Revista ARACÊ
ISSN: 2358-2472

SYNERGY BETWEEN 3D MODELING AND ARTIFICIAL NEURAL NETWORKS IN THE OPTIMIZATION OF ADDITIVE MANUFACTURING IN THE CONTEXT OF INDUSTRY 4.0

https://doi.org/10.56238/arev6n4-297

Submitted on: 18/11/2024 **Publication date:** 18/12/2024

Jonathan Oliveira Dias[1], Milton Vieira Junior[2], Jandecy Cabral Leite[3] and Genilson Roberto Maciel Ferreira[4]

ABSTRACT

Additive manufacturing (AM), widely known as 3D printing, emerges as one of the fundamental technologies of Industry 4.0, enabling the manufacture of parts with high geometric complexity and customization. This study investigates how the integration between 3D modeling and Artificial Neural Networks (ANNs) enhances the efficiency and quality of AM processes. 3D modeling provides support for detailed simulations of the behavior of materials and manufacturing processes, while ANNs offer predictive analysis and learning from large volumes of data, allowing automatic and dynamic adjustments to parameters such as speed, temperature, and fill patterns. The results demonstrate significant improvements in reliability, waste reduction and energy consumption, aligning production with sustainability demands. In addition, the degree of maturity of Industry 4.0 contributes to this integration, with the use of tools such as IoT, cloud computing, and big data, creating an intelligent and connected production environment. Despite the challenges related to technological infrastructure, the qualification of the workforce and the development of algorithms for ANNs, the benefits overcome the obstacles, resulting in greater flexibility and customization of production processes. This work concludes that the integration of 3D modeling and ANNs in additive manufacturing represents a milestone in the digital transformation and competitiveness of the industrial sector, standing out as a promising approach for process optimization and data-driven decision making.

Keywords: 3D Modeling, Artificial Neural Networks (ANN), Process Optimization, Additive Manufacturing, Industry 4.0.

[1] Postgraduate student in the Professional Master's Degree in Engineering, Process Management, Systems and Environment at the Galileo Institute of Technology and Education of the Amazon (EPMSA/ITEGAM)
ORCID: 0009-0007-6760-2371
[2] Professor of the Professional Master's Degree in Engineering, Process Management, Systems and Environment at the Galileu Institute of Technology and Education of the Amazon (EPMSA/ITEGAM)
ORCID: 0000-0002-8333-289X
[3] Professor of the Professional Master's Degree in Engineering, Process Management, Systems and Environment at the Galileo Institute of Technology and Education of the Amazon (EPMSA/ITEGAM)
ORCID: 0000-0002-1337-3549
[4] Bachelor of Information Systems
Institute for Technological Development (INDT)
ORCID:0009-0006-2720-9228

Revista ARACÊ
ISSN: 2358-2472

INTRODUCTION

For (Gao et al., 2015), Industry 4.0 refers to the fourth industrial revolution, characterized by the integration of advanced digital technologies into production and manufacturing processes. It combines automation, artificial intelligence, the Internet of Things (IoT), big data, and cyber-physical systems to create smart factories, where machines, devices, and systems communicate and operate autonomously and optimally. The main objective of Industry 4.0 is to increase the efficiency, flexibility and personalization of production processes, allowing greater adaptation to market needs and better use of resources.

Digital Manufacturing involves the use of advanced digital technologies to automate and optimize production processes. According to Silva and Andrade (2020), this approach uses tools such as 3D modeling, simulation, artificial intelligence, and real-time data integration to intelligently connect industrial operations. In this way, it allows the entire product/project life cycle to be managed digitally. According to Almeida (2019), this model favors the customization of products, cost reduction, and improved efficiency, which allows for a more agile adaptation to market changes

The present work aims to investigate the behavior of parts produced through additive manufacturing in comparison to parts produced through other conventional manufacturing methods, seeking optimization with the use of resources from the integration of CAD/CAM/CAE, in the context of Industry 4.0 and application of Artificial Neural Networks (ANN) in the learning of the results obtained from simulations, for decision-making regarding the best material properties.

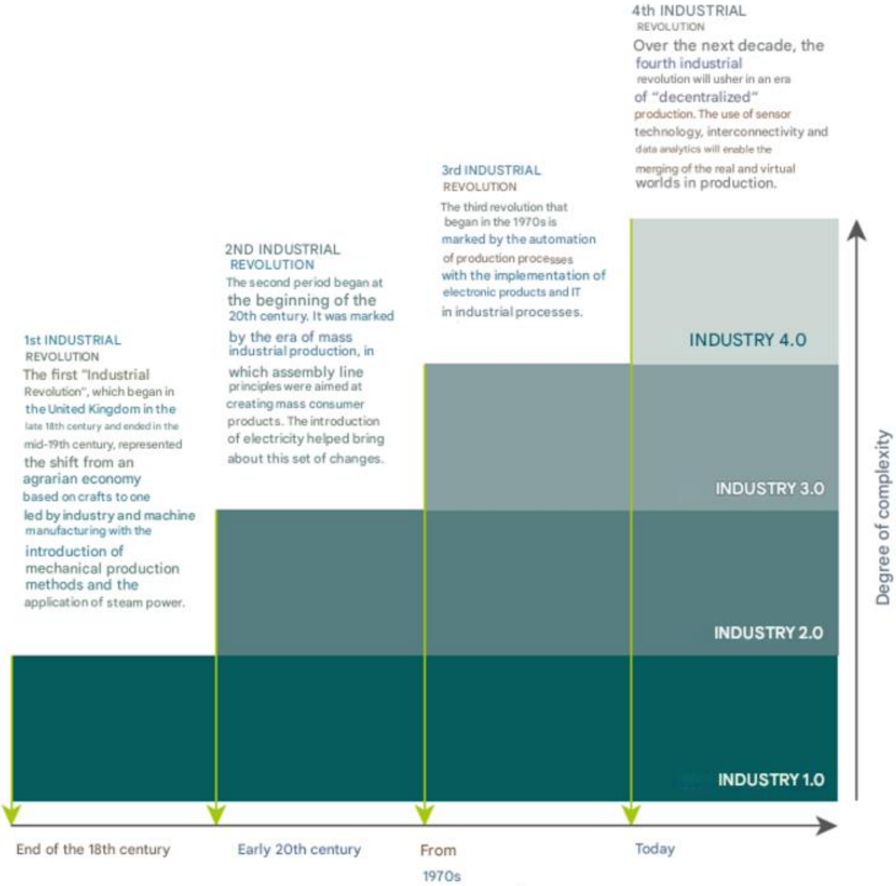
LITERATURE REVIEW

FUNDAMENTALS OF INDUSTRY 4.0

For CNI (2024), Industry 4.0, also known as the fourth industrial revolution, represents the integration of advanced digital technologies in the industrial environment. It is characterized by the adoption of cyber-physical systems, the Internet of Things (IoT), cloud computing, big data, artificial intelligence, and additive manufacturing. Figure 1 shows this evolution over time, as pointed out by DELOITTE (2015, apud FIRJAN, 2016). It should be noted that I4.0 is based on decentralized production and connectivity.

Revista ARACÊ
ISSN: 2358-2472

FIGURE 1: THE FOUR INDUSTRIAL REVOLUTIONS.



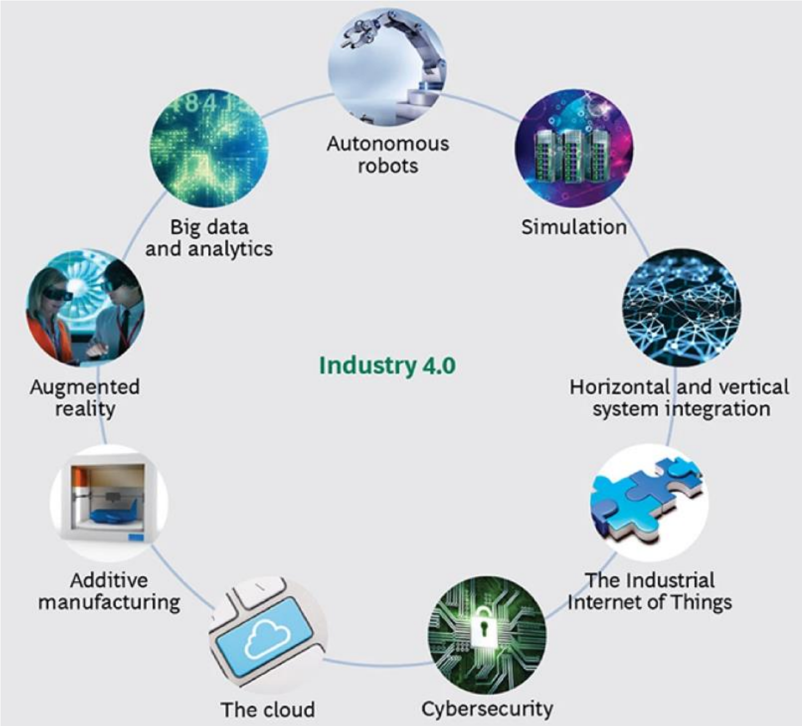
Fonte: Adapted from DELOITTE, (2015).

