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Machine Learning-Based Control System Simulation for In-Situ Monitoring of Additive Manufacturing Process

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Abstract: The current study presents a novel approach for optimizing process velocity for a desired cooling rate in additive manufacturing (AM) through a machine learning-based control system, aligning with Industry 4.0 principles of smart manufacturing. Focusing on Directed Energy Deposition (DED) and extending its principles to Powder Bed Fusion (PBF) and Fused Deposition Modelling (FDM), the study uses infrared pyrometers for in-situ monitoring of temperature variations during deposition. Data from varying scan speeds (600, 800, 1000, and 1200 mm/min) were used to train a machine-learning (ML) model to control the real-time cooling rate. Simulations evaluated the model's effectiveness, revealing consistent cooling rates throughout the deposition process. This research promotes sustainable production practices, contributing to the United Nations Sustainable Development Goals (SDGs).

Keywords: Additive Manufacturing (AM), Machine Learning (ML), Sustainable Development Goals (SDGs), Data Driven Manufacturing, Simulation and Modelling.

1. Introduction

1.1. Additive Manufacturing

Additive Manufacturing (AM) is a technology that builds parts layer by layer directly from digital models, which has revolutionized product design and production. Unlike traditional methods that remove material, AM enables greater design flexibility, the production of complex geometries, and the economical use of materials with little waste [1]. This strategy is essential for sectors requiring high-performance parts, such as aerospace, automotive, and defense. AM promotes clean manufacturing by reducing material waste, conserving resources, and supporting sustainable production practices [1].

1.2. Importance of cooling rate in AM

Controlling the cooling rate in AM processes is essential for achieving the desired material properties, such as hardness and strength while preventing defects like cracks and residual stresses [6]. A stable cooling rate ensures the homogeneity of the final parts, optimizes the process, and minimizes thermal distortion [10]. Controlling the cooling rates also helps control the dimensional accuracy and the microstructure, which influences the mechanical performance [11]. In-situ monitoring of the cooling rate is crucial for real-time adjustments and maintaining quality standards of the manufacturing process [2].

1.3. Role of Machine Learning (ML)

ML enhances AM by predicting the cooling rate during the deposition process, providing the parametric changes necessary to control the cooling rates [4]. This improves process stability and product homogeneity. By reducing human intervention, ML reduces the chances of operator-related errors, optimizing efficiency and supporting key Sustainable Development Goals (SDGs). Specifically, it drives innovation and improves manufacturing technologies (SDG 9), encourages responsible use of resources by minimizing waste (SDG 12), and reduces energy consumption, which helps lower the carbon footprint (SDG 13) [5,7]. These contributions promote lean, sustainable manufacturing practices that benefit both industry and the environment.

2. Literature Review

2.1. Evolution and Advancements in AM technologies

AM has transitioned from a basic prototyping tool to a crucial technology in modern manufacturing. Early techniques like Stereolithography (SLA) and Fused Deposition Modelling (FDM) laid the groundwork, while advancements like Selective Laser Sintering (SLS) employed laser in AM and enabled more complex processes. Direct Energy Deposition (DED) further expanded AM's capabilities to manufacturing metal components, aiding aerospace and defense sectors by allowing the production and repair of large metal components with minimal waste [1]. However, challenges in material performance and precision remain, prompting ongoing research to refine these technologies. The integration of in situ monitoring is increasingly essential for enhancing precision and quality [1].

2.2. Effect of Cooling Rate on Microstructure and Mechanical Properties in AM

The cooling rate during AM significantly influences the microstructure and mechanical properties of the final parts [6]. A higher cooling rate results in finer microstructures, enhancing the hardness and tensile strength, while a lower cooling rate can result in coarse microstructures. In a fusion-based AM process, such as DED, these cooling rates can vary with an increase in the part height (especially for thin parts) due to effects such as heat accumulation and reduced heat conduction as the deposition height increases [10]. This can result in inhomogeneity in the properties of the component dependent on the part height. Thermal modeling combined with in-situ monitoring is used to maintain the cooling rates [11]. Effective management of the cooling rate is crucial for producing mechanically homogeneous reliable AM parts, making it a vital focus for continued research [2].

