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Hybrid Additive Manufacturing and AI for Electromechanical Component Optimization: A Review

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Abstract: **Hybrid Additive Manufacturing (HAM) has emerged as an effective approach to overcome the limitations of conventional metal additive manufacturing by combining layer-by-layer deposition with the precision of CNC machining. In parallel, artificial intelligence (AI) has enabled significant advances in process monitoring, defect prediction, and adaptive control. This study presents a systematized review of 52 research articles published between 2015 and 2025 to analyze the capabilities, limitations, and applications of HAM and AI in the design and fabrication of electromechanical components. The findings indicate that medium and high integration levels in hybrid systems improve dimensional accuracy, surface quality, and mechanical performance. AI-based methods further enhance process reliability by enabling parameter optimization, early defect detection, and improved repeatability. Despite these advances, challenges remain regarding standardization, limited industrial adoption, and the lack of comparative studies between AM, HAM, and CNC machining. This review provides a conceptual framework that supports future research and guides the implementation of HAM and AI in the development of advanced electromechanical components.**

Keywords: **hybrid additive manufacturing, artificial intelligence, metal AM, electromechanical systems, process optimization**

I. INTRODUCTION

The fabrication of electromechanical components presents significant challenges for conventional manufacturing methods. Subtractive machining offers high dimensional accuracy but restricts the production of complex geometries and generates considerable material waste. In contrast, additive manufacturing (AM) enables layer-by-layer fabrication from digital models, allowing the production of intricate designs with improved material efficiency [1,2]. In metal-based applications, processes such as Powder Bed Fusion (PBF/LPBF) and Directed Energy Deposition (DED) have demonstrated strong capabilities for producing high-complexity and high-strength components [3-5]. However, issues such as porosity, mechanical anisotropy, and residual stresses remain persistent challenges that affect final quality and structural reliability [3,4,6,7].

Hybrid Additive Manufacturing (HAM) has emerged as a promising strategy to address these limitations by combining AM's geometric freedom with the precision of CNC machining. This approach integrates material deposition and machining operations within a single process flow, enabling the fabrication of near-net-shape components with improved dimensional control, enhanced surface finish, and reduced post-processing requirements [6,8–10]. Several studies highlight the advantages of HAM for high-responsibility metal components, where accuracy in housing features, contact surfaces, and shaft interfaces is critical for system performance [11–14]. Recent advances in artificial intelligence (AI) and machine learning have also begun to transform manufacturing workflows. AI-driven methods can analyze large volumes of sensor, thermal, and image data to enable real-time parameter adjustment, early defect detection, and prediction of microstructural and mechanical behavior [15–19]. These capabilities position AI as a key enabler for enhancing process stability, repeatability, and part quality in both AM and HAM environments [20–22].

For electromechanical engineering, the convergence of HAM and AI opens new opportunities for redesigning housings, gears, structural supports, rotating elements, and thermal management components. This integration supports optimized geometries, internal channels, and functional surfaces that are not feasible with traditional methods [12–14,23]. Despite growing interest, the literature still lacks a consolidated framework that systematically integrates HAM processes, AI-based control strategies, and the specific requirements of electromechanical systems.

Therefore, this study aims to characterize the current state of Hybrid Additive Manufacturing, identify integration levels, analyze its advantages and limitations, and examine the role of artificial intelligence in optimizing electromechanical components. Through a systematized literature review, this work provides a conceptual foundation for future research and practical applications in the design, fabrication, and performance improvement of electromechanical systems. The article is organized as follows: Section 2 presents the state of the art of metal AM, HAM, and AI applications; Section 3 describes the review methodology; Section 4 presents the main results; Section 5 discusses the implications for electromechanical engineering; and Section 6 concludes with future research directions.

A. State of the Art

A1. Metal Additive Manufacturing: Capabilities and Challenges

Metal additive manufacturing has evolved from a rapid prototyping technique to a core technology within Industry 4.0, enabling the production of final components for aerospace, medical, automotive, and energy applications [1,2,7,24]. Processes such as Powder Bed Fusion (PBF/LPBF) and Directed Energy Deposition (DED) have demonstrated strong capabilities for producing geometrically complex and mechanically robust parts [3,4,25,26]. Despite these advances, metal AM still faces inherent limitations, including porosity, residual stresses, mechanical anisotropy, size constraints, and relatively high surface roughness [3, 4,6,7,27]. These issues directly affect the structural reliability and service life of components—especially in applications requiring tight tolerances and high repeatability, such as electromechanical systems [13,23].

