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Additive manufacturing expert system (AMES): a case study for effective automotive plastic parts manufacturing

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Abstract

Additive manufacturing (AM), commonly referred to as 3D printing, has emerged as a transformative technology in automotive production, enabling the fabrication of complex, lightweight, and customized components. The effective execution of additive manufacturing for plastic components in the automotive industry requires specialized knowledge to optimize material selection, process parameters, and design considerations. The goal of this research is to develop and implement the Additive Manufacturing Expert System (AMES), an intelligent decision-support tool that aims to improve the efficiency and quality of automotive plastic parts production. This study performs a comprehensive review of current literature to evaluate advancements in additive manufacturing technology, focusing on their application to automotive plastic components. Fundamental domains include material properties, process optimization, and integration with automobile manufacturing processes. The AMES framework uses artificial intelligence (AI) methodologies, i.e. expert systems, to assist users in selecting the most suitable materials, procedures and designs for specific automotive applications. The report also provides a case study illustrating the implementation of AMES in the optimized fabrication of plastic parts. The results show a substantial reduction in production duration and material waste, accompanied by improved component performance. Results demonstrate a substantial decrease in production duration and material waste, accompanied by enhancements in component performance. This study emphasizes the capability of expert systems to address the knowledge deficit in additive manufacturing, offering car manufacturers an effective and scalable alternative for the production of plastic components. The results emphasize the necessity of incorporating AI-driven technologies into additive manufacturing processes to promote innovation, decrease expenses, and improve sustainability in the automobile industry.

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Keywords

Additive manufacturing expert system, Parts manufacturing, Automotive plastic parts

Introduction

The automotive industry faces increasing challenges to innovate in response to the demand for lightweight components, customized designs, and sustainability[1–3]. Additive manufacturing (AM), also known as 3D printing, has developed as a revolutionary technique that tackles industrial difficulties. The automobile sector highly acknowledges the promise of additive manufacturing, which offers benefits such as the production of lighter, tailored components and the optimization of supply chain processes [4–6]. In recent decades, additive manufacturing has evolved from prototyping to production technology, enabling the fabrication of complex structures and the implementation of innovative design strategies [7,8]. This has led to its wide adoption in various industries, including the automotive sector, where the technology is used to manufacture end-use parts [9]. However, achieving consistent quality and efficiency in AM processes remains a significant hurdle. This paper introduces the Additive Manufacturing Expert System, an AI-powered solution designed to optimize the production of automotive plastic parts.

Despite the potential of AM technologies, their adoption for mass manufacturing of automotive plastic parts remains constrained by challenges such as material selection, process optimization, and quality assurance. The need for expert knowledge to address these challenges has spurred interest in developing intelligent systems that integrate domain expertise with computational tools. Expert systems, a subset of artificial intelligence (AI), are particularly well-suited for this purpose, as they leverage rule-based reasoning and data-driven insights to simulate human expertise and guide decision-making [10,11].

A thorough examination of the current literature indicates an increasing volume of research on the amalgamation of additive manufacturing and expert systems within manufacturing sectors. However, there is a notable lack of implementation of these systems, particularly in the production of plastic automobile components. This research consolidates the present information, highlights gaps in existing methodologies, and delineates the prospective advantages of using AMES in the automobile industry. This study introduces the Additive Manufacturing Expert System (AMES) as a strategic approach to enhance the manufacturing process for automotive plastic components. AMES tries to solve important problems by using real-life case studies. These problems include picking the right additive manufacturing methods, finding the best process parameters, and making sure that plastic parts are mechanically sound. The study highlights the significance of AMES in optimizing manufacturing processes, decreasing lead times, and enhancing the overall cost-effectiveness of production systems.

Method

The proposed optimal Additive Manufacturing technology process is carried out in seven main steps as described in Figure 1.