2.3. Traditional vs. ML Approaches in Controlling Cooling Rate

Traditional methods for controlling cooling rates in AM often rely on static settings and manual adjustments, which can lead to inconsistent product quality. Machine Learning (ML) offers a more dynamic solution, utilizing techniques like neural networks and predictive modelling to analyze the data in real-time and adjust cooling rates accordingly [3]. This in situ approach leads to more stable processes, better product quality, and enhanced sustainability, aligning with the principles of Industry 4.0, which emphasizes the integration of advanced technologies in manufacturing [4].

2.4. Sustainable Development Goals (SDGs) and AM

Integrating AM with ML plays a crucial role in advancing sustainability, directly supporting key United Nations Sustainable Development Goals (SDGs). Specifically, SDG 9 (Industry, Innovation, and Infrastructure) is enhanced by fostering innovation and reducing material waste. SDG 12 (Responsible Consumption and Production) benefits from improved resource efficiency and minimized waste, while SDG 13 (Climate Action) is supported through reduced energy consumption and lower carbon emissions. The use of in situ monitoring and control within AM processes not only improves process control and product quality but also drives sustainable and responsible manufacturing practices, underscoring the importance of further research in this area [7].

3. Methodology

3.1. Experimental Setup and Calculation of Cooling Rate

Fig. 1 shows the experimental setup used for determining the cooling rate during the deposition process. To determine the cooling rate, two infrared (IR) pyrometers are strategically positioned to measure temperatures at the molten pool (T1) and at a distance of 7 mm from the molten pool (T2), towards the trailing side of the molten pool. A single-axis CNC is used to control the movement of the substrate while the position of the deposition head and the pyrometers are fixed. The laser source used for this study is a 2 kW Nd:YAG fiber laser (Coherent HighLight FL) with a coaxial cladding head (Precitec YC52). Gas-atomized spherical Inconel 718 powder was used for the deposition.

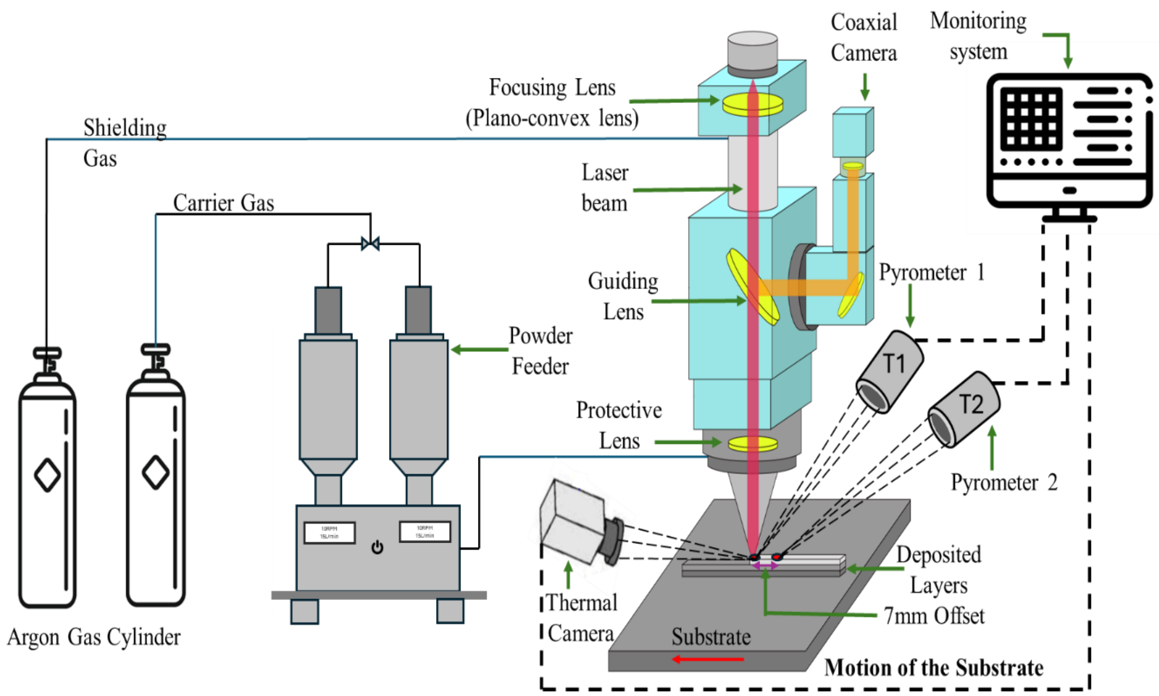

Fig. 1. Schematic of the experimental setup for in-situ process monitoring

Fig. 2 represents the molten pool temperature, the trailing edge temperature, and the calculated cooling rate for scan speeds of (a) 600 mm/min, (b) 800 mm/min, (c) 1000 mm/min, and (d) 1200 mm/min.

