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Application of the Fog Computing Paradigm to Additive Manufacturing Process Monitoring and Control

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Abstract

Monitoring and controlling Additive Manufacturing (AM) processes play a critical role in enabling the production of quality parts. AM processes generate large volumes of structured and unstructured in-situ measurement data. The ability to analyze this volume and variety of data in real-time is necessary for effective closed-loop control and decision-making. Existing control architectures are unable to handle this level of data volume and speed. This paper investigates the functional and computational requirements for real-time closed-loop AM process control. The paper uses those requirements to propose a function architecture for AM process monitoring and control. That architecture leads to a fog-computing solution to address the big data and real-time control challenges.

Keywords: Additive Manufacturing, Fog Computing, Monitoring & Control, Functional Architecture, Control Architecture, Data Analytics.

Section-1. Introduction

Within the next decade, the goal of AM is to become one of the primary manufacturing processes. Requirements for achieving this goal include 1) AM software for high-complexity product design and engineering, 2) AM machines for high-quality and low-cost part fabrication, 3) AM sensors for in-situ monitoring of various AM processes, and 4) controllers that can analyze big data and make optimal decisions in real-time [1]. Vendors have been providing similar capabilities to address these requirements for traditional manufacturing for decades. So what is different about AM?

AM is an additive fabrication process. AM processes create parts directly from 3D computer-aided-design (CAD) files. For example, powder bed fusion adds, and then melts, metal or polymer powders in a layer-upon-layer fashion. The melting process varies depending on the technology underlying the heat source used in the process. Despite of the enormous potential benefits of AM, manufacturers are facing a major problem of the production technology: even under the identical process parameters and machine conditions, the quality of the AM products can vary substantially and often unacceptably [2]. Various factors contribute to this problem, including the variability in feedstock materials, process parameters, and build function execution. To reduce the part quality uncertainty, AM process monitoring and control become critical.

Unlike the process monitoring of subtractive processes, AM in-situ monitoring relies on multi-modal sensors that generate a large amount of 1d, 2d and 3d data during fabrication. The data are used to estimate the current states of both AM processes and parts, as well as to predict the final states of the parts. The in-situ data can also be used for part qualification and to improve the design and engineering of future AM products.

In addition, AM requires multi-loop feedback control, meaning that the measurement and quality monitoring data are used for process control and decision making at multiple sampling rates. AM in-situ monitoring data, generated in real-time from various sensors at different intervals, becomes feedback to machine controllers. The controllers analyze the data, modify process parameters in real-time or near real-time, or stop the build as necessary.

In this paper, we focus on defining a reference architecture for AM process monitoring and control, including 1) identifying the relevant analytics and control functions, 2) proposing a control architecture, and 3) using fog computing to implement them. In Section 2, we describe the limitation of the traditional hierarchical control architecture. In Section 3, we present a multi-loop control framework for AM process monitoring and control; Section 4 describes the computing requirements for near real-time process monitoring and control functions; Section 5 presents a fog computing based architecture for AM process monitoring and control

2. Is ISA 95 the Right, Control Architecture for AM

The ISA Model

For decades, the ISA 95 model defined by the International Society of Automation (ISA) has been the hierarchical-control choice for traditional manufacturing systems [3]. ISA 95 divides the functions of those systems into levels based on three aligned decompositions: spatial, functional, and temporal. In Figure 1, the triangle represents the ISA functional hierarchical decomposition, with the temporal aspects (the timeframes) of the hierarchy shown on the left. It is important to note that those timeframes are holdovers from the time when humans performed those functions. The spatial aspects, which are not shown, go from an individual machine to an entire factory. The shaded boxes on the right of Figure 1 show the various software applications that have been developed to implement the functions in each level. That implementation is constrained by the timeframe assigned to each level.

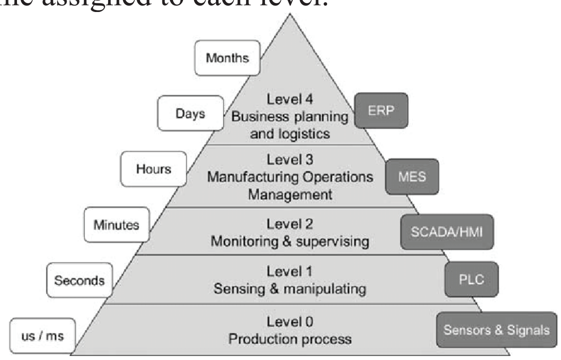

Figure 1. The ISA Hierarchy

The ISA views this functional hierarchy as a control hierarchy, meaning that each function is associated with a controller. That controller's job is to use the designated software application to manage the execution of that function. There are rigid rules about 1) the kinds of inter-level "command-feedback" communications and 2) the information exchanges between the software applications that create those communications. As noted above, those rigid rules were originally developed before the computer revolution, and well before the explosion of commercially available, domain-specific, software applications [3].

