Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
April 28, 2022
A Regional Conference of the Society for Industrial and Systems Engineering

Quality Inspection and Process Monitoring for Directed Energy Deposition Manufacturing Using a Cyber Physical System

Patrick Imbornoni, Matthew Kirk, Damon Mertens, Christian Pena, Zimo Wang, Yu Jin, and Fuda Ning

Department of Systems Science and Industrial Engineering
State University of New York at Binghamton
Binghamton, NY 13902

Corresponding Author's Email: dmertens1@binghamton.edu

Author Note: Patrick Imbornoni, Matthew Kirk, Damon Mertens, and Christian Pena are senior Industrial and Systems Engineering students at Binghamton University. Dr. Wang, Dr Jin, and Dr Ning are Professor in the Systems Science and Industrial Engineering department at Binghamton University and served as the team's Capstone advisors.

Abstract: A cyber physical system (CPS) connects multiple devices so that data can be shared between them. One such process a CPS can assist in optimizing is directed energy deposition (DED); an additive manufacturing technique that uses focused thermal energy to melt metal powder or wire as it is being deposited. During this process, a melt pool is created that can lead to structural defects in the object being produced. The melt pool and defects are correlated to the process parameters. By creating applications on the IBM Cloud, the data received from sensors and cameras (thermal and high speed) during the process can be stored, organized, and visualized to draw conclusions that can help to optimize the process and reduce defects.

Keywords: Cyber Physical System, Internet of Things, Directed Energy Deposition, Image Processing

1. Introduction

Additive manufacturing (AM) is a manufacturing process that creates objects by joining materials together layer by layer in the form of a three-dimensional computer-designed object. Directed energy deposition (DED), one of the seven categories of AM, is a manufacturing process that simultaneously deposits a wired or powdered-based material and provides an energy source, usually a laser or electron beam. DED produces objects by melting materials as they are being introduced to the object using thermal energy (Ning, 2022).

A Global EY Report from 2019 shows that in 2019 65% of companies surveyed have applied AM to their business, and another 18% are considering it. Ernst and Young report a significant increase from 2016 when only 24% of these same companies had applied, and 12% initiated the transformation. A more widespread understanding of the technology and its beneficial use cases has led to increased adaptation within businesses. The Global EY Report describes how companies can become more efficient, grow, and transform their business through AM. On-demand printing, smaller lot sizes, and customizability help create more efficient business and supply chains. AM also allows cost-effective design parts to fit unique customer needs better. Finally, a business adopting AM opens itself up to new markets and endless opportunities in the rapidly growing AM supply chain (Ernst and Young, 2019). AM is an emerging area that seeks wide applications across multiple fields. The development of this technology keeps progressing.

An Internet of Things platform (IoT) creates digital data from physical objects and processes. This physical information is collected using data collectors such as sensors and cameras. These data collectors send digital information to computers that are connected to each other. The network created by these sensors and computers allows for data to be viewed remotely. Overall, this platform allows communication between machines and computers, allowing for the process to be monitored and controlled, adjusting to ensure the quality of parts and more efficient production rates (Wang, 2019).

For AM to become a reliable tool for production, each process must be further developed and optimized to reduce part deformities, making the process more efficient. This research attempts to correlate process parameters for a DED process to the object's porosity and microstructure, which both determine the quality of the surface finish. Using sensors, Raspberry Pis, and the IBM Internet of Things platform, this research creates a CPS in which data collected during the manufacturing process is stored and visualized, allowing for interpolation of data that can be used to determine the optimal process parameters needed to create a quality product.

2. Literature Review

DED manufacturing is no exception to these benefits and limitations of traditional AM processes. AM continues to be a popular tool for initial prototype testing. Inexpensive prototype prints verify that CAD models are correct and allow for physical testing. Additive manufacturing has zero lead time, and unlimited design space, and allows for a variety of designs because there are no specialized molds or tools needed (Ning, 2022). Based on the nature of the process, DED can use strong, durable metal alloys for production such as stainless steel, titanium alloys, and aluminum alloys. This gives DED-produced objects better mechanical properties as compared to other AM processes. The material used in DED manufacturing can be fed into the machine during production which allows for larger and multi-material parts. With high initial machinery costs, slow production rates, limitations in production size, and quality issues, there is room for improvement in the DED process. DED-produced parts tend to have poor object resolution and rougher surface finish which leads to each object requiring post-production finishing (Svetlizky et al., 2021).