ADDITIVE MANUFATURA

Additive Manufacturing (AM), as established by ISO/ASTM 52900 (2015), is a manufacturing process that involves joining materials, usually layer by layer, to create physical objects from a three-dimensional digital model. This method differs from traditional manufacturing processes, such as subtractive, where material is removed to shape the object, and formative, in which the material is molded to achieve the desired shape. Figure 2 presents the technologies known as pillars of industry 4.0, of which AM is a part.

Revista ARACÊ
ISSN: 2358-2472

FIGURE 2: INDUSTRY 4.0 PILLARS



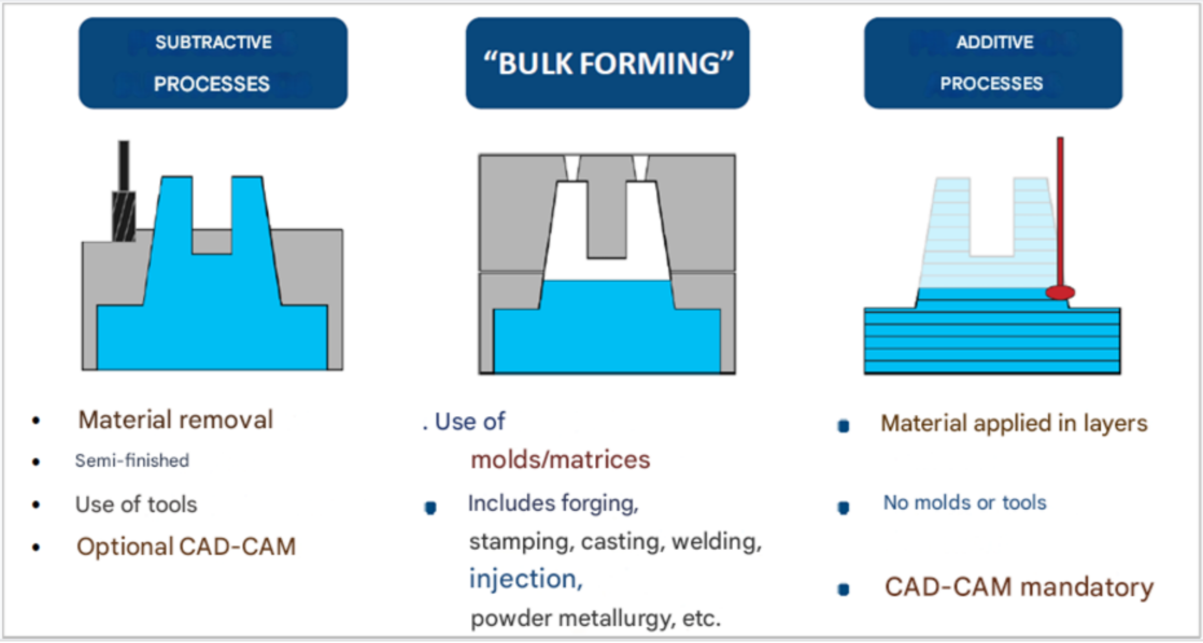
Fonte: RÜßMANN *at al,*. (2015).

Among the advantages of additive manufacturing, when compared to other conventional forms of manufacturing, the following can be mentioned: 1. Geometric freedom; 2. Material and Energy Efficiency; 3. Reduction of the Need for Specific Tools; 4. Agility in Prototyping and Production of Small Batches.

Among the disadvantages of additive manufacturing, when compared to other conventional forms of manufacturing, the following can be mentioned: 1. Surface and Dimensional Quality; 2. Limitation of Available Materials; 3. High cost; 4. Distortions and Warping; 5. Lower Production Speed:

Revista ARACÊ
ISSN: 2358-2472

FIGURE 3: COMPARISON BETWEEN THE MOST USED MANUFACTURING PROCESSES



Source: Portal edisciplica.usp.br; Additive Manufacturing Discipline. Accessed: 28.11.2024.

Main processes and technologies of additive manufacturing.

According to the Additive Manufacturing Technology Standards ASTM F2792, the main types of additive manufacturing technologies are:

- FDM - Fused Deposition Modeling.
- SLA - Estereolithography (Stereolithography).
- SLS - Selective Laser Sintering.
- DMLS – Direct Metal Laser Sintering
- LENS - Laser Engineered Net Shaping
- LOM - Lamined Object Manufacturing.
- SGC - Cura Sólida na Base (Solid Ground Curing).
- MJT - Inkjet Printing (Multi Jet Modeling).

3D MODELING AND COMPUTATIONAL TOOLS

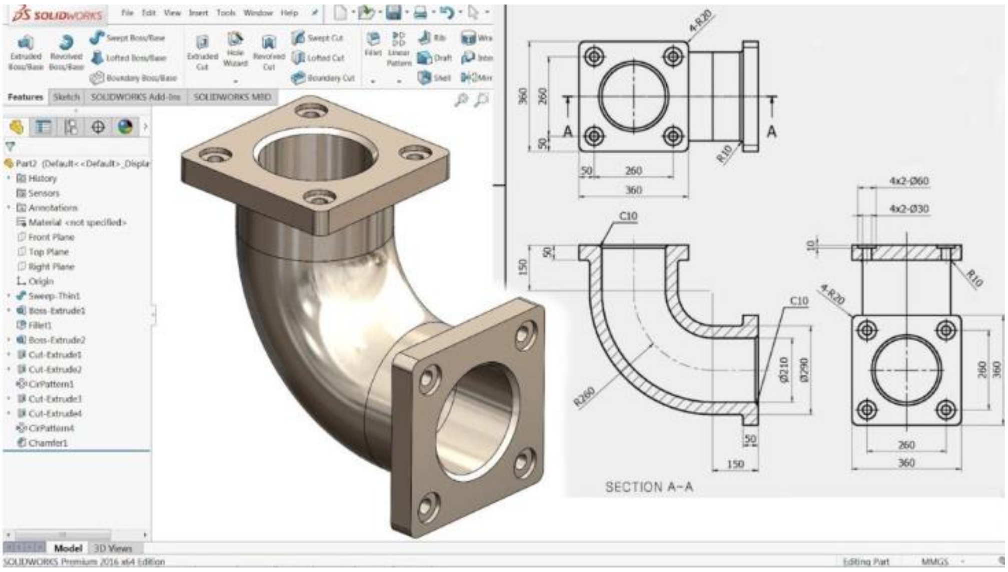
3D Modeling is carried out through CAD systems. With the evolution of CAD systems, functionalities have expanded to include simulation and analysis of project performance, integrating with CAE and CAM tools. These tools not only facilitate technical drawing, but also allow detailed simulation of the characteristics and physical properties of components, as well as performance tests.

Revista ARACÊ
ISSN: 2358-2472

2Computer-Aided Design (CAD)

CAD provides a number of advantages over traditional drafting methods (Figure 4), including improved accuracy, efficiency, and the ability to make quick and cost-effective design changes (SALDANHA, 2017; SILVA *et al*., 2019).

FIGURE 4: EXAMPLE OF SOLIDWORKS BEING USED AS CAD SOFTWARE.



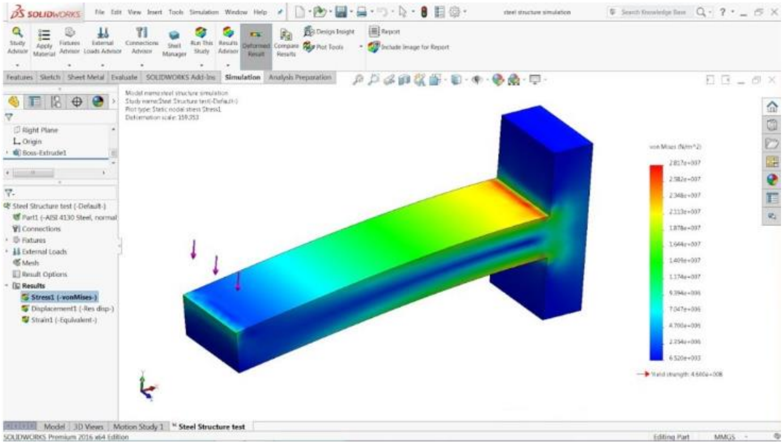
SOURCE: HTTPS://VFGENGENHARIA.COM/ENTENDA-A-DIFERENCA-ENTRE-CAD-CAE-E-CAM/, (2024).

Computer Simulation and Analysis (CAE)

CAE, or "Computer Aided Engineering", plays a key role in the product development process, which involves the use of software to perform simulations and analyses that evaluate the behavior and performance of products under different conditions. These analyses include simulations of stress, fluid dynamics, and heat transfer, as shown in Figure 5, allowing the identification of problems before physical manufacturing (NASCIMENTO *et al*., 2017).