To mitigate these challenges, research has focused on design approaches such as topology optimization, which redistributes material according to load paths to improve structural efficiency [14,28], as well as on lattice or graded structures that reduce weight without compromising mechanical performance [29–31]. Nevertheless, even with advanced design strategies, metal AM often requires extensive post-processing machining, heat treatment, and surface finishing to meet industrial quality and precision standards [32–34]. Layer bonding mechanisms also directly affect mechanical integrity and fatigue behavior [27,35]. Structural and load-bearing applications have additionally been explored using metal AM technologies, demonstrating its potential beyond prototyping and lightweight components [36,37]. In summary, metal AM offers high geometric freedom and substantial potential for innovation in electromechanical components; however, its microstructural and surface limitations justify exploring hybrid solutions that combine AM's advantages with the precision of subtractive machining.

A2. Hybrid Additive Manufacturing (HAM): Definition, Integration, and Scope

Hybrid Additive Manufacturing (HAM) has emerged as a manufacturing solution that integrates the geometric flexibility of additive manufacturing (AM) with the dimensional accuracy of conventional CNC machining. Saini [38] defines HAM as the synergistic combination of additive and subtractive operations within a unified workflow to produce robust and geometrically complex components with high accuracy. Recent reviews categorize HAM into two main implementation approaches: integrated (in-machine) systems and process-chain systems [8–10,39,40].

- In-machine systems perform both deposition and machining operations on the same platform without part repositioning, thereby improving dimensional accuracy and reducing human intervention [8,10]. However, the tight integration of hybrid machining systems also increases process complexity and control requirements [41].

- Process-chain systems distribute additive and subtractive steps across separate machines, offering increased flexibility for large-scale or multi-material components. This approach, however, introduces greater challenges related to alignment, logistics, and inter-process consistency [11,40]. Nevertheless, hybrid additive–subtractive systems within process chains have demonstrated the ability to enable precision manufacturing of complex metal components [42].

The literature consistently highlights several advantages of HAM compared to standalone AM or CNC machining, including reduced surface defects, near-net-shape fabrication, internal cavity machining, shorter post-processing times, and localized mechanical enhancement [9], [10,15,33]. Despite these benefits, significant challenges remain, such as high equipment costs, programming complexity, advanced fixturing requirements, and difficulties in integrating real-time sensing and quality control systems [11,40,43]. Overall, these findings suggest that HAM is particularly promising for applications requiring complex geometries combined with precision functional surfaces—characteristics commonly found in electromechanical components.

A3. Applications of AM and HAM in Electromechanical Components

Although most AM and HAM research focuses on aerospace and biomedical sectors, the principles and benefits are highly relevant to electromechanical systems [12,13,23]. Several emerging applications include:

- Motor housings with optimized internal channels
- Rotors and stators with improved geometric precision
- Robotic components with functional gradients
- Heat-dissipating structures with engineered microchannels

HAM is especially advantageous in these contexts, enabling reinforced critical areas, precision-machined functional surfaces, and internal geometries unattainable through conventional processes. Studies also highlight the potential of AM for electric machine components, including high-speed rotors and housings with embedded cooling channels, improving thermal behavior and power density [13,23,35,44]. Despite these advances, specialized research on the systematic application of HAM in electromechanical systems remains limited, reinforcing the need for methodological frameworks that connect design, process selection, quality control, and performance evaluation. Recent advances in metallic additive manufacturing have strengthened the industrial relevance of hybrid approaches [10,37].

A4. Role of Artificial Intelligence in AM and HAM

Artificial intelligence has gained momentum in manufacturing due to its ability to analyze large datasets from sensors, cameras, and thermal systems. In the context of AM and HAM, AI is applied primarily to:

1. process parameter optimization,
2. early defect detection,
3. real-time quality control, and
4. geometry and structural optimization using data-driven models [12,16–22].

Machine learning and deep learning techniques have been used to detect porosity, lack of fusion, and other defects in LPBF components based on optical or thermal imaging [16]–[18]. Other studies focus on predictive models linking process parameters, thermal responses, and mechanical properties to reduce experimental testing and accelerate development [19–21]. Thermo-mechanical optimization remains essential to reduce residual stresses and distortion [6,45].

Complementary technologies such as augmented reality have also shown potential for improving human–machine interaction, precision in technical tasks, and efficiency in industrial environments [53]. In hybrid systems, AI can support adaptive control strategies that adjust machining paths based on real-time defect identification or modify additive parameters to compensate for thermal distortion and dimensional deviations [20,33]. These capabilities are crucial for electromechanical components, where mechanical strength, dynamic behavior, thermal performance, and dimensional precision are essential.