DED has become a reliable tool in repair and maintenance, with many applications in the aerospace and automotive industries (Piscopo & Iuliano, 2022). The nature of these two industries, aerospace and automotive, necessitates that the process produces reliable and quality objects. Previous studies researched how each part of the DED process affects the quality and reliability of the object produced. A critical aspect discovered is the melt pool. The melt pool is described as the area around the energy source where melted metal powders form a droplet. The energy source's interaction with the melt pool as well as the thermal field of the object works together to determine the physical properties of the object's surface finish. Additionally, local temperature differences on the surface of the object can help predict the microstructure of the object. This helps determine the reliability of an object as defects formation and strength can be assessed. Observations using a thermal camera show how cooling rates can determine these thermal properties in objects (Svetlizky et al., 2021). Traverse speed, laser power, spot size, and other related process parameters are used to predict the thermal gradient and then thus make inferences on the surface finish. Thermal imaging is used to create a thermal map of the process using techniques such as edge detection and noise reduction algorithms. From these crevices, pores, scratches, and other physical defects can be found during printing which will allow for immediate fixes for these errors (Chen et al., 2020).

Cloud manufacturing is a growing technology in which real-time sensor data of a manufacturing process can be viewed and analyzed anywhere with an internet connection. Decisions and adjustments can be made in real-time which helps reduce waste, increase efficiency, and overall optimize the process to better adapt to real-world changes currently happening (Jin, et al, 2020). Cloud manufacturing provides the ability to monitor the build quality, by either viewing historical data and optimizing process parameters or adjusting in real-time. The cloud capabilities allow for a larger amount of data to be analyzed than a local stored system. The cloud also allows for multiple parties to monitor and analyze the data from wherever and whenever in the world. An IoT platform is a relatively inexpensive way to create a network of sensors, cloud databases, and computers. The IoT platform allows for programs and applications to be built into the data analysis process. For example, machine learning and image processing code can be used to alter the process parameters if corrective action is deemed necessary at the moment (Zhon., 2017).

3. Approach/methodology

The proposed CPS consists of three parts, which when combined, create a quality inspection and process monitoring platform for the DED Process. Figure 1 provides an overview of a basic implementation of IoT by integrating the Data Acquisition System, Image Processing, and the IBM Cloud platform.

The Data Acquisition System, consisting of a Raspberry Pi single-board computer and sensors collect data directly from the DED Process. This data is then sent to an IBM Cloud application to be processed and organized. The Image Processing portion of this design receives thermal camera data, analyzes the data to determine the melt pool size, and outputs this new data to be uploaded to the IBM Cloud. This cloud system can then be implemented in a DED process as a quality check for the process (Bothcha et. al., 2018.)

The Data Acquisition system was designed to collect data directly from a DED process. To collect and process this data, a Raspberry Pi single-board computer serves as the main processing component. Connected to the Raspberry Pi is a temperature sensor to collect data, which is sent to the cloud Application and graphed in real-time. This proved the ability to connect our Data Acquisition System to the cloud Application.

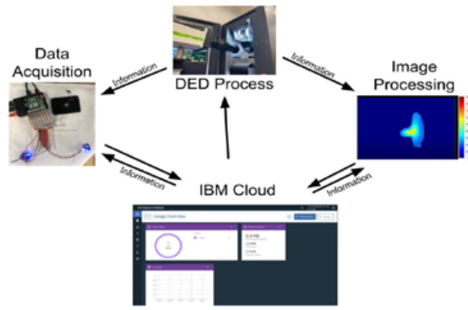

Figure 1. Overview of Proposed CPS for DED process.

Image Processing involved collecting data from a thermal imaging camera, analyzing this data, and once again uploading it to the cloud application. Data provided from an experiment capturing a thermal video of a similar AM process was used to develop and test the code for this section of the design (Miller, 2021.) The thermal camera was situated 15 cm outside the DED machine at a slight angle. Each frame of the captured video is read by a code written in MATLAB to find the temperature reading for the entire image. From this data, a colormap is created for the entire process, and the image is segmented by removing all points under a certain value, leaving only the melt pool. For this dataset, the specified value was 30.0. With this removed data, a video created shows the size and shape of the melt pool. After this data is processed, additional graphs detailing the location and temperature of the hottest point of each frame are created. The completed video and two graphs make it possible to identify possible locations where defects may have occurred. Potential causes for errors include a significant change in melt pool size or shape, fluctuations in temperature, or significant movement of the maximum point in the image.

