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APPLICATION OF DIGITAL TWINS TO LASER POWDER BED FUSION ADDITIVE MANUFACTURING PROCESS CONTROL

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ABSTRACT

Digital twins for additive manufacturing (AM) have drawn much research attention recently, thanks to advancements in artificial intelligence and machine learning. Machine learning takes the process and measurement data from the manufacturing process to build data-driven models instead of physics-based descriptive models. The latter are usually hard to obtain for complex AM processes such as laser powder bed fusion. This study proposed a digital twin framework for the laser powder bed fusion AM process control and optimization. The framework is created based on the recently developed advanced point-wise scan control method. It consists of four components: digital twin of process design, digital twin of process control, digital twin of process monitoring, and digital twin of printed part. Their construction is detailed, and potential applications are demonstrated/discussed.

1. INTRODUCTION

Laser powder bed fusion (LPBF) additive manufacturing (AM) uses a high-power laser to melt and solidify thin layers of metal powder in areas of geometric patterns sliced from a three-dimensional (3D) computer-aided design (CAD) representation of parts [1]. A typical LPBF process scans a laser beam following the designed path to completely cover the designated cross-section area of each layer. The main advantage of the LPBF process is its ability to directly manufacture metal components with highly complex geometries that are often not possible with conventional manufacturing processes. However, there are still many challenges in the LPBF process that prevent its widespread application. These challenges include, but are not limited to, part distortion due to residual stress, internal defects such as lack of fusion (LOF) or keyhole pores [2], dimensional error due to poor laser or build platform calibration, and failures caused by difficult-to-build geometries such as overhangs. In this paper, we proposed a digital twin framework to systematically study and address the issues in the LPBF process.

In a broader sense, a digital twin is defined as a digital representation of assets, processes, or systems [3]. Various studies were undertaken to develop this technology for AM. DebRoy and his co-workers carried out pioneering work in the construction of digital twins for AM process [4–6]. They suggested that a digital twin of 3D printing hardware should consist of a mechanistic model, a sensing and control model, a statistical model, big data, and machine learning (ML). They also presented a framework of mechanistic models to predict the melt pool (MP) level phenomena and estimate the metallurgical attributes such as the transient temperature field, solidification morphology, grain structure, phases present, and susceptibilities to defect formation. The inputs to these mechanistic models include printing techniques, process parameters, and material properties. It is a very comprehensive framework, but it is also difficult to implement and optimize, as many physics-based descriptive models are involved. Grieves first defined a digital twin "as a virtual representation of what has been produced" [7]. This is quite different from the process-based digital twins by DebRoy. In his later publications [8], Grieve further extends the scope of digital twin to digital twin prototype (DTP), digital twin instance (DTI), and digital twin aggregate (DTA), and he also connected product life cycle management to digital twins under this framework.

We started our AM process digital twin development with process control and monitoring [9] and extended the scope to the printed part and process design. Instead of the product lifecycle management Grieve discussed, our digital twin framework is focused on AM process lifecycle management (Figure 1). It optimizes the process design and control through process monitoring and part qualification. The foundation of our digital twin framework is pointwise AM control [10]. It provides a platform-independent unambiguous description of the scan strategy and control. More details on pointwise control will be discussed in section 2. The construction and sample applications of the digital twins will be provided in section 3.

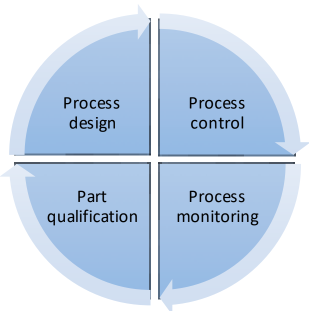

Figure 1. AM process lifecycle.

2. AM PROCESS CONTROL AND MONITORING

For the LPBF process, the laser beam is guided to the build layer by a pair of mirrors driven by galvanometer (galvo) motors. Galvo is a limited-rotation direct current (DC) motor; its angular position is proportional to the DC voltage applied to the galvanometer coil. This is similar to the conventional computer numerical machine tool control. To scan a line, the line is first interpolated into a sequence of points according to the programmed velocity profile. The corresponding angular position of the galvo for each point is calculated and converted to the voltage value. This voltage value is then sent to the galvo driver at a regular time interval to move the mirror position.