Cooling Rate Calculation

The cooling rate is calculated using the formula:

$$CR = \frac{(T1-T2)\times v}{7} \tag{1}$$

where:

- T1 is the temperature at the molten pool.
- T2 is the temperature 7 mm away, towards the trailing side of the molten pool.
- v is the scan speed (in mm/s).

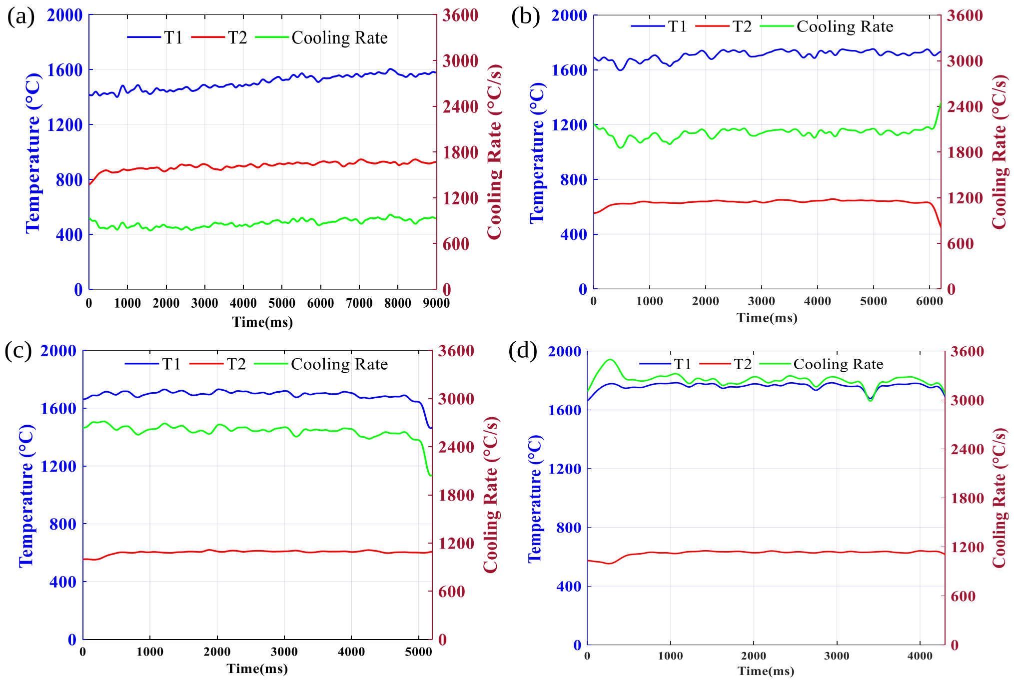

Fig. 2. T1, T2, and calculated cooling rate for (a) 600 mm/min, (b) 800 mm/min, (c) 1000 mm/min, and (d) 1200 mm/min

3.2. Data Preparation and Exploratory Data Analysis

Historic data refers to previously collected data used for training models, consisting of input features and corresponding outcomes or labels from past events or observations. Key operations on this data include data cleaning, where missing values are handled, and irrelevant columns are removed. Features and labels are then separated, with the input variables and target variables extracted. Exploratory Data Analysis (EDA) is then applied to analyze and understand the data as shown in Fig 3(a), involving visualization to reveal patterns and relationships and identifying trends, correlations, and anomalies.

3.3. ML Model Development and Evaluation

An ML model has been developed for the current study to predict and control the cooling rate. This involved processing collected data, including temperature readings and scan speed, to calculate the cooling rate, which serves as the target variable for training. A Random Forest Regressor was selected for its effectiveness in handling complex data [9]. The model was trained using historical data where cooling rates were manually controlled. Once trained, it accurately predicts the cooling rate based on current data inputs. To assess the model's performance, metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) have been used. The results are shown in Fig. 3(b) with an MSE of 31.87, an RMSE of 5.65, and an R^2 of 0.99996. These metrics indicate that the model has high accuracy and explains nearly all the variability in the data, demonstrating its reliability in predicting cooling rates.