Stage 1: The initial stage involves identifying the ideal Additive Manufacturing Technology process through the application of the integrated fuzzy AHP approach. The application requirement, material selection, volume requirement, and quality requirement form the basis of this selection. We established the criteria to create opportunities for improving the additive manufacturing production process. Therefore, it is possible to apply each of these classifications to the others. Consequently, the procedure is more comprehensive and precise, facilitating a more straightforward and accurate subsequent selection phase. We also establish a hierarchical tree that encompasses several criteria and options. Experts utilize their experience to evaluate the significance of criteria and the prioritization of alternatives via pairwise comparisons. The system then evaluates the ultimate priority of each decision alternative to determine the recommendation. The database automatically generates rules for identifying the list of alternatives based on the specified beginning circumstances and stores them as default data for subsequent steps.

Step 2: During this phase, the calculation model establishes several critical dimensions for each aim. The input variables serve as the primary dimensions of the criterion, thereby guiding the selection process through their evaluation.

Step 3: Based on Application Requirement Selection, Application Requirement Selection is determined from the database which includes indoor and outdoor.

Step 4: Material search process selection process is performed in the material database to determine material parameters such as strength, stiffness, durability, density, elastic, soft, impact resistant, heat resistant, chemically resistant, and UV resistant in the material data base.

Step 5: This step deals with volume demand. Volume determination used X-axis, Y-axis, and Z-axis criteria. The volume data is obtained from manual size input or direct image input.

Step 6: This step deals with Quality Requirements. The quality determination is based on the criteria of Speed, Layer Height, Top Button Thickness, Wall Thickness, Surface, Finish, and Infill.

Step 7: This step deals with alternatives as production parameters of the optimal Additive Manufacturing technology. These alternatives include; 1) Application Requirement (Temperature, Speed, Layer Height, Top Button Thickness, Wall Thickness, Surface Finish, Infill), 2) Material Selection (PLA, ABS, TPU, PC, ASA, PETG, NYLON). 3) Volume Requirement (Low, Medium, Hight), 4) Quality Requirement (Rough, Semi Finishing, Finishing).