Figure 2 shows the typical steps in AM process preparation. The 3D CAD part is digitally sliced into two-dimensional (2D) layers first; scan paths are then created to cover each layer. These scan lines can be described by AM G-code [10], or other formats such as Common Layer Interface (CLI) [11] or eXtensible Markup Language (XML). The scan lines need to be interpolated into points to execute. On most existing commercial machines or galvo controllers, this interpolation is done by the embedded software and the result is not user accessible. Therefore, the users only have line-wise control. This greatly limits the development of advanced scan strategies that require synchronization of laser power, speed, and position [12].

Based on the point-wise AM control developed [10], user accessible time-stepped digital command files of the format in Figure 2e are generated. The file is a n x m numerical array, where n is the number of time steps in 10 µs increments, in agreement with the 100 kHz command transmission frequency defined by the xy2-100 transmission protocol [13]. m is the number of control parameters, which includes X and Y for laser coordinates in mm, L for laser power in watt, D for laser spot size (position of the linear motor for laser focusing) in mm, and T for triggers. Triggers are for synchronizing process monitoring sensors, such as the coaxial melt-pool monitoring (MPM) camera. For example, T = 3 will send a Transistor–transistor logic (TTL) high to both channels 0 and 1, since ‘3’ is ‘0011’ in binary format.

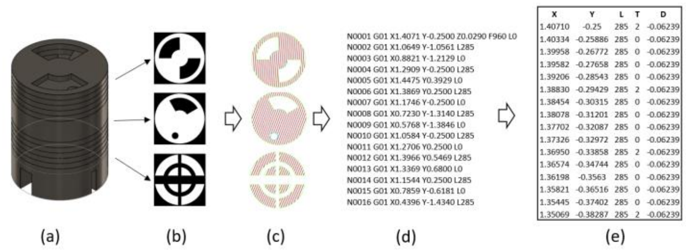

Figure 2. AM process preparation. (a) 3D CAD part. (b) Sliced layer. (c) Path created to cover each layer. (d) AM G-code describing the path. (e) Time-stepped digital commands.

Figure 3 shows how the time-stepped digital commands are executed. One line is executed at a time step. X and Y are sent to galvo motors to position the mirrors, L is sent to the laser unit to set the laser power, D is used to position the laser focusing lens by a linear motor, and T is sent to the monitoring devices. Feedback from the x-galvo, y-galvo, linear motor position encoders, and the laser power monitoring module are sampled at every time step. These feedback signals are then put into the same format as the time-stepped digital commands to create a one-to-one mapping between commands and feedback.

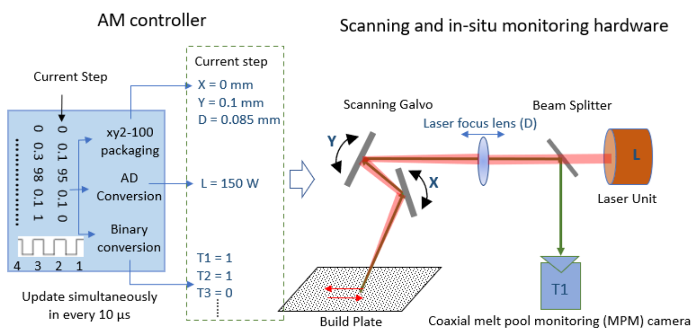

Figure 3: Time-stepped digital command execution.

3. DIGITAL TWINS FOR ADDITIVE MANUFACTURING PROCESS

The proposed AM digital twin framework consists of four components: digital twin of process design (DTPD), digital twin of process control (DTPC), digital twin of process monitoring (DTPM), and digital twin of printed parts (DTPP). These digital twins correspond to each stage of the AM process lifecycle, as shown in Figure 4. Each digital twin consists of a collection of raw data, and virtual volumes constructed from these data. The virtual volume is a three-dimensional (3D) representation of the AM part at different stages of the process. All virtual volumes are constructed on the same coordinates as the time-stepped digital command, and the digital twins are correlated through this virtual volume.