The IBM Cloud serves as the communication center and allows the user to visualize all the collected data for a process and make informed decisions about the DED process. The IBM IoT application is used as it allows a direct connection to our Raspberry Pi data acquisition system. This connection is made through the Node-Red Application. With this connection, a Graphical User Interface (GUI) is created to graph the data collected from our sensors and pictures of the thermal field, collected from the image processing portion, at set time frames.

The proposed platform provides an effective way to monitor the DED process for reducing quality nonconformities. A user looking at the IoT application can monitor and analyze the visualized sensors' input or process parameters from DED processes using different starting conditions, such as vibration or temperature. From here the user will be able to make decisions based on this data and decide which process would result in the least number of defects, which decreases overall waste for the process.

4. Experimental Results and Analysis

Throughout the project it was discussed what kind of sensor data would be collected during the DED process, this included data from thermal and high-speed cameras as well as data concerning acceleration, force, and acoustics taken from sensors connected to Raspberry Pi’s. One of the first objectives with this data is to organize the data received in the IBM cloud which allows the user to pick specific data sets for the desired run to analyze it. One way to do this would be to make a table that contains the sensor readings. The design is just three columns, one for each sensor. The length of this table would vary depending on the sampling rate, which is measured in a range between kHz and MHz meaning that the tables can be long and difficult to navigate. This is where the graphing comes in to help visualize the data. By being able to see the data points plotted out over time, a better understanding can be made of the data trends, and it can be communicated more efficiently.

Using the data from the different sensors, three graphs corresponding to each column’s values can be made in the IBM cloud to visualize the readings over the course of the DED process. These graphs receive data directly from the connected Raspberry Pi’s where it is accumulated and simultaneously plotted. When looking at the graphs, notes are taken on any irregularities or extreme fluctuations in the graph that indicate possible disturbances in the process that could correlate to structural defects in the finished product. Data collected can be graphed simultaneously on the IBM cloud, the y-axis indicates temperature while the x-axis shows the time. This instantaneous data collection allows the user to detect unusually high or low values that may correlate to an increase in porosity and a larger melt pool as the process is underway.

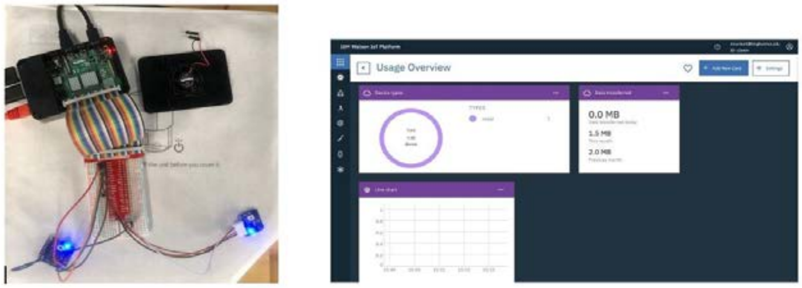

Figure 2. Raspberry Pi Sensor Setup (Left) and Watson IoT Dashboard (Right).

Camera data in the form of .tiff and .hdf5 files can be read and visualized using MATLAB scripts. The thermal behavior of the melting pool is obtained based on the hdf5 file readings, which contains the temperature profile for each pixel in an image. Then a thermal map is created with the given values for the image segmentation and edge detection to extract the full melt pool. Figure 3 shows the result of a frame after isolating the melt pool. Next, the detailed characteristics of the melt pool can be calculated and uploaded to the IBM Cloud for monitoring the process.

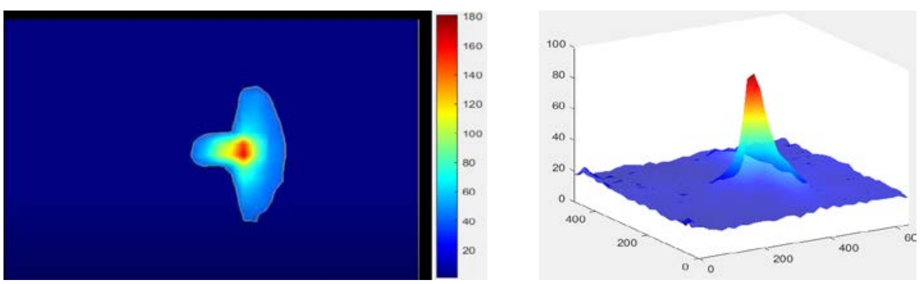

Figure 3. Extracted Thermal Images. Here the colormap shows the thermal field of the melting pool during DED printing.

Using the extracted image from the data files, the team utilizes edge detection and image segmentation techniques to analyze the area of the melt pool that was created during the process. This can then be uploaded to the IBM cloud and organized with the corresponding set of sensor data.

When combining the sensor data graphs with the processed camera data, conclusions can be drawn about the process. By looking at timestamps from both the graph and video, the user can select times when abnormalities are spotted on camera and match them with the data received from the sensors. The collected data indicates values, whether acceleration (motion), force, or acoustics, that can indicate a larger melt pool area. Looking at the values in either the tables or, more likely, the graphs (due to a possible sampling rate that will record many data points, making the table itself challenging to read), the user can find values for each of the three sensor measurements that indicate something abnormal about the process. Regarding acoustics, a steady average level of intensity would indicate that the process is running smoothly; any erratic jumps in the acoustic emissions could indicate abnormalities during the process (Hauser et al., 2022). Another example of abnormalities is high vibrations recorded on the accelerometer that adversely affect the process, as high levels of vibration can increase porosity and melt pool size (Ning et al., 2020). The thermal imaging portion also plays a role in detecting anomalies. Figure 4 below shows a graph detailing the maximum reading from each sample data frame. The camera itself did not detect the melt pool, so anomalies elsewhere are examined. While a possible one was found, no conclusion could be made using the images alone. It reinforces the need for the other sensors to provide other data types; the user can look at the time on this image and reference it with the graphs. The visualized readings tell the user if something went wrong at this point during the process.

ISBN: 97819384962-2-6

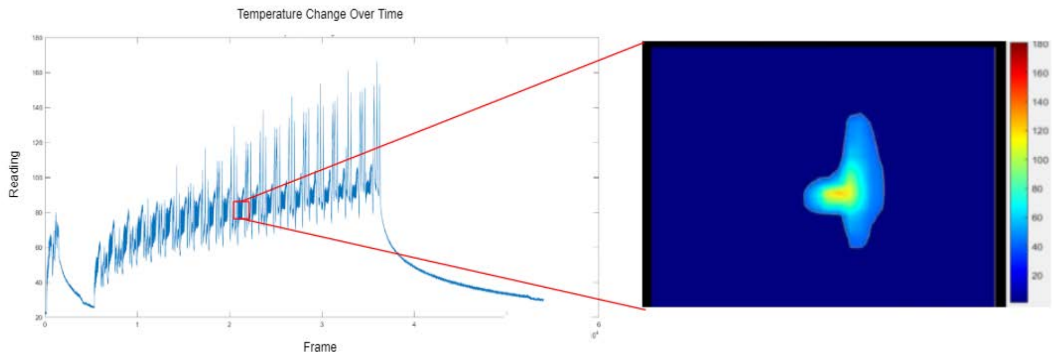

Figure 4. Temperature profile for entire DED Process and example frame from the process

This real-time data collection and visualization of the thermal dynamics will promote communication between engineers on the in-process thermal dynamics during DED printing. The line charts plotted in real-time on the IBM cloud allow instant access to the monitored process. The information analyzed provides crucial insight into their manufacturing process on what can be causing structural defects in the finished product to support decision-making on the process--using different materials with higher melting points, adjusting laser intensity, using different precursors (powder vs. wire). The data from the thermal images also portray the thermal gradients and the evolutions of the thermal dynamics within the melting pool. Manufacturers can access the online data remotely via connected devices by utilizing the cloud server. This presented framework allows the adaption of a legacy machine into a digital CPS, which allows the manufacturer to communicate through online data management and visualization tools by the cloud applications.

5. Conclusion and Future Work

With the complete development of a CPS, the user will be able to effectively collect, store, communicate and visualize data gathered from the DED process into the IBM Cloud. This CPS will improve the process by minimizing the area of the melt pool, which in turn reduces structural defects. An improved DED process can lead to high productivity, effectiveness, and competency in the global market. This improvement of the quality of this process may lead to an increased presence in the manufacturing industry, as a refined process will result in greater flexibility, reduction of lead time materials being produced more efficiently, less waste involved, and thus a reduction in costs. With more time, much more can be added to the system, such as the addition of a theoretical simulation which would provide additional data that could be further used to find correlations in defects. With the collected data gathered, predictive modeling can be done in which a model can predict and analyze in real-time when defects appear within the process. Future work may also include applying the DED process being used in the aerospace industry, where there is an increased demand for complex, durable parts to be produced quickly and cheaply.

ISBN: 97819384962-2-6

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