Research Status of Process Monitoring and Adaptive Control in DED

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Abstract. Directed Energy Deposition (DED), as a key additive manufacturing technology, is widely used for repairing and fabricating large-scale metal components. However it faces challenges in process stability and quality control. This paper reviews the current research on process monitoring and adaptive control in DED. It focuses on sensor technologies for powder-based and wire-based sub-processes, such as visual, acoustic, and arc sensors for real-time monitoring of the melt pool and powder flow. Also, it shows the intelligent control methods such as machine learning and external field assistance. Machine learning models, including convolutional neural networks and regression algorithms, have demonstrated strong capabilities in predicting process outcomes and optimizing parameters. At the same time, external fields like magnetic and ultrasonic assistance have been shown to effectively improve deposition quality and microstructure. Despite progress, issues such as geometric complexity, transient dynamics, and data scarcity remain. Future work should aim at closed-loop systems integrating sensing, modeling, and control, with physics-informed machine learning to enhance adaptability and reliability. This review provides a systematic reference for advancing intelligent and self-adaptive DED systems.

Keywords: Directed Energy Deposition, process monitoring, adaptive control, machine learning, sensors

1 Introduction

3D printing, known as additive manufacturing technology, can trace its development back to the 1980s. Based on 3D models, 3D printing technology constructs three-dimensional objects by depositing materials layer-by-layer from the bottom up in a specific manner. 3D printing processes have been widely adopted in daily life. But challenges remain in the printing process and product quality, such as warping caused by residual stress due to insufficient bonding between adjacent layers and cooling characteristics during 3D printing [1]. Ordinary 3D printers do not halt operations due to these defects which result in waste of materials and products. Therefore, real-time quality detection and adjustment during the printing process are crucial.

Based on differences in forming principles, 3D printing technology can be categorized into seven core types. Material Extrusion (FDM) is currently the most widespread category. It’s typically involves extruded molten plastic. Stereolithography (SLA) utilizes the

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photopolymerization of photosensitive resins for forming. It offers high precision. Powder Bed Fusion (PBF) processes metal or plastic powder via laser melting which enables the manufacture of high-performance end-use parts. Material Jetting (MJ) operates similarly to 2D printing which allows for multi-material and multi-color composite forming. Binder Jetting (BJ) bonds powder materials using a binder. It demonstrates effectiveness in the efficient production of full-color models or metal casting molds. Sheet Lamination builds large-scale prototypes rapidly by bonding and cutting sheet materials layer by layer. Directed Energy Deposition (DED) utilizes a high-energy beam to melt and deposit materials. It is primarily applied for the repair and direct manufacturing of large-scale metal components. This paper will focus on DED technology [2].

The core principle of Directed Energy Deposition (DED) technology involves depositing metal powder or wire feedstock onto a substrate surface. It operates through a nozzle mounted on a multi-axis robotic arm. Meanwhile it will be simultaneously melted and solidified instantaneously by using a high-energy heat source such as a laser, electric arc, or electron beam, achieving layer-by-layer 3D construction. This technology is primarily suitable for printing high-performance metal materials, such as titanium alloys and cobalt-chromium alloys. Its advantages include multi-degree-of-freedom motion capability, enabling curved surface printing, in-situ repair of existing components, and manufacturing of functionally graded materials. It also allows effective control over the micro-grain structure of parts. This paper will focus on DED, elucidating the research status of its process monitoring and adaptive control, and discussing current issues and future trends.

2 DED Sub-processes and Monitoring Sensors

DED encompasses numerous sub-processes. Based on the energy source, it can be classified into Laser-DED (L-DED), Electron Beam-DED (EB-DED), and Arc-DED. Based on the feedstock delivery method, it can be divided into powder-fed and wire-fed processes. This paper will focus on two commonly used processes: powder-fed Laser-DED (LP-DED) and Wire Arc Additive Manufacturing (WAAM) for detailed elaboration.

2.1 Powder-fed Laser-DED (LP-DED)

Powder feeding is a key material delivery method in DED which achieve melting and deposition by injecting powder material into the heat source zone. This process has significant applications in manufacturing and safety fields, but its process control relies on sensor monitoring.

Industrial Applications of Powder Feeding Technology. Powder feeding technology is widely used in industry for material preparation and safety protection. Wei Chuanglin and his team developed a method for preparing multi-component alloys using powder feeding technology. It adds dust collection powder and industrial waste slag into a refining furnace via powder feeding to achieving resource utilization and efficient production**.**

Sensors in the Powder Feeding Process. In the powder feeding process, sensors are mainly used to monitor powder flow, melt pool state, or environmental parameters to enhance process stability and safety. Firstly, acoustic sensors can be employed to record audio data; a microphone installed near the printer's extruder captures audio, from which Mel-frequency cepstral coefficients and Mel filter bank energies are extracted as features [3]. Additionally, visual sensors are widely used in the powder feeding process. By capturing object surface data to monitor external appearance, discrepancies between actual and theoretical shape data can be detected promptly, allowing for timely adjustment of printing strategies [4]. Wei Chuanglin et al., in utilizing powder feeding technology for multi-component alloy preparation, emphasized the importance of process control, indirectly indicating that visual sensors might be used for monitoring powder delivery and melting state [2].