Revista ARACÊ
ISSN: 2358-2472

FIGURE 5: EXAMPLE OF SOLIDWORKS BEING USED AS CAE SOFTWARE.

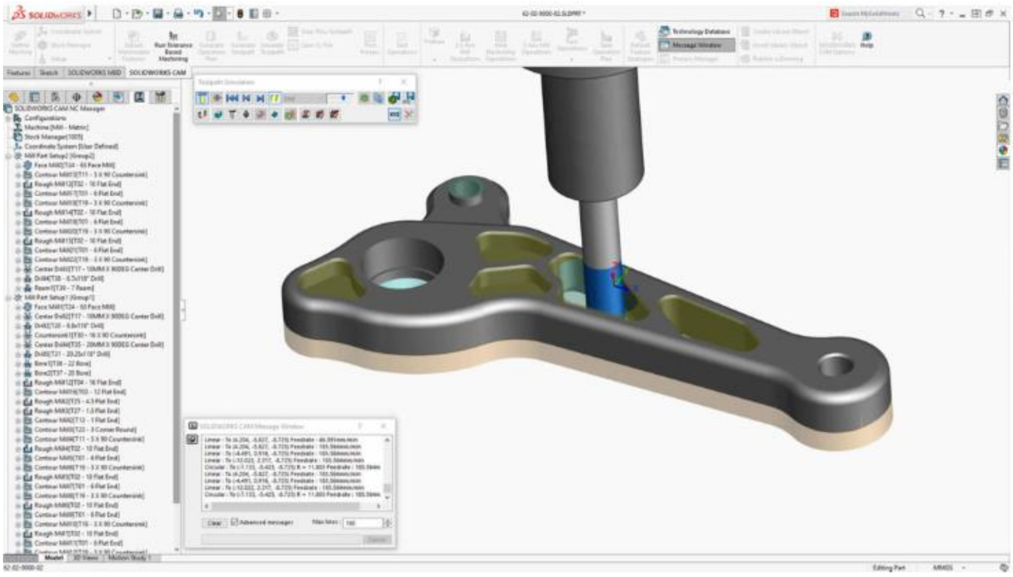


Source: https://vfgengenharia.com/entenda-a-diferenca-entre-cad-cae-e-cam/, (2024).

Computer-Aided Manufacturing (CAM)

The term CAM, which stands for "Computer Aided Manufacturing," refers to the use of computer systems to control the manufacturing process. CAM emerged as an extension of CAD, with the objective of improving automation and precision in the production of parts and components as shown in Figure 6.

FIGURE 6: EXAMPLE OF SOLIDWORKS BEING USED AS CAM SOFTWARE.



Source: https://vfgengenharia.com/entenda-a-diferenca-entre-cad-cae-e-cam/, (2024).

MAIN MECHANICAL PROPERTIES OF MATERIALS

In order for CAD/CAE/CAM integration to be carried out, with a complete analysis of the behavior of parts designed in simulation, it is necessary to know the main mechanical properties that can interfere with the performance of the parts, as detailed below.

Revista ARACÊ
ISSN: 2358-2472

Modulus of elasticity (Young's modulus)

It measures the stiffness of the material, indicating how it behaves under tension. This property expresses the relationship between the applied force per unit area and the resulting deformation in the material, and is represented in units of pressure, such as N/m² (Pascal). According to Callister and Rethwisch (2014), the modulus of elasticity allows the evaluation of the material's resistance to elastic deformation under load.

Yield strength

Defines the maximum stress that a material can withstand before it begins to undergo permanent plastic deformation. When a material has a higher yield strength, it indicates that it can withstand more intense forces without irreversibly deforming, compared to materials with a lower yield strength.

Tensile and compressive strength

These are mechanical properties that describe how a material responds to different types of applied forces. Tensile strength refers to a material's ability to withstand forces that tend to stretch or elongate it, while compressive strength measures the material's ability to resist forces that tend to compact or crush it.

Specific mass

Also known as density. According to Callister and Rethwisch (2014), a higher specific mass can mean that the material is more robust and offers a greater resistance to external forces, which is beneficial in structural applications where strength and durability are important. In contrast, materials with lower specific mass are lighter and can therefore be more advantageous in situations where weight reduction is important, for example in mechanisms and drive systems. Tensile and compressive strength.

ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial neural networks (ANNs) are computational systems inspired by the structure and functioning of the human brain and consist of layers of interconnected artificial neurons that process information through mathematical algorithms. Each connection has convenient weights, these are calibrated during a training stage, with the intention of improving the ability to predict or qualify. ANNs, as Artificial Neural Networks are called, are widely used in

Revista ARACÊ
ISSN: 2358-2472

areas such as pattern recognition, image processing, and decision-making, allowing advanced advances in artificial intelligence, having their algorithms structured and developed in various types of programming languages (DataGeeks, 2023; CAPES, 2023).

In the Brazilian academic and industrial sphere, ANNs are essential tools to solve complex problems involving large volumes of data. In areas such as health and safety, they enable more accurate diagnoses and efficient surveillance systems. In research areas, they allow the learning of complex situations and are applied mainly to avoid failures in processes. In addition, technologies such as backpropagation and regularization mitigate overfitting problems, which allows greater robustness of the developed models. The use of ANNs requires great computational capacity and careful planning to avoid biases or misinterpretations that improve their effectiveness (DataGeeks, 2023; CAPES, 2023).

Despite the challenges, ANNs represent an expanding field, with increasing application in Brazil. Continuous studies and investments allow the development of more accessible and effective solutions. An example is the integration of neural networks in industrial systems to predict failures and improve production processes, which contributes to greater competitiveness and innovation, especially when integrated with other technologies and industry 4.0. This evolution highlights the relevance of ANNs not only as technical tools, but also as engines of social and economic transformation (CAPES, 2023; DataGeeks, 2023).

MATERIALS AND METHODS

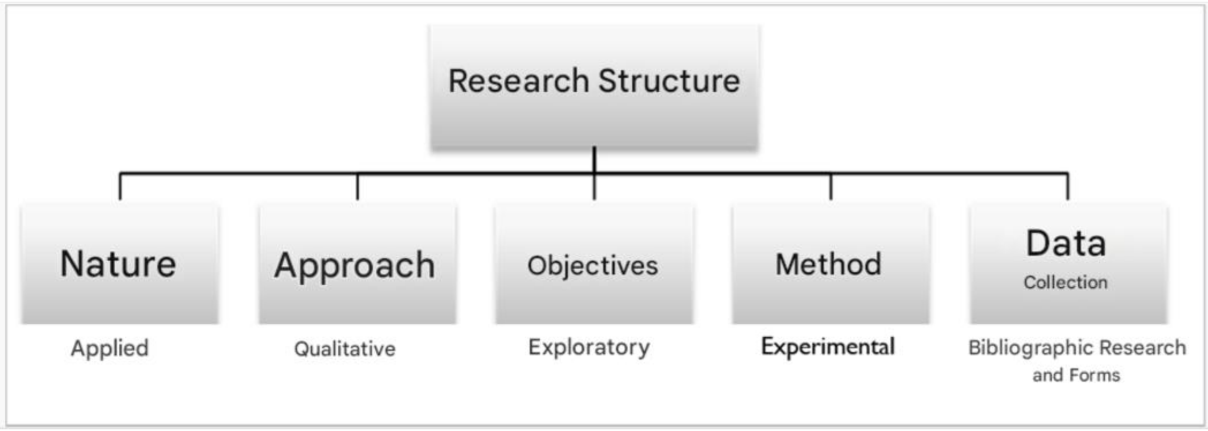
The research methodology adopted in this study is based on the development and analysis of the flow of manufacturing steps of the prototype of a mechanical part, using the digital manufacturing process, of Industry 4.0, with a focus on Additive Manufacturing (AM). It is intended to model, simulate, prototype and compare the results obtained between the AM process and the conventional manufacturing process by CNC machining. as well as to investigate the benefits and advantages of using modeling and simulation software (CAD/CAM/CAE).

The work can be classified as a research of applied nature, as it focuses on use in an industrial environment, and with a qualitative approach; It has exploratory objectives, as it seeks to know more about the so-called digital manufacturing and additive manufacturing. Regarding the research method, the work is characterized as experimental, as it is based on conventional manufacturing experiments and additive manufacturing experiments. And

Revista ARACÊ
ISSN: 2358-2472

data collection will be through the use of forms with results of observations of experiments and documentary studies (Figure 7).

FIGURE 7: STRUCTURE OF THE APPLIED METHODOLOGICAL CLASSIFICATION.

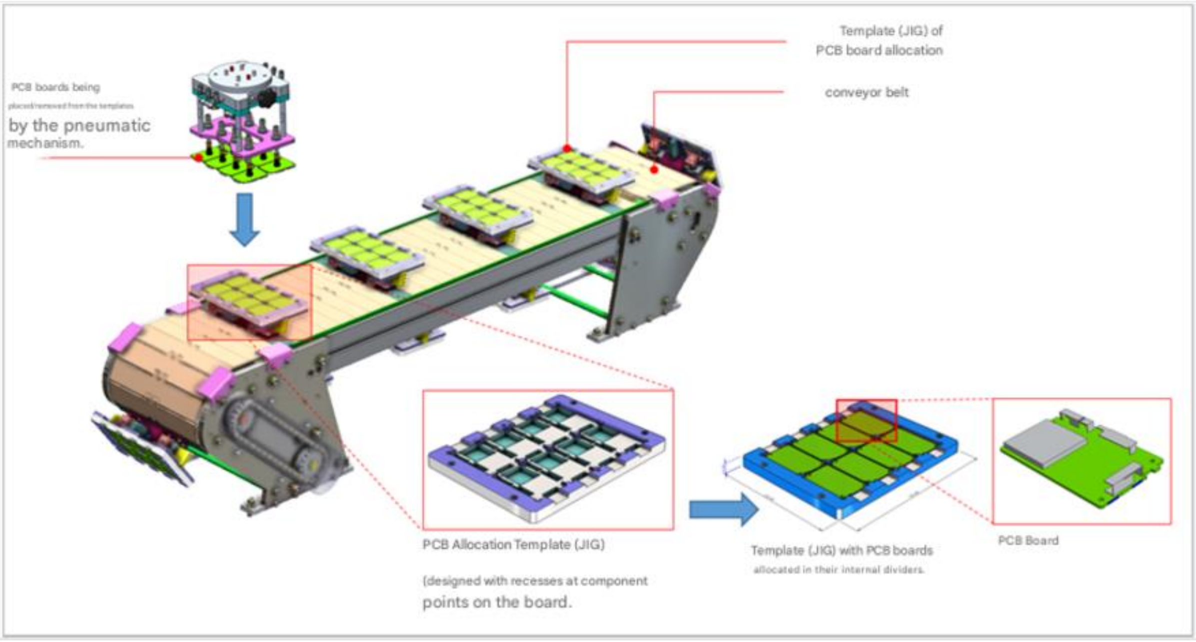


Source: Authors, (2024).

The part to be prototyped belongs to an automation and R&D project developed by the IBBI Institute, in partnership with a company from the Manaus Industrial Complex. This piece will be a template (also called JIG), with 08 internal partitions, intended for the allocation of 08 (eight) printed circuit boards (PCB) in each. This template will be mounted on the mobile structure of a conveyor belt, with a total of 10 templates mounted on this belt, which will be used in an automated SMT production line, as indicated in the Figure below the detailing of the template and the assembly of the PCB boards. This conveyor belt will have the function of transporting the PCB boards between two workstations, where the PCB boards will be placed and removed by industrial robots equipped with a system with pneumatic suction cups, as indicated in Figure 8 the detailing of the template and assembly of the PCB boards.

Revista ARACÊ
ISSN: 2358-2472

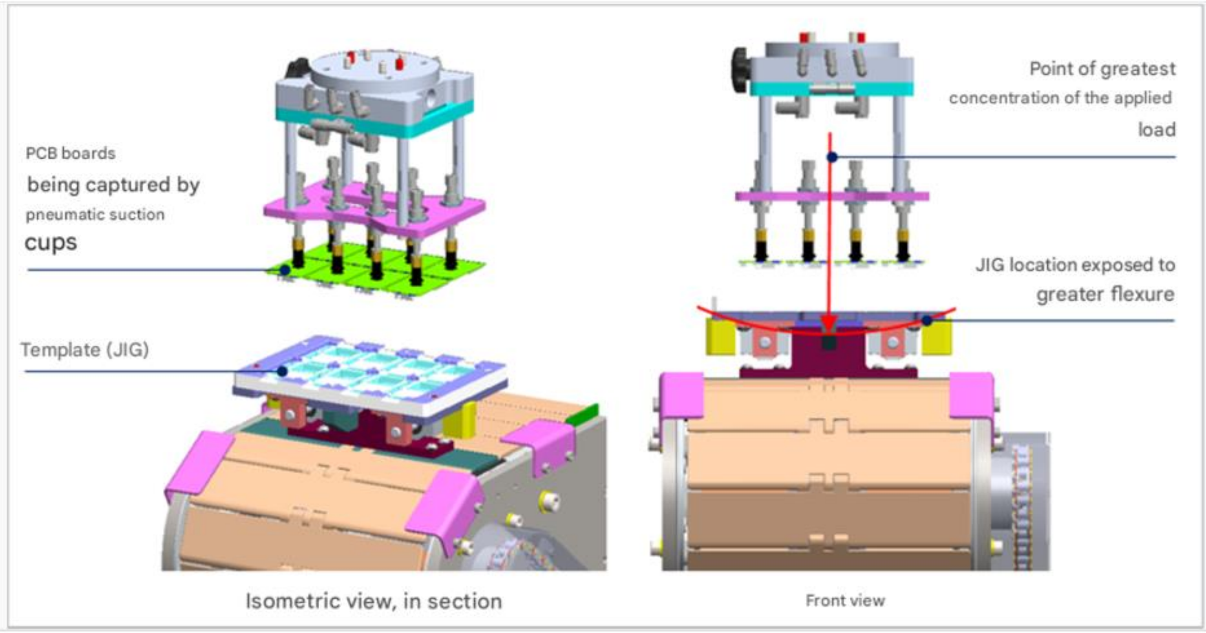
Figure 8: Detailing of the jig (JIG) for the assembly of PCB boards, an item to be developed by IBBI.



Source: Authors, (2024).

At the entrance of the conveyor, an industrial robot, equipped with a claw with pneumatic suction cups, will position the PCB boards inside the partitions of the template and at the end of the conveyor belt, another robot with a similar system will remove the PCB boards from the template and move them to another stage of the production process. The template must be manufactured in material that resists the process of continuous movement of the belt, and the constant application of loads, resulting from the pressure exerted by the suction cups on the claws of the robots, at the entrance and exit of the conveyor belt. Figure 9 illustrates the details of the positioning of the PCB boards in the template (part to be developed and prototyped in this project), in addition to emphasizing the load point and the region that will be most prone to bending, a condition that should be avoided, through analysis and simulations, followed by the choice of the best material and process, with the help of software simulations and AM prototyping.

Figure 9: Breakdown of the positioning of the PCB boards on the jig (JIG) of the conveyor belt



Source: Authors, (2024).

DESIGN AND REQUIREMENTS OF THE PART TO BE PROTOTYPED

The product (part) was initially designed in 3D CAD, using the Solidworks® software, and previously designed to ensure the following characteristics below, according to the analysis of the process and the customer's definition, as project requirements.

- Have mechanical resistance to static loads arising from the pressure exerted by pneumatic suction cups during the allocation and removal of PCB boards. Consider a maximum load of 5N;
- Withstand working temperatures up to 80°C, close to the Servo motor and 50°C in contact with the PCB, already considering a wide tolerance of 20%;
- Withstand working pressure of 50Kgf or 5N;
- The mass of the jig (JIG) must not exceed 0.9 Kg, as there will be 10 JIGs mounted on the conveyor belt (project requirement, requested by the customer);

The first stage consisted of defining the functional and performance requirements of the part (template). The second stage consisted of the selection of some materials applicable to traditional (subtractive) and additive manufacturing, and that fully or partially meet the aforementioned characteristics, and commercial availability, place of acquisition of materials and list of approved materials, for internal use in the customer's assembly lines.

For additive manufacturing, the following materials were selected, based on the information gathered in the prerequisites of the part/prototype: 1. PLA (Polylactic Acid) filament; 2. PETG (Polyethylene Terephthalate Glycol) filament; 3. PP (polypropylene) filament. For traditional manufacturing, the following materials were selected, based on the information gathered in the prerequisites of the part/prototype; 1. Acetal Copolymer (POM); 2. Aluminum Alloy 1060; 3. Phenolite plate. The equipment available for use are: 1. Equipment and mechanical tools, such as caliper, bench milling cutter, drill/screwdriver, drills, screws, among other fastening elements; 2. CNC (Computer Numerical Control) Machine: Yamazak; 3. 3D Printer: Creality Ender 3 V2®.

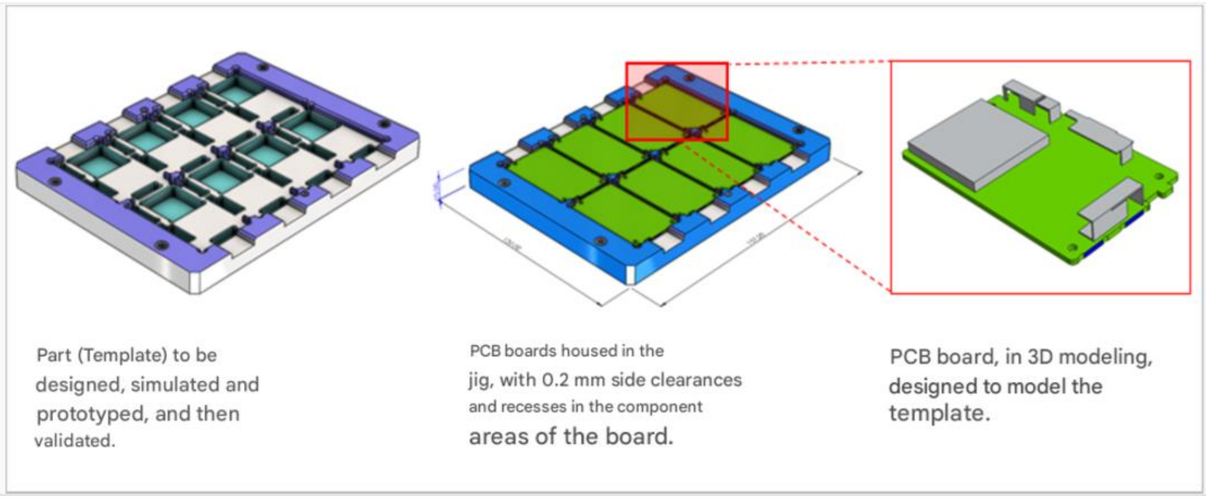
Software used:

- Solidworks 2022®: Software with CAD/CAM/CAE tooling support, used in 3D modeling of designs, simulations, and manufacturing.
- FlashPrint 5®: Free and open source 3D printing software.

RESULTS AND DISCUSSIONS

The comparative analysis between the Additive and Subtractive Manufacturing processes, integrated with 3D modeling (CAD), simulations (CAM/CAE) and prototyping tools, were carried out in the context of Industry 4.0, seeking to identify the most efficient and appropriate method for the production of a specific component (Template), according to the 3D modeling illustrated in Figure 10.

Figure 10: 3D modeling and sizing of the PCB boards to be stored in the cradles (jigs)



Source: Authors, (2024).

Revista ARACÊ
ISSN: 2358-2472

ANALYSIS OF MECHANICAL PROPERTIES

The main mechanical properties evaluated were modulus of elasticity, yield strength, tensile strength, compression, and specific mass. These properties are made available by the modeling and simulation software, from the insertion of information on the type of material, surface treatments, 3D drawing of the part and other available data. According to Figure 11, among the three pre-selected materials intended for additive manufacturing, the filament that presents the best mechanical properties was the PLA (polylactic acid) filament, followed by the PETG (polyethylene terephthalate glycol). among the three pre-selected materials, intended for subtractive or conventional manufacturing, the Phenolite sheet presented the best performance, followed by the aluminum plate (commercial alloy).

Figure 11: Comparison of the main mechanical properties of some materials used in the additive and subtractive manufacturing process

Mechanical properties	Unit	Additive Manufacturing (AM)			Subtractive manufacturing		
		PLA (Polylactic Acid) Filament	PETG (Polyethylene Terephthalate Glycol) Filament	Braskem PP (polypropylene) filament	Acetal Copolymer (POM)	1060 Aluminum Alloy	phenolite sheet
Elastic modulus:	x 10^9 N/m²	3.5	2.1	1.6	2.7	6.9	10
Poisson's ratio:	N/A	0.36	0.38	0.42	0.35	0.33	0.35
Shear modulus:	x 10^9 N/m²	1.2	0.8	0.6	1	26	4.1
Specific mass:	Kg/m³	1250	1270	900	1410	2700	1350
Tensile strength:	x 10^6 N/m²	60	50	30	70	110	70
Compression resistance:	x 10^6 N/m²	60	50	30	70	110	180
Yield limit:	x 10^6 N/m²	48	45	25	50	40	55
Thermal expansion coefficient:	1x 10-6/K	68	75	100	80	24	20
Thermal conductivity:	W/(m.K)	0.13	0.22	0.22	0.3	237	0.2
Specific heat:	J/(Kg.K)	1800	1200	2000	1500	900	1300

Caption:
Better mechanical properties, by material type.
Best material, by manufacturing type (additive and subtractive)

Source: Authors, (2024).

The choice of material depends, in addition to the analysis of the mechanical properties, on the application for which it will be intended. A material may have lower mechanical characteristics than others, but meet other important requirements and are economically more viable, easier to manufacture, store, transport, etc.

Revista ARACÊ
ISSN: 2358-2472

MODELING AND SIMULATIONS: ANALYSIS OF MESHES BY THE FINITE ELEMENT METHOD (FEM)

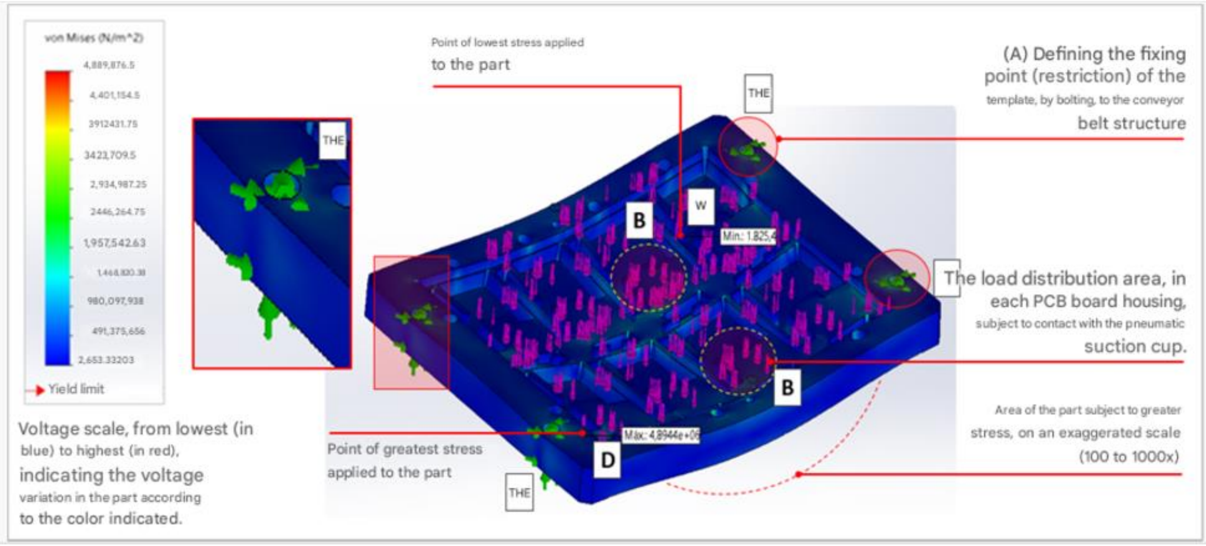
In finite element analysis (FEA) performed in Solidworks® or other simulation software, three of the main results obtained are Von Mises stress, displacement, and strain. These three results form the basis of the evaluation of a finite element analysis, allowing to predict the behavior of the part or structure under real operating conditions.

During the preparation stage of the simulation environment, it is necessary to define the type of simulation, type of applied load (force or pressure), point or area of application and the points or areas of fixation of the part and type of fixture, to then generate the meshes and perform the simulation by the finite element method. For this study, the simulation of static analysis was selected, and a load of force equal to 50N, on the entire surface of contact of the PCB board with the template (cradle), the area that will receive the load from the pressure exerted by the contact of the pneumatic suction cup with the PCB board. It is known that the actual contact pressure of the suction cup with the PCB board is much lower, but this value was defined by the customer by the application to simulate an extrapolated (exaggerated) condition and thus obtain better results, since it is possible to better evidence the distinction of results between the different materials. The next step was to define the fixation points (crimping) of the part, and the fixation accessories, metric screws of the Allen type type cylindrical head M5 and plain washers, to then generate the meshes and plot the simulation values

After defining the input parameters, the meshes for the part under study are then generated, as well as plotted graphs and tables with the data of maximum and minimum stress, strain and displacement, type of mesh, size of elements, size of nodes, simulation time, among others. Figure 12 exemplifies an analysis by FEM, with emphasis on the Von Misses stress to which each element is submitted, the displacement of each node and the deformation in each element.

Revista
ARACÊ
ISSN: 2358-2472

Figure 12: Finite Element Method (FEM) mesh analysis



Source: Authors, (2024).

The simulations carried out were useful, as they inform, in an estimated way, the points where the part is more subject to damage due to fatigue and stress and prone to collapse or suffer some damage or excessive wear and faster. The data obtained guide the choice of the best material or the decision making regarding the cost-benefit ratio of the material to be used, manufacturing method and design corrections, with the addition or removal of material, relief points, chamfers, etc. Figure 13 presents the summarized data from the FEM simulation, applied to the selected materials the additive and subtractive manufacturing process.

Revista ARACÊ
ISSN: 2358-2472

Figure 13: Topics of analysis by the FEM, applied to materials intended for additive manufacturing.

Topics for analysis by MEF		Unit	Additive Manufacturing (AM): PLA (Polylactic Acid) Filament	Additive Manufacturing (AM): PETG (Polyethylene Terephthalate Glycol) Filament	Additive Manufacturing (AM): PP (polypropylene) filament	Subtractive manufacturing: Acetal Copolymer (POM)	Subtractive manufacturing: 1060 Aluminum Alloy	Subtractive manufacturing: phenolite sheet
Strengths	Resultant force	N		50 N			50	
Volumetric properties	Mass	kg	0.14317	0.14546	0.10308	0.15920		0.15462
		m^3	0,00011	0,00011	0.00011	0.00011		0,00011
	Density	Kg/m^3	1250	1270	900	1390		1350
	Weight	N	1,40302	1,4255	1.01018	1.56016		1.51526
von Mises voltage	Von Mises stress max.	N/m^2	4889876.5	4893539	4899759.5	4894369.5		4888347.5
	Von Mises stress min.	N/m^2	2653.33	1855.98	1999.13	1825.41		2687.39
	Yield limit	N/m^2	48000000	45000000	25000000	50000000		55000000
	Percentage yield limit	N/m^2	10%	11%	20%	10%	#DIV/0!	9%
Resulting displacement	Max displacement.	mm	0.079031	0.131317	0.170965	0.105956		0.027697 0
	Min displacement.	mm	0	0	0	0		
Equivalent Deformation	Max. deformation (mm)	mm	0.00086	0.00146	0.00197	0.00183		0,00030
	Max. deformation (mm)	mm	4,032E-07	7,461E-07	1,447E-06	6,430E-07		1,416E-07

Caption:
Better mechanical properties, by material type.
Best material, by manufacturing type (additive and subtractive)

Source: Authors, (2024).

Among the materials used in subtractive (conventional) manufacturing, the part manufactured in phenolite presented the best performance, with the lowest resulting stress, displacement and deformation, which indicates greater mechanical strength and dimensional stability for applications involving machining processes. For additive manufacturing (3D printing), PLA stood out as the material that presented the lowest values of resulting stress, displacement and strain. These results suggest that PLA is a suitable material for 3D printing in scenarios that demand a lower susceptibility to deformations and stresses.

Overall, considering all materials evaluated in the two manufacturing approaches, phenolite demonstrated, on average, the best results. It exhibited a superior combination of mechanical properties, making it an ideal choice for projects that require high stability under loads and minimal dimensional variations.

APPLICATION OF ARTIFICIAL NEURAL NETWORKS (ANN) IN THE SELECTION OF THE MATERIAL WITH THE BEST MECHANICAL PROPERTIES

The simulation tools presented effective results in the analysis of the type of material, by the Finite Element Method (FEM), and the scenarios in which they will be applied. However, in situations that require the evaluation of multiple materials or scenarios

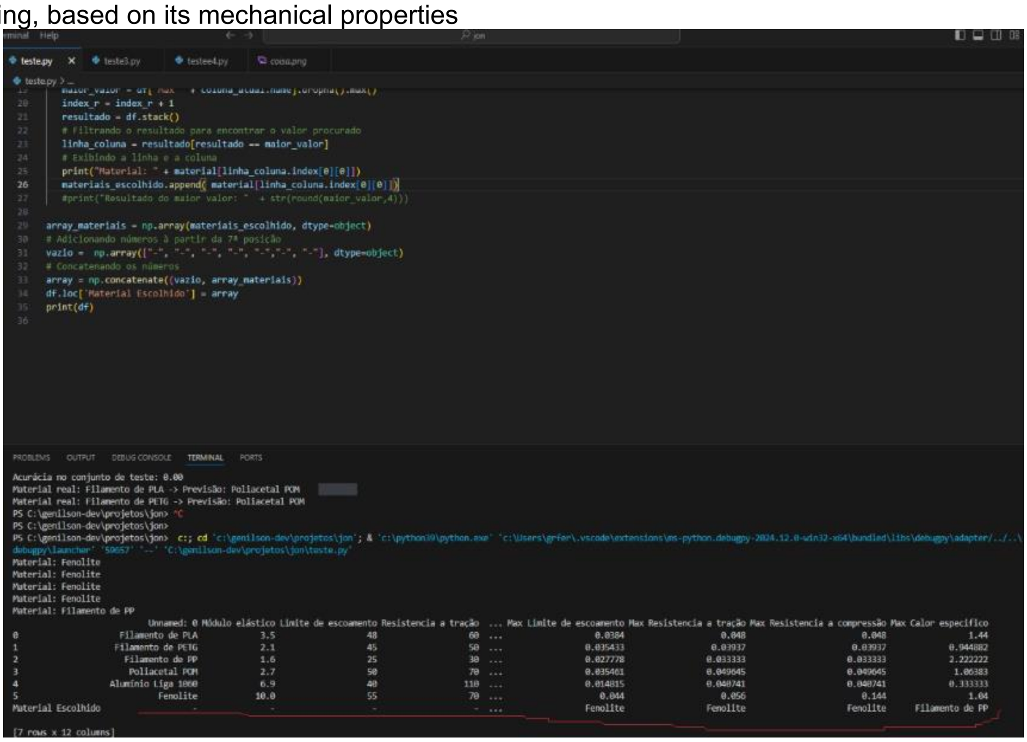
Revista ARACÊ
ISSN: 2358-2472

simultaneously, it is necessary to compile all the data generated to perform a comparative analysis and identify the most promising results efficiently and accurately.

With the integration of learning algorithms based on artificial neural networks, it is possible to organize and synthesize information from various CAD/CAE/CAE simulations, such as the mechanical properties of materials applied to specific manufacturing, in a consolidated format, such as spreadsheets or databases. This data can be processed into algorithms implemented in specific programming languages, such as Python, allowing the identification of the most suitable material for each application. In addition, the use of neural networks enables storage and continuous learning from the data obtained, providing faster and more accurate comparisons in future simulations.

This approach not only optimizes the decision-making process, but also creates an improved knowledge base, allowing information from past materials and simulations to be applied to new projects as shown in Figure 14.

Figure 14: Neural Network Algorithm, programmed in Python, for the selection of the best material for manufacturing, based on its mechanical properties



Source: Authors, (2024).

The data obtained through the simulations carried out in the software must be organized, manually or automatically, in a file in .xlsx format. The algorithm designed for this application will access the information directly from this file, which, for standardization purposes, will be saved as "materiais.xlsx". After processing, the algorithm consolidates the results and generates a new spreadsheet, renamed "classificação_material_resultado.xlsx", stored in the same directory as the original file.

The generated spreadsheet will present the detailed data in a structured way and highlight the most suitable material based on the mechanical properties evaluated. In addition, the results will also be displayed directly in the Python language compiler interface, providing an immediate and complementary preview of the data that has been processed. This approach not only facilitates data management and analysis, but also automates process steps, reducing the risk of manual errors and speeding up the identification of the ideal material for the application in question.

Table 1: Spreadsheet generated from the algorithm programmed in Python, with the identification of the best material for manufacturing, based on its mechanical properties

Unnamed: 0	Max elastic modulus	Max Yield Limit	Max tensile strength	Max Resistance the compression	Max Specific Heat	Highest Repetition
PLA Filament	0.0028	0.0384	0.048	0.048	1.44	
PETG Filament	0.001653543	0.035433071	0.039370079	0.039370079	0.94488189	
PP Filament	0.001777778	0.027777778	0,033333333	0,033333333	2,222222222	
POM polyacetal	0.001914894	0.035460993	0.04964539	0.04964539	1.063829787	
Aluminum Alloy 1060	0.002555556	0.014814815	0.040740741	0.040740741	0,333333333	
Fenolite	0.008	0.044	0.056	0.144	1.04	
						Fenolite

Source: Authors, (2024).

PROTOTYPING WITH ADDITIVE MANUFACTURING

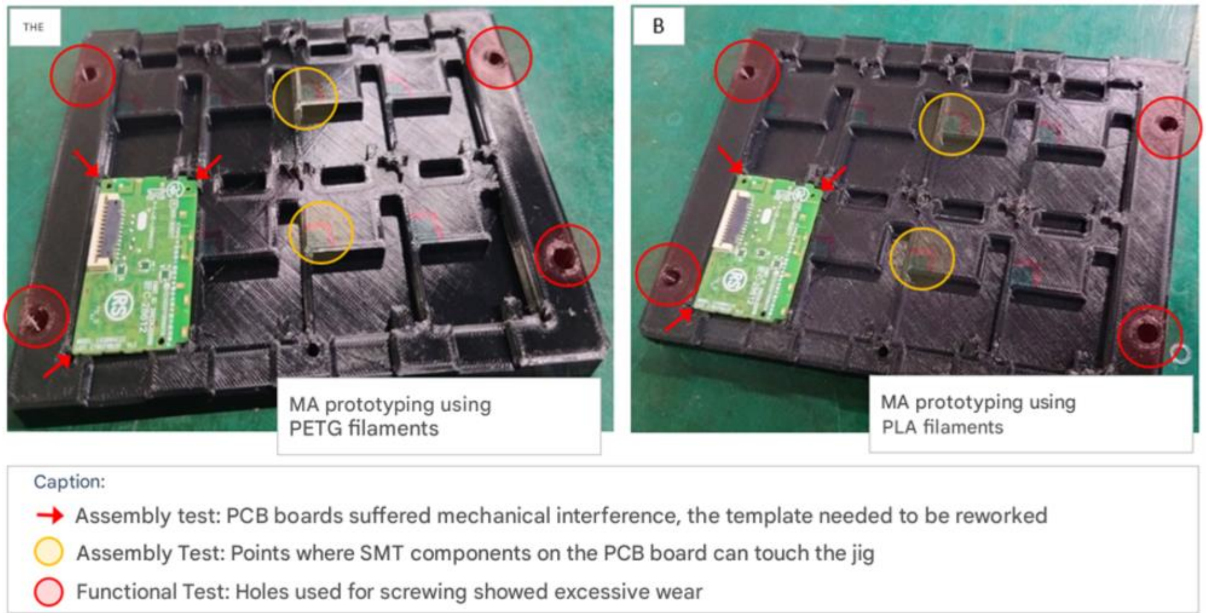
Regarding the properties of the materials used, the prototypes were manufactured through 3D printing with PLA (polylactic acid) and PETG (polyethylene terephthalate glycol) filaments. The choice of these materials was made after preliminary analyses using the Finite Element Method (FEM), in which the polypropylene (PP) filament did not present satisfactory performance when compared to the other materials evaluated. After printing, the prototypes were subjected to a series of assembly tests, with the aim of verifying their feasibility and suitability for the proposed operating environment.

The results indicated that both PLA and PETG presented problems related to dimensional accuracy, the allocation of PCB boards occurred with mechanical interferences, but in the design of the project, a gap of 0.2 mm with symmetrical tolerance of 0.05 mm should be respected. Both materials demonstrated limitations in terms of mechanical resistance in the conditions of assembly and continuous operation, in addition to wear at the bolting points of the template on the conveyor belt, after the end of the tests, where a specific torque was applied and the screwing and unscrewing process was carried

ISSN: 2358-2472

out 10 to 20 times, according to the parameters specified by the Carlsson screw torque table, and followed as the customer's internal rule according to Figure 15.

Figure 15; Assembly test on the jigs manufactured by MA, using PETG (A) and PLA (B) filaments



Source: Authors, (2024).

Despite the flaws and improvements pointed out throughout the process, the templates manufactured in PLA and PETG showed satisfactory performance in the functional tests performed on a test conveyor belt. The prototypes did not suffer collapses, significant physical wear, dimensional variations, or any damage that would compromise their functionality. During fatigue testing and trials, the belt was configured to simulate real operating conditions, with move and stop cycles every 5 seconds, including continuous forward and reverse movements. These cycles were maintained for a period of 8 hours a day, over 30 days. The results suggest that jigs are suitable for use, withstanding the operational rigors without loss of structural integrity.

PROTOTYPING WITH SUBTRACTIVE MANUFACTURING (MACHINING/TRADITIONAL)

Regarding the properties of the materials used, the prototypes were manufactured by CNC machining, using as raw material a sample of Phenolite (and Aluminum) sheet.

After machining, the prototypes were subjected to a series of assembly tests, with the aim of verifying their feasibility and suitability for the proposed operating environment.

Unlike parts prototyped by additive manufacturing, the subtractive manufacturing process (CNC machining) requires a step of raw material preparation, since it is necessary

Revista ARACÊ
ISSN: 2358-2472

to cut a sample of the sheets to a specific size of the machining table, clean the surfaces and open holes for fixing the sheet sample to the machining table.

After the machining was completed, the visual and dimensional inspection of the main assembly dimensions of the part was carried out and the assembly and mechanical fatigue tests were carried out, the results indicated that the phenolite and aluminum plate did not present problems related to dimensional accuracy. Both materials have not demonstrated significant limitations in terms of mechanical strength under the conditions of assembly and continuous operation. Slight wear was also observed at the bolting points of the template on the conveyor belt, after the fatigue tests, in which a specific torque was applied and the bolting and unscrewing process was carried out 10 to 20 times, according to the parameters specified by the Carlsson screw torque table, but without causing structural damage to the part (prototype).

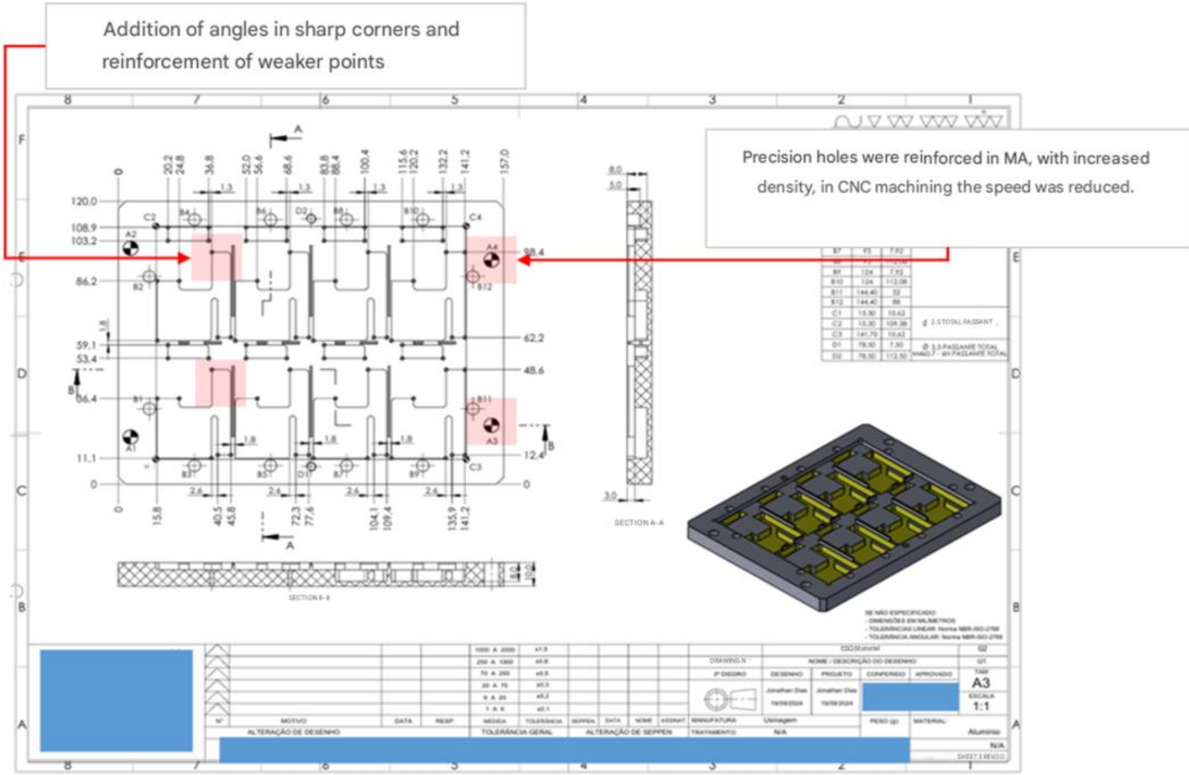
Prototyping by subtractive manufacturing (CNC machining) stands out for providing better precision of the parts produced and a shorter sample manufacturing time, better surface finish, but as negative points the sample preparation time and the cost of manufacturing new samples, in case of failures and points of improvement, need to be mentioned. After initial tests, new parts were made and the points of non-conformity ***were corrected.***

REVISED 3D MECHANICAL DRAWING

After the adjustments and corrections in the 3D drawing were finalized, the 2D technical drawing was generated for the purpose of recording documentation, detailed according to the ABNT NBR technical standards for technical drawing.

Revista
ARACÊ
ISSN: 2358-2472

Figure 13: Assembly test on the jigs manufactured by MA, using PETG (A) and PLA (B) filaments



Source: Authors, (2024).

COST ANALYSIS

For a comprehensive analysis of costs in the manufacturing process, several fundamental variables were considered, such as the characteristics of the product, material and equipment, and labor. Table 2 presents the data obtained from analyses carried out during 3D modeling and manufacturing process simulations (CAM), enabling the comparison between the initial mass of the raw material and the final mass of the finished product, after the manufacturing process. For additive manufacturing (AM), the percentage of losses was approximately 15% of the material, while in CNC machining there was a significantly higher loss rate of 162%. This difference highlights the material efficiency of additive manufacturing compared to conventional machining methods, making it a more sustainable option in terms of material consumption and waste generation.

Revista ARACÊ
ISSN: 2358-2472

Table 2: Raw material losses by additive manufacturing (FDM) x conventional (CNC) processes.

Additive Manufacturing (FDM)						
	Density	Initial Volume	Volume Final	Starting Dough	Final dough	Losses (Mass)
PLA	1250	0.000132	0.000115	0.164594	0.1432	-15%
PETG	1270	0.000132	0.000115	0.167227	0.1455	-15%
PP	900	0.000132	0.000115	0.118508	0.1031	-15%

Conventional Manufacturing (CNC)						
	Density	Initial Volume	Volume Final	Starting Dough	Final dough	Losses (Mass)
POM	1390	0.0003	0.000115	0.417	0.1592	-162%
Al.1060	2600	0.0003	0.000115	0.78	0.2977	-162%
Fenolite	1350	0.0003	0.000115	0.405	0.1546	-162%

Source: Authors, (2024).

Based on the information collected, the total monetary cost (in reais) for the production of the prototype of a template was estimated, taking into account determining factors such as the manufacturing time, the nature of the item (whether prototype/customization or mass production), type and cost of raw materials, and the cost of labor, direct and indirect. These elements were quantified and presented in Table 3.

Revista
ARACÊ
ISSN: 2358-2472

Table 13: (R$) Costs of manufacturing the prototype, by the AM (FDM) x conventional (CNC) processes

Item	Term	CNC Phenonite	MA (FDM) PLA	Definition
Product	mt	0.405	0.154594	Total mass used in the part process (Kg)
	m	0.1546	0.1432	Useful mass of the part (discarding supports, scraps...) (Kg)
	[illegible]	4	5.5	Construction time (hour)
	N	1	1	Number of pieces to be made
	(Tℓ)	2	1.5	Labor time on part (hours)
Material and equipment	[illegible]	R$ 100.000,00	R$ 1.800,00	Machinery purchase price
	cm	R$ 300,00	R$ 146,10	Material price (R$/kg)
	Fatigue	0.95	0.95	tolerance/fatigue factor
	Hours	10	10	Daily hours (average)
	Days	20	20	Monthly days (average)
	Months	12	12	Months per year (average)
	Life	15	5	years of life, for good maintenance
work	(TP)	180	180	Monthly labor time (hours)
	(Rm)	R$ 9.000,00	R$ 4.000,00	Monthly remuneration
	(Nm)	2	3	Number of machines per employee
Hand Parameters calculations auxiliaries	Yvida	36000	12000	Usage hours or lifetime (h)
	CoS	R$ 2,78	R$ 0,15	Operating rate (R$/hour)
	Kr	0.62	0.13	Recycling factor
	Ks	1.62	1.13	Support material factor
	CL	R$ 25,00	R$ 7,41	Labor rate (R$/hour)
Cost items and general costs	PS	R$ 11,70	R$ 0,87	Machinery purchase cost
	OS	R$ 1.011,11	R$ 275,83	Cost of operating the machinery
	M	R$ 69,61	R$ 4,61	Raw material cost (estimated)
	L	R$ 50,00	R$ 11,11	Labor cost
	CMA	R$ 1.142,41	R$ 292.41	General manufacturing cost - (with good maintenance)

Source: Authors, (2024).

According to the data in Table 4.4, the cost of producing the template prototype by the conventional method was 74% higher than the cost obtained using digital manufacturing, evidencing the economic viability of additive manufacturing. However, it is important to consider additional factors that can influence this analysis, such as the fact that it is a prototyping process, the different nature of the materials used in each method, and other factors that can impact costs, such as the scale of production and the complexity of the part.

These considerations are fundamental for a balanced analysis of the costs and advantages associated with each manufacturing method, helping to choose the most appropriate process for each production context. From the perspective of mechanical properties, costs involved and ease of manufacture, the study showed differences between additive manufacturing (AM) processes and subtractive manufacturing methods, with the use of CNC. For applications involving customization or prototyping, in which industrial-scale production is not required, the additive manufacturing process showed better performance, which included a significant reduction in costs associated with labor, raw materials and machinery. While conventional production requires specialized operations and robust manufacturing infrastructure, additive manufacturing requires smaller physical area, lower cost equipment and operators with lower levels of technical qualification, which reflects economic orientations of the process. Still in the context of prototyping and customization, when integrated into the development of a product design, additive manufacturing has presented additional benefits. Among them, the significant reduction in the time required to complete the development curve, the simplification of project steps, and the possibility of obtaining faster and more accurate feedback during the design and validation process stand out. These advantages are particularly relevant for scenarios that require high flexibility and agility, reinforcing the potential of AM as a strategic solution in low-scale and highly complex projects.

However, about manufacturing quality, the FDM (Fused Deposition Modeling) additive production method presented limitations when compared to the conventional machining process. The machining achieved greater dimensional accuracy and better surface finishes, important characteristics in applications that require tight tolerances and highly refined surfaces. Although there are additive production technologies capable of achieving high levels of quality, these were not the object of study in this work, being restricted to general mentions. Regarding the mechanical properties of the materials used, we found that the materials used in conventional subtractive manufacturing still have superior performance in terms of strength and durability. However, when comparing the properties of the materials with the specific requirements of the application proposal, it was observed that both processes are technically feasible and meet specific criteria. Thus, the choice of process can be made based on other factors, such as cost, time, and flexibility, without compromising the functional performance of the final product.

CONCLUSIONS

The integration of Industry 4.0 technologies into digital and conventional manufacturing provides greater accuracy in 3D modeling and prototyping, which allows for continuous real-time adjustments, predictive simulations, and process monitoring. The combination of CAD, CAM, and CAE software creates a digitized and optimized production ecosystem, resulting in more accurate designs, manufacturing processes with less incidence of failures, and structural validations that reduce costs, increase quality, and minimize environmental impacts, which contributes to increasing the competitiveness and sustainability of companies. Despite implementation challenges, such as high costs and workforce reskilling, the benefits of Industry 4.0, such as increased efficiency, flexibility, sustainability, and decision-making support, make it essential to meet the demands of an increasingly competitive market. Comparing conventional (CNC machining) and digital (additive manufacturing, with an emphasis on the FDM process) manufacturing, it is observed that machining is more suitable for applications that require greater precision and mechanical strength. On the other hand, additive manufacturing has shown significant advantages in the production of functional prototypes and customizations, due to its flexibility and cost reduction. The CAD/CAM/CAE integration in the context of Industry 4.0 facilitates the optimization of projects and production processes, which allows quick adjustments in the design and evaluation of structural performance before manufacturing, guiding decisions such as material selection and design modifications. The results indicate that the choice of manufacturing method and material should consider the application criteria and operating conditions. Additive manufacturing, although limited in mechanical strength when compared to traditional machining, has advantages in speed and ease of adaptations and prototyping. Future research may include long-term tests to validate performance in operation and the development of decision-making tools integrated with CAD/CAE/CAM software, considering costs, mechanical and dimensional properties based on simulations performed.

ACKNOWLEDGMENTS

To the Graduate Program in Engineering, Process, Systems and Environmental Management of the Galileo Institute of Technology and Education of the Amazon (PPG. EGPSA/ITEGAM), to ITEGAM and the companies Salcomp, Foxconn, Procomp/Diebold, Inventus Power, Coelmatic through Law no. 8.387/1991 on Informatics to encourage RD&I Projects with financial support PUR044/2023/CITS to the Master's project through the Coordinator of the Priority Program for Industry 4.0 and Industrial Modernization, the International Center for Software Technology (CITS)/CAPDA/SUFRAMA/MDIC.

Revista ARACÊ
ISSN: 2358-2472

REFERENCES

1. Additive Manufacturing Technology Standards ASTM F2792.

2. Almeida, J. R. A. (2019). Manufatura digital e seus impactos na indústria moderna. São Paulo: Editora Técnica.

3. Callister, W. D., & Rethwisch, D. G. (2014). Ciência e engenharia de materiais: uma introdução. Wiley.

4. CAPES. (n.d.). Redes Neurais Artificiais: uma abordagem para sala de aula. Disponível em: https://educapes.capes.gov.br. Acesso em: 28 nov. 2024.

5. CNI – Confederação Nacional da Indústria. (2024). Disponível em: https://firjan.com.br/pagina-inicial.htm. Acesso em: 28 nov. 2024.

6. Dados. (n.d.). Redes Neurais: desvendando o cérebro artificial. Disponível em: https://www.datageeks.com.br. Acesso em: 28 nov. 2024.

7. Gao, W., et al. (2015). O status, os desafios e o futuro da produção aditiva na engenharia. Design Assistido por Computador, 69, 65-89.

8. Nascimento, J. L. (2016). Propriedades mecânicas de polímeros na produção aditiva. Revista Brasileira de Engenharia de Materiais, 3, 245-253.

9. Rüßmann, M., et al. (2015). Indústria 4.0: O Futuro da Produtividade e do Crescimento nas Indústrias de Manufatura. BCG Publicações.

10. Silva, M. F., & Andrade, P. L. (2020). Indústria 4.0: fundamentos e aplicações. Rio de Janeiro: Editora ABC.

11. Volpato, N. (2017). Manual de impressão 3D: tecnologias e aplicações (1ª ed.). São Paulo: Elsevier.

12. Norma ISO/ASTM 52900:2015.