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Recent Advances in Closed-Loop Control Techniques for Additive Manufacturing: A Review

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ABSTRACT
Additive manufacturing (AM) has transformed modern manufacturing by enabling the layer-by-layer fabrication of complex components directly from digital models. However, variations in process parameters, material behavior, thermal conditions, and machine dynamics can significantly affect product quality, dimensional accuracy, and process stability. This review examines advanced closed-loop control techniques for additive manufacturing, emphasizing real-time monitoring, feedback control, and intelligent process regulation. The AM process, major printing technologies, and conventional closed-loop control concepts are first discussed to establish the fundamental framework. In-situ monitoring techniques, including imaging and acoustic sensing, are examined for real-time defect detection and process validation. Advanced control strategies such as Proportional-Integral-Derivative (PID) control, Adaptive Control, Gain Scheduling, Model Reference Adaptive Systems (MRAS), and fuzzy logic-based control are then reviewed. These approaches enable dynamic adjustment of printing parameters in response to process deviations, thereby improving manufacturing consistency and reducing defects. The review also highlights an integration of AI with closed-loop systems to support predictive and autonomous control. Finally, current challenges and research opportunities are identified, emphasizing intelligent sensing, adaptive algorithms, and data-driven control for reliable and autonomous additive manufacturing.

1. INTRODUCTION

Additive manufacturing, or 3D printing as it is more often known, has come a long way from its 1980s origins as a rapid prototype tool to its current status as a versatile production technique with many practical uses. AM is being employed in a variety of industries, including aerospace, automotive, healthcare, and fashion, due to developments in materials, technology, and software [1]. These days, 3D printing is praised for its unparalleled customisation options, reduced waste, and ability to create intricate geometries that are challenging or impossible to achieve with traditional production methods. This progression has evolved AM into a complex array of methods that cater to a variety of materials, including polymers, metals, ceramics, and composites, propelling advances across multiple industries [2]. As AM develops, it will transform supply chains, production methods, and product design globally, demonstrating its importance as a game-changing technology in the manufacturing sector and paving the way for on-demand customised production to become a reality across industries [3].

A manufacturing process may benefit from a monitoring system for many different reasons. Aside from being error-free, modern manufacturing equipment must be sustainable, adaptable, and able to function with little to no human intervention. Frequent downtimes caused by tool wear and tool breakage are two big issues in the area of metal cutting [4]. Tool breakage is a common source of unexpected stoppages in machining environments, costing both time and capital. Previous research has shown that the typical

machine tool has 6.8% downtime due to cutter breakage.

Arnold Kadish revolutionised insulin administration in the early 1960s with his first closed-loop method. The "servomechanism for blood glucose control" that Kadish devised had an intravenous catheter, two syringe pumps that could provide insulin, glucose, or glucagon, and an auto analyser that could continuously check blood glucose levels. The insulin pump was triggered when the blood glucose level exceeded the higher threshold, and the glucose or glucagon pump was triggered when it fell below the lower threshold. Both pumps were turned off when the blood glucose level fell within a predetermined target range [5][6]. In 1963, Kadish reported closed-loop control methods for additive manufacturing based on a successful testing of his system in a single diabetic volunteer. It examines real-time process optimisation techniques, intelligent control systems, feedback mechanisms, and monitoring techniques [7]. Additionally, the analysis emphasises future prospects for creating dependable, adaptable, and autonomous additive manufacturing systems, compares current methods, and identifies major obstacles and research gaps [8].

A. Structure of the paper

The structure of the paper: Section II presents the overview, processes, and classification of additive manufacturing. Section III discusses closed-loop control concepts and existing systems. Section IV reviews advanced closed-loop techniques, including monitoring, PID, adaptive, and fuzzy control. Section V presents literature review and research gaps. Section VI concludes the paper and discusses future work.

II. OVERVIEW OF ADDITIVE MANUFACTURING

The definition of AM, also known as freeform fabrication, fast prototyping, or 3D printing, is "the process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies" like machining [9]. Rapid prototyping is a process used in a variety of sectors to quickly create a physical model of a component or system before it is manufactured. Rapid prototyping, as applied to technology that creates physical prototypes from digital data, is a phrase often used in the context of product development. It is no longer valid to refer to finished components as prototypes since many of them are now printed directly in AM machines.