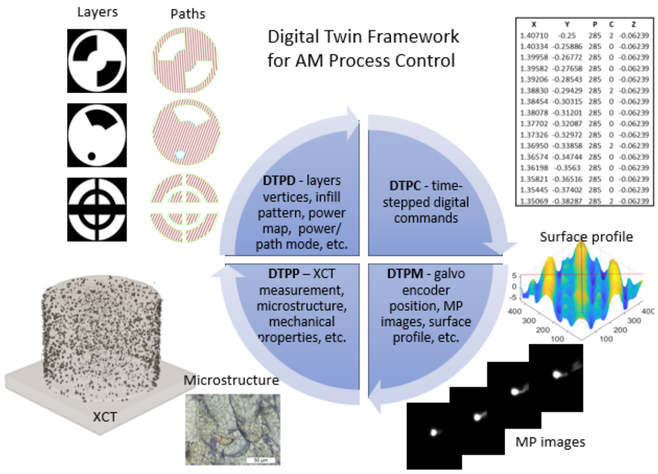

Figure 4.The AM digital twin framework

3.1. Digital twin of process design

The AM process lifecycle (Figure 1) starts with AM process design. It creates scan paths from the 3D model. The first step of the process design is slicing the 3D model into build layers; then layer-wise process parameters, such as infill pattern, laser speed, laser power, path mode, power mode, power map, etc. can be applied to create scan paths. The sliced layers are described by their vertices. Together with the process parameters, these are referred to as the digital twin of process design (DTPD). The virtual volume of DTPD is defined by the vertices. Figure 5a shows an example of how the vertices are created. The intersecting points of a 3D model (represented by tessellated surfaces) with the slice planes are first determined. The redundant points in each layer are then eliminated by fitting straight lines and arcs. Eventually, four vertices are left to define the layer in the example. Note these vertices determine the final part geometry, not the 3D model. For example, a smooth inclined surface in a 3D model can only be approximated by the staircase created by the layers defined by the vertices.

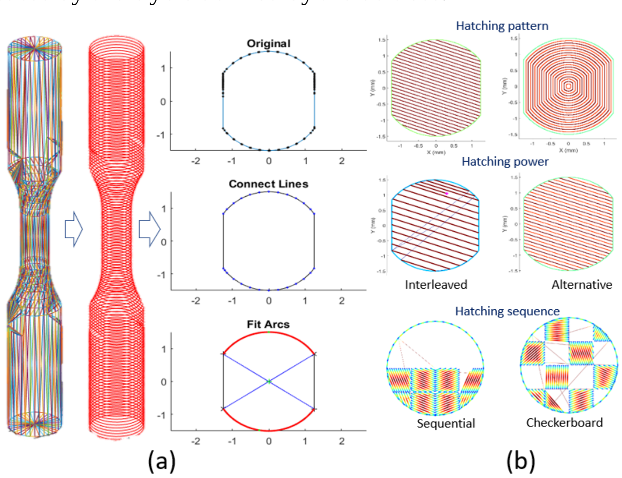

Figure 5: AM process design. (a) Slicing. (b) Infill options.

The process design parameters include layer thickness, infill pattern, contour smoothness, layer-specified scan strategies, support structures, layer pre-heating/post-heating, path mode, power mode, velocity profile, etc. Figure 5 shows sample infill options provided in Simple AM software (SAM) [10], an in-house developed AM software. SAM allows a different combination of hatching patterns, power, and sequence for different layers. The layer-wise process design information is embedded into each layer in the DTPD and can be correlated to other digital twins in the framework through their virtual volumes.

The DTPD can be used to verify the tolerance of the final part (certification for part dimension). The vertices can be converted into checkpoints in 3D space, and the part can be measured against these checkpoints. The DTPD is also used to create the process control commands. That is discussed in the next section.

3.2. Digital twin of process control

The time-stepped digital commands (Figure 2e) enable a full and unambiguous description of the scan strategy and the geometry of a part [14]. Since an AM part can be created based on the digital command, the digital command is, in fact, a digital twin for the AM part. The digital commands can be thought of as a point cloud in the 3D space. Since laser power is assigned to each point, whether this point is melted or not is known. This information can be used to create a virtual part as shown in Figure 6, where a voxel in the cube is marked as melted if a point with laser power on falls into it. Similarly, a MP volume can also be assigned to each point, this volume can be a geometrical approximation or from physics-based simulation. For example, at any point (time step), a snapshot can be taken from the finite element model-based thermal process simulation, and volume above melting point can be assigned to the point as its MP volume. The voxel can be defined at any high resolution, where the voxel that falls into the MP volume can be marked as melted.