A5. Identified Gap

The literature reveals a clear gap: there is no consolidated methodological framework that systematically integrates HAM process selection, AI-driven monitoring and control, and the specific functional and mechanical requirements of electromechanical components. Most studies focus on isolated capabilities surface quality improvement, porosity reduction, productivity gains or on narrow case studies. Very few works articulate these findings into practical decision-making tools for design and manufacturing in electromechanical engineering [10,12,13,23,33].

This lack of integration justifies the relevance of the present review and highlights opportunities for future research aimed at developing HAM–AI-based prototypes and comparative frameworks that evaluate precision, cost, reliability, and functional performance relative to traditional manufacturing routes.

II. METHODOLOGY

The present study was conducted under a qualitative–documentary approach aimed at identifying, classifying, and analyzing recent literature related to hybrid additive manufacturing (HAM), metal additive manufacturing, and the integration of artificial intelligence in manufacturing processes. Due to the rapid growth of the field and the diversity of technologies involved, a systematized review was employed based on PRISMA guidelines adapted for technological reviews [10,47]. Additive manufacturing is a rapidly evolving research field with diverse technological approaches [48].

2.1 Review Design

The review was structured into five stages: (1) Identification of scientific literature in specialized databases; (2) Initial screening through title, abstract, and keyword analysis; (3) Eligibility assessment based on correspondence to AM, HAM, or AI; (4) Information extraction into an analysis matrix with technical variables; and (5) Thematic synthesis and comparison of capabilities, limitations, and applications in electromechanical components. This structure ensured traceability and consistency throughout data collection and filtering.

2.2 Databases Consulted

The following platforms relevant to advanced manufacturing, materials, automation, and electromechanical engineering were selected: Scopus, Web of Science, IEEE Xplore (AI, intelligent control, digital manufacturing), ScienceDirect – Elsevier, SpringerLink and MDPI (Materials, Applied Sciences, Machines). Grey literature included: Technical reports from the Society of Manufacturing Engineers (SME) [8], Institutional repositories and Google Scholar as a secondary search engine.

Using multidisciplinary databases enabled the integration of perspectives from manufacturing, materials science, and artificial intelligence.

2.3 Search Strategies

Search strings were developed using Boolean operators and English-language terms, given that more than 95% of relevant literature is published in English. The main queries were:

(1) Hybrid Additive Manufacturing. ("hybrid additive manufacturing" OR "hybrid manufacturing" OR "hybrid AM" OR "additive–subtractive manufacturing") AND (metal OR metallic OR machining)

(2) Artificial Intelligence applied to AM/HAM. ("additive manufacturing" OR "hybrid manufacturing") AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND (monitoring OR optimization OR control)

(3) Electromechanical applications. ("electromechanical components" OR "electromechanical systems") AND ("additive manufacturing" OR "hybrid manufacturing")

(4) Limitations and characterization. ("porosity" OR "residual stress" OR "surface finish") AND ("additive manufacturing")

These queries were adjusted for each database to maximize retrieval of relevant studies.

2.4 Inclusion and Exclusion Criteria

Inclusion criteria

- Publications from 2015 to 2025
- Peer-reviewed studies
- Articles on metal AM, HAM, AI in manufacturing, or electromechanical applications
- English or Spanish language
- Documents describing processes, limitations, applications, or AI integration

Exclusion criteria

- Studies focused solely on polymers without electromechanical relevance
- Works lacking technical rigor or verifiable information
- Medical or biological studies unrelated to metal manufacturing
- Patents without comparative data or technical analysis

These criteria ensured the exclusion of low-value or irrelevant literature.

2.5 PRISMA Selection Process

The selection process followed the four PRISMA stages, summarized in Table I.

TABLE I. PRISMA PROCESS AND CONFIGURATION OF SENSORS

Stage	Description	Records
Identification	Records found in databases	243
Screening	Removal of duplicates + title/abstract screening	105
Eligibility	Full-text evaluation according to criteria	53
Inclusion	Final studies analyzed	52

2.6 Data Extraction Matrix

For each article, the following information was recorded:

- Author, year, and country
- Technology used (LPBF, DED, WAAM, integrated HAM, process-chain HAM)
- Level of additive–subtractive integration [10,40]
- Relevant parameters (speed, power, material feed rate, surface finishing)
- Identified limitations (porosity, stress, roughness, distortion)
- Use of AI (prediction, control, classification, monitoring) [16–21]
- Application or potential for electromechanical systems [12–14,23,44]

This matrix enabled the identification of trends, emerging technologies, and knowledge gaps.