A. Additive Manufacturing Process

AM, popularly known as 3D printing, has revolutionised the way items are made, ranging from basic models to sophisticated structures utilised in numerous industries [10]. In contrast to typical subtractive manufacturing processes, the procedure includes layering material to produce items from 3D model data. The accuracy, quality, and functionality of the finished product are all influenced by a number of crucial processes in the AM pipeline. Figure 1 shows the general procedure for additive manufacturing:

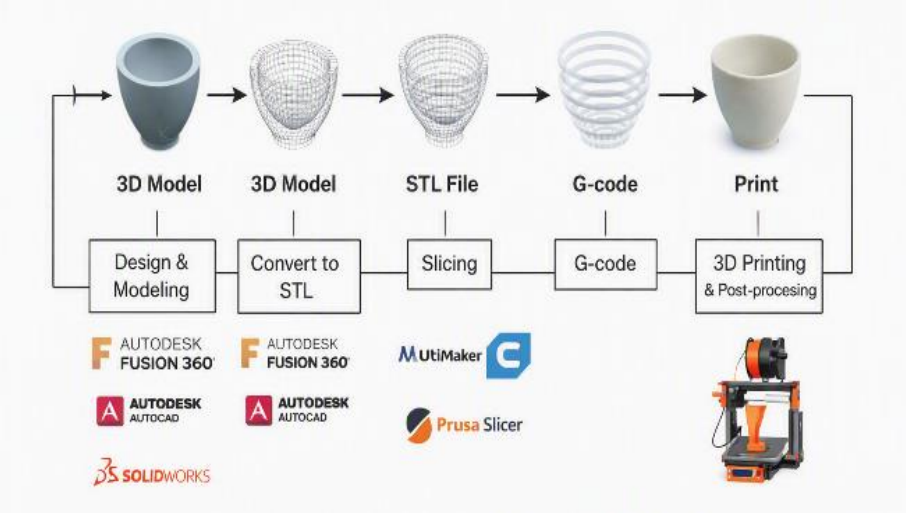


Fig. 1. Overall workflow of the Additive Manufacturing Process.

1) Design and Modeling

The design phase is the first step in the AM process, which relies heavily on the creation of 3D models. Intricate and complex digital models of the target object may be generated by designers and engineers using CAD software [11]. This stage is characterised by meticulous planning of every part of the model, making sure that every curve, edge, and dimension precisely matches the requirements of the final product. The design process is impacted by many significant factors.

2) Conversion to STL

The 3D model is finished by creating an STL file. The transformation of 3-D models into stereolithography (STL) files is an essential part of the three-dimensional printing process because it bridges the gap between digital design and physical execution [12]. This method involves translating a 3D design into a format that can be used by 3D printers to create objects layer by layer.

3) Slicing

After the STL file is formed, the next important step is slicing, which is a critical process whereby the STL file is divided into many thin, horizontal layers using specialist software, often referred to as a slicer. This conversion is crucial because it transforms the complex geometry of the model into a stack of manageable, printable layers, turning the digital design into a physical product. The slicing program does a number of tasks throughout the 3D printing process.

4) Preparation, Printing, and Post-Processing

The G-code has been generated, and the 3D printer is prepared for production. To obtain best performance and print quality, a 3D printer must be ready for operation via a number of crucial processes [13]. The first step, which differs from printer to printer, is to install the material: A filament has to be inserted into the extruder of an FDM printer, while a resin tank needs to be filled with liquid for a SLA printer. After that, make sure the first layer adheres properly by levelling the print bed. This step may be done manually or using the printer's auto-levelling capabilities; it depends on the model.

B. Classification of 3d printing process

The International Organization for Standardization (ISO) divides additive manufacturing technology into seven different categories. These categories, as shown in Figure 2, offer a consistent foundation for comprehending and categorising diverse additive manufacturing processes. Different approaches and strategies for constructing three-dimensional objects layer by layer characterise each approach to additive manufacturing [14]. This globalisation of additive manufacturing processes is made possible by these categorisations, which allow for the transparent comparison and communication of AM technology across sectors and uses.

