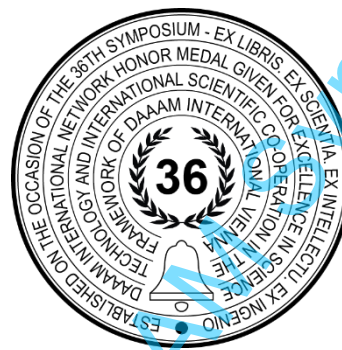


APPLICATION OF ARTIFICIAL INTELLIGENCE IN A CAM SYSTEM FOR GEOMETRICALLY SIMILAR COMPONENTS

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Abstract

This paper focuses on the application of Artificial Intelligence (AI) in Computer-Aided Manufacturing (CAM) systems, specifically examining the capabilities of the CAM Assist module within the Fusion software. The primary objective of this research is to evaluate the consistency of the AI when programming four geometrically and technologically similar components. To ensure an objective comparison, identical input parameters were established for all component variants, including the tool library, workholding setup, and stock material. The analysis of the generated CAM programs revealed that the AI does not approach similar models in a strictly identical manner. Although the system demonstrated partial logical consistency during roughing operations and stock detection, significant discrepancies were identified in the selection of finishing tools, the total number of operations, and the ability to recognize specific geometric features (e.g., threaded holes). These findings confirm that the full autonomy of AI tools in real-world industrial practice is not yet attainable. The generated programs require subsequent optimization, thereby transforming the role of the CAM programmer from a manual creator into an auditor of the CAM program.

Keywords: AI; CAM; CAM Assist; geometrically similar components; toolpath generation

1. Introduction

Within the framework of Industry 4.0, Artificial Intelligence (AI) introduces an unprecedented capability into Computer-Aided Manufacturing (CAM) systems to analyse massive datasets and make complex decisions in a manner that closely mimics human cognitive processes [1], [2]. The deployment of AI and advanced Machine Learning (ML) algorithms fundamentally optimizes manufacturing operations, rapidly reduces the necessity for manual programmer intervention, and ultimately eliminates human errors during the technological preparation of production [4], [15]. These systems offer advantages not only in core automation but also in long-term sustainability through the enhanced management of material flows and the reduction of overall process energy consumption [2]. However, the successful implementation of these innovations in a real production environment depends not exclusively on the technological maturity of the software solutions, but primarily on the degree of their acceptance by the employees within industrial enterprises [9]. Building trust in autonomous systems and understanding their tangible benefits are essential prerequisites

for the full integration of digitalization into industrial practice [9]. In this context, the implementation of Explainable Artificial Intelligence (Explainable AI - XAI) plays a pivotal role [12]. It not only uncovers the hidden causes of inefficiency but also, due to the transparency of its outputs, builds the necessary trust among operators [12]. Simultaneously, its application shifts the paradigm of evaluating overall manufacturing efficiency; the focus of optimization moves from merely reducing pure machining time to radically shortening setup phases and technological preparation (setup time), thereby minimizing downtime and substantially enhancing production agility [12].

In the repetitive manufacturing of geometrically and morphologically similar components, the primary objective of the manufacturing engineer is to minimize programming time and ensure the technological consistency of the outputs. Traditional approaches in modern CAM systems leverage the identification of this similarity to apply predefined rules and static machining strategies [7]. The systematic utilization of CAM templates for families of similar parts, standardly implemented in software such as Fusion, enables an exceptionally high degree of process standardization, thereby directly eliminating the risk of errors during repetitive tasks and substantially reducing the overall preparation time [6], [7]. While this approach is highly productive, its flexibility remains strictly constrained by the fixed rules and boundaries of the template, which fail when encountering more significant geometric modifications to the model [6]. Consequently, the logical evolutionary step is the transition to artificial intelligence algorithms capable of dynamically analysing the topology of 3D CAD models and automating G-code generation, even in the presence of more pronounced morphological variations that a conventional static template would be unable to process [4].

Contemporary intelligent systems utilize Deep Learning models not only for the initial generation of toolpaths but also for the comprehensive prediction of machined surface quality, the selection of optimal cutting parameters, and the overall optimization of the material removal process [1], [2]. Simultaneously, modern industrial automation combines the computational power of neural networks with the continuous real-time monitoring of sensor signals, enabling machines to instantly detect anomalies and process deviations directly during machining [10]. The principle of adaptive control of complex and highly dynamic parameters, currently applied with high success even in critical and strictly regulated systems such as the cooling circuits of nuclear reactors, demonstrates the immense and universal potential of AI. This potential is fully transferable and applicable to the autonomous adjustment of cutting conditions directly within CAM software [8]. The capability of algorithms to instantaneously process massive volumes of data and evaluate thousands of technological alternatives radically accelerates the preparatory phase of production. Consequently, artificial intelligence transforms from a purely computational tool into an essential element of comprehensive support for complex decision-making processes within the enterprise, thereby freeing up the capacities of process engineers to address more critical strategic tasks [11].

A prevailing trend is the direct implementation of AI solutions in the form of integrated modules (plug-ins), such as the CAM Assist software developed by CloudNC. According to the official technical documentation, this innovative technology is capable of analysing part geometry and autonomously executing the majority of CAM programming within a matter of minutes; furthermore, it proactively identifies missing material allowances or geometric irregularities prior to the actual toolpath calculation [5].

Despite this declared potential, the full autonomy of artificial intelligence in real-world production environments encounters exceptionally severe technological and safety limitations. Experimental testing conducted directly during CNC milling has demonstrated that although generative language models can, in certain specific scenarios, reduce machining time and significantly improve surface roughness, they frequently commit fatal and unpredictable errors. These systems exhibit a tendency to "optimize" the code merely through the visual reduction of text length, operating completely without any semantic understanding of the component's spatial geometry. This leads to the uncontrolled omission of essential operations and critical safety commands (such as G43 or G28), which could result in a destructive collision of the CNC machine [3], [14]. Consequently, the role of an experienced manufacturing engineer inevitably transforms from that of a manual creator into a process auditor. This shift is directly supported by Intelligent Digital Machine Twins (IDMT), which serve as the ultimate verification mechanism. These systems can virtually simulate the generated NC code, autonomously detect impending collisions or missing features, and propose strategy optimizations to the programmer prior to actual milling [13]. Therefore, the physical presence and expert oversight of the process engineer remain absolutely indispensable for the verification of AI outputs [3], [9].

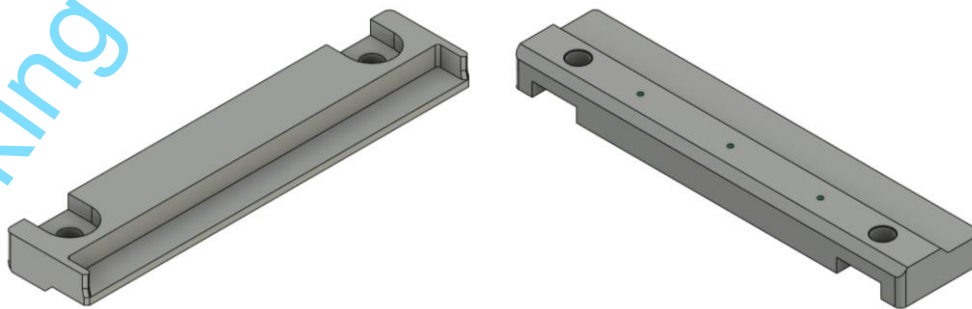


Fig. 1. Part 1

The objective of this paper is to investigate the capabilities of AI in CAM, specifically focusing on the CAM Assist plug-in module within the Fusion software. The aim is to evaluate whether the AI will "think" consistently when processing similar components—that is, whether it will employ typologically identical operations and tools to generate the CAM program for all parts, even if various individual features across the components are modified, provided that the overall technological similarity is preserved.

The representative component serves as a cross-member. This cross-member is utilized as a connecting element between tubes, where it is subsequently welded in place. These tubes are then employed in the manufacturing of roller coaster tracks. The baseline component, which serves as the primary reference, is depicted in Fig. 1. The remaining three components represent various design variants of such cross-members.

2. Preparatory operations prior to executing CAM Assist

Initially, it is necessary to specifically define which inputs in this research will remain identical prior to the actual submission of data to CAM Assist, namely: the tool library, workholding setup, coordinate system, machine kinematics and stock material.

The first critical identical element is the tool library, which had to be created. It is important to note that the tools were not defined in exhaustive detail, but rather in a simplified manner. For the purposes of this comparative research, this approach was sufficient. Similarly, the exact cutting parameters for each tool were not precisely defined, as the AI autonomously adapts these values; furthermore, this did not represent a critical parameter for the objectives of the study. The tool library was populated with tools such as high-feed mills, face mills, flat end mills, ball nose end mills, and bull nose end mills, with both short and long variants provided for these cutters. Additionally, drills, spot drills, chamfer mills, and taps were included. The specified tools featured a variety of diameters. In this manner, a diverse tool library was established to provide the AI with a broad selection, allowing it to choose the most appropriate tool for a specific machining operation. Subsequently, it is only necessary to export the created tool library and import it directly into the CAM Assist interface.

The workholding of the stock material will be identical for all components across both machining setups. The machining operations will be simulated on a 3-axis CNC machine. Likewise, the zero point and the coordinate system will be defined in the exact same manner for all components. The stock material will be designed such that the component's thickness is already at its final dimension, and the outer profile of the component is pre-cut to the finished net shape. Fig. 2 illustrates the configured setups, and the setups for the remaining three components will be established using this identical approach.

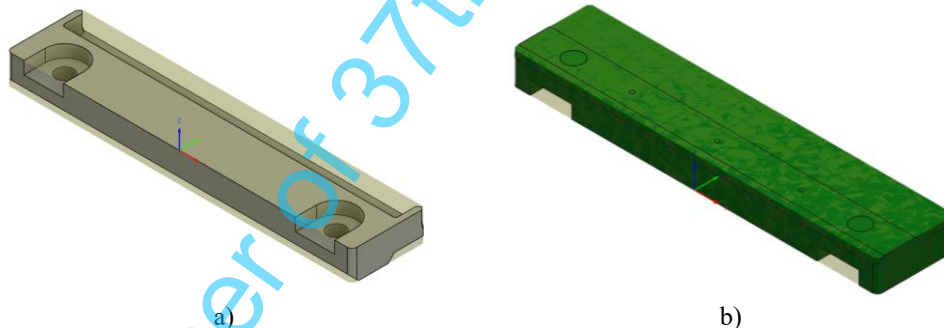


Fig. 2. Setups for Part 1
a) Setup 1, b) Setup 2

3. Generating the program using CAM Assist

Following the completion of all preparatory operations, CAM Assist was initiated. Within the CAM Assist interface, the initial step required importing the previously created tool library to provide the AI with the ability to select from the designated tools. The machine kinematics were defined as 3-axis, necessitating the machining of the component from two sides. The specific machine parameter is not critical for this study; therefore, the exact CNC machine intended for manufacturing the component was not explicitly specified. The material of the component was defined as steel, though this parameter was similarly non-essential for the scope of this research, as the material remains identical across all evaluated components. Subsequently, the custom-built tool library was selected. Following the input of the remaining parameters, the generation of the CAM program using AI was initiated.

Following the AI's analysis of the component within CAM Assist, a report is generated. This report serves to analyse the machinability of the component, enabling the AI to predict in advance which surfaces cannot be machined due to various constraints. These constraints include, for example: the AI failing to identify a suitable tool for machining a specific surface or feature, insufficient tool length to access a given surface or feature, or the AI's inability to select an appropriate machining operation for a particular surface or feature, among others. Certain notifications from this report

can be resolved directly within the CAM Assist interface; in some instances, the AI autonomously proposes a corrective solution.

In this instance, the AI failed to correctly evaluate the hole (thread), which introduces the first limitation. During component modelling, the specific method used to define the drilled hole is of critical importance. Similarly, when modelling a blind hole, the geometry of the hole bottom (the drill point angle) is crucial, as this directly dictates whether a corresponding suitable tool can be identified within the tool library. Consequently, two scenarios may occur. Either the AI fails to recognize the feature as a hole (thread) and reports it as unmachinable, or, for a clearly defined hole, it employs a milling tool instead of a drill, rendering the solution entirely unsuitable from a practical manufacturing perspective.

Following the component machinability analysis, the proposed operations can be generated and exported directly into the CAM software. Fig. 3 illustrates the generated operations for Setup 1 and Setup 2. The entire process of "creating" the CAM program in this manner via AI requires only a matter of minutes. Once the operations are generated, they can be interacted with within the Fusion CAM environment exactly as if they had been programmed manually. Consequently, various operation parameters can be subsequently adjusted according to the engineer's discretion and specific machining requirements. In this research, CAM programs generated using this methodology will be compared across other geometrically similar components.

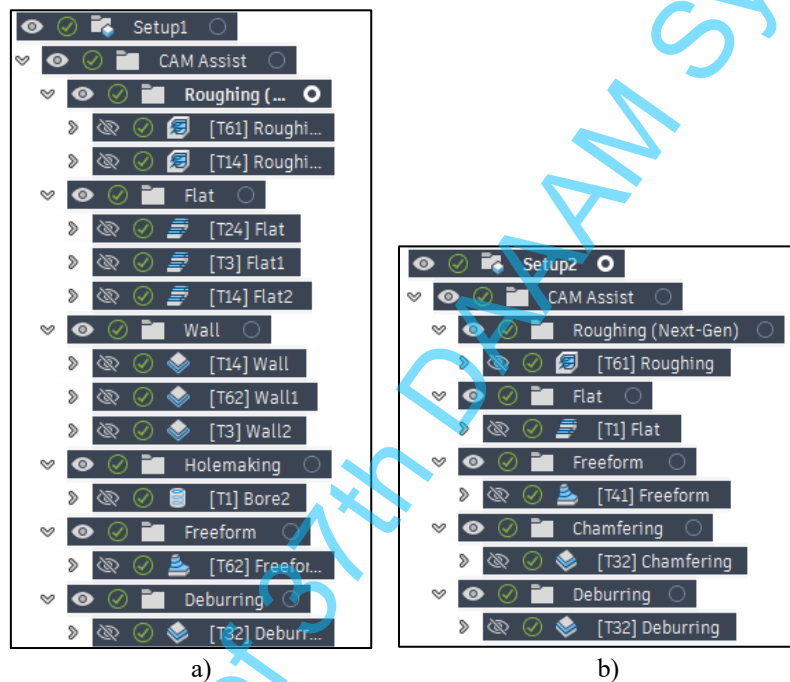


Fig. 3. Program generated by CAM Assist for Part 1
a) Setup 1, b) Setup 2

4. Comparison and evaluation of CAM programs for similar components

All preparatory operations had to be configured identically to those used for Part 1, with particular emphasis on the tool library. The parameters within CAM Assist were configured in the exact same manner. These steps ensured uniform conditions across all similar components, thereby enabling an objective comparison of the programs generated by CAM Assist.

The first examined aspect is CAM Assist itself. As is evident at first glance in Fig. 4, the highlighted issues are identical across all four components. Regarding the yellow warning triangle, where the specific notification refers to already finished surfaces, it can be concluded that the AI evaluated this correctly for all four parts. This means that, based on the design of the stock material, this notification is accurate; consequently, the AI logically does not propose machining operations in areas without excess material. This consistent behaviour was replicated across all four components.

The second orange exclamation mark highlighted an insufficient tool length. This indicates that the AI identified a tool type within the tool library that it deemed suitable, but it lacked the necessary length to machine the designated feature on the component. Upon examining this notification, it was found that the AI proposed modifying this tool. The suggested tool was an 8 mm diameter solid flat end mill, which the AI determined to be too short. The underlying issue here is that the AI failed to accurately analyse the hole (thread) on the component, interpreting it merely as a pocket to be milled. If this specific misinterpretation is set aside for the purposes of this research, a positive finding is that the AI consistently produced this identical notification across all of the similar components.

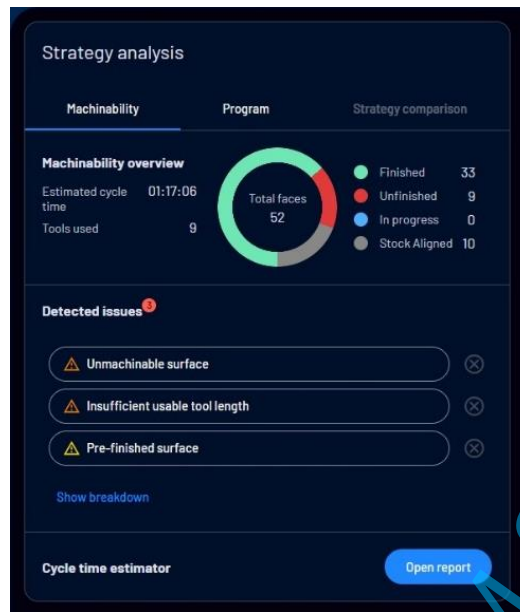
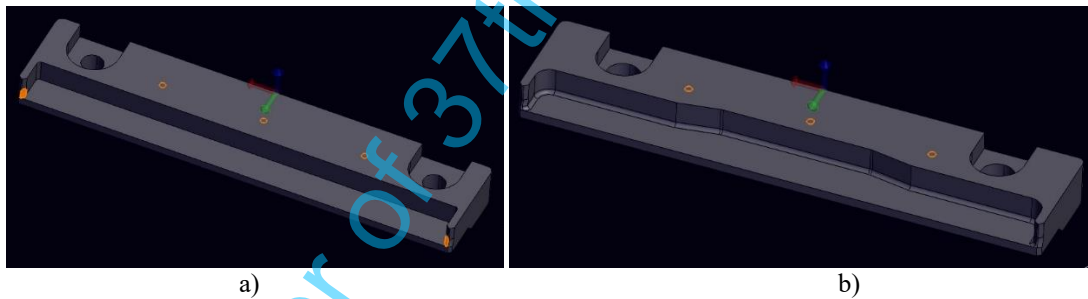


Fig. 4. Analysis of Part 1 in CAM Assist

In Fig. 5, the surfaces that the AI recognized and determined to be unmachinable in any orientation and with any tool from the library are highlighted in orange. This notification was displayed upon expanding the first orange triangle in Fig. 4. Furthermore, it stated that it is necessary to either modify the 3D model or proceed to the CAM environment and ignore this warning. The first discrepancy arose regarding these unmachinable surfaces. It should be noted that across all four components, there was an issue with the hole bottom (thread), specifically the drill point geometry, which the AI consequently evaluated as unmachinable. However, a difference occurred at the edges of the component, where the weld preparation chamfer is located. For Part 1 and Part 2, the AI evaluated this chamfer as unmachinable, whereas for Part 3 and Part 4, it determined that this chamfer could be machined.

Fig. 5. Comparison of unmachinable surfaces
a) Part 1, b) Part 3

The CAM programs were compared relative to the first one, i.e., the CAM program for Part 1. At first glance, it might be argued that the AI "thought" identically across the similar components; however, a more detailed evaluation may reveal the opposite.

Setup 1 was examined first across all four components. As can be seen in Fig. 6, the AI selected adaptive clearing for material removal across all four components. This indicates that even though the shape and dimensions of the components varied partially, the AI selected the identical operation for roughing. A discrepancy arises in the selection of tools. For Part 1, the AI selected a 20 mm diameter solid bull nose end mill with a 3 mm corner radius for roughing. As shown in Fig. 6 a), an additional tool was still required for corner rest roughing. For this rest roughing operation, the AI chose a 10 mm diameter solid flat end mill. In comparison with Part 2 (Fig. 6 b)), the AI selected essentially the same type of solid end mill for roughing, but utilized the longer variant of that tool. For some reason, the AI opted for the longer tool variant, although from the perspective of this study, there is no adequate justification for this choice. In comparison with Part 3 and Part 4, the AI selected the same tool, as illustrated in Fig. 6 c). It must be emphasized that for the remaining three components, it was unnecessary to employ an additional tool for rest roughing due to larger corner radii.

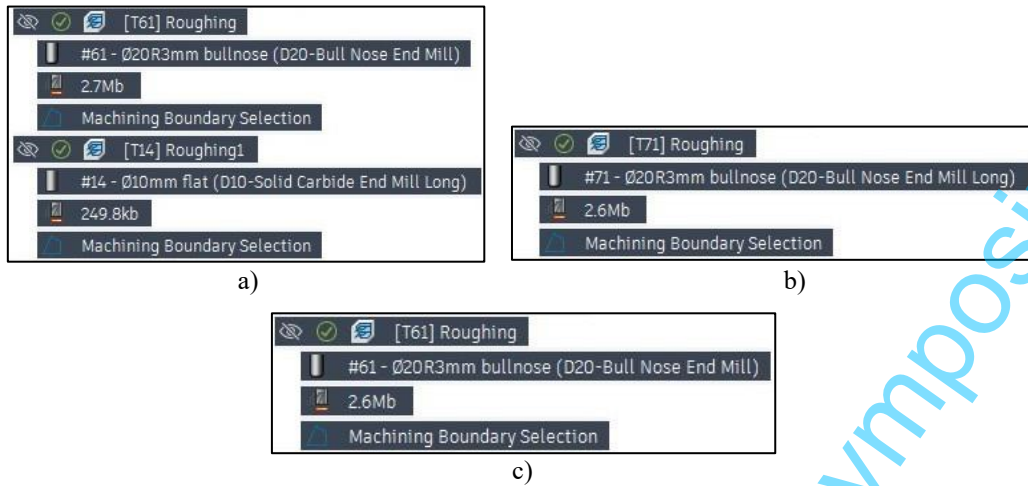


Fig. 6. Comparison of roughing for Setup 1
a) Part 1, b) Part 2, c) Part 3

Another discrepancy in the generated operations occurred during surface finishing. The type of selected operation was chosen identically for each component. As shown in Fig. 7 a) for Part 1, the AI selected three operations for surface finishing. To finish the pocket surface, it used an indexable cutter defined as a high-feed milling cutter; however, the AI failed to recognize this and treated it as an indexable cutter with radius inserts, applying the tool appropriately for the given operation. For the shoulder, it selected a 12 mm diameter solid flat end mill, and again for corner finishing, it used a smaller 10 mm diameter solid flat end mill. In Fig. 7 b) for Part 2, the AI opted for a simpler solution, namely that surface finishing was performed using a single tool—a 20 mm diameter solid flat end mill. For Part 3 and Part 4, the AI once again selected the same strategy (Fig. 7 c)). To finish the pocket surface, it chose a 20 mm diameter solid bull nose end mill with a 3 mm corner radius. For the shoulder, it selected the same tool as for Part 1. These discrepancies are likely due to minor differences between the components and, primarily, changes in the corner radii.

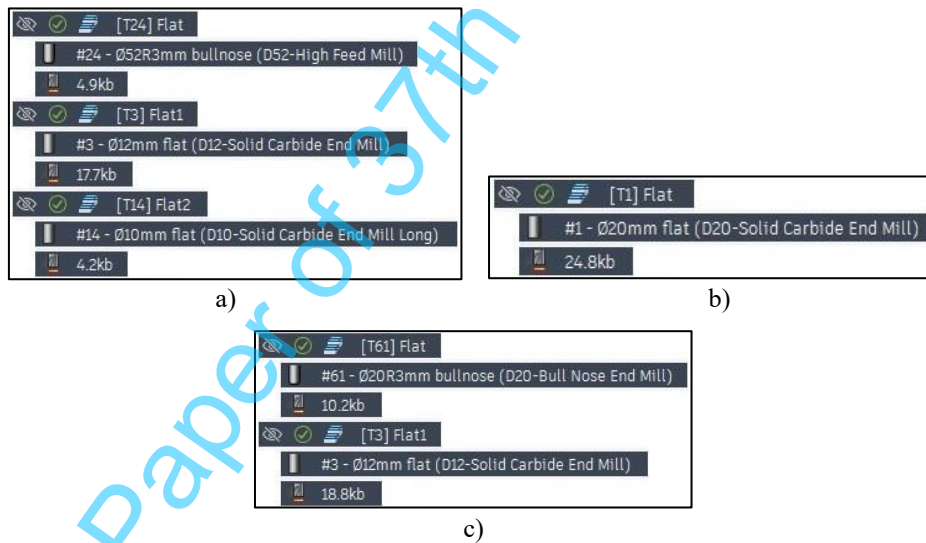


Fig. 7. Comparison of surface finishing for Setup 1
a) Part 1, b) Part 2, c) Part 3

Fig. 8 illustrates the tools selected by the AI for wall finishing. For each component, it selected three operations of the same operation type. In this case, it can be stated that the AI did not use identical tools for at least two similar components in any single instance. It is worth noting in particular that for Part 2 and Part 3, the same tool was used for two operations (a different tool for each component), which is evaluated positively. For Parts 1, 3 and 4, the same tool was used for finishing the shoulder wall—a 12 mm diameter solid flat end mill. For finishing the wall above the chamfer, the AI selected the same tool for Part 1 and Part 2, and similarly, the AI selected the same tool for finishing the pocket wall for Part 3 and Part 4.



Fig. 8. Comparison of wall finishing for Setup 1
a) Part 1, b) Part 2, c) Part 3, d) Part 4

Fig. 9 illustrates the comparison of freeform surface finishing. As already mentioned in the CAM Assist analysis, since unmachinable surfaces are present in Part 1 and Part 2, only a single operation for chamfer finishing was created for both components. This can be seen in Fig. 9 a). A 16 mm diameter solid bull nose end mill with a 3 mm corner radius was selected for both components. For chamfer finishing, a 3D contour strategy was chosen for all components. For Part 3 and Part 4, a logical change and the addition of further operations occur due to component modifications, specifically the addition of a radius at the pocket bottom. For finishing the bottom radius (Part 3 and Part 4), the 3D Blend strategy was selected. Fig. 9 b) shows that the same tool—a 20 mm diameter solid bull nose end mill with a 3 mm corner radius—is selected for all operations, which is evaluated positively. Furthermore, it can be seen that a different tool was used three times for chamfer finishing (excluding Part 1 and Part 2).

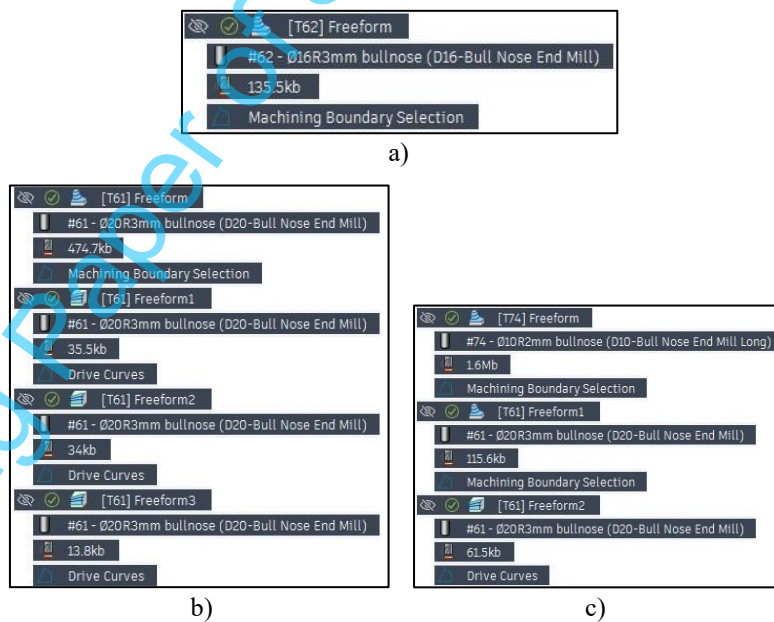


Fig. 9. Comparison of freeform surface finishing for Setup 1
a) Part 1, b) Part 3, c) Part 4

The chamfer was created identically across all four components. The same operation with the same tool was selected. There were only negligible minimal differences that were not the subject of comparison.

Fig. 10 illustrates the comparison of roughing for Setup 2. Roughing was identical for Parts 1, 2 and 3. For Part 2, although the same tool type was used—namely a 20 mm diameter solid bull nose end mill with a 3 mm corner radius—the longer variant of the tool was employed.



Fig. 10. Comparison of roughing for Setup 2
a) Part 1, b) Part 2

The subsequent surface finishing and raster chamfer finishing operations were designed identically—utilizing the same tool and the same operation type (for each operation individually).

For Parts 3 and 4, a hole milling operation was added, which, according to the AI, was not necessary for Parts 1 and 2. This was likely chosen because, for Parts 1 and 2, the respective hole had already been milled in Setup 1. This is considered a rather significant discrepancy for similar components. Furthermore, as can be seen in Fig. 11, a different tool was selected for each component, even though the operation type remains the same.



Fig. 11. Comparison of hole milling for Setup 2
a) Part 3, b) Part 4

The chamfer for Part 1 and Part 2 was identical. The same operation type and the same tool were used. Similarly, the chamfer for Part 4 was created on a similar principle, as can be seen in Fig. 12. The operation type was selected identically, but the difference lies in the tools used between the operations. A 10 mm chamfer mill was selected for the chamfer on the larger holes, whereas a 6 mm chamfer mill was chosen for component deburring. It must be noted that this could have been machined with a single tool, eliminating the need for two different tools. A logical change occurs in Part 3, where no $2 \times 45^\circ$ chamfer was present on the larger holes from this side, and therefore this operation is not proposed. Consequently, only component deburring is proposed in Fig. 12 b).

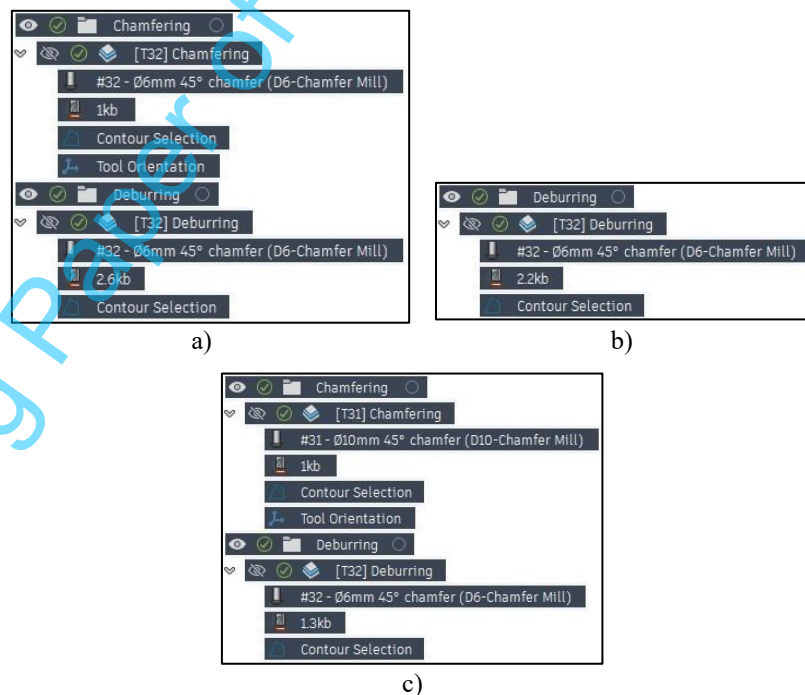


Fig. 12. Comparison of chamfering for Setup 2
a) Part 1, b) Part 3, c) Part 4

In addition to the qualitative comparison of the generated operations, a quantitative comparison of the CAM programs was also carried out. For each component, the total estimated cycle time, the number of tools used and the total number of analysed faces, together with their breakdown into finished, unfinished and stock-aligned faces, were read directly from the Machinability overview in CAM Assist. The number of tool changes and the time required to generate the CAM program were determined in the Fusion CAM software. The values obtained are presented in Table 1.

Monitored parameter	Part 1	Part 2	Part 3	Part 4
Total estimated cycle time [hh:mm:ss]	01:17:06	01:12:00	01:59:17	01:03:31
Number of tools used [pcs]	9	5	6	7
Number of tool changes [pcs]	14	10	9	11
Total number of analysed faces [pcs]	52	59	66	58
Finished faces [pcs]	33	40	49	41
Unfinished faces [pcs]	9	9	7	7
Stock-aligned faces [pcs]	10	10	10	10
CAM program generation time [min:s]	02:15	02:00	03:00	01:45

Table 1. Quantitative comparison of the generated CAM programs

Table 1 shows that the differences between the individual components manifested themselves not only in the type of tools selected, but also in the overall indicators of the generated CAM program. The shortest total estimated cycle time was achieved for Part 4 (01:03:31) and the longest for Part 3 (01:59:17), which represents a difference of approximately 88 %. It is significant that this difference does not correspond to the number of tools used. For Part 1 the AI selected nine tools and for Part 2 only five, yet their cycle times are almost identical (01:17:06 and 01:12:00). In contrast, Part 3, with the longest cycle time, managed with six tools. The higher cycle time for Part 3 was therefore not caused by a greater number of tools, but by a higher number of finished faces (49 out of 66), which is related to the radius added at the pocket bottom and to the subsequent 3D operations.

The inconsistency in the machinability evaluation can also be documented quantitatively. The number of unfinished faces was 9 for both Part 1 and Part 2, whereas it was 7 for both Part 3 and Part 4, which corresponds to the previously described difference in the evaluation of the weld preparation chamfer. Conversely, the number of stock-aligned faces was identical for all four components (10), which confirms that the stock material was recognized consistently. From the perspective of production preparation, the most significant finding is the spread in the number of tools used, ranging from five to nine – for technologically similar components this means a different occupancy of the machine tool magazine and additional time required for tool presetting. Directly related to this is the number of tool changes, which ranged from nine for Part 3 to fourteen for Part 1, although the components belong to the same technological family. At the same time, the time required to generate the CAM program itself remained comparable for all four components – from 01:45 to 03:00 min, which confirms the declared speed of AI tools regardless of the change in component geometry.

In conclusion, it is important to note that the CAM AI has its limits and constraints. The components used in this research also encounter these limitations, as they were not machined completely and flawlessly. On the other hand, it must be stated that it might be possible to machine the components by utilizing different settings within CAM Assist itself. However, this did not pose an obstacle for the present research, as it was not the subject of the investigation.

On the basis of the limitations identified, several recommendations can be formulated for the creation of 3D models that increase the success rate of feature recognition by artificial intelligence. Holes should be modelled as dedicated features (hole features) rather than as general extruded cuts, because a hole created in this way carries information about its type. For blind holes, the drill point angle must be aligned with the point angle of the drills available in the tool library (most commonly 118° or 140°); otherwise the AI will not find a suitable tool and will mark the face as unmachinable. Threaded holes should be modelled with a thread attribute so that they are not interpreted as a pocket to be milled, as occurred in this research.

A further recommendation is the unification of the geometry across the entire family of similar components – identical chamfer dimensions, identical corner radii and an identical method of modelling the weld preparation chamfer. It is also advisable to make use of face attributes, for example colour coding of functional faces or feature naming, which makes it possible to distinguish unambiguously between faces already machined to the final dimension and faces intended for machining. Adhering to these principles during modelling reduces the number of notifications in the machinability analysis and increases the probability that the AI will propose comparable operations and tools for geometrically similar components.

5. Conclusion

The main goal of this research was to evaluate whether the AI (specifically the CAM Assist module within the Fusion environment) approaches the programming of geometrically and technologically similar components consistently and whether it proposes identical operations and tools for the given components. Based on the comparative analysis of four

component variants (cross-members), it can be concluded that the AI does not think completely identically for similar models.

Although the AI demonstrated partial consistency in proposing certain operations and tool selections—for instance, by correctly evaluating the stock for all components (already machined surfaces), warning about the unmachinability of a hole, and applying adaptive clearing to all four components—differences manifested in the tool selection for various operations and in certain finishing operations. Some of these include:

- **Edge chamfering (machinability):** For Parts 1 and 2, the AI failed to machine it, whereas for Parts 3 and 4, it did.
- **Tool length for roughing:** For Part 2, the AI selected a longer version of the cutter entirely without justification compared to the other three components.
- **Number of operations for planar surfaces:** Part 1 required three operations, Part 2 only one, and Parts 3 and 4 identically two operations each.
- **Tools for wall finishing:** The AI did not use the same set of tools for any two components.
- **Hole milling (in Setup 2):** This operation was missing for Parts 1 and 2, whereas the AI added it for Parts 3 and 4, using a different tool each time.
- **Deburring and chamfering (in Setup 2):** For Part 4, the AI unnecessarily split this chamfering across two different tools, although it used only a single tool for the others.

The findings directly confirm the theoretical assumptions defined in the introduction of the paper. Although AI tools radically accelerate the initial phase of toolpath generation (down to a matter of minutes), their full autonomy in practice is not yet possible. The generated CAM program exhibits gaps in terms of tool unification and machining logic.

Therefore, the physical presence and expert oversight of the CAM programmer remain completely irreplaceable. When utilizing these tools, the role of the CAM programmer transforms from a manual creator into a CAM program controller, whose task is to unify the generated operations, optimize tool selection, eliminate errors resulting from incorrect component topology recognition, and supplement any additional CAM program operations that the AI failed to create.

In conclusion, it is essential to highlight the importance of such AI tools emerging in mechanical engineering, specifically in CNC machining. It is important to explore what AI can achieve in CAM programming, as elements like these push the boundaries of machining itself. AI in CAM still holds immense potential for further exploration and advancement.

6. Acknowledgments

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