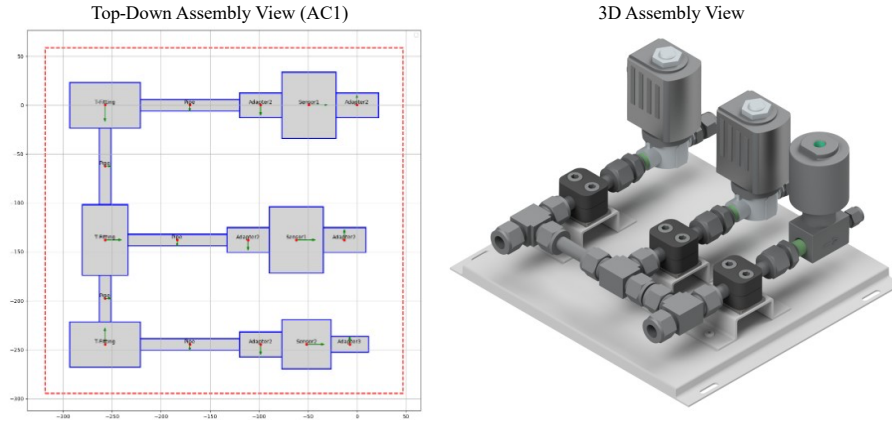


Figure 2: Visualization of the product class under consideration for DFA/DFAA Evaluation

For the rule-based combination, a parts library was created that describes a total of 27 different components of an instrument panel. Each of these components is enclosed by six enclosures, with each two-dimensional surface being specified by additional features such as cutouts and contact surfaces. A connection matrix was then used to determine which side of component A could be connected to other components N. This resulted in a side-by-side description of each component.

The algorithm selects a random starting component and then the permissible connection components for the next step. This process is repeated until the specified number of pipe components is reached. The components are then positioned according to the contact surfaces in the plane, and the instrument panel's overall dimensions are calculated. A random selection of connecting components then ensures the mechanical connection between the piping system and the mounting plate. However, only one connection type is selected per panel. For dataset creation, the number of components per product was set to n , with the range $n \in [5, 30]$. At this step, each product instance is represented as a hierarchical product description in CAEX-compliant XML.

3.2 Labeling methodology

This approach uses supervised learning to predict the suitability of automated assembly, so the dataset must be labeled accordingly. A dedicated evaluation model, aligned with CAEX-compliant XML product descriptions and inspired by the approach in [28], was developed. Adjustments to the membership functions within the knowledge base ensured close alignment of results with existing evaluation methods. Based on the identified key factors and the existing relevance of the established methods, all criteria used by at least 20 % of the contributions and by more than one established method were considered in the evaluation algorithm. This resulted in the first 20 criteria from Figure 1 and the criterion *assembly stability*.

To validate the evaluation algorithm, 35 sample products were evaluated using the established Lucas and B&D methods as described in [45], as well as Eskilander, and the results were compared with those of the evaluation algorithm. Due to limited access to the Hitachi-AEM method and its underlying valuation logic, the method could not be used for validation. Using fuzzy sets and defining support points of the membership functions, the evaluation algorithm's results were adjusted to match the methods' results, ensuring a correlation between them. The sample products are based partly on real products (5) and partly on the synthetic reproduction (30) already described. Products with between 5 and 30 components are covered. When generating the validation data set, the number of components in the 35 sample products was varied, excluding the panel and its fasteners, so that the first 10 evaluations

used products with $n_i \in [10, 20]$ instrument parts. The second batch (10 products) was generated with products with $n_i \in [5, 10]$ instrument elements, and their ratings were compared. Finally, a comparison was made with very large product variations (number of instrument parts $n_i \in [20, 30]$). The final validation result yields the correlation shown in Figure 3. Significant correlations could be established in comparison to the evaluations according to Lucas and the design efficiency according to B&D. The negative correlation with Lucas is due to the contrasting waiting areas of the two methods: Lucas states that everything above 2.5 should be revised. In contrast, the DFA evaluation algorithm states that everything below 60% should be revised.

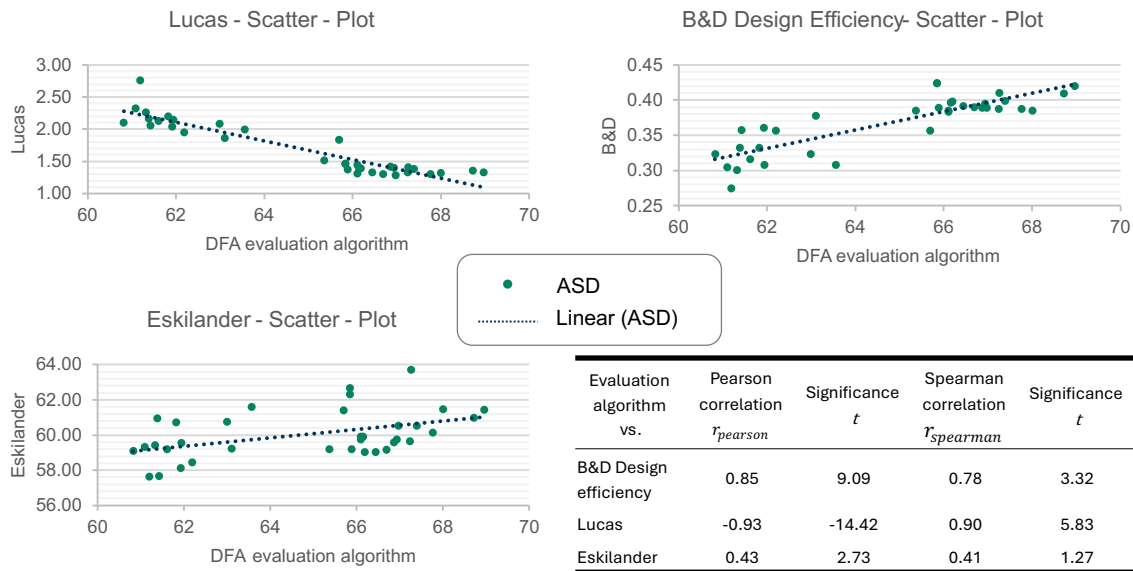


Figure 3: Linear relationship between the output of the evaluation algorithm and the state of the art

Compared to Eskilander's assessment, the correlation with the DFA-evaluation algorithm remains significant ($|t| > 2 \rightarrow$ significant at the $p < 0.05$ level), but is lower than with the other methods considered. An in-depth analysis of the sample data shows that SynthData 10 to SynthData 20 products exhibit a significant increase in the assembly-to-component ratio (ratio > 0.2). At the same time, the deviation between the Eskilander assembly rating and the evaluation algorithm also increases significantly (s. Figure 44). In the other batches, there are also isolated products with a ratio above 0.2; however, batch 2 is entirely above this threshold. If these batches are excluded from the analysis, a high correlation of $r_{pearson} = 0.72$ can be observed between the two evaluation methods. These results suggest that the underlying evaluation model reaches its limits for ratios above 0.2. In particular, the algorithm's quality appears significantly reduced for products with a small number of components distributed across many assemblies.

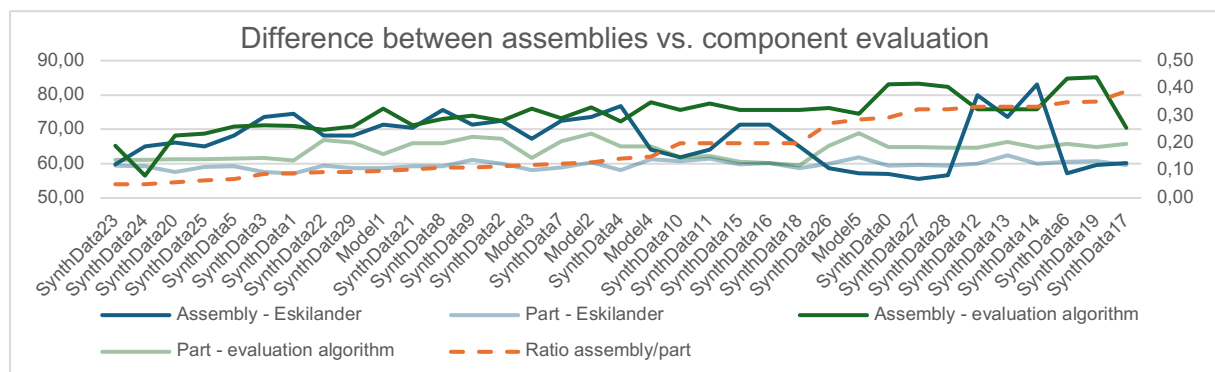


Figure 4: Differences between assemblies vs. component evaluation in comparison to the ratio of assemblies and parts

3.3 Machine learning approach

To answer RQ2, a graph isomorphism network (GIN) based supervised learning model was used. The advantage of GINs lies in their ability to model relational dependencies between neighboring nodes via message passing explicitly. In addition, GINs are theoretically as powerful as the Weisfeiler–Lehman graph isomorphism test and can therefore distinguish a wide class of non-isomorphic graphs (graphs that do not have the same structure), which is a prerequisite for the scenario described here, given the variability of components. Compared with classical regression methods, this approach enables automatic, data-driven extraction of relevant structural features directly from the graph representation. [46]

Each hierarchical product description (AML file) is modeled as an undirected graph $G = (V, E)$, where V denotes the set of nodes and $E \subseteq \{\{u, v\} \mid u, v \in V\}$ denotes the set of undirected edges. Although connections in the AML specification can have a semantic direction, this information is not used in the present model; the graph representation is therefore undirected. In this representation, each element in the product description corresponds to a node, while edges represent hierarchical relationships between elements, encoded as undirected connections in the graph. For example, the six enclosures of a part are modeled as child nodes of the corresponding part element and connected to it via edges. In addition, as described in [28], physical connections between two parts are modeled by links and are likewise represented as edges in the graph. Furthermore, a feature vector $x_v \in \mathbb{R}^{14}$, which represents numerical attributes of the respective component, such as dimension, material, or weight information, is assigned to each node $v \in V$. To improve numerical stability, the target variable is standardized. The mean μ and standard deviation σ are calculated for the training data. During training, the mean square error (MSE) on the scaled target variable is minimized. For inference, a back transformation to the original target space is performed. The model was initially trained using an 80/10/10 train/validation/test split with early stopping. In addition, a 5-fold cross-validation was conducted to assess the robustness of the results. Finally, the trained model was evaluated on 35 previously unseen sample products. This results in the mean absolute errors (MAE) and the coefficient of determination (R^2) shown in Table 1. Using the previously evaluated sample products, the deviations and correlations were obtained relative to the evaluation algorithm.

Table 1: Validation of the GIN

First Training- Early stopping after 64 epochs with adaptive learning rate (LR)	Test - MAE	0.334
	Test - R^2	0.972
Using 5-fold cross-validation	Test - MAE	0.292
	Test - R^2	0.976
Validation with the 35 sample products	Sample products - MAE	1.24
	Sample products - RMSE	1.60
	Pearson correlation to the evaluation algorithm	0.92

4 Discussion

Looking at the validation results in Table 1, the MAE for the sample products is significantly higher than for the test set: GINs tend to overfit training-specific graph patterns more than simpler GNN architectures (e.g., GCNs), especially with small or homogeneous datasets. Although the sample products belong to the same product family, the deviations between their structural representations and the dataset remain to be investigated. Dwivedi et al. describe similar behavior in GINs, which achieve very low training error but also exhibit higher variance and poorer performance on out-of-distribution

data. In addition, the authors conclude that GINs are more prone to overfitting than less expressive GNNs [47]. The observed increase in prediction error for previously unseen sample products highlights limitations in the trained model's generalization capability. While the underlying DFA criteria are largely product-independent, the training dataset is based on a synthetic representation of a specific product family. As a result, the model primarily generalizes within the structural and topological patterns represented in the dataset.

Despite the increased MAE, the results still show a high Pearson correlation of $r_{\text{pearson}} = 0.92$ between the model predictions and the evaluation algorithm. This suggests that the model captures the relative relationships and trends of the target variable very well, even if the absolute scaling is less accurate for previously unseen products. Therefore, the current model should be interpreted as a proof of concept demonstrating the feasibility of learning automation suitability from structured product descriptions, rather than as a universally applicable predictor across arbitrary product families. In practical applications where rankings or relative differences are particularly relevant, this represents an important strength of the approach.

5 Conclusion and further outlook

From a hybrid intelligence standpoint, the presented approach demonstrates how expert knowledge can be preserved, formalized, and extended through machine learning. The surrogate model captures relational and structural patterns that are difficult to quantify manually, while still remaining grounded in established evaluation logic. Human designers remain essential for interpreting results, refining criteria, and making final decisions.

This work has shown that established methods for evaluating automated assemblies are still relevant and that the selected criteria are also reflected in the current state of research. Furthermore, it has been shown that GINs can be used to make valid predictions of ASD, thereby validating the key factors for reliable evaluation mentioned in Chapter 2. The GIN-based model exhibits high internal validity and robustness, as demonstrated by cross-validation and test-set results. However, the increased deviation in the sample products underscores the importance of a training database as broad and representative as possible. Future work could investigate the integration of directed edges, additional domain-specific node features, or targeted domain adaptation to further improve the model's generalization. Furthermore, future work should compare different AI models and their performance to ensure that the most powerful model is used for this application. In addition, the transferability to other product families must be investigated.

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