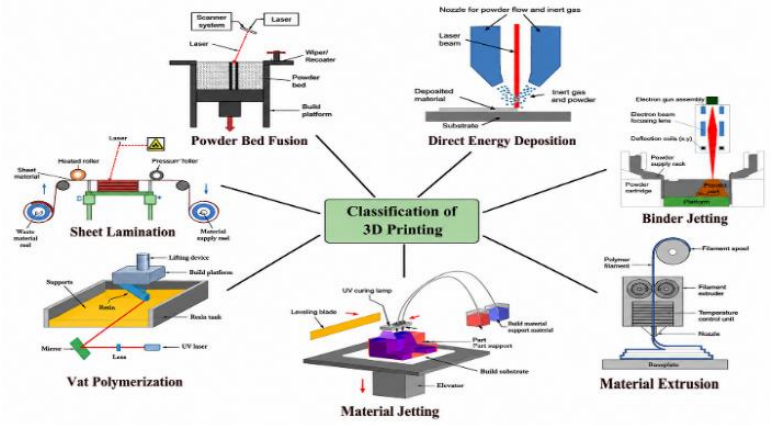


Fig. 2. Different types of 3D printing processes

1) Material extrusion

Fused deposition modelling (FDM), also known as material extrusion, is a widely used additive manufacturing technique [15]. The procedure entails melting thermoplastic filaments in a heated nozzle before extruding them in successive layers onto a construction platform. Each deposited layer links to the one before it, eventually generating the desired object. FDM is a popular option for prototyping, custom production, and educational applications because of its well-known adaptability, affordability, and ease of use.

2) Vat polymerization

Digital Light Processing (DLP) and Stereolithography (SLA) are two examples of vat polymerisation processes that use a vat of liquid photopolymer resin as the material for the construction. A UV light source, such as a laser or projector, is used to cure the resin in layers, leading to the finished product. Applications requiring fine details and smooth finishes, including jewellery, dental equipment, and visual assistance prototypes, may benefit from SLA and DLP's high resolution and superior surface quality [16].

3) Powder bed fusion

A variety of AM techniques, including DirectMetal LaserSintering (DMLS) and Selective Laser Sintering (SLS), are included in powder bed fusion. These techniques include applying a small layer of powdered material—such as ceramic, metal, or plastic—to a build platform. A laser or electron beam selectively melts the powder particles, forming solid layers that ultimately come together to create the desired item [17]. Powder bed fusion is well known for its ability to create functional parts with exceptional mechanical qualities and complicated geometries, making it perfect for use in the automotive, medical, and aerospace sectors.

4) Material jetting

An inkjet-like printhead selectively deposits droplets of liquid photopolymer or other materials onto a build platform in material jetting, a method of three-dimensional printing. Subsequently, the droplets reach a solid state via curing or solidifying. High resolution and the capacity to print with numerous materials at once make material jetting suitable for applications including consumer products, medical models, and architectural prototypes that call for exact details and multi-material qualities [18].

5) Binder jetting

An additive manufacturing technique called binder jetting uses powdered materials like metal, sand, or ceramic. This method creates the required item by layer-by-layer hardening a bed of powdered material with a liquid binding agent. Large components, composite geometries, and sand moulds for casting applications in sectors like foundries, automotive, and aerospace may all benefit from binder jetting's reputation for efficiency and rapidity.

6) Directed energy deposition (DED)

The AM process known as Directed Energy Deposition (DED) involves melting and depositing material onto a substrate or layers that have already been produced using focused energy sources like electron beams or lasers. In addition to being able to work with a variety of materials, such as metals, polymers, and ceramics, DED also has the ability to repair and modify existing parts, as well as fast deposition rates and material efficiency [19]. DED has widespread use in the aerospace, defence, and maintenance and repair sectors.

7) Sheet lamination

The final product is formed by connecting layers or sheets of material using sheet lamination processes like Ultrasonic Additive Manufacturing (UAM) and Laminated Object Manufacturing (LOM). UAM uses ultrasonic vibrations to layer-by-layer bind metal foils, while LOM uses heat, pressure, or glue to connect layers of paper, plastic, or metal sheets [20]. Sheet lamination technologies are great for tooling, low-volume

manufacturing, and prototyping due to their versatility, ease of use, and low production costs.

III. CLOSED-LOOP CONTROL IN ADDITIVE MANUFACTURING

Closed-loop control in additive manufacturing uses real-time feedback to monitor and regulate printing processes. Sensors continuously collect information about temperature, melt-pool behaviour, geometry, and defects, while controllers adjust process parameters accordingly. This approach improves dimensional accuracy, material deposition, process stability, product quality, and overall manufacturing reliability.

A. Concept of Closed-Loop Control

A closed-system finds applications in heating, ventilation and air conditioning HVAC) systems to maintain desired indoor temperature in residential, commercial, and industrial environments. This ensures comfortable living and working conditions, as well as energy -efficient operation. It is also important in temperature-sensitive experiments and processes, such as those requiring chemical reactions or even biological samples like incubators, ovens, or water baths to maintain precise and stable temperatures [21]. For many industrial processes, such as chemical reactions, food processing, or pharmaceutical manufacturing, closed-system temperature control mechanisms are required to maintain specific temperatures for quality assurance, safety, and overall process efficiency.

1) Conventional Systems

A typical closed-loop system consists of the following components: input, set point, controller, actuator, plant/process, output, and feedback. This kind of system entails establishing the value of the relevant parameter and then utilising the control element to keep the plant or process at this setpoint, as shown in Figure 3. When a signal is sent to the plant and actuator, the process value is set to the designated value.

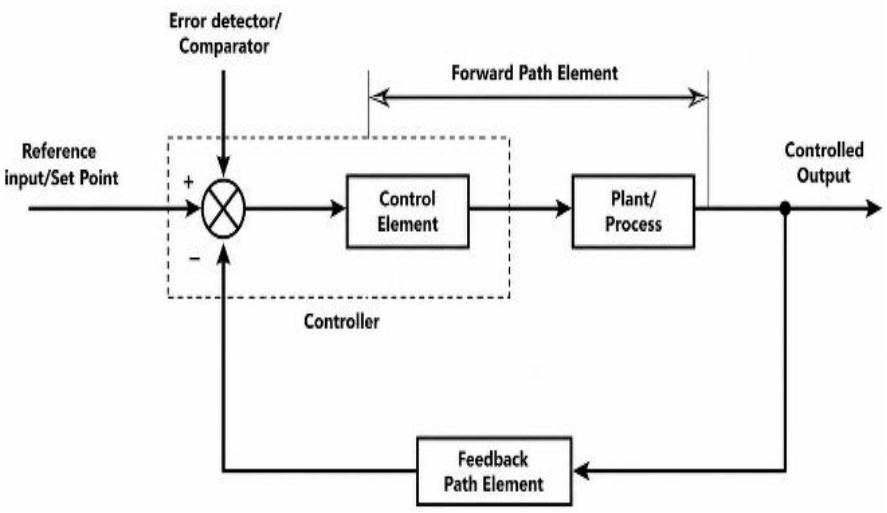


Fig. 3. Conventional Closed-Loop Block Diagram of Automatic Control System

2) Proposed AI-Based Closed-Loop System

AI is integrated into the system with specific functions in the suggested concept of a closed-loop system. Data is collected and saved at the process or plant's output. Its purpose is to build a model and teach the AI how to accomplish the goal, which is the input value. It is compared to the intended value, and if there is a difference, a signal is transmitted to the control element. The information is utilised to drive the actuator in proportion to the error signal in the case of a deviation. In addition to helping the controller carry out its duties, the AI saves the recorded data. Figure 4 displays the proposed block diagram of the system.

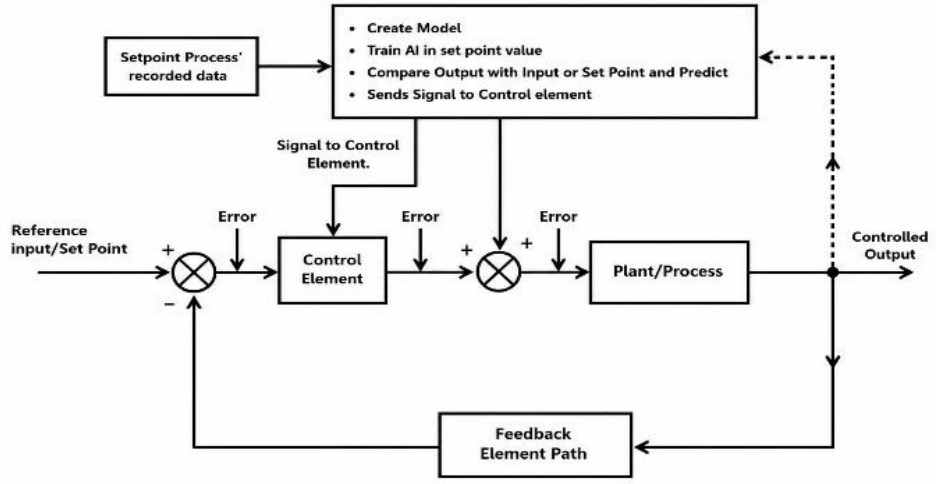


Fig. 4. Proposed Closed-Loop Block Diagram for AI Control System Design

B. Control systems in additive manufacturing

AM approaches have been the subject of research for decades. Technological developments have made it feasible to quickly and simply create objects with intricate geometry using a variety of materials. As a result, the usage of this kind of technology for a variety of purposes has been approved by several industrial sectors and research projects [22]. However, there are drawbacks to additive manufacturing, such as material constraints, uncertainty about the quality of the parts, and a lack of measurement and standard compliance in the production process.

1) Commercial products

An increasing number of 3D printer manufacturers are looking at ways to enhance the additive manufacturing process by using closed-loop mechanisms that use a variety of factors (such as temperature, velocity, material flow, etc.) [23]. The sections that follow include case studies of commercial printers that incorporate a control system into their printing process.

- Zmorph: A Polish business called ZMorph produces 3D printers with built-in closed-loop control systems. Five step motors provide position feedback at the start of the control operation. Encoder sensors are used to monitor each motor's angular position.

- Stella Move: The Stella Move 3D printers are designed by a Korean business that uses the FFF technology. The majority of this company's innovations are on closed-loop control systems that allow for feedback and control at specific elements' locations during printing.

- Inkbit : Inkbit is a spin-off of MIT. It produces material-jetting printers that are helpful for industrial production and can print many materials at once.

- Control for Laser Additive Manufacturing—Infrared: A directed energy deposition process known as Control for Laser Additive Manufacturing—Infrared (CLAMIR) uses real-time infrared thermography to tailor its approach to laser metal deposition[24]. This system continuously monitors the melt pool, adjusting the laser intensity to ensure continuous material deposition.

2) Theses and academic articles

The academic world also wants to make additive manufacturing technologies better [25]. There have been a lot of academic articles and theses published about how closed-loop control systems may improve printing accuracy, decrease printing error, and provide better products.

IV. ADVANCED CLOSED-LOOP CONTROL TECHNIQUES FOR ADDITIVE MANUFACTURING

Advanced closed-loop control techniques in additive manufacturing use real-time feedback, sensors, and intelligent algorithms to regulate printing processes. These approaches monitor process parameters, detect deviations, and automatically adjust operating conditions. AI, machine learning, predictive control, and adaptive strategies improve dimensional accuracy, reduce defects, enhance process stability, and support autonomous manufacturing.

A. In-Situ Process Monitoring And Defect Detection In LAM (Laser Additive Manufacturing)

The latest advancements in in-situ monitoring in LAM are presented, emphasizing its pivotal role in early defect detection to prevent quality deterioration and potential build failure [26]. This review connects directly to previous discussion on LAM defects, underscoring in-situ monitoring as a key solution. It offers a holistic exploration of diverse in-situ sensing methodologies.

1) Data validation strategies

Data validation procedures allow for the correlation and overlaying of data, as well as the extraction of insights from monitoring data [27]. This review cites two popular methods from the literature: (1) Post-Process Validation and (2) A-Priori Identification. The former requires collecting data using in-situ measures and then comparing them to data obtained via ex-situ methods.

2) Imaging methods

Imaging techniques include thermal and visual monitoring using tools like X-ray imaging, CMOS cameras, CCD cameras, and infrared imaging cameras. They provide a non-contact approach for measuring heat flow, thermal distortion, and changes in the geometry of a 3D print by monitoring the printing process in specified space and time [28]. Surface melt pool dynamics, thermal signatures, and the emergence of vapour plumes in the printed component may be crucially assessed using high-speed visible light communication (VLC) and IR thermal imaging.

3) Acoustic methods

Acoustic techniques include inline coherent imaging (ICI), acoustic emission (AE) sensing, and ultrasonic measurements by intentional stimulation. Piezoelectric acoustic sensors, which are used in AE sensing, transform the energy from stress waves, or acoustic signals, into electrical signals that are subsequently measured [29]. ICI is described as an acoustic approach because it employs acoustic interferometers to detect physical features of sound waves, a low-coherent interferometric imaging technique.

B. PID Control Strategy

The PID controller is a widely used control system for regulating variables in engineering systems, including voltage and temperature. In its setup, the PID controller works by combining three main components: proportional (P), integral (I), and derivative (D). The integral component (I) has an important function in reducing steady-state errors over time, by accumulating errors and adjusting the output to slowly but surely correct deviations [30]. Meanwhile, the derivative component (D) helps predict future errors by analysing the rate of error change, thereby helping prevent overshoots or excessive spikes in the system.

C. Adaptive Control Techniques

Parameter adaptive control approaches are presented in a unified framework that includes gain scheduling, model reference control, and self-tuning regulators. A conventional feedback control loop with a process and a regulator with modifiable parameters serves as the starting point [31]. The most difficult part is figuring out how to quickly modify the regulator settings in response to disturbances and changes in the process dynamics. The optimisation of the regulator's settings is the only differentiating factor among the systems.

1) Gain scheduling

At times, it is feasible to identify auxiliary variables that exhibit a strong correlation with the modifications in process dynamics. It is then feasible to mitigate the consequences of parameter fluctuations by converting the regulator parameters into functions of the auxiliary variables. Gain scheduling is the name given to this method since it was first designed to account primarily for variations in process gain.

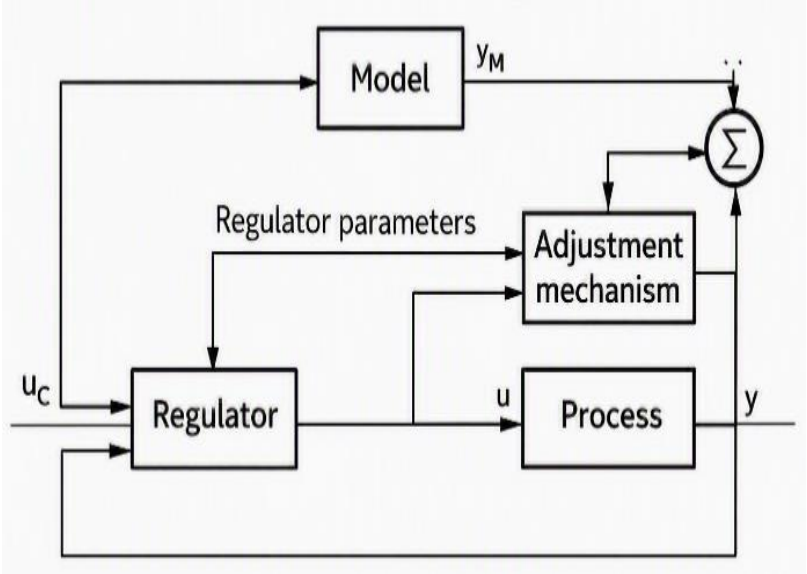


Fig. 5. Block Diagram of Model Reference Adaptive System (MRAS)

2) Model reference adaptive systems MRAS

The servo problem is an additional method for adjusting the regulator's parameters. In Figure. 5, the requirements are laid out in relation to a reference model that explains the optimum response of the process output to the command signal. In the control system, you may find the reference model. There are two loops that make up the regulator. The process and regulator make up the inner loop, which is an ordinary control loop. The regulator's settings are tweaked by the outer loop to ensure that the error bet is minimised.

D. Fuzzy Logic-Based Control

The fuzzy-logic-based control system has the advantage of intelligence as compared to conventional control approaches [32]. Figure 6 depicts fuzzy-logic-based control, a subfield of intelligent control that significantly contributes to the advancement of control systems' intelligence. In recent years, fuzzy-logic-based control has been progressively used to enhance the conventional control scheme, leading to greater control performance and intelligence.

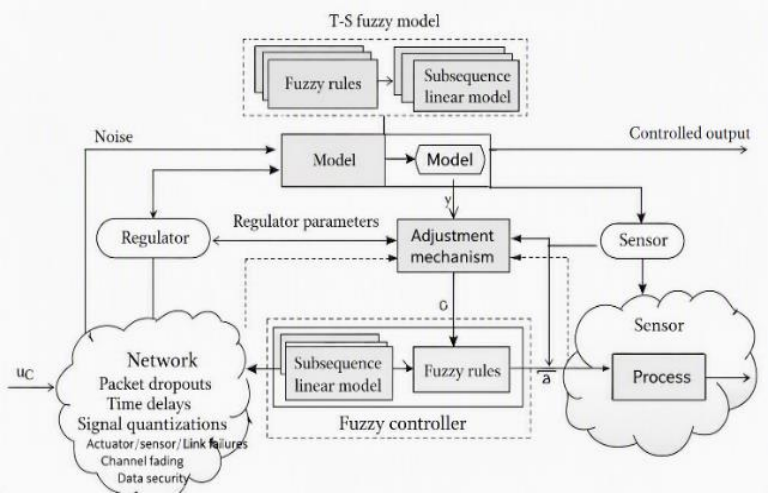


Fig. 6. Fuzzy-logic-based control in NCSs

1) Fuzzy-Logic-Based General Control

A fundamental and critical concern in NCSs is the stability of the networked system. Many issues, such as network-induced phenomena including unpredictable network load, unpredictability, and channel restrictions, might impact the controller design for NCSs, differing from conventional systems [33]. Additionally, there are substantial technological obstacles to resolving NCS control issues caused by the distant transmission of signals across networks with restricted bandwidth.

2) Fuzzy Adaptive Control

Adaptive control is a subfield of contemporary control theory that has seen rapid growth in popularity as a result of its widespread use in fields such as digital communication, navigation, industrial control, seismic monitoring, and radar and sonar. The three main ways that parameter-adaptive control is often implemented are self-tuning regulators, model reference control, and gain scheduling.

3) Fuzzy Tracking Control

A growing number of industries, including those dealing with aerial vehicles, photovoltaic systems, mobile robots, hydraulic servos, and articulated vehicles, have begun to rely on tracking control in recent years [34]. The primary goal of tracking control is to ensure that the output of the plant closely resembles the output of the reference model. A typical control problem, tracking is significantly more challenging than traditional stabilisation, particularly for nonlinear systems.

V. LITERATURE REVIEW

Recent research on closed-loop control in additive manufacturing focuses on improving process monitoring, manufacturing accuracy, quality, and stability. Various control techniques are being explored to provide real-time feedback and optimize process parameters. These developments support reliable, efficient, and adaptive manufacturing while reducing defects and improving overall production performance.

H. Ma, et al. (2026) developed a novel additive grayscale manufacturing process. By employing a laser with tunable parameters to induce a localized thermal oxidation reaction on the surface of a nano-meter-thick MoS2 film, the process promotes the redeposition of lower-density amorphous MoOx, thereby forming grayscale structures with heights significantly greater than the thickness of the original film. Furthermore, the influence trends of various laser parameters on the additive height were investigated. The laser-based additive grayscale manufacturing process founded on the principle of thermal oxidation provides a new pathway for customizing complex three-dimensional grayscale structures on nanomaterial surfaces [35].

E. Yu et al. (2026) proposed a defect closed-loop control system driven by test traceability, developed a high-fidelity reflow soldering digital twin model, integrated the three parameters of temperature zone thermal field, chain speed disturbance and wind speed flow, built a mapping association of dynamic processes, relied on the fusion of multi-source perception and detection data, completed the accurate tracing of test point abnormal instances and process links, and took "perception-judgment-optimization-execution-verification" as the core process to build a logical framework of closed-loop control. Empirical research is carried out in the prototype system deployed in the real production line [36].

J. Sousa et al. (2025) present a systematic review of AI applications for real-time control of laser-based manufacturing processes, analyzing 16 relevant articles sourced from Scopus, IEEE Xplore, and Web of Science databases. The primary objective of this work is to contribute to the advancement of autonomous manufacturing systems capable of self-monitoring and self-correction, ensuring optimal part quality, enhanced efficiency, and reduced human intervention. Its findings indicate that 62.5 % of the 16 analyzed studies have deployed AI-driven controllers in real-world scenarios, with over 56 % using AI for control strategies, such as Reinforcement Learning. Furthermore, 62.5 % of the studies employed AI for process modeling or monitoring, which was integral to the development or data pipelines of the controllers [37].

R. Phukan et al. (2025) propose techniques to handle start-up for immittance converters. Additionally, to

cater to wide DC bus input voltage range, a multi-level stacked half-bridge converter is used as primary side, for which a universal closed-loop controller with active DC bus voltage balancing is proposed. The start-up and closed-loop control scheme is verified on a 6.6 kW on-board charger prototype [38].

G. Nijhawan, et al., (2024) describe a series of approaches that improve wire additive manufacturing (WAAM) for manufacturing many metal items. ATM, MCA 2, ALTC 2, and RSM are the five techniques in the framework. Ablation research examined each approach and how they work together to improve WAAM accuracy, distortion, and material compatibility. The thorough performance comparison, including photographs, indicates that WAAM is better in deposition rate, surface quality, clarity, material diversity, cost-effectiveness, and scalability. The integrated framework enables dynamic modifications, tracking, and iterative improvements. This makes WAAM the optimal additive manufacturing process for many applications. The data indicates how significant each strategy is and how they work together to improve WAAM [39].

L. Chen, et al. (2024) propose a novel technique to directly infer melt pool visual characteristics in LAM by synergizing acoustic signal features with robotic tool-center-point (TCP) motion data. Acoustic monitoring has shown great promise in tasks typically reliant on vision sensors. In addition, the dynamics of the LAM process and defect occurrences are spatially dependent, primarily due to heat accumulation. By combining acoustic signals with spatial data from robot TCP motion, method tracks melt pool variations with an R2 score above 0.7. An ablation study demonstrated that the proposed method outperforms the acoustic-only models. The findings suggest that the integration of a simple microphone sensor with robot motion information emerges as a flexible, cost-effective alternative for capturing dynamic melt pool behavior [40].

R. Soloperto et al. (2023) propose a novel learning-based model predictive control framework for nonlinear systems which is able to guarantee closed-loop learning of the controlled system. It considers a cost function that combines a general economic cost with a user-defined learning cost function that aims at incentivizing learning of the unknown system. In particular, due to the finite horizon of the MPC scheme and to the presence of disturbances, the open-loop trajectory usually differs from the closed-loop one. Such a mismatch causes existing learning-based MPC schemes to only show a learning phase in the open-loop prediction, without providing any formal guarantee on the actual closed-loop learning 30[41].

Despite advances in closed-loop control for additive manufacturing, existing studies remain fragmented across processes, sensing technologies, and control strategies. Most approaches focus on process monitoring, defect detection, or parameter optimization rather than integrating these functions into a unified real-time feedback framework. AI-based methods show promising prediction and autonomous control capabilities, but process-specific datasets limit generalization across materials, machines, and operating conditions. Multimodal sensing improves process understanding, yet efficient fusion of thermal, visual, acoustic, and geometric information remains challenging. Digital-twin-based methods enhance process representation, but their integration with fast real-time corrective control requires further investigation. Learning-based MPC also faces computational and disturbance-handling limitations. Furthermore, standardized benchmarks for evaluating closed-loop AM systems remain lacking. The comparative findings in Table I highlight these limitations and indicate the need for an integrated, adaptive, AI-enabled closed-loop framework combining multimodal sensing, real-time prediction, defect correction, and process optimization for reliable autonomous additive manufacturing.

Table I SUMMARY OF KEY STUDIES ON RECENT ADVANCES IN CLOSED-LOOP CONTROL TECHNIQUES FOR ADDITIVE MANUFACTURING

Reference	Study On	Approach	Key Findings	Challenges	Future Direction
H. Ma et al. (2026)	Laser-based additive grayscale manufacturing	Tunable laser and thermal oxidation of MoS_2	Produced complex 3D grayscale structures with controllable additive height	Limited real-time monitoring and closed-loop feedback	Developed real-time laser feedback and adaptive control

E. Yu et al. (2026)	Defect closed-loop control	Digital twin and multi-source perception	Enabled accurate defect tracing and process optimization	Data integration and system complexity	Develop adaptive digital-twin-based AM control
J. Sousa et al. (2025)	AI-based real-time manufacturing control	AI and Reinforcement Learning	Supported self-monitoring, self-correction, and autonomous control	Limited real-world validation	Develop robust AI controllers for industrial AM
R. Phukan et al. (2025)	Closed-loop control of power conversion systems	Multi-level stacked half-bridge converter with universal closed-loop controller and active DC-bus voltage balancing	Verified effective start-up and closed-loop control using a 6.6 kW onboard charger prototype	Application is outside AM and focuses on power-electronic control	Adapt robust closed-loop control principles for AM energy and process management
G. Nijhawan et al. (2024)	WAAM process improvement	Integrated monitoring and iterative control	Improved accuracy, surface quality, material compatibility, and scalability	Complex integration of control strategies	Develop real-time adaptive WAAM control
L. Chen et al. (2024)	Melt-pool monitoring	Acoustic sensing and robotic TCP data	Achieved melt-pool prediction with $R^2 > 0.7$	Monitoring not fully integrated with corrective control	Integrate multimodal sensing with closed-loop correction
R. Soloperto et al. (2023)	Learning-based control	Learning-based Model Predictive Control (MPC)	Enabled learning within closed-loop control under nonlinear system conditions	Disturbances and computational complexity	Apply learning-based MPC to real-time AM processes

VI. CONCLUSION AND FUTURE WORK

Additive manufacturing has emerged as an important advanced manufacturing technology for producing complex components with high flexibility and reduced material waste. However, variations in process conditions, material properties, thermal behaviour, and machine dynamics can negatively affect product quality and dimensional accuracy. This review examined advanced closed-loop control techniques that address these limitations through real-time sensing, feedback, and automatic process regulation. In-situ monitoring using imaging and acoustic methods enables early detection of defects and supports continuous process validation. Conventional PID control provides reliable regulation, while adaptive control, gain scheduling, MRAS, and fuzzy logic techniques offer improved performance under changing and uncertain process conditions. The integration of artificial intelligence further enhances closed-loop control by enabling predictive analysis, adaptive parameter adjustment, and autonomous decision-making. Despite these advances, challenges remain in sensor integration, data processing, model generalization, and real-time implementation. Future research should focus on intelligent, data-driven, and autonomous control frameworks to achieve reliable, accurate, and scalable additive manufacturing systems for industrial applications.

Future research should focus on integrating AI, ML, and digital twins with closed-loop control systems for additive manufacturing. Advanced sensor fusion, real-time defect prediction, adaptive parameter optimization, and autonomous decision-making can improve process reliability. Further studies should validate these approaches using industrial-scale datasets, diverse materials, and complex manufacturing environments.

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