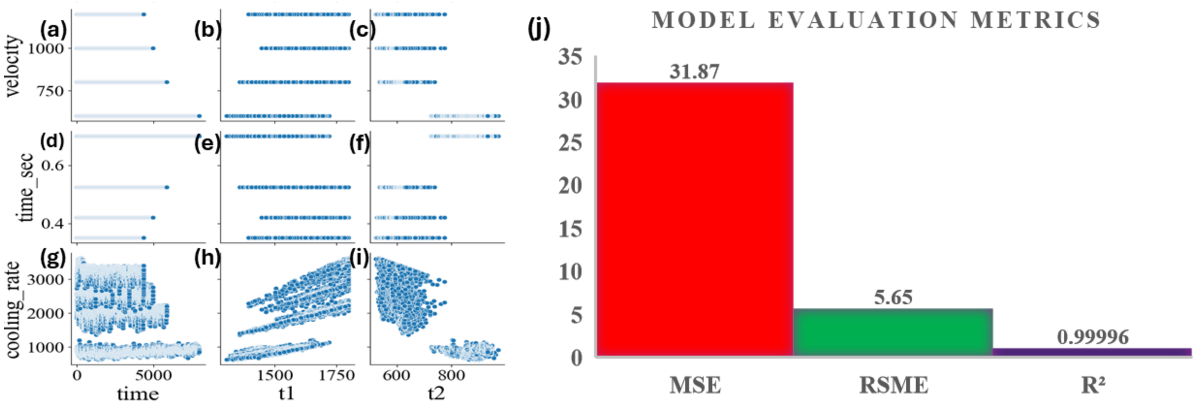

Fig. 3 (a) Exploratory Data Analysis and (b) Model Evaluation Metrics

3.4. Real-Time Control System Simulation

In the simulation, temperatures T1 and T2 are generated to replicate the thermal behavior of the DED process, with T1 centered around 1500°C and T2 around 300°C. These temperatures include sinusoidal fluctuations to simulate natural thermal oscillations, with additional noise introduced based on the platform's velocity. The generated temperatures are then integrated into an ML model to predict the cooling rate. The control system adjusts the platform's velocity in real-time using the formulae shown in Fig. 4. This dynamic adjustment ensures the cooling rate stays within desired limits, preventing defects like cracks, and is a critical step in validating the model's performance before real-world deployment [8].

```python
# Simulate temperature data based on velocity with reduced noise
def simulate_temperature(velocity, time):
    time = np.array(time)  # Ensure time is a NumPy array
    t1 = 1500 + 100 * np.sin(0.01 * time) + velocity * np.random.normal(0, 1, len(time))  # Reduce noise
    t2 = 300 + 20 * np.sin(0.01 * time) + (velocity / 2) * np.random.normal(0, 0.5, len(time))  # Reduce noise
    return t1, t2

# Control logic to adjust velocity
def adjust_velocity(current_velocity, predicted_cooling_rate, desired_cooling_rate):
    error = desired_cooling_rate - predicted_cooling_rate
    adjustment = error * 0.05  # Adjusting the gain to show the effect more clearly
    new_velocity = current_velocity + adjustment
    return new_velocity
```

Fig. 4. Simulation of temperatures T1 and T2 and velocity adjustment based on predicted temperatures and cooling rates

4. Results and Discussion

Fig. 5 shows the predicted cooling rates and the adjusted velocity for different desired cooling rates from the ML model and real-time simulation. In Fig 5(a), with the desired cooling rate set to 1500°C/s, the graph shows the predicted cooling rate and corresponding velocity adjustments. Similarly, Fig 5(b) illustrates the results for a desired cooling rate of 2000°C/s, Fig. 5(c) presents the outcomes for a desired cooling rate of 2500°C/s, Fig 5(d) presents the outcomes for a desired cooling rate of 3000°C/s highlighting the system's adaptive response in each scenario.

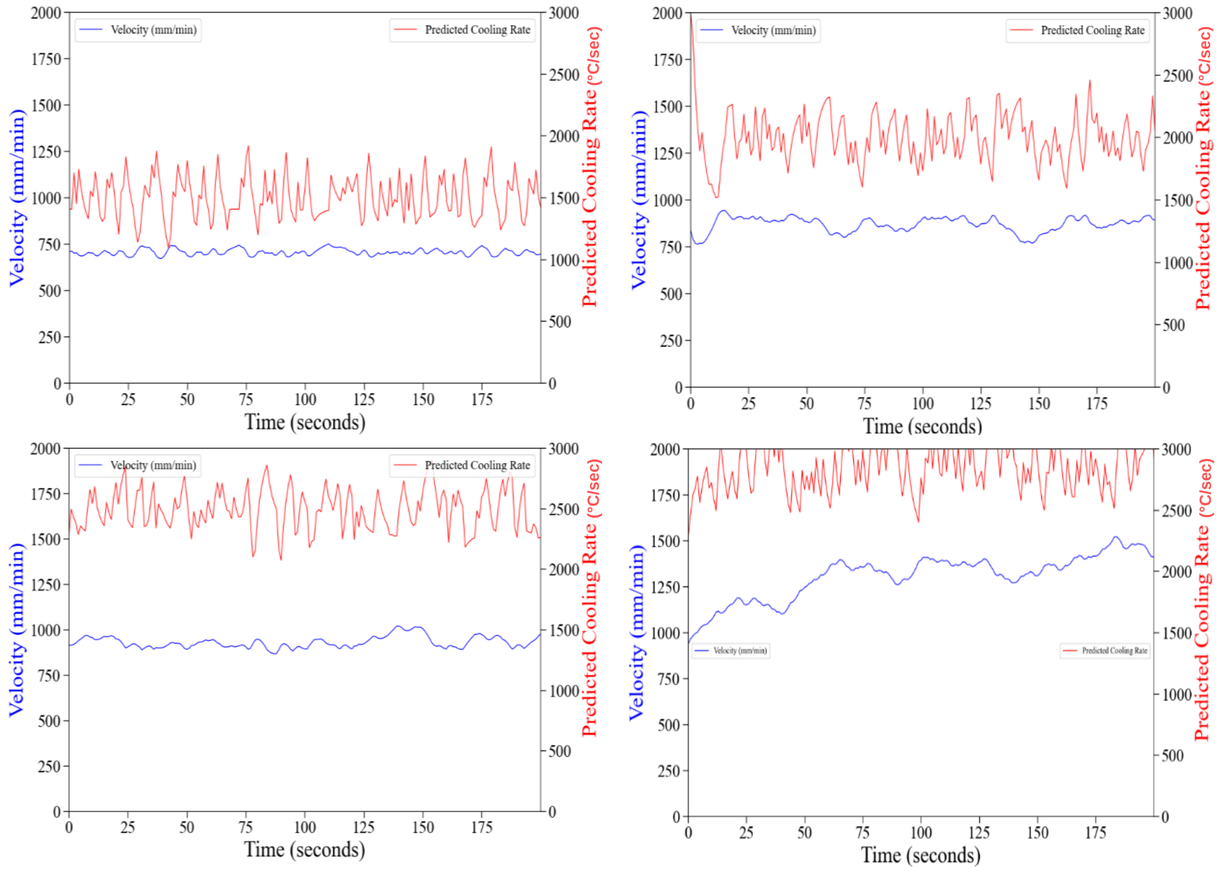

Fig. 5. Predicted cooling rates and adjusted velocity for required cooling rates of (a) 1500°C/s, (b) 2000°C/s, (c) 2500°C/s, and (d) 3000°C/s

5. Conclusion

This research demonstrates the effectiveness of a machine learning-based control system in optimizing cooling rates during the Directed Energy Deposition (DED) process. By integrating real-time temperature data with predictive models, the system dynamically adjusts the process velocity to maintain desired cooling rates, thereby reducing defects and enhancing product quality. The high accuracy of the model, as evidenced by the low error metrics, highlights its potential for real-world application. This approach not only improves manufacturing efficiency but also aligns with sustainable production practices, contributing to the advancement of smart manufacturing technologies.

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