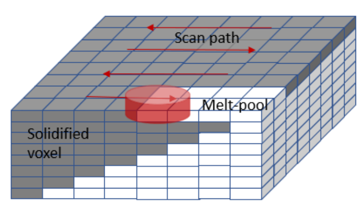

Figure 6: Build a virtual 3D volume using digital command. The dark color voxel is when the laser power is on. The arrows indicate the scan path, and the circle indicates the current laser spot position.

By following the digital commands, a virtual part can be built layer by layer, just like the actual 3D printing process. Figure 7 shows an example, where simulated MP images are superimposed by their intensity at the locations they were taken, to create a virtual track. The tracks joined together to form layers, and layers stacked together to form the virtual volume. The MP images can also be obtained by a ML model, which is usually much faster than a finite element simulation. The MP image in a layer can be thought of as an approximation of the MP volume with uniform cross-section and meltpool depth of the layer thickness.

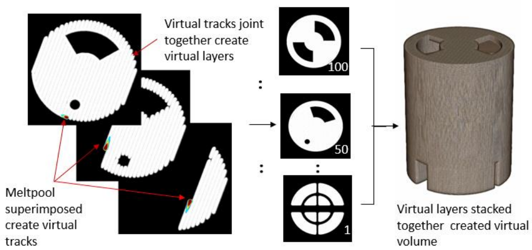

Figure 7: Build a virtual 3D volume using simulated MP images.

If the interest is only the geometry of the part, a binary MP volume is good enough to create the virtual volume, such as in Figure 6. Otherwise, a grayscale MP volume generated from an ML or physics-based model can be used, with the grayscale intensity representing the temperature. Since the digital command is time-sequenced, the thermal history of any voxel in the part can also be traced. The virtual volume created from digital commands can be used to predict the part defects or microstructure, or simply visualize the potential processing error.

The digital command, the simulation model, and the virtual volume are referred to as digital twin of process control (DTPC). The DTPC provides all the control information necessary to build the part and can also be 'self-optimized;' examples can be found in [14,15]. In [14], the as-built geometry created by the method in Figure 6 is used to account for the conductivity changes for an overhang structure. A geometric conductivity factor (GCF) is assigned to each point, and the laser power at the point is adjusted according to the GCF. In [15] the thermal condition of the current scanning point is estimated based on previously scanned points in its neighborhood. A residual heat factor (RHF) is assigned to each point and the laser power of the point is adjusted according to the RHF. Both GCF and RHF are completely based on the DTPC itself, therefore it is 'self-optimized'. The DTPC optimization can also be carried out based on real-time monitoring feedback, which will be discussed next.

On many existing commercial AM machines, a DTPD equivalent is sent directly to the machine to execute, without a DTPC intermediate step. The process control is handled by the embedded algorithm on the machine, which is not user accessible or changeable. Pointwise control and optimization, such as laser power-position synchronization, real-time feedback/feedforward control, GCF/RHF compensation, etc., is then not possible. Therefore, the DTPC creation is also an indication of the controllability of the physical system.

3.3. Digital twin of process monitoring

The point-wise AM control enables synchronized in-situ process monitoring. The actual laser position and power can be measured and stored in the same format as the digital command. Instead of using simulated MP, the actual MP images can be used to repeat the virtual volume creation in the DTPC (Figure 7). This is referred to as MP intensity volume (MPIV). Similarly, an MP area volume (MPAV) can also be created. It is shown in [9] that MPIV can be used to predict LOF pores and MPAV for keyhole pores. Different types of virtual volume can be created based on different monitoring data. The process monitoring data and the virtual volumes created are referred to as the digital twin of process monitoring (DTPM), as it is a digital representation of the as-built part.

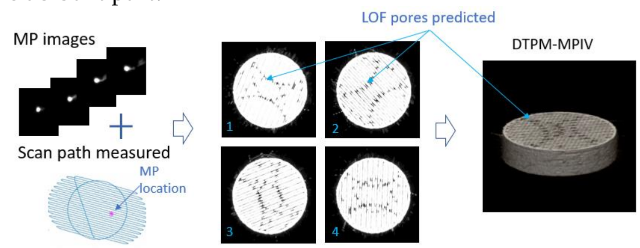

Figure 8: MPIV creation. MP images superimposed by the image intensity at the locations they were taken to create virtual layers and hence virtual volume.