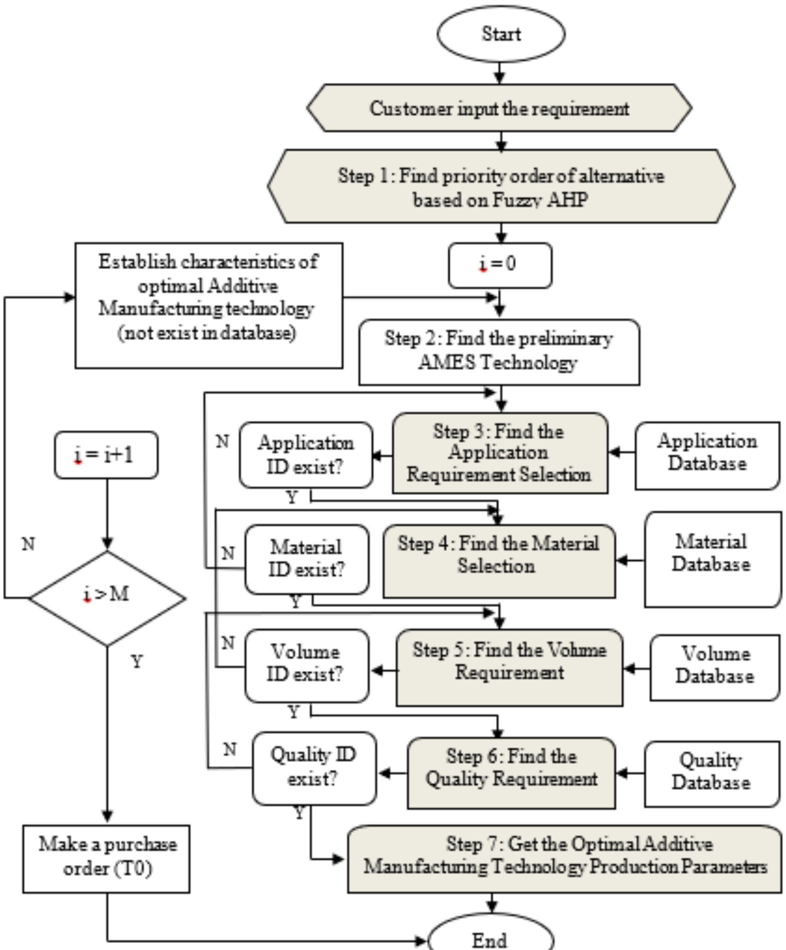

Figure 1. Optimal additive manufacturing technology production flow

Results and Discussion

Development of Additive Manufacturing Expert System

We created AMES in the XAMPP environment using PHP 7.4, JavaScript, and the MySQL 6.4.1 database toolkit. Figure 1 illustrates the primary structure of AMES. AMES comprises three primary components: 1) User Interface (UI), 2) Knowledge-Based System (KBS), and 3) Database (DB). The KBS comprises three principal components: 1) Selection and update. The selection area aids users in choosing processes that align with their requirements. The update area allows users to modify the database with application requests, material selection, volume, and quality. The selection component of the KBS has two primary stages: the eligibility stage and the selection stage [12,13]. Figure 2 shows the general framework of the selection part of the KBS.

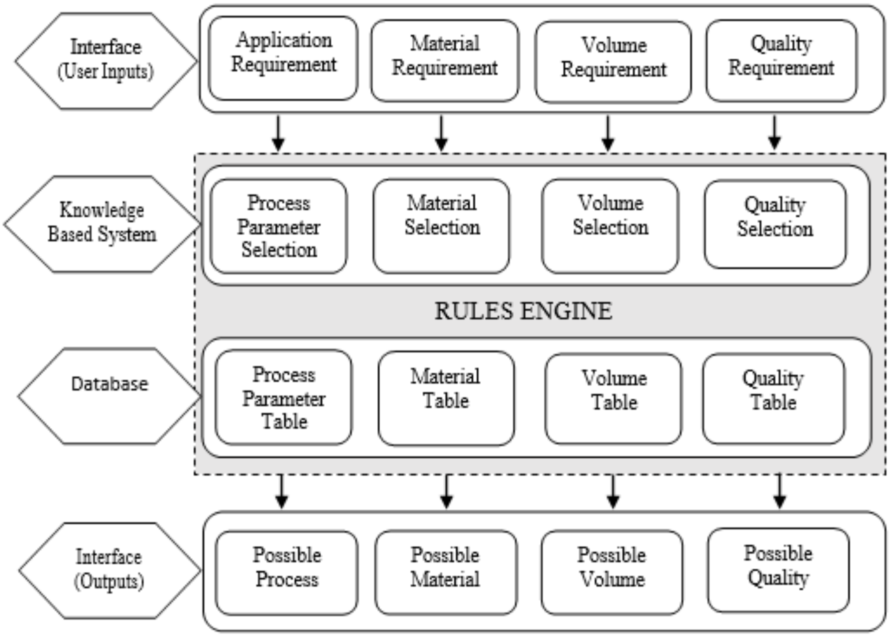

Figure 2. General framework from the start of AMES selection

Phase 1: Feasibility Phase

The initial phase is the additive manufacturing feasibility phase, executed in two stages:

The initial phase is selecting a design, offering two options: "With Design" and "Customize," to ascertain if the buyer possesses an existing design drawing. The subsequent application request presents two options: "Indoor" and "Outdoor." This section solely identifies the primary requirements for the portion utilization plan, which will be developed based on the application. In the subsequent phase, the user delineates the component specifications, including volume derived from dimensions, quantity, material designation and classification, as well as any technical drawings, if applicable. The outcome of this phase is the identification of potential processes that can meet the component specifications or process parameters. KBS accesses the database, performs queries, and retrieves the processes that meet these criteria.

In the second step, the user engages in material screening, selecting from a variety of material properties. These include general attributes such as density and color, mechanical characteristics like strength, hardness, impact resistance, fatigue resistance, and elasticity, thermal properties like temperature and heat resistance, and environmental factors like water resistance, chemical resistance, and UV resistance. The outcome of this phase is a potential material suitable for the task identified in the initial step.

Phase 2: Selection Phase

During the second phase, AMES assists the user in identifying appropriate procedures and materials based on their criteria. Additionally, the user may choose the materials and finishing options for the product. Figure 3 delineates the material selection criterion, comprising 13 process parameters.

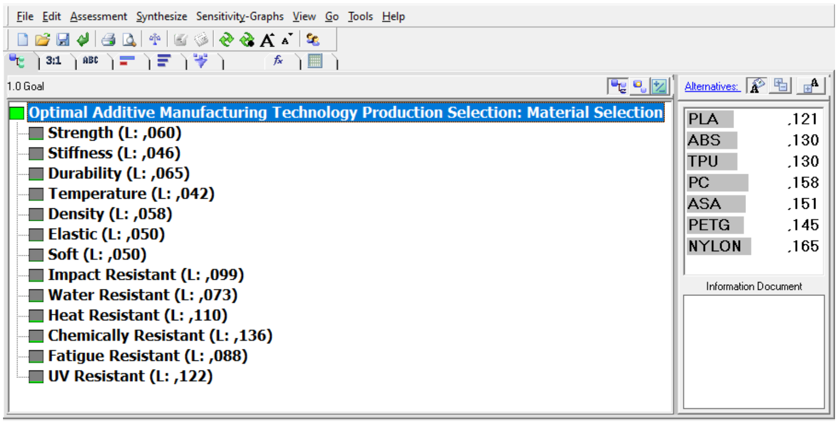

Figure 3. Material selection criteria

Figure 4 is the volume selection, where the criteria used are X (is the right-left plane), Y (is the front-back plane, and Z (is the bottom-up plane). Thus, the volume calculation is obtained by calculating the dimensions of the workpiece.

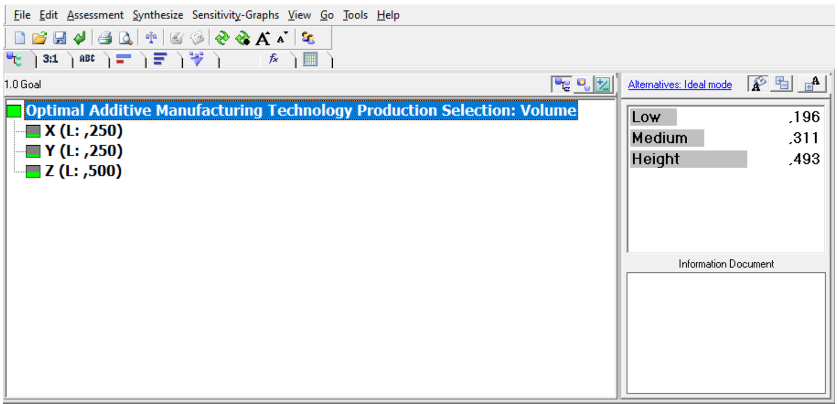

Figure 4. Volume selection criteria

Figure 5 is the quality selection, where the criteria used are temperature, speed, layer height, top and bottom distance, wall thickness, finish and fill density.

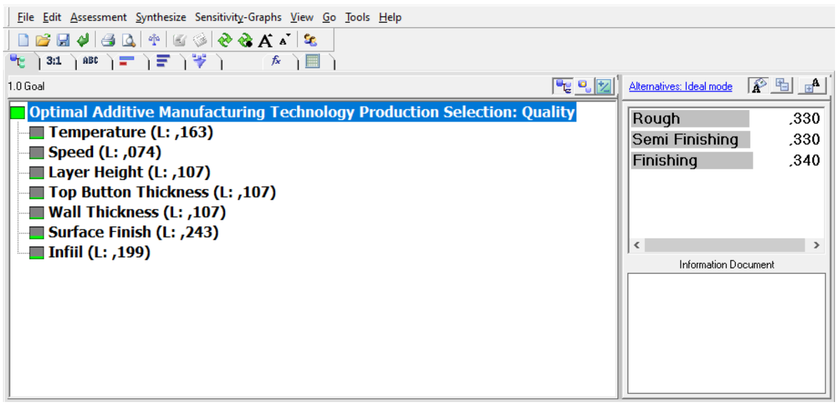

Figure 5. Quality selection criteria

Case study of AMES implementation in industry

A case study is given to create a turbo impeller component. where the component is designed to test the performance of AMES as shown in Figure 6.