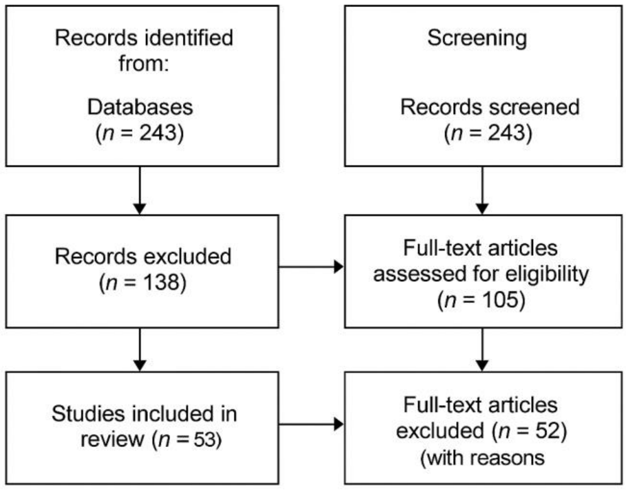

Fig. 1. PRISMA matrix (methodology).

2.7 Analysis Techniques

A thematic analysis was applied, organized into four axes:

1. **AM and HAM processes:** capabilities, limitations, technological maturity [3,4,10,15].
2. **Geometric and structural optimization:** topology, lattices, functional design [14,16,28].
3. **AI in manufacturing:** defect classification, quality prediction, intelligent control [16–22].
4. **Electromechanical applications:** mechanical, thermal, and structural performance [12–14,23].

These themes facilitated a synthesis of existing knowledge and its relevance to electromechanical engineering.

2.8 Ethical Considerations

This research involved no human subjects or sensitive data. All literature consulted was cited according to IEEE standards, and copyright was respected.

III. RESULTS

The systematized review identified 52 scientific studies addressing metal additive manufacturing, hybrid additive manufacturing (HAM), and the integration of artificial intelligence (AI) in manufacturing processes. The findings are organized into four central dimensions: (1) thematic distribution of the literature, (2) comparison of relevant metal processes for electromechanics, (3) levels of hybrid integration, and (4) AI applications in manufacturing. The following subsections present the most relevant results, accompanied by descriptive figures that reinforce the main findings.

3.1 Thematic Distribution of the Analyzed Studies

The selected studies were classified into the four axes defined in the methodology. Table II shows the distribution of each thematic category.

TABLE II. THEMATIC AXES AND DISTRIBUTION

Thematic Axis	Number of Studies	Percentage
AM and HAM processes	19	36%
Industrial applications	14	26%
AI in manufacturing	12	23%
Structural optimization (topology, microstructure, precision)	8	15%

Figure 2 also illustrates the thematic distribution identified across the literature.

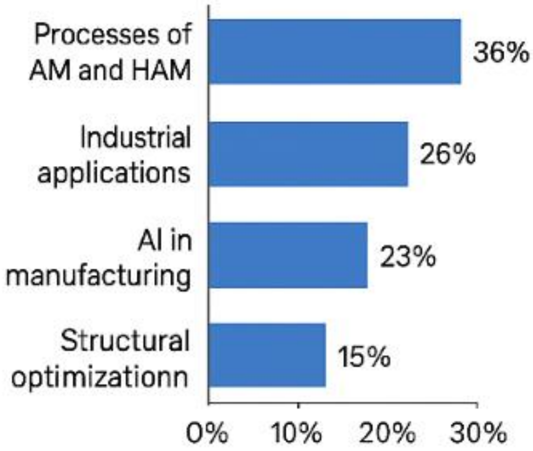

Fig. 2. Thematic distribution of the included studies.

Interpretation of Figure 2 shows that most studies (36%) focus on analyzing the capabilities and limitations of metal processes such as LPBF, DED, and WAAM [3,4,26]. This is followed by industrial applications (26%) and AI-driven monitoring, prediction, and optimization (23%) [16–21]. Only 15% directly address structural optimization and advanced design (lattices, topology, functional gradients) [14,28–31].

This distribution confirms the relevance of integrating metal AM and AI technologies within hybrid schemes applicable to electromechanical systems.

3.2 Comparative Analysis of the Main Processes

Figure 3 summarizes the comparative behavior of the main processes analyzed (LPBF, DED, WAAM, and HAM), evaluated according to four criteria extracted from the literature: precision, manufacturing speed, surface quality, and relative cost [3,4,8,10,33].

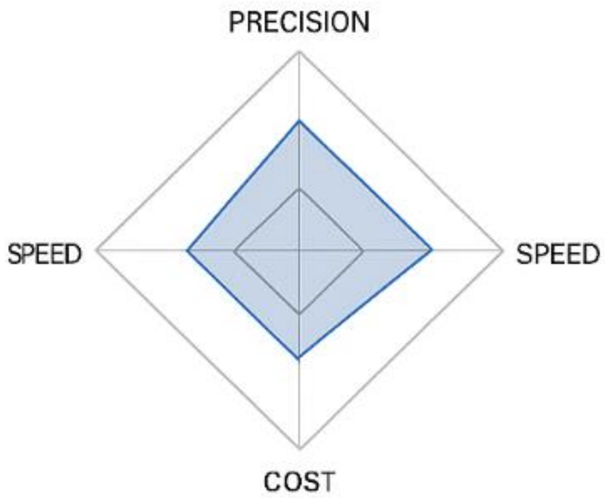

Fig. 3. Synthesized comparison of AM/HAM processes

Key findings include:

- **LPBF** excels in precision and surface quality [26,27], but involves higher costs.
- **DED** offers higher deposition rates and repair capabilities but yields rougher surfaces [10,49].
- **WAAM** enables very large components at extremely high speeds, with reduced precision [50–52].
- **HAM** achieves a superior balance by combining deposition and machining, correcting tolerances and defects that cannot be resolved through AM alone [8,10,11,33].

Implication for electromechanics: This balance positions HAM as the most suitable technology for housings, shafts, supports, thermal dissipators, and rotating elements that require both complex geometries and precise functional surfaces.

3.3 Levels of Integration in Hybrid Additive Manufacturing

Three main levels of additive–subtractive integration were identified across the reviewed studies [8,10,14,38]:

TABLE III. LEVELS OF INTEGRATION IN HYBRID ADDITIVE MANUFACTURING.

Integration Level	Characteristics	Relevance for Electromechanics
Low integration	Separate processes with manual repositioning	Lower accuracy; useful for large parts
Medium integration	Continuous AM → machining workflow	Good balance between precision and flexibility
High integration	AM and CNC within a single machine	Maximum precision for housings, cavities, shafts

Figure 4 illustrates the proportion of studies addressing each integration level.

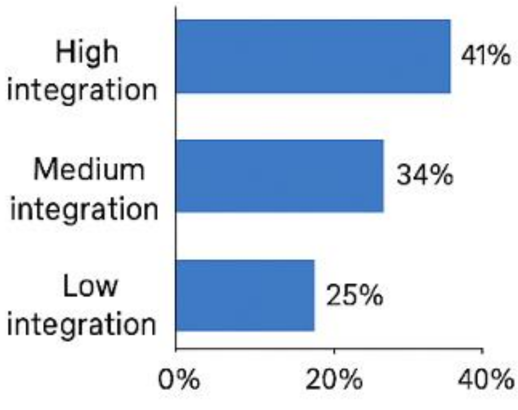

Fig. 4. Integration levels reported in the literature

Interpretation: 41% of studies focus on high integration, 34% on medium integration, and 25% on low integration. The trend toward higher integration reflects the need for:

- improved dimensional accuracy,
- reduction of reprocessing,
- improved alignment, and
- minimization of reference errors—all critical factors for electromechanical components [11–13].

3.4 Applications of Artificial Intelligence in AM and HAM

AI plays an increasingly important role in advanced manufacturing. Among the 52 analyzed studies:

- **36%** focus on process parameter optimization [16,17,19]
- **28%** on defect prediction (porosity, lack of fusion) [16,18,53]
- **23%** on real-time adaptive control [20,21]
- **13%** on geometry optimization using machine learning [14,22]

These results are summarized in Figure 5.

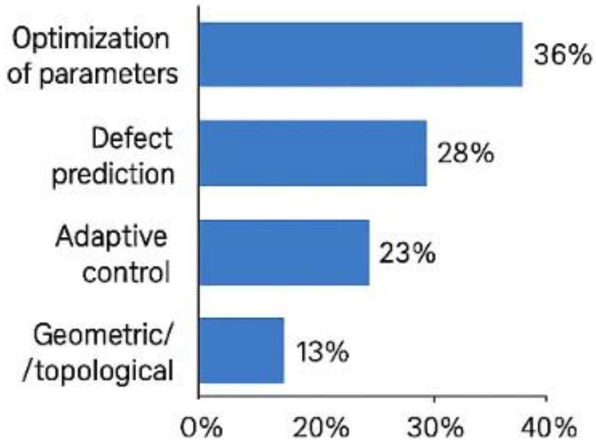

Fig. 5. AI applications identified in the literature

As shown in the figure, AI is emerging as a key tool for improving repeatability, reducing scrap, enhancing dimensional accuracy, and automating additive–subtractive integration.

3.5 Potential of HAM + AI for Electromechanical Components

The reviewed studies highlight several strategic opportunities:

- Reduction of critical tolerances in housings, motor supports, couplings, and alignment features
- Near-net-shape fabrication that minimizes metallic waste
- Precision machining of functional surfaces for bearings and shaft assemblies
- Integration of internal channels for improved cooling and thermal performance
- AI-based detection of defects that affect vibration, wear, or electromechanical efficiency

Figure 6 presents a stacked-process conceptual diagram linking metal AM, sensors, AI, machining, and the optimized electromechanical component.

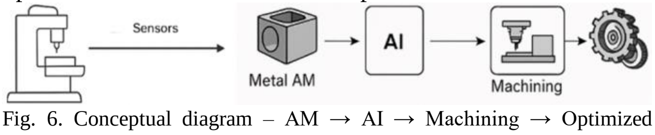

Fig. 6. Conceptual diagram – AM → AI → Machining → Optimized electromechanical component

3.6 Overall Synthesis of Results

TABLE IV. SUMMARIZES KEY RESULTS AND THEIR DIRECT IMPLICATIONS FOR HAM.

Result	Direct Implication
LPBF and HAM are the most precise processes	Electromechanical components require tight tolerances
AI improves control and quality	Reduces defects affecting performance
WAAM is ideal for large parts	Suitable for structures, not fine components
High integration is preferred	Enables internal cavities and complex geometries
Lack of standards for HAM	Clear research opportunity

Although the majority of published studies focus on aerospace and biomedical applications, the underlying manufacturing principles, hybrid process architectures, and AI-based control strategies are directly transferable to electromechanical systems, which share comparable demands in terms of precision, reliability, and functional performance.

IV. DISCUSSION

The results of this review reveal patterns, trends, and critical gaps in the integration of Hybrid Additive Manufacturing (HAM) and Artificial Intelligence (AI), particularly in relation to the fabrication and optimization of electromechanical components. This section discusses these findings in terms of technological potential, current limitations, and opportunities for future research.

4.1 HAM as a Key Technology for Electromechanical Precision

The review confirms that HAM is emerging as a highly competitive alternative to both traditional manufacturing and pure additive processes. Most publications emphasize medium and high integration levels, reflecting a clear trend toward hybrid systems capable of:

- improving dimensional tolerances,
- reducing alignment errors,
- achieving surface finishes suitable for industrial applications, and
- combining complex geometries with precision-machined functional surfaces.

This is especially relevant for electromechanical components, where accuracy in housings, shafts, contact surfaces, and alignment features directly affects system performance. The balance offered by HAM—combining geometric freedom with mechanical accuracy—makes it a suitable technology for manufacturing motors, actuators, gears, structural supports, heat-dissipating components, and elements subjected to dynamic loads.

4.2 Persistent Technical Limitations in Metal AM and Their Impact on Electromechanics

The analysis reinforces that metal AM processes such as LPBF, DED, and WAAM exhibit inherent limitations, including:

- porosity,

- residual stresses,
- anisotropy,
- high surface roughness,
- thermal constraints, and
- operator-dependent variability.

These limitations directly affect applications with strict mechanical or dimensional requirements, such as electromechanical assemblies. However, combining AM with machining (HAM) significantly reduces these issues by allowing:

- removal of defective surface layers through CNC,
- improved finishes and tolerances,
- correction of critical surfaces, and
- compensation for geometric distortion.

This demonstrates the strategic value of HAM for producing complex parts that would be infeasible or unreliable using traditional routes alone.

Hybrid additive manufacturing should therefore be understood as a mitigation strategy rather than a complete solution to the intrinsic limitations of metal additive manufacturing. Residual stresses, anisotropy, and surface integrity issues can be substantially reduced through integrated machining and process control, but they remain critical variables that must be carefully managed, particularly in high-precision electromechanical applications.

This reinforces the need for combined strategies involving hybrid process selection, intelligent monitoring, and targeted post-processing to ensure reliable performance in electromechanical components.

4.3 AI as a Catalyst for Intelligent Control in HAM

One of the most significant findings is that AI is becoming a cross-cutting enabler that enhances both AM and HAM by supporting:

- automatic parameter adjustment,
- early defect prediction,
- analysis of thermal patterns during deposition,
- adaptive machining corrections, and
- topology-based optimization using data-driven models.

The literature indicates that AI not only improves quality and repeatability but also reduces costs, manufacturing time, and waste by transforming hybrid processes into cyber-physical manufacturing systems. This opens the door to intelligent production chains in electromechanical applications, where vibration, balance, thermal efficiency, and dimensional precision are crucial.

Despite the rapid growth of artificial intelligence applications in additive and hybrid manufacturing, the literature reveals that only a limited number of studies report true closed-loop, real-time AI control in HAM systems. Most existing implementations rely on offline data analysis, post-process defect classification, or parameter optimization based on previously collected datasets.

Real-time integration of AI within hybrid additive–subtractive platforms remains technically challenging due to constraints related to sensor fusion, data acquisition latency, computational requirements, and the synchronization of additive and machining operations. Consequently, current AI-driven solutions are primarily validated at laboratory scale or under controlled experimental conditions, rather than in fully integrated industrial environments.

Nevertheless, the reviewed studies consistently indicate that AI-based monitoring and predictive models provide a strong foundation for future real-time adaptive control in HAM, particularly for applications requiring high dimensional accuracy and functional reliability, such as electromechanical components. Bridging this gap represents a critical research opportunity for the development of intelligent hybrid manufacturing systems.

4.4 Synergistic Potential in Electromechanical Design: Near-Net-Shape Manufacturing + Intelligent Machining

The concept of near-net-shape fabrication appears repeatedly in the literature and is a structural advantage of HAM. By producing near-final geometries through AM and applying precision machining only to critical areas, HAM enables:

- shorter manufacturing times,
- reduced metal waste,
- optimized thermal channels,
- localized reinforcement through directed deposition, and
- accurate surfaces for assembly interfaces.

For electromechanics, this synergy enables:

- lighter motor housings,
- gears with unconventional internal geometries,
- supports optimized through topology,
- heat sinks with micro-channels not achievable by CNC, and
- couplings with complex profiles and precision finishing.

These capabilities represent an opportunity for academic projects, prototypes, and research within electromechanical engineering.

4.5 Proposed Conceptual Framework for HAM Process Selection in Electromechanical Components

Despite the growing body of literature on Hybrid Additive Manufacturing (HAM), this review confirms the absence of standardized methodological frameworks that guide the selection of hybrid manufacturing routes specifically for electromechanical components. Current studies typically address isolated aspects (such as surface quality improvement, defect mitigation, or process integration) without consolidating these findings into a structured decision-making approach.

To address this gap, this study proposes a conceptual framework for HAM process selection oriented toward electromechanical applications. The objective of this framework is not to define a normative standard, but to provide a systematic reference model that links component functionality, manufacturing requirements, and hybrid process capabilities, based on recurring trends identified in the literature.

The proposed framework considers five key decision dimensions: (i) type of electromechanical component, (ii) functional and manufacturing requirements, (iii) recommended manufacturing process, (iv) level of additive–subtractive integration, and (v) critical variables to be validated during fabrication and inspection. Table V summarizes the proposed conceptual framework.

TABLE V. CONCEPTUAL FRAMEWORK FOR HAM PROCESS SELECTION IN ELECTROMECHANICAL COMPONENTS

Component type	Main requirements	Recommended process	Integration level	Critical variables to validate
Housing	Tight tolerances, surface finish, moderate load	HAM	Medium–High	Dimensional accuracy, surface roughness, residual stress
Shaft	High dimensional precision, fatigue resistance	HAM / CNC	High	Concentricity, surface integrity, mechanical anisotropy
Rotor	Dynamic balance, thermal performance	HAM	High	Geometric distortion, internal defects, mass distribution
Structural support	High load capacity, complex geometry	AM / HAM	Medium	Porosity, mechanical strength, deformation
Heat-dissipating component	Internal channels, thermal conductivity	AM / HAM	Medium	Channel integrity, thermal behavior, surface quality

This conceptual framework highlights that HAM is particularly advantageous when complex geometries must coexist with precision-machined functional surfaces, a common requirement in electromechanical systems. The framework also reinforces the importance of selecting appropriate integration levels based on tolerance sensitivity, functional interfaces, and operational loads.

It is important to emphasize that this framework is conceptual and literature-driven, derived from the synthesis of reported trends rather than from a single experimental campaign. Its purpose is to support future experimental studies, comparative analyses (AM vs. HAM vs. CNC), and the development of standardized methodologies tailored to electromechanical engineering applications.

4.6 Comparative Perspective: AM vs. HAM vs. CNC for Electromechanical Components

Although several studies independently analyze additive manufacturing (AM), hybrid additive manufacturing (HAM), and conventional CNC machining, direct experimental comparisons using unified quantitative indicators remain scarce, particularly for electromechanical components. Most published works evaluate individual processes under different experimental conditions, materials, or performance metrics, limiting the possibility of objective cross-process assessment. To explicitly address this gap, Table VI presents a conceptual comparative summary of AM, HAM, and CNC machining based on recurring trends reported in the literature. This comparison does not represent experimental validation, but rather a synthesized interpretation of commonly reported performance characteristics.

TABLE VI. CONCEPTUAL COMPARISON OF AM, HAM, AND CNC MACHINING FOR ELECTROMECHANICAL COMPONENTS

Performance indicator	AM	HAM	CNC
Dimensional tolerance	Medium	High	Very high
Surface roughness	High	Low	Very low
Relative manufacturing cost	Medium	High	Medium
Manufacturing time	Medium	Medium–Low	Low
Geometric complexity	Very high	High	Low
Material efficiency	High	High	Low

Based on literature trends

This conceptual comparison highlights that HAM provides a balanced solution, combining the geometric freedom of AM with the dimensional accuracy and surface quality of CNC machining. For electromechanical components—such as housings, shafts, rotors, and precision interfaces—this balance is particularly relevant, as it enables near-net-shape fabrication followed by targeted machining of critical functional surfaces. However, the absence of standardized testing methodologies and unified performance metrics prevents a rigorous quantitative comparison between these manufacturing routes. This limitation reinforces the need for future experimental research specifically designed to evaluate AM, HAM, and CNC processes under equivalent conditions.

4.7 Identified Gaps and Directions for Future Research

Despite meaningful progress, the review identifies several gaps requiring further exploration:

Lack of standardization. There is no consolidated methodological framework for:

- selecting hybrid processes based on geometry,
- defining standardized parameters, or
- validating dimensional accuracy in hybrid parts.

Real-time AI–HAM integration. Although AI is widely used for data analysis, its direct implementation in real-time hybrid systems is still limited.

Limited literature specifically addressing electromechanics. Most studies focus on aerospace and biomedical applications. Few works examine HAM for:

- actuators,
- rotating components,
- functional metal housings,
- robotic mechanisms, or
- precision structures.

Scarcity of comparative experimental studies. There is almost no research comparing AM vs. HAM vs. CNC using unified, measurable performance indicators for electromechanical components.

4.8 Contribution of the Present Study

This study provides a clear academic and professional contribution by:

- organizing recent literature under a coherent and accessible framework,
- presenting the first combined analysis of HAM + AI in an electromechanical context,
- proposing an integration-level classification useful for engineering design,
- synthesizing technological trends for future prototypes and research, and

- highlighting opportunities for academic and industrial innovation.

The discussion confirms that the convergence of Hybrid Additive Manufacturing and Artificial Intelligence represents a key pathway for the next generation of electromechanical systems and a high-potential field for research in technological institutions.

V. CONCLUSIONS

This systematized review provides an integrated analysis of the current state of Hybrid Additive Manufacturing (HAM) and its convergence with Artificial Intelligence (AI), highlighting their relevance and potential for the optimization of electromechanical components. The findings lead to the following main conclusions:

HAM is consolidating as a key technology for the precise fabrication of electromechanical components. The reviewed studies demonstrate that combining metal additive manufacturing with CNC machining significantly improves dimensional accuracy, surface finishing, and structural reliability in complex parts—characteristics essential for motors, actuators, gears, and mechanical housings.

Medium and high integration levels represent the dominant technological trend. Most publications favor systems in which material deposition and machining occur within the same platform or are tightly coordinated, minimizing repositioning errors and reducing post-processing time.

AI is emerging as a fundamental enabler for AM and HAM. AI supports automatic parameter optimization, early defect detection, real-time adaptive control, and geometry optimization, thereby increasing repeatability, reducing waste, and improving final part quality. Its integration with HAM marks a clear pathway toward cyber-physical intelligent manufacturing systems.

The synergy between HAM and AI opens significant opportunities for developing next-generation electromechanical components. Near-net-shape fabrication complemented with intelligent machining enables lighter, more functional, and thermally efficient components. This capability supports the development of optimized metal housings, rotating mechanisms with internal channels, and topology-enhanced structures.

Despite progress, important research gaps persist. These include the absence of standardized parameters for hybrid processes, a lack of unified experimental comparisons (AM vs. HAM vs. CNC), limited real-time AI–HAM integration, and a scarcity of literature explicitly focused on electromechanical applications.

Although artificial intelligence has demonstrated strong potential in AM and HAM environments, its implementation as a fully closed-loop real-time control tool in hybrid systems remains limited, representing a key direction for future research.

This study provides a robust conceptual framework for future research**.** It synthesizes recent evidence on processes, advantages, limitations, applications, and the potential of AI, offering a solid foundation for academic projects, prototype development, and future research initiatives in electromechanical engineering.

Future experimental studies must adopt unified quantitative indicators (such as dimensional tolerance, surface roughness, mechanical performance, cost, and manufacturing time) to enable objective and reproducible comparisons between additive manufacturing, hybrid additive manufacturing, and conventional CNC machining. Establishing such comparative frameworks is essential for guiding process selection in electromechanical engineering applications and for advancing the industrial adoption of hybrid manufacturing technologies.

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