The DTPM provides a way to process the large amount of data collected from the in-situ monitoring of the LPBF process. The virtual volumes thus created provide direct visualization of the potential build issues, such as LOF pores. Figure 8 shows an example, where a cylindrical part was built at a nominal laser power of 285W, but lowered to 40 W for 0.2 ms for every 2 ms period. This is to simulate that a spatter or plume blocks the laser path and causes a drop in the laser energy, a typical issue in the LPBF process. The LOF pattern is clearly visible in the MPIV. Although the LOF pores thus predicted may be recovered in the physical part by remelting from the top layers, it is still a good indication of potential quality issues.

DTPC can be compared with DTPM to identify and address potential process control issues. Figure 9 shows the laser power-path plots for the first layer of the part in Figure 8. DTPM shows the laser power was switched on slightly earlier than it should be. This could cause side surface roughness and subsurface pores [16], and they can be addressed by adding a laser-galvo delay time in the digital command. DTPM also shows following errors at the sharp corners, but they can be safely ignored since the laser power was off.

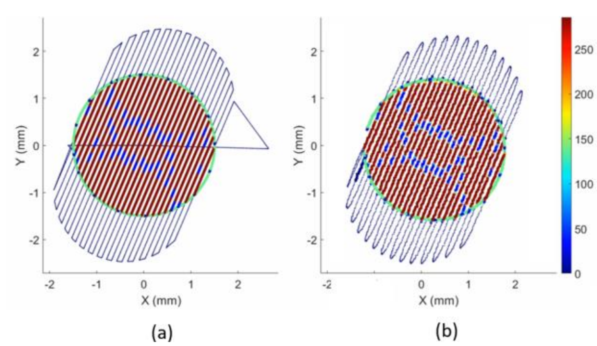

Figure 9: Laser power-path plots based on (a) DTPC, and (b) DTPM.

DTPM can also be used for feedback control. For example, it is a well-known phenomenon that as the number of layers increases, the part temperature increases due to the residual heat buildup and conductivity reduction [17]. This issue can be addressed by scaling the laser power in DTPC for the next layer based on the DTPM of the current layer. The conductivity variation at each point can be estimated based on the MP area, laser power density, and scan sequence derived from DTPM. Assuming the RHF factor can be isolated, power maps can be created from the current DTPM layer and used to scale lase power of the next layer. A power map is a grayscale image, and it scales the laser power according to its pixel value. Power maps can be created in DTPD, DTPC, or DTPM. Figure 10 shows power maps created in DTPD from the CAD model, and the GCF model [14] is a power map created in DTPC.

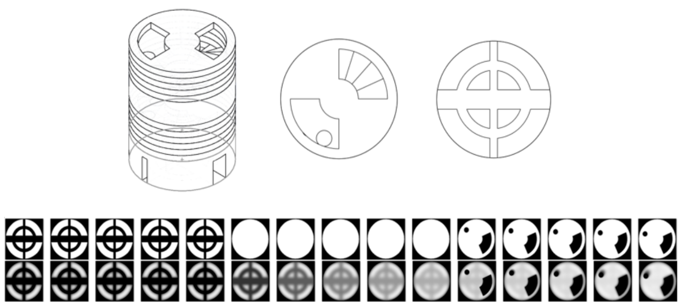

Figure 10: Power map created in DTPD based on the part geometry.

An ML model can be trained to predict the DTPM from DTPC. This ML model, instead of the traditional physics-based model, can be used to describe the build process. The MP area prediction model in [18] provides such an example.

3.4. Digital twin of printed part

Different measurements and characterization can be conducted on the printed part. These measurements can be used to create the digital twin of the printed part (DTPP) since they describe the printed part. In this study, we limit the DTPP discussion to the X-ray computer tomography (XCT) measurement. The XCT images can be used to create a virtual volume, as shown in Figure 11. This is referred to as XCT volume (XCTV). The first step to constructing the DTPP is to convert XCTV to the same coordinates as DTPC/DTPM. There are three steps involved: tilting, scaling, and rotation. Tilting is done by aligning the XCTV to a reference surface (such as the build plate) or aligning the top surface of the part to the build direction. Scaling is done by interpolating the XCT images to the same resolution as the MPIV. Rotation is done by aligning the same patterns in MPIV and XCTