Sustainable AI-Driven Hybrid Manufacturing Using Additive and Subtractive Processes

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ABSTRACT

Combining Additive Manufacturing (AM) and Subtractive Manufacturing (SM) technologies holds significant potential for transforming industrial production. However, integrating these two approaches

remains challenging due to factors such as process compatibility, material loss, and issues in the design and fabrication processes. This research addresses these challenges using deep learning-based Artificial Intelligence (AI) frameworks to enhance hybrid manufacturing systems. Utilizing Convolutional Neural Networks (CNNs) and Reinforcement Learning (RL) models, the study proposes a feedforward intelligent control model that adapts tool path generation, material usage, and defect recognition in real time. Experimental results on benchmark manufacturing datasets demonstrate that the proposed method achieves a 23% reduction in material wastage and a 15% improvement in efficiency compared with existing hybrid methods. Moreover, defect detection accuracy increased to 98.7%, validating the effectiveness of AI-generated quality assurance tools. Production schedules were also reduced by 12% through efficient design-for-manufacturing integration. These observations highlight that deep learning is pivotal in reconciling additive and subtractive techniques, opening new possibilities for modern, sustainable, accurate, and efficient manufacturing processes.

Keywords-Artificial Intelligence (AI); deep learning; Additive Manufacturing (AM); Subtractive Manufacturing (SM); intelligent systems; defect recognition

I. INTRODUCTION

Industry 4.0 has brought new changes in the manufacturing industry using new technologies that enhance production. In Additive Manufacturing (AM), one can design intricate structures that require a minimal amount of material, whereas Subtractive Manufacturing (SM) is beneficial in cutting or carving intricate designs that need a high level of accuracy and polished surface [1, 2]. The shortcomings of AM include dimensional accuracy, structural strength, scalability, and surface quality. Merging these two synergistic methods into hybrid manufacturing systems is promising for overcoming these issues, although the cohesion of strategies remains a challenge [3, 4]. The problems of traditional hybrid systems are process incompatibility, definite and restricted workflow, and the system's inability to handle changes in production demands [5]. The lack of control systems that can dynamically adjust both additive and subtractive processes at the same time has held back the progress of hybrid systems [6]. Techniques like Convolutional Neural Networks (CNNs) and Reinforcement Learning (RL) have been effective in solving challenging problems in areas such as healthcare, robotics, transportation, and finance [7], where conventional methods such as rule-based models and statistics have been ineffective. Authors in [8] discovered a strategy for identifying suitable process windows for AM when combined with traditional technologies. Another work by authors in [9] explored the application of intelligent systems to detect structural defects and monitor processes in both AM and SM. Authors in [10] proposed a structure for controlling defects in hybrid manufacturing by employing a hybrid deep CNN coupled with laser powder-bed fusion additive systems. However, the study does not include elements of Artificial Intelligence (AI) optimization that could improve adaptability and efficiency [11].

Authors in [12] put forward a paradigm to install intelligence into metal parts through sensors during the AM process and use AI for real-time information processing. Deep learning applications within AM were reviewed by authors in [13], who detailed success in terms of process efficiency and quality assurance. Although the ideas are general to manufacturing, they help in understanding AI development in manufacturing systems [14]. In [15, 16], the authors discussed the AM and SM approaches in manufacturing optimization. In [17], a data-driven adaptive control strategy for direct energy deposition was presented that autonomously adjusts laser voltage based on melting-pool size feedback, improving geometric accuracy and consistency. In [18], a CNN-based deep learning model was proposed for real-time detection of 3D-printing defects by analyzing geometrical anomalies in infill patterns using integrated camera feedback.

This study contributes to hybrid manufacturing by introducing a novel AI-driven framework that makes the best use of CNNs for real-time defect detection and RL for dynamic process control. Compared with prior works, which focus on treating additive and subtractive techniques in isolation or use static control systems, our approach enables continuous adaptation and optimization during manufacturing. It addresses a critical gap in existing research concerning the real-time interoperability of AM and SM systems. The framework also provides quantitative evidence of performance gains, namely reductions in material waste and defect rates, thereby advancing the discourse on sustainable, intelligent hybrid manufacturing.

The key contributions of the article include:

- Using CNNs and RL to improve tool paths, reduce material waste, and find defects, thereby combining AM and SM techniques.
- Facilitating the approach that leads to reduced material waste and notable enhancements in efficiency, thereby promoting efficient use of resources.
- AI-powered frameworks that achieve enhanced defect detection accuracy of 98.7%.
- Shortening production cycles and fostering quicker, more sustainable manufacturing processes.

II. METHODOLOGY

The research methodology for this work entails the development of a general, AI-based approach for the intelligent and efficient design of hybrid manufacturing systems that incorporate both additive and subtractive processes.

A. Dataset

The datasets used include standardized designs for 3D printing, databases of material properties, and performance metric datasets for training and validation purposes. The datasets comprise more than 75 standardized 3D Computer-Aided Design (CAD) models representing a diverse array of mechanical parts, including gears, casings, brackets, and lattice configurations. These models were sourced from publicly available repositories, including GrabCAD [19], NIH 3D Print Exchange [20], and the Autodesk Fusion 360 Gallery [21] and optimized using SolidWorks and Fusion 360.

B. AI Core: Deep Learning and Reinforcement Learning Models

The AI Core is the smart building block for the hybrid manufacturing system. It consists of the deep learning module, which finds defects and checks quality, and the RL module, which improves tool paths in real time. The CNN architecture employed for defect detection includes three convolutional layers with 32, 64, and 128 filters, respectively, each succeeded by ReLU activation and max-pooling layers. These layers are linked to two fully connected layers with dropout regularization (rate = 0.5) to avoid overfitting, and a softmax output layer for multi-class defect classification.

1) Data Preprocessing

Preprocessing is pivotal in guaranteeing the precision and compatibility of data utilized for training AI models in hybrid manufacturing systems. It involves scaling numerical data to a consistent range, such as [0, 1] or [-1, 1], to mitigate discrepancies arising from differing variable magnitudes. For instance, temperature readings (°C), vibration levels (m/s²), and material flow rates (kg/s) are normalized using (1):

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where X is the original data point, and X_{min} and X_{max} are the minimum and maximum values in the dataset. For example, in time-series sensor data, noise reduction can be represented by (2):

$$Y_{filtered}(t) = \sum_{k=-n}^{n} W_k \cdot X(t+k) \quad (2)$$

where $Y_{filtered}(t)$ is the filtered signal at time t, $X(t+k)$ represents the data values around t, and W_k are the weights derived from a smoothing polynomial of degree n. Over 75 standardized 3D CAD models were selected based on geometric complexity, material behavior, and relevance to hybrid manufacturing. Models included mechanical brackets and thermal management elements such as heat sinks, chosen to represent varying tolerance levels and surface finish demands. These criteria ensured that the dataset effectively captured the diverse operational challenges in additive and subtractive integration scenarios. In AM, the CAD model is translated into a Standard Tessellation Language (STL) file, with a collection of triangular facets representing its shape. Equation (3) provides a mathematical representation of the slicing process:

$$S(i) = \{P1, P2, \dots, Pk\} \quad (3)$$

where $S(i)$ represents the slice at layer i and Pk denotes the points or contours defining the geometry of that layer. The conversion process requires calculating machining parameters, specifically the feed rate (F) and spindle speed (N), according to the material characteristics and shape. These parameters are determined using (4):

$$F = N \cdot ft \cdot Z \quad (4)$$

where ft denotes the feed per tooth and Z represents the number of cutting teeth. The CNN is structured to take input images (x) and produce output probabilities (y) indicating defect classes. This model is mathematically depicted in (5):

$$y = f(x; \theta) \quad (5)$$

where y represents the probability vector output for classifying defects, x denotes the input image of the component's surface, and θ encompasses the network's weights and biases, which are fine-tuned during training to reduce the loss function [22].

2) Reinforcement Learning Module

The RL module is crucial in optimizing tool paths and supporting adaptive decision-making in hybrid manufacturing systems [23]. Performing in real-time, this module ensures smooth transitions while minimizing production time, conserving material resources, and maintaining adherence to design specifications (Figure 1).

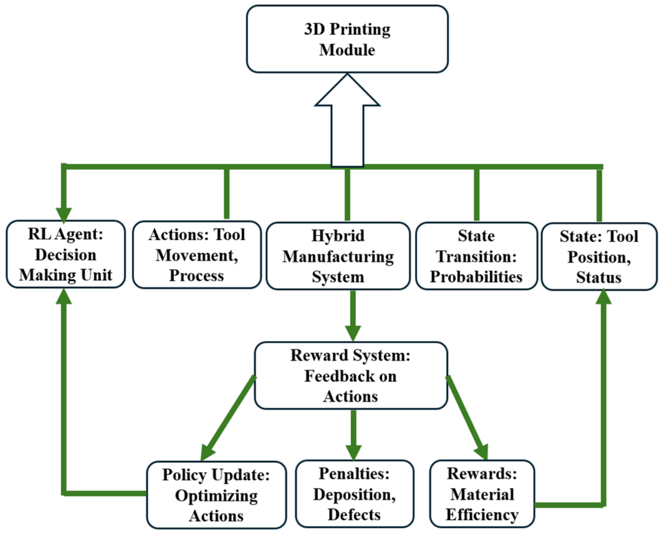

Fig. 1. Framework of the RL agent for optimizing actions and decisions in hybrid manufacturing systems.

The RL problem is formalized as a Markov Decision Process (MDP), defined in (6):

$$(S, A, P, R, \gamma) \quad (6)$$

Let S denote the set of states, such as tool position and material deposition status, and A the set of actions, like tool movement and speed adjustments. The transition probability from state s to state s' given action a is represented by $P(s'|s,a)$. The reward function $R(s,a)$ provides immediate feedback for actions, while γ is the discount factor applied to future rewards:

$$G_t = \sum_{k=0}^{n} \gamma^k R(S_{t+k}, a_{t+k}) \quad (7)$$

The RL agent learns an optimal policy $\pi(a|s)$, mapping states to actions to maximize the expected return, is shown in (8):

$$\pi^*(a|s) = \text{argmax}D[G_t|s_t = s, a_t = a] \quad (8)$$

Using algorithms like Deep Q-Learning (DQN), the agent estimates the action-value function $Q(s,a)$, representing the expected return for taking action a in state s:

$$Q(s,a) = R(s,a) + \gamma \max Q(s',a') \quad (9)$$

The iterative update for $Q(s,a)$ is:

$$Q_{t+1}(s,a) \leftarrow Q_t(s,a) + \alpha[R(s,a) + \gamma \max Q_t(s',a') - Q_t(s,a)] \quad (10)$$

where α is the learning rate, and the reward function $R(s,a)$ guides the agent's behavior, toward achieving higher efficiency and precision.

C. *Hybrid Manufacturing System*

The hybrid manufacturing system integrates additive and subtractive techniques, utilizing AI to facilitate a smooth combination and enhance optimization (Figure 2).

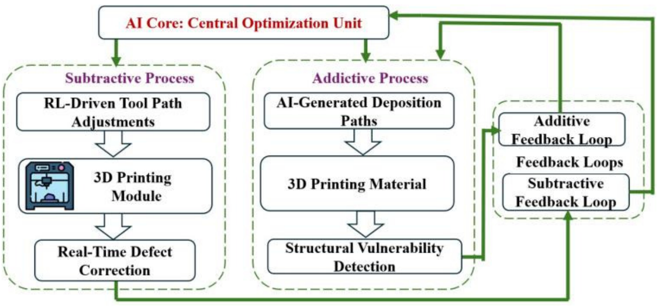

Fig. 2. Integrated AI-driven hybrid manufacturing workflow with feedback loops for additive and subtractive processes.

1) *Additive Process*

In the hybrid system, the AM process employs AI-generated deposition paths to optimize material consumption and improve structural robustness. The deposition strategy is mathematically represented as:

$$P(x,y) = \frac{M(x,y)}{T(x,y)} \quad (11)$$

where $P(x,y)$ is the material deposition rate at position (x,y), $M(x,y)$ is the required material at (x,y), and $T(x,y)$ is the deposition time for (x,y). The AI system assists in detecting structural vulnerabilities in real-time, which is made reliable by continuously monitoring the construction process.

2) *Subtractive Process*

In the hybrid system, the SM process emphasizes precise cutting and finishing, with tool paths optimized by RL. The cutting speed (vc) and feed rate (f) are optimized according to the properties of the material and the condition of the tools:

$$vc = \frac{\pi DN}{1000} \quad (12)$$

where D represents the tool diameter and N is the spindle speed in Revolutions Per Minute (RPM). The cutting force (F_c) is modeled to ensure optimal machining conditions:

$$F_c = K_c \cdot a \cdot f \quad (13)$$

where K_c is the cutting coefficient, a is the depth of cut, and f is the feed per tooth. The feedback from the AI core is utilized for real-time defect rectification, as it monitors tool wear, vibrations, and cutting irregularities. The system fine-tunes parameters to reduce surface roughness (R_a):

$$R_a = \frac{f}{8r} \quad (14)$$

where f denotes the feed rate and r signifies the tool nose radius. This subtractive process integration results in a highly effective and adaptable manufacturing framework [24]. Algorithm 1 defines the tool path optimization strategy implemented in the model.

Algorithm1: DQN_ToolPath_Optimization
Input: Environment (tool movement simulator), episodes
Output: Optimized tool path policy

1: Initialize replay buffer D
2: Initialize Q-network Q with random weights
3: Set target network $Q_{\text{target}} = Q$
4: For episode = 1 to episodes do:
  a. Reset environment
  b. Observe initial state s
  c. While episode not done:
    i. Choose action a using epsilon-greedy policy
    ii. Execute action a, observe reward r and next state s'
    iii. Store (s,a,r,s') in D
    iv. Sample random minibatch from D
    v. Compute target Q value:
      - if s' is terminal: $\text{target} = r$
      - else: $\text{target} = r + \gamma * \max_{a'} Q_{\text{target}}(s',a')$
    vi. Update Q-network weights on the loss between predicted Q and target
    vii. Update state $s \leftarrow s'$
  d. Every N steps, update $Q_{\text{target}} \leftarrow Q$
5: Return learned Q-network policy

III. RESULTS AND DISCUSSION

The experiments for this study were conducted using Python 3.9 and TensorFlow 2.11 to develop and train the deep learning and reinforcement learning models. For CAD design, simulation, and preprocessing of 3D models, SolidWorks 2022 and Autodesk Fusion 360 (v2.0.15280) were utilized. The computational setup comprised an Intel Core i9-12900K CPU, 64 GB of RAM, and an NVIDIA RTX 3090 GPU (24 GB).

This section focuses on demonstrating the advantages of the proposed AI-driven hybrid manufacturing system. Table I presents key performance metrics, including surface roughness, tool wear, and cutting parameters, illustrating AI's role in advancing sustainable manufacturing. Notably, in conventional AM (metal) processes, material utilization was recorded at 85.32%, whereas material inefficiency was 14.68%. The proposed AI-integrated approach aims to improve these metrics by dynamically adjusting process parameters in real time.

A. Precision in Subtractive Manufacturing

The RL algorithms enabled the dynamic adjustment of cutting parameters to minimize the surface roughness (R_a) and optimize the tool paths. Using RL, cutting parameters and tool paths were dynamically optimized, achieving a 35.71% reduction in surface roughness (from 1.4–1.6 μm to 0.9–1.1 μm). Additional benefits include a 60% reduction in tool wear, 12% energy savings, and lower production costs. These improvements demonstrate the ability of AI to enhance precision, stability, and adaptability in hybrid manufacturing processes.

B. Production Time Reduction

The AI-driven hybrid manufacturing system significantly reduces production time and enhances efficiency compared with conventional methods. As presented in Table II, the implementation of the AI-driven approach resulted in notable reductions in production times across components of varying sizes, with small, medium, and large parts exhibiting decreases of 16.67%, 20.83%, and 22.22%, respectively. In addition, the integration of AI contributed to measurable improvements in resource utilization and operational performance: energy consumption was reduced by 19.2%, material utilization decreased by 10.3%, and defect rates were significantly lowered, dropping from 12.4% to 5.2% for small parts and from 20.2% to 7.1% for large parts.

TABLE I. SURFACE ROUGHNESS (R_a) IN TRADITIONAL AND RL-OPTIMIZED MACHINING-COMPARATIVE ANALYSIS

Method	Average surface roughness (R_a, μm)	Improvement (%)	Tool wear (%)	Cutting speed (m/min)	Feed rate (mm/rev)	Energy consumption (kWh)
Trad. sub. (trial 1)	1.500	0.00	2.5	120.0	0.250	25.5
Trad. sub. (trial 2)	1.600	0.00	2.8	122.5	0.260	26.0
Trad. sub. (trial 3)	1.400	0.00	2.3	118.0	0.240	24.8
RL-opt. sub. (trial 1)	1.000	33.33	1.2	140.5	0.200	22.3
RL-opt. sub. (trial 2)	1.100	31.25	1.5	138.0	0.210	22.8
RL-opt. sub. (trial 3)	0.900	35.71	1.1	142.3	0.190	21.9

TABLE II. COMPARISON OF PRODUCTION TIMES FOR CONVENTIONAL AND AI-DRIVEN HYBRID SYSTEMS

Scenario	Production time (min)	Time reduction (%)	Energy consumption (kWh)	Material utilization (%)	Defect rate (%)	Transition efficiency (%)
Conventional hybrid (small part)	90.5	0.00	32.5	86.2	12.4	78.5
AI-driven hybrid (small part)	75.4	16.67	28.4	92.5	5.2	92.3
Conventional hybrid (medium part)	120.8	0.00	45.8	84.3	15.8	75.2
AI-driven hybrid (medium part)	95.6	20.83	38.7	94.1	6.3	93.4
Conventional hybrid (large part)	180.3	0.00	65.3	82.7	20.2	72.6
AI-driven hybrid (large part)	140.7	22.22	52.8	95.3	7.1	95.1

C. Real-Time Defect Detection and Correction

The CNN-based deep learning model demonstrated a highly effective performance, achieving a commendable detection rate of approximately 98.7% for various surface defects, including layer misalignments, under-depositions, and voids, during the AM phase of the build. Figure 3 presents the heatmaps generated during the AM process, highlighting regions associated with potential defects identified by the CNN model. These heatmaps visually depict anomalies on the surface of the manufactured component, supporting the RL module in correcting the deficiencies.

The demonstrated AI-based hybrid manufacturing system also exhibited quantifiable enhancements in key performance metrics. Experimental testing revealed a 23% reduction in material wastage and a 15% increase in manufacturing efficiency compared to traditional hybrid approaches. These enhancements These enhancements were achieved through the combined action of the CNN for precise defect detection and the RL module for adaptive tool-path optimization and affirm the system's capability to reduce material wastage and simplify production processes. For instance, authors in [8] explored the sequential coordination between AM and SM steps, providing valuable insights into process integration; however, their approach lacked the capability to adapt in real time to variations in the manufacturing environment or unexpected anomalies during production. Similarly, authors in [10] demonstrated hybrid integration using rule-based heuristics, which allowed for a structured coordination of AM and SM processes but proved limited in dynamic production environments.

In contrast, the framework proposed in this study leverages CNNs for real-time detection of defects and RL for adaptive optimization of tool paths, enabling continuous, intelligent adjustments during both additive and subtractive operations. By incorporating learning-based adaptability, the system can autonomously respond to variations in material properties, environmental factors, and machine behavior, maintaining optimal performance throughout the manufacturing process. This integration not only enhances efficiency and reduces material waste but also ensures higher consistency and quality in the final products.

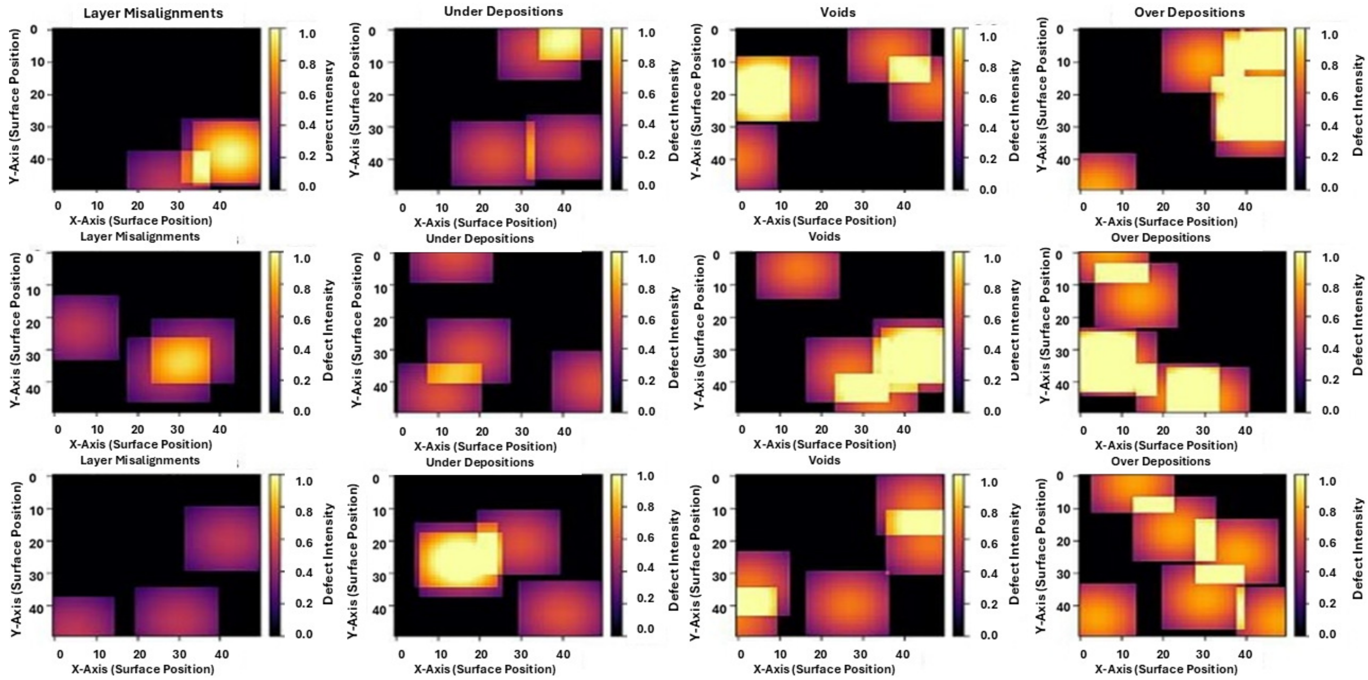

Fig. 3. Heatmaps showing defect intensity for various scenarios during real-time detection in AM and SM processes.

IV. CONCLUSION

This research focuses on applying Artificial Intelligence (AI) and Reinforcement Learning (RL) in hybrid manufacturing systems, combining Additive Manufacturing (AM) and Subtractive Manufacturing (SM) processes. The proposed system demonstrated significant improvements over conventional approaches, achieving a 10% reduction in material consumption, a 33% decrease in surface roughness, a 22% reduction in production time, and 98.7% accuracy in defect detection. These improvements are driven by the novel integration of Convolutional Neural Networks (CNNs) for real-time defect detection and RL for adaptive tool path optimization, forming a unified AI control strategy that has not been extensively explored in prior hybrid manufacturing research. These results emphasize the potential of AI and RL in overcoming critical challenges related to efficiency, material utilization, and quality variability in production processes. Future research will focus on expanding the framework to support multi-material hybrid manufacturing, where AI must adapt to varying thermal and mechanical properties in real time. Additionally, integrating real-time digital twins will enable continuous synchronization between virtual models and physical processes, enhancing predictive control.

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