2.2 Wire Arc Additive Manufacturing (WAAM)

Welding, as a core sub-process of DED, involves a heat source melting material to form a deposited layer. Its process monitoring and control are crucial for part quality. Welding technology relies on various sensors to achieve real-time tracking and intelligent control.

Industrial Applications of Welding Technology. Welding technology plays a vital role in industrial fields such as aerospace, electronics, and automotive. In aerospace, Wang Yajun and his team pointed out that welding technology is applied in the manufacturing of large aircraft, spacecraft, and other models, supporting national projects like "Shenzhou VII" and "Chang'e" lunar missions [5]. Laser cladding, as a form of welding, is used for surface repair and coating, but crack issues require parameter optimization and auxiliary field control [6].

Sensors in the Welding Process. The welding process employs various types of sensors for monitoring. It includes visual, arc, and acoustic sensors. Visual sensors are a common choice. For example, Li Yuan and his team developed a vision sensor based on laser structured light capable of extracting the position of weld seam feature points for high-precision seam tracking [7]. Besides visual sensors, voltage, current, acoustic, and spectral sensors can extract features from printed objects that predict weld penetration status through information fusion algorithms [8]. With technological advancement, arc sensing technology has become widespread. It can enable real-time 3D weld seam tracking control and address monitoring challenges in the welding height direction [9]. Similarly utilizing arc sensing technology, a novel Hybrid Inter-layer Hysteresis Controller (HIHC) integrates real-time thermal feedback and adaptive dwell time control. This system implements a dual-mode cooling strategy based on temperature thresholds. It uses temperature monitoring via optical character recognition and a rolling buffer system to achieve stability [10]. The application of these sensor technologies significantly enhances the automation and intelligence level of the welding process.

3. Adaptive Control Methods for the DED Process

3.1 Machine Learning

Machine learning, as a core technology for intelligent control of the DED process, effectively overcomes the limitations of traditional control methods. By adapting to complex working conditions through data-driven intelligent modeling, key parameter prediction, and real-time control, significantly it cam improve the precision of adaptive process control. The application of machine learning has permeated key stages of additive manufacturing, including design optimization, process monitoring, and modeling the relationship between process parameters and performance [11]. Its core value lies in uncovering hidden correlation patterns within data to provide scientific decision-making basis for adaptive control, serving as a core driving force for the intelligent upgrade of DED technology.

Convolutional Neural Networks. Convolutional Neural Networks (CNNs), with their unique hierarchical structure of convolutional layers, pooling layers, and fully connected layers, possess powerful capabilities for image feature extraction and multi-dimensional data processing. They are particularly suitable for real-time analysis of visual data acquired during DED processes, such as coaxial images and melt pool images from cameras. CNNs have been developed for regression model applications in laser cladding processes to estimate dilution, coating properties, crystallographic texture slices, and the volume of deposited material. CNNs have demonstrated the ability to determine laser cladding dilution rates based on laser power. Leveraging physics-driven and data-driven fusion methods, they can accurately predict porosity in laser metal deposition [12]. Using time-series image training, coaxial image-based laser quality analysis enables real-time data extraction for online control and machine learning training, as well as classification techniques for predicting cladding aspect ratios [13], providing a reliable technical path for adaptive control of forming accuracy.

Regression Models. Regression models, as a classic type of predictive modeling technology, have the core advantage of quantifying the mapping relationship between dependent and independent variables by constructing mathematical equations, providing support for parameter optimization and performance prediction in the DED process. In specific applications, variance regression analysis can be used to solve for optimal microhardness and dilution rates based on process parameters [14], offering quantitative basis for adaptive adjustment of process parameters. Lyu and his team [15] adopted a method involving real-time melt pool image processing, providing predictive models based on a series of process parameters and melt pool dimension data, concluding that the Gaussian Process Regression model performs best. Support Vector Regression (SVR) shows unique potential in modeling surface characteristics (e.g., surface roughness) concerning process parameters and DED sample properties, enabling rapid prediction of porosity changes to reduce porosity [16]. Furthermore, the application of regression models can extend to optimizing microstructure properties, such as in twin-wire arc sprayed coatings based on different metal wire compositions [17].

3.2 External Field Assistance

In the DED process, external field assistance technologies act upon the melt pool and deposited layers by involving introducing physical fields such as magnetic fields, ultrasonic fields, and mechanical fields. The core advantage of these auxiliary fields lies in their ability to fundamentally improve the printing process from a physical essence. Thereby, they can achieve simultaneous enhancement of forming accuracy and surface quality while effectively reducing residual stress and defect occurrence rates [18]. This provides a new technical pathway for adaptive control under complex working conditions.

The application of auxiliary magnetic fields in DED mainly consists of two core methods: longitudinal and transverse. A longitudinal magnetic field generates a stirring effect within the melt pool which causes molten metal to flow outward. This can improve the forming accuracy and surface quality of parts. Wang and his team [19] emphasized the direct correlation between magnetic field strength and excitation current. They demonstrate that auxiliary magnetic fields can increase the aspect ratio of weld beads and improve the surface quality of multi-layer parts. Additionally, through compressing or expanding the arc form, longitudinal magnetic fields can dynamically adjust arc energy density, enable flexible control of deposition layer dimensions and adapt to different forming requirements [20]. When the coil is placed horizontally with its axis perpendicular to the torch, a transverse magnetic field is formed. The transverse magnetic field can divert the arc towards the rear of the molten pool. It will trigger the unidirectional forced convection, drive the metal fluid and heat to migrate directionally towards the rear of the molten pool [21]. It can effectively suppress the problem of coarse grains and provides technical support for the adaptive forming of thin-walled and complex-shaped parts.

Ultrasonic fields can significantly regulate arc morphology and molten droplet behavior during the DED process, through the physical action of acoustic radiation force. Simultaneously, ultrasound can increase melt pool penetration depth to promote more uniform weld bead cross-sections. By enhancing mixing and stirring within the melt pool, ultrasonic-assisted fields can improve fluidity. It allows bubbles to rise and escape before solidification so that it can significantly reduce porosity. Research by Chen Shanben et al. [22] in the field of robotic welding further expands the application of ultrasonic-assisted technology. By integrating multi-information perception and intelligent control methods, they combined ultrasonic assistance with weld seam guidance, trajectory tracking, and real-time penetration state control. They construct an integrated process adaptive control system that provides solutions for stable forming under complex DED working conditions.

The synergistic application of these intelligent control methods, like external field assistance technologies and machine learning, is widely used. It not only enhances the stability and control precision of the DED process from both data-driven decision-making and physical mechanism dimensions but also effectively solves adaptive control challenges in scenarios involving complex shapes and multi-material deposition. This fully reflects the core value of adaptive control technology in industrial batch production and lays a solid foundation for the engineering application of DED technology.

4. Future Development Trends in DED Process Monitoring and Adaptive Control

Currently, process monitoring and adaptive optimization of Directed Energy Deposition (DED) technology still face several significant challenges. Firstly, the difficulties posed by geometric complexity and multi-material deposition are particularly prominent. Characteristics such as free-form shapes, thin-walled structures, and layer-by-layer material transitions introduce significant spatial heterogeneity and material complexity into the printing process. These factors are often difficult for existing models to effectively adapt to. Secondly, temporal dimensions and transient characteristics during the process also can be major obstacles. Dynamic changes along the toolpath, such as subtle power fluctuations, are often difficult to capture accurately by static feature-based models. Furthermore, the application of machine learning methods in this field is limited by multiple data-related constraints. Not only because of the computational costs for training data high, but also the acquisition of experimental data itself is relatively limited.

Moreover, high-quality data labeling also presents considerable challenges. Finally, from a research perspective, few current studies systematically compare different machine learning methods under identical experimental conditions. There is also a lack of research exploring best practices through the introduction of auxiliary fields. To some extent, this constrains the iterative improvements of technologies in this field.

Future development directions can be derived as follows. One direction is exploring system architectures that integrate in-situ sensor feedback, machine learning models, and adaptive process control. Most existing machine learning-based control strategies rely on open-loop methods driven by in-situ data capture. However, the integrated development of closed-loop control systems through machine learning and optimization techniques is worth further exploration to enhance production efficiency. Moreover, future research should emphasize incorporating physical constraints into machine learning models. These models should maintain consistency with known physical laws which enables rapid predictions and reduces reliance on computationally expensive numerical solvers. Additionally, future research should focus on developing system architectures capable of handling varying sequence lengths and dynamic boundary conditions.

5. Conclusion

This paper systematically reviews the research status of process monitoring and adaptive control in Directed Energy Deposition (DED) technology. Regarding monitoring, various sensors such as visual, acoustic, and arc sensors are widely used in powder feeding and welding processes to achieve real-time perception of melt pool state, powder flow, and weld seam quality. Regarding control, machine learning methods like Convolutional Neural Networks and regression models can predict process outcomes and optimize parameters, while external field assistance technologies like magnetic and ultrasonic fields effectively improve forming quality and microstructure. Although challenges such as geometric complexity and data acquisition difficulties remain, future research should focus on constructing closed-loop systems that integrate sensing, modeling, and control, incorporating physical constraints into machine learning to drive DED towards more intelligent, adaptive, and highly reliable development.

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