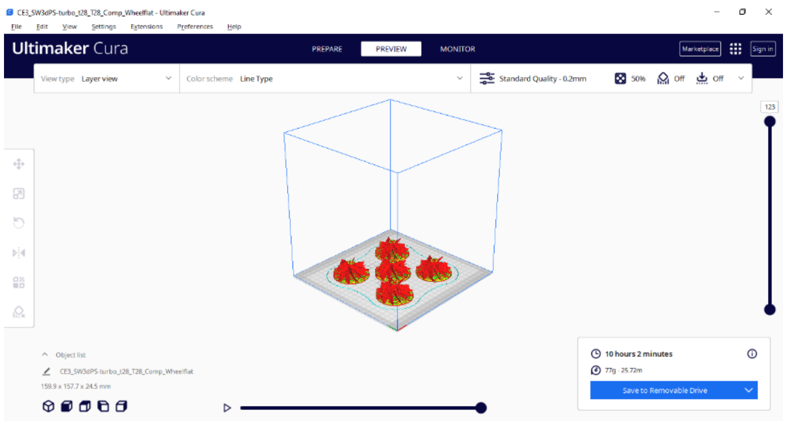

Figure 6. Design of turbo impeller component

The first selection interface outlines the request for the selection procedure within the AMES system. The user then fulfils this request, as illustrated in Figure 7. We utilize two methodologies to ascertain the preliminary selection. The first choice entails selecting between a pre-existing or custom drawing design. The expert system will directly convert these values into selection types based on the criteria specified in the application requirements, following the defined rules. The alternate method enables the direct selection of the type for each requirement.

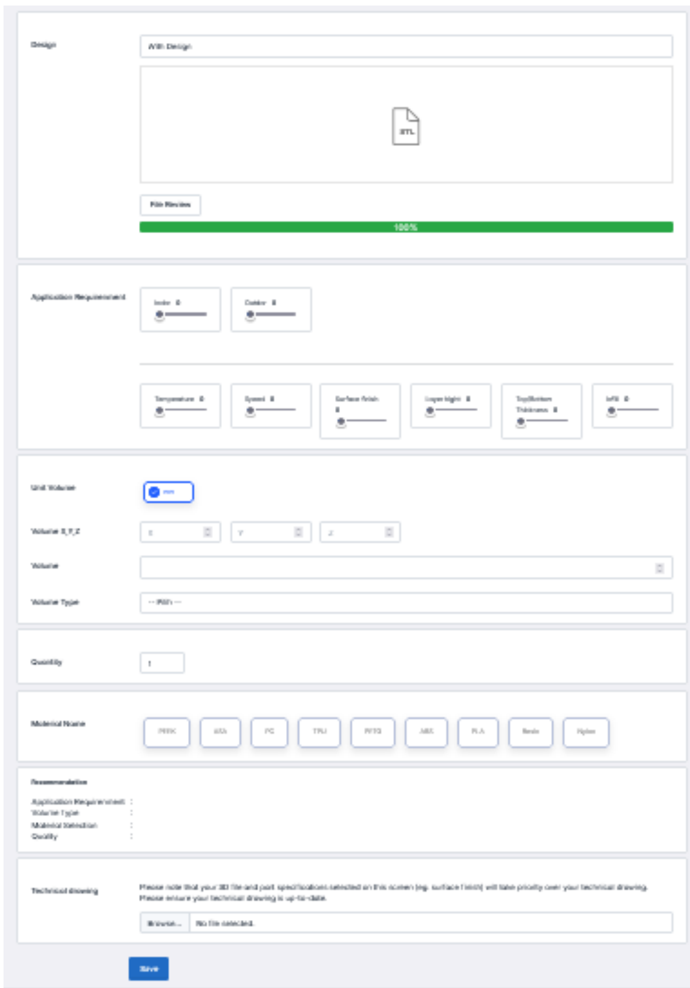

Figure 7. The user interface of AMES

The aggregation of possibilities characterizes the subsequent phase in the procedure, as illustrated in Figure 8. The integrated fuzzy AHP approach has significant advantages regarding its simplicity and applicability. The proposed method facilitates the generation of a prioritized list of candidates derived from a pairwise comparison matrix. Consequently, it is appropriate for applications in additive manufacturing. Unlike the rules that were made by hand in earlier studies [11,14], the suggested expert system might be able to make rules on its own for choosing AM technology processes based on certain criteria. This can significantly reduce errors that arise from manually formulating multiple intricate rules. Ultimately, additional traits like as stability and adaptability are also taken into account.

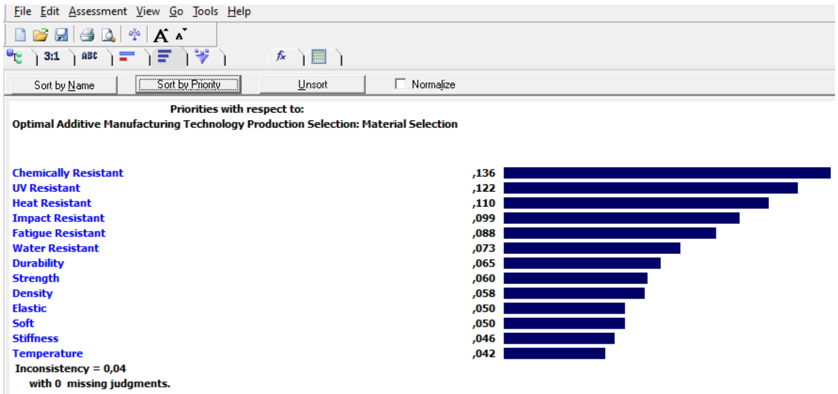

Figure 8. Design parameters used

Figure 9 illustrates that nylon material is the most highly recommended for use based on performance sensitivity analysis. This can substantially diminish the faults that occur when manually devising intricate rules.

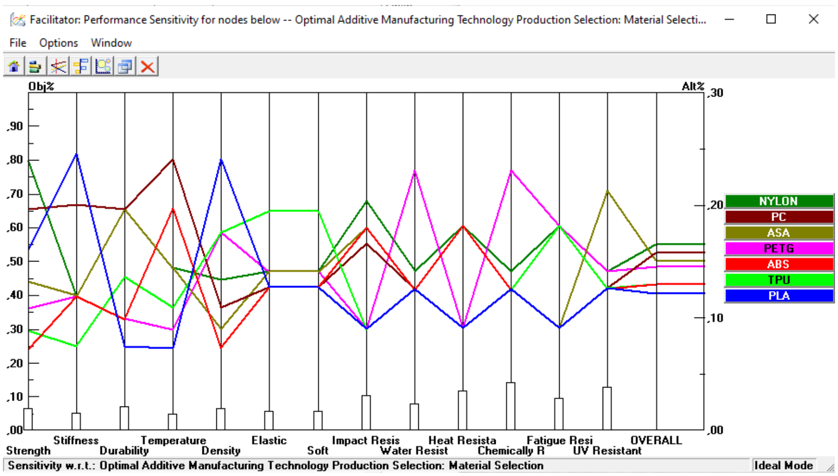

Figure 9. Performance sensitivity

The created expert system may identify the additive manufacturing technology process based on multiple specified conditions, using only minimal input, without necessitating expert knowledge in additive manufacturing. Consequently, mistakes do not occur throughout the choosing procedure. Furthermore, expert systems assist process planners in developing tailored selection models appropriate for certain industry conditions.

Conclusion

The creation and execution of the Additive Manufacturing Expert System (AMES) represent a significant advancement in the production of automotive plastic parts. This case study illustrates that AMES enhances manufacturing efficiency by integrating expert knowledge with advanced additive manufacturing techniques. The system's ability to optimize design parameters, reduce material waste, and improve production workflows underscores its potential as a transformative tool in the automotive industry. Employing AMES allows businesses to achieve more precision and customization, leading to improved product quality and reduced lead times. The expert system's adaptability in many industrial contexts illustrates its wider usefulness across multiple areas of the automobile industry. Future research could concentrate on enhancing the system's capabilities by utilizing real-time data analysis and machine learning algorithms to enhance the production process. AMES signifies a significant advancement in sustainable and efficient production techniques, corresponding with the industry's shifting need for innovation and environmental accountability.

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