Since ISA's standardization, both the use of hierarchical principles and the ISA control hierarchy itself have been adopted, and adapted, in many manufacturing domains. The domain-specific software applications, which began to infiltrate the manufacturing sector in 1990s, were run according to the predetermined ISA timeframes. For example, as shown in Figure 1, ERP would run once a day, MES would run once an hour, and so on. Of course, once the required integration problems were solved, these applications could have been run at any time. But, for a variety of reasons mostly associated with keeping the four aspects in Figure 1 completely aligned, they were not.

Does ISA Work for AM

The beginnings of Industry 4.0, new advances in information technology, and a variety of new AI tools are obviating the need for an AM-centric control architecture. A key point of Industry 4.0 systems is decentralized, data-driven decision-making. The purpose is to make each entity more autonomous, with the capability to communicate directly with any other part of the system [3].

Advances in information technology include cloud services, camera sensors, fog computing, and edge computing. Cloud services provide a good option for implementing AM design and AM engineering functions. The economic benefits of using cloud services and computing come from efficient resource allocation. Resource management plays a major part in increasing system performance, thereby enhancing user satisfaction [4]. Nevertheless, cloud services naturally clash with both the new Industry 4.0 design principles and the need for reliable, real-time control of AM machines and processes during the "build" function [5].

That need depends on the ability to analyze the large amounts of in-situ measurement data being collected by a variety of cameras. Since there are very few physics-based AM process models, that analysis, and hence control, warrants the use of machine learning tools. Many of these tools exist in the cloud. Hence the in-situ data collected at level 1 must also be sent directly to level 3 and 4 functions for off-line analysis. While the cloud services can certainly be used for understanding AM processes and analyzing the final-part's quality for inspection purposes, they cannot be used for real-time control. For real-time control, in-situ measurement, analysis, and prediction are required to optimize the process parameters and thereby control the machine and process. These real-time or near real-time functions also demand intensive computation power, which cannot be provided by typical edge nodes, such as PLCs or AM machine on-board computing units.

In the remainder of the paper, we first propose a multi-loop feedback control architecture for the "build" monitoring and control. We then propose the use of both fog and edge computing as a way of implementing the corresponding functions.

3. Multi-Loop AM Process Monitoring and Control Functions

The proposed multi-loop AM process and control architecture is shown in Figure 2. It has three major loops: 1) sub-second real-time control 2) Layer wise scan optimization and 3) offline build planning and data driven modeling. Process Monitoring provides multirate data curation functions, including sensing, data acquisition, data fusion and data analytics.

The outmost loop "Build Planning" is an engineering task, usually done with human in the loop. The main outputs of Build Planning include 1) a build plan - the process parameters and other information needed to fabricate the product, and 2) the information (models) used to assess the current state of the process and the parts, and to predict the final state of those parts. The planning process involves two major types of tasks: 1) process specific tasks including lattice, support design and build orientation selection; 2) machine specific tasks to convert the build plan into the formats required by a particular AM machine, usually done by using machine specific software tools.

The innermost loop is for real-time control. Based on in-situ feedback measurements, real-time controllers change the process parameters to stabilize process. The feedback measurements can include melt pool temperatures and sizes, sampled at many KHz.-And the process parameters include energy power, material feeding rate etc. As of today, only a few AM machine models have the real-time feedback control capabilities.

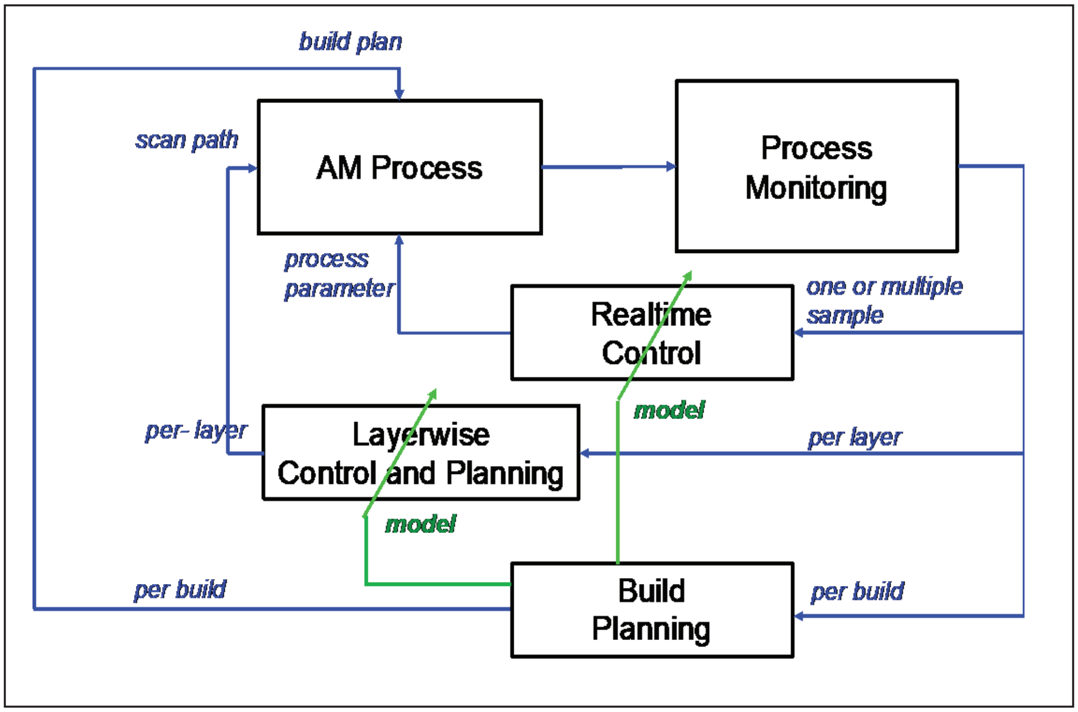

Figure.2 Multi-loop Control Architecture for the Build Function

The middle loop "Layer-wise Control and Planning" makes adjustments of scan path and process parameters for the next layer based on the monitoring information from the previous layers. For PBF, this task has to be done before the recoating process finishes to avoid build time increasing.

The multi-loop monitoring and control functions use a variety of machine learning techniques to determine the current states of the process and the parts, to make a prediction about the final state of the part and to generate real-time or near real-time control to bring back the part quality from deviations. The models used for real-time and near real-time control can be learned from past builds and simulations which are usually trained in clouds. The process monitoring functions supporting real-time or near real-time control have to provide process and part state estimation within micro seconds or several seconds to enable the feedback loop. For layer-wise re-planning, multi-modal sensor fusion and model predictive control are involved for defect detection and scan path re-planning. These tasks are also computational intensive, beyond the capability of the traditional edge computation nodes such as PLCs or embedded controllers. In order to identify appropriate computation infrastructure for the AM process monitoring and control, we will first analyze the functions for in-situ monitoring and control and group them in a function architecture, which will be described in this section.

AM Process Monitoring and Control Function Architecture

Figure 3 shows a reference function architecture of AM process monitoring and control. Analytics and control functions are grouped and illustrated based on the time criticality.

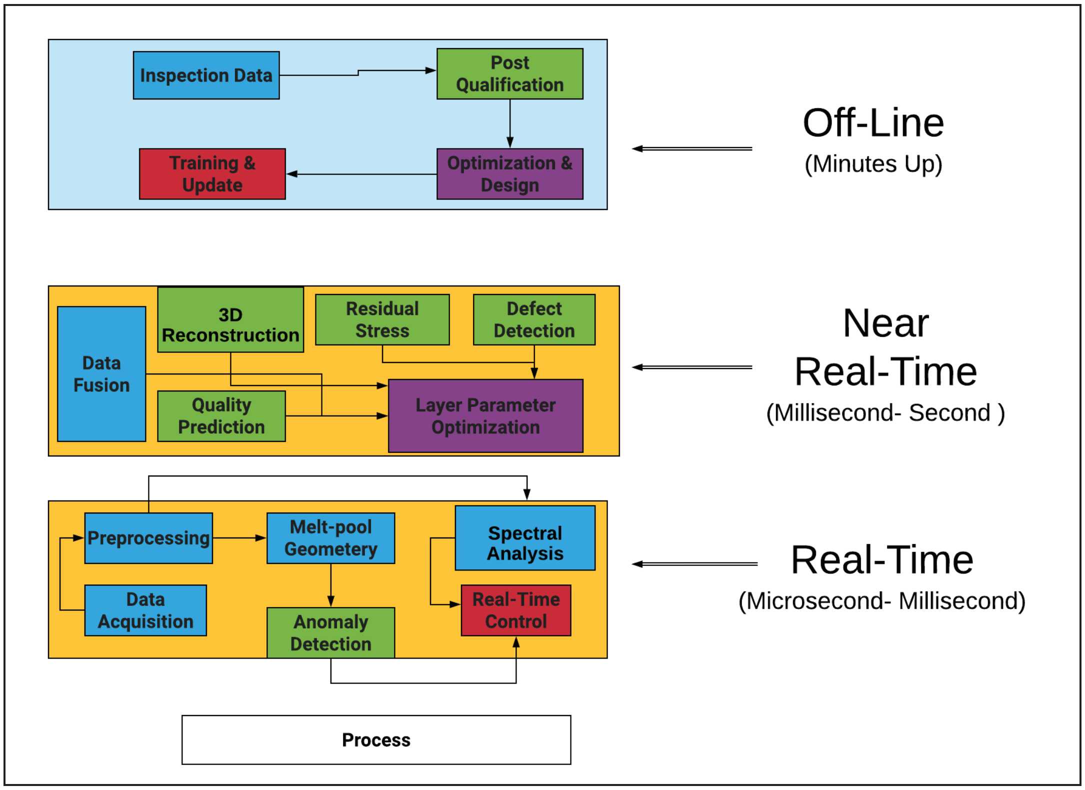

Figure.3 AM Process Monitoring and Control Function Architecture

Real-time functions include data acquisition from in-situ monitoring system, measurement data preprocessing - cleaning and tagging, melt pool geometry characterization, fast spectrum analysis of acoustic measurements, anomaly detection, real-time feedback control generation, and emergency reaction, such as build stop.

Near real-time functions fuse the process monitoring data obtained from previous layers, conduct layer-wise process and part state evaluation and make decision if the build should be continued or stopped. If the build shall continue, a scan plan adjustment function may be necessary based on the evaluation or prediction of part quality. With hybrid manufacturing, the layer-wise controller can make a decision to machine off the defected layers and then resume the layer-by-layer process.

Offline functions include data analytics for engineering decision. In-situ monitoring and control data from multiple past builds, as well as the part development lifecycle data, are aggregated for analysis. The data can be used for training to correlate process settings with process signatures, microstructure properties and mechanical properties. The resulted models are used for build plan generation. Machine learning can also be used to train models which are used in real or near real-time process monitoring and control.

In this paper, we focus on the analysis and prediction functions for in-process control. Many of the tasks associated with these functions are shown in Figure 3, including tasks in the real-time group and tasks in the near real-time-group. In the remainder of this paper, we will discuss the near real-time functions, which demand the use of fog computing for implementation.

Near Real-Time Functions

The main purpose of the near real-time process monitoring and control functions is for layerwise decision making. Multiple commercial AM systems and third party in-situ monitoring systems are equipped with such capability. The cycle time for layerwise decision making varies from seconds to minutes, depending on the design of the parts, the scan patterns and the process parameters. The middle layer of Figure 3 lists the mostly reported layerwise data analytics and control functions. They are sensor data fusion, residual stress estimation, 3d model reconstruction, defect detection, process and part quality prediction, and layer parameters optimization.

Multiple in-situ sensors are being utilized in AM machine for monitoring and controlling AM part quality. The sampling rates and volumes of the sensor data vary. For real-time monitoring and control, these sensors data such as temperature, melt pool geometry, acoustic signal, process parameters, etc. need to be registered correctly and fused effectively. Sensors data fusion is a major area of research for better understanding of the AM process [6, 7].

3D in-situ measurement such as Optical coherence tomography (OCT) is used for both surface and inner-structure defect detection, as well as dimension analysis. Due to its high resolution and non-destructive nature, it also useful for surface-void detection, loose powder detection, and subsurface feature detection. OCT is also used to find cracks and un-melted powder areas during production [8, 9].

Accurate residual stress estimation is a key step in attaining maximum dimensional accuracy and avoiding early fatigue failure [10]. Many process parameters affect the residual stress in AM [11]. The estimated residual stress based on in-situ thermal measurements can be used as the inputs to re- plan scan paths and optimize process parameters for the next build layer. Therefore, they work as a promising tool for AM part quality control.

Finding defects using layerwise images provides timely control over the ongoing manufacturing process. By detecting a catastrophic defect during the process, we can stop a failed build early, reduce the cost and avoid the waste. There are many existing methods to find defects such as ANN, Bayesian classifier, support vector machines (SVM), and Convolutional Neural Networks (CNN). CNNs earned attention due to the accuracy and fast execution time as compared to other methods. The execution speed of a CNN is enhanced through the use of high-performance computing resources such as advanced GPU. The output of the function can be used for (layer-wise) process control, supplementary process decisions, or remedial actions [12-14]. Some researchers use an acoustic signal for in-situ quality prediction in AM using deep learning [15-16].

Automatic virtual metrology (AVM) is a technique in which the quality of the manufactured part can be predicted without actual manufacturing by utilizing previously obtained in-process measurements. For AM quality prediction, the AVM system is based on in-situ data sensed during prior manufacturing [17-18].

Layerwise parameter-optimization functions re-plan the process settings for the subsequent layer. These functions consider outputs from the quality prediction, OCT, the residual stress estimation, and the defect detection functions, and perform path re-planning using ANNs or genetic algorithms [19].

Today's AM machines are instrumented with a myriad of sensors. In addition, many of 3rd party provided sensors can be easily integrated which generate and produce data over extremely short periods of time. Not like the traditional machine tools using 1d sensors, many of today's AM-sensors are generating vast amounts of 2d (image data) and even 3d data at increasingly faster rates – much different than the traditional numerical data. Tens of thousands images from high speed co-axial cameras are generated each layer. In addition, staring cameras produces multiple high-definition global view images each layer. Fusing the images with the machine control commands and other sensor measurements are critical for layer-wise control, planning and decision making. The computation requirements to perform the data analytics and control are very high.

4. Computing Requirements in AM

Computational speed is the major issue for the real-time control system. The traditional method can deliver precise melt pool measurement but deficiencies of processing efficiency. For real-time control in AM, a major problem is that current single node systems cannot meet the real-time computing requirements. For example, a traditional melt pool classification method takes 3.5 milliseconds to process a melt pool image. If a co-axial camera generates approximately 3000 images each layer, classifying the full layer of melt pool images would require approximately 10 seconds. This calculated time does not include the data transfer time; sending such a large amount of data to the cloud for processing will require additional time for transferring and processing. Due to these problems, currently manufacturing automation systems fail to meet the AM requirements for real-time monitoring and control [20].

The computing requirements for AM processes are dictated by the volume, velocity, variety, and veracity of the data. According to Wang et al., there are up to 2.3 trillion voxels in a typical build volume; about 600 variables logged during AM processes on a per seconds basis, giving up to 300 MB of data per build; and up to 0.5 TB of data collected per build using in-situ monitoring [21]. Photodiodes and pyrometers are the most common devices used in SLM monitoring systems due to their fast response and easy integration. Both devices boast acquisition rates above 50 kHz. If process is monitored with a high-resolution camera (20 kHz or more) for a few seconds, even for very short time interval, several GB of data per second can be collected.

Figure 4 shows the correlation between camera frame rate and resulting data. Clearly the high volume of data cannot be transferred using current industrial interface communication protocols [22]. For real-time data acquirement and transfer, the data rate may not exceed the

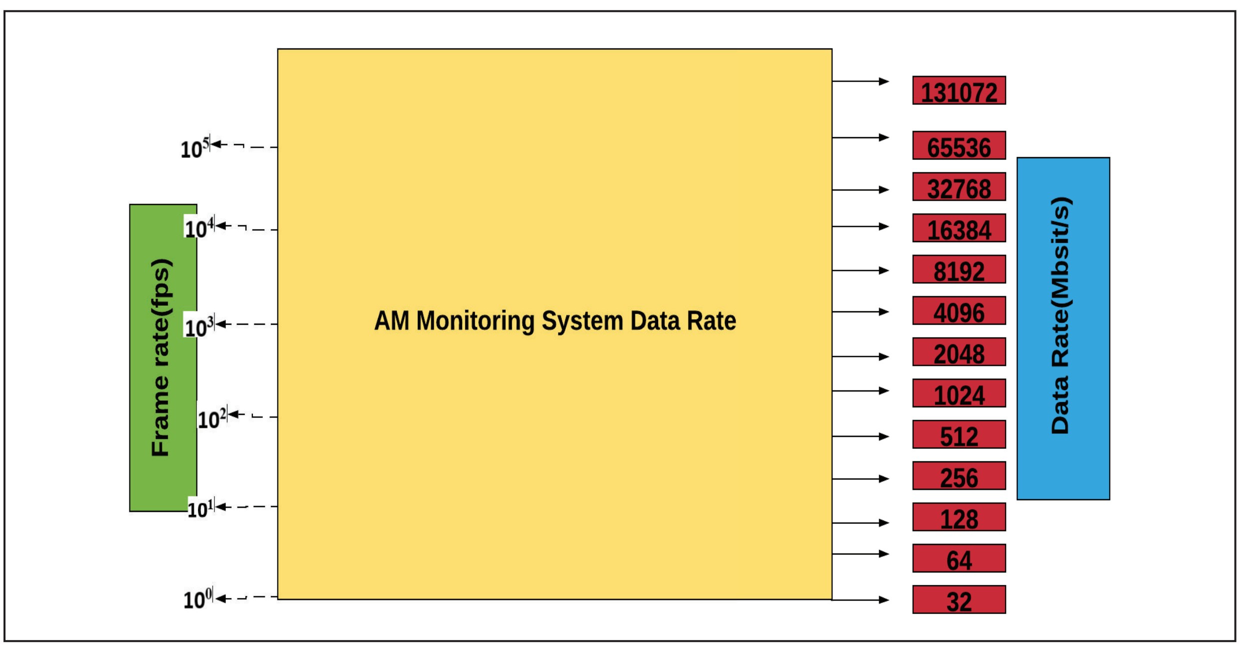

Figure.4 Ratio of FPS to Data Rate

limit defined by communication protocol; for example, USB3.0 can handle a maximum rate of 640 Mbps. Studies show that data rate is fairly higher than range of the current available communication protocol [22]. AM in-situ monitoring data processing for near real-time control is a big data problem. In the following sections we propose an AM process monitoring and control architecture based on fog computing.

5. Fog Computing and Architecture

Owing to the amount of data and the data's dynamic nature, processing it within the time constraints required for real-time applications is a big challenge in AM. In the AM process, the huge amount of data produced in a very short time leads to time constraints and latency problems. Both problems make it impractical to use a cloud-computing architecture for real-time, process-control applications.

The cloud model can be organized using three major concepts: infrastructure as a service, platform as service, and software as service. Some of the main benefits of the cloud model are virtualization, scalability, on-demand self-service resource pooling, and location freedom. In contrast with cloud-based manufacturing, fog computing shifts the heavy data workload from the centralized cloud to near edge devices. Due to the latency problem, the amount of data communicated using the cloud must be reduced for online, real-time machine monitoring, diagnosis and control. In fog-empowered architectures, manufacturers can save sensitive data on local machines while using the intelligence, data analysis and training applications provided by high-performance, cloud computing [23].

Fog Based Systems

Fog computing works as an intermediate layer between IIoT (Industrial Internet of Things) and cloud for more responsive services. In fog computing, each computer node works independently to provide intelligence on the outer edge of ubiquitous networks, without requiring a persistent network connection. This reduces network traffic and enhances scalability and security [24-25]. Fog computing is a geographically distributed computing architecture with a resource pool consisting of one or more ubiquitously connected heterogeneous devices (including edge devices) at the edge of the network and not exclusively seamlessly backed by cloud service. The architecture provides elastic computation, storage and communication in isolated environments to several clients in proximity [26].

Wu et al. proposed a real-time remote computational framework based on fog architecture for process monitoring and prognosis in cyber physical system (CPS). That framework utilized the wireless sensors, cloud, and machine learning [27-28]. Fog was shown to perform well in smart city applications including data demonstration, feature extraction, anomalous and hazardous event classification, and security measures. A fog-based distributed architecture was proposed to support the data collection and analysis in fast response applications [29-30]. A combination of PMML-encoded ML models and fog computing was proposed for gaining the key ideas of decentralization, security, reliability, and privacy in Industry 4.0 [31]. We could not find any literature on fog-based functional and control architectures specialized to AM.

Fog-centered computing models are currently utilized more and more to fulfill the requirement of IIoT, CPS, and mobile computing. It is suitable for applications where instant feedback and response are required. To handle time limitations, fog computing architecture plays an important role in real-time application [32]. In the remainder of this paper, we will discuss our proposed architecture to deal with AM, time constraints.

Proposed Fog Based Architecture

The proposed architecture is a combination of edge, fog, and cloud methods, as shown in Figure 5, which mirrors the temporal decomposition of control functions shown in Figure 3. As shown in Figure 5, The Intelligent In-Situ Monitoring and Computing System (IIMCS) comprises five major layers: sensors, intelligent edge per sample, intelligent fog per layer and per build decision making, and cloud. The corresponding data residency is divided in terms of sources, models, knowledge and database; the time flow represents the general time required by each component of the IIMS data analytics function for processing.

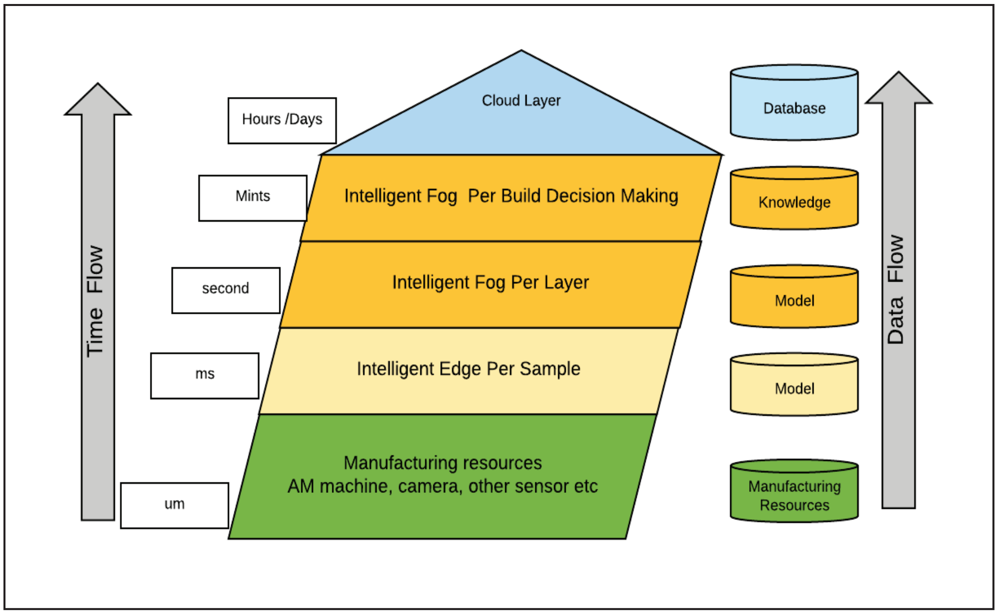

Figure.5 Intelligent AM In-situ Monitoring and Control System

Intelligent Edge Per Sample

In AM, advanced, high-speed sensors capture variations in the process to improve quality control at the lowest possible scale. These sensors capture huge amounts of image data (on the order of gigabytes) within an extremely short period of time (on the order of seconds). To 1) transfer this amount data to the cloud, then 2) to analyze the data using some kind of AI tool, and, finally 3) to return it to AM controller who then must make a decision will certainly take more than the microseconds allowed for the analysis of each sample (on the order of microseconds). Consequently, utilizing service to perform that analysis, the cloud is not possible – primarily due to communication delays (latency). The reason is that no currently available communication protocol supports the transfer of that amount of data involved within the time constraints required for real-time AM quality control.

As an example, we describe a concept for a new, open-source, **smart** camera that eliminates the need to transfer image data to the cloud (see Figure 6 left side). Our smart camera is an edge device that both collects and analyzes melt-pool images in real time. Analysis operations are performed as part of the real-time, monitoring functions shown in Figure 3. The smart camera performs various different kinds of operations, such as anomaly detection, preprocessing and feature extraction, on the images obtained in monitoring the melt pool.

If no anomaly is detected, the smart camera outputs the feature data to the fog layer for further analysis. If an anomaly is detected, the relevant raw data is sent to the fog layer for further analysis. The smart cameras only send raw data from involved images to the fog layer for in-depth analysis if they find abnormalities in the melt pool.

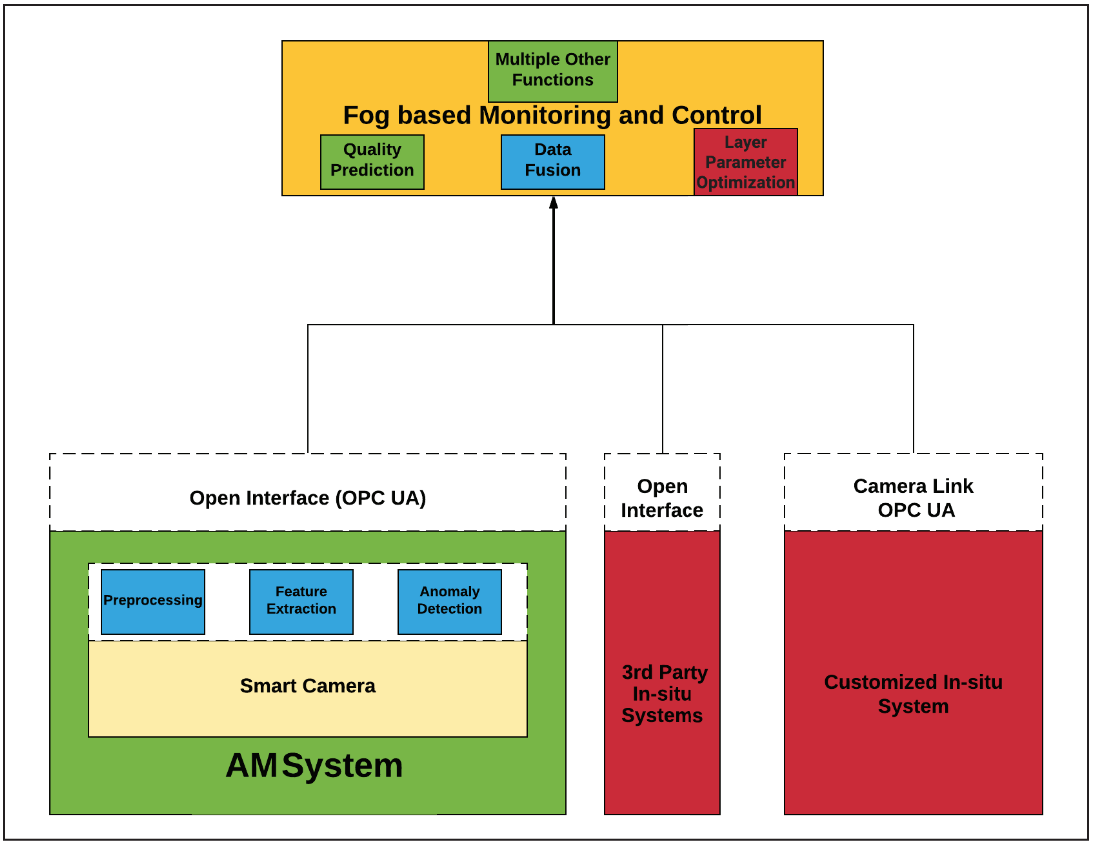

Figure.6 Fog based Monitoring and Control System

Intelligent Fog Per Layer

This layer consist of multiple near real-time functions run on the dedicated fog node, which will likely reside on the AM process control computer. This lower layer of fog fuses the data from multiple sensor systems as shown in Figure 6. It then uses the data to control multiple systems including the scanning system, the environmental system, and in-situ systems [33]. There are many, third-party, commercial, in-situ control systems available such as SLM solutions, Stratonics , EOSSTATE, QM melt pool 3D and Sigma Labs [34]. To achieve successful real-time control, data from the AM system, as well as from any utilized commercial and custom systems, needs to be fused for further analysis.

This fog component deals with the layer-by-layer data of the AM process. The area of the melt pool and correlates that estimate with the current laser power and scan speed. Layerwise data analytics provides the information needed to adjust the parameters before the next fabrication layer begins, if that information indicated any kind of problem in the process. Our design provides feedback in real-time. Thus we need to analyze the layerwise data and provide suggestions or warnings to a feedback controller for better process parameters adjustment as soon as possible. Layerwise analysis function data transfer to the parameters adjustment as soon as possible. Layerwise analysis function data transfer to the next layer for build level decision.

Intelligent Fog Per Build Decision Making

The intelligent fog per build consists of knowledge decides whether to continue or stop the process, based on current data. This component controls the main functionalities of the proposed architecture. The designed architecture performs all these tasks locally within the boundary of the factory, which enhances the trust of manufactures in term of data security. Due to privacy and security concerns, technology manufacturers do not want to send their data outside the factory.

Why Fog-based Architecture?

The proposed architecture is a combination of cloud and fog services. The advantages of fog computing are location awareness, mobility, low latency and physical dispersion. Fog computing is not an alternative to cloud computing. Rather, it eliminates the drawbacks of cloud computing and improves the efficiency [4]. Fog computing has the following advantages compared to cloud-based solutions: [35, 36]

1) Latency Constraint

   Fog computing has the capability of solving any latency issues by performing data analysis, control and time-restricted tasks near to the end user. Cloud technology often fails in time-restricted applications because it works in a centralized fashion; all processing is done in a distant location requiring a substantial amount of time to transfer data, process data, and send it back to the user's location. In AM quality-control processes continuously generate huge amounts of data and require near instantaneous feedback for effective quality control. Consequently, typical Cloud technology, owing to its substantial latency, is not a feasible computing choice for AM control.

2) Network Bandwidth Constraint

   Fog supports hierarchical data processing in conjunction with the cloud. It creates balance among application conditions and available computer resources by allowing different processing at different levels or locations. In this way, fog reduces the quantity of data transferred to the cloud that requires higher bandwidth. The frame rate is very high for in-situ AM measurements, making it impossible to transfer these large amounts of data in a very short period to the cloud. Fog technologies, however, have the capability to perform operations on large amounts of data without transferring them to the cloud. In the suggested architecture, the fog dedicated layer handles the complex task of data allocation for real-time analysis.

3) Resources Constrained Devices

   Cameras and pyrometers are examples of resource-constrained devices because they possess very small amounts of both processing power and storage memory. That means the data they collect must be communicated somewhere and processed very quickly. These devices typically are incapable of sending data to the cloud due to reasons like power, bandwidth, and cost. Fog address this limitation.

4) Uninterrupted Service/Irregular Connectivity with Cloud

   Fog systems provide services even when there is an irregular connection with the cloud.

5) Security Challenges

   Fog systems work as proxies for all limited-resource devices for software and security authorization updates. Further, as limited-resource devices have poor security capabilities, the fog system can provide antivirus scanners.

6) Reduce data movement across the network

   By limiting data movement across the network, fog systems significantly reduce network congestion, remove the drawbacks of centralized computing systems, allow the necessary data to stay closer to the end user, and provide enhanced scalability arising from the use of virtualized systems.

7) Removes the core computing environment
   By removing the central computing setting, fog systems make real-time quality control in AM manufacturing possible.
8) Faster response
   In addition to providing a sub-second response to end users, it also delivers high levels of scalability, reliability and fault tolerance.

Conclusion

The proposed fog-based architecture addresses the challenges of the real-time quality control for additive manufacturing using big data. The fog architecture shifts the high bandwidth and latency-sensitive processing to near-the-edge devices in order to perform necessary functions without sending data to the cloud. The intermediate layer of fog solves the problems of insufficient bandwidth and latency for real-time data analytics and decision making applications in the AM process. The proposed architecture also helps the machine builders, in-situ system providers, and software vendors to understand the function requirements for better integration of their products and services.

In future work, the proposed control architecture will be prototyped in a research environment for validation, and performance will be measured and shared with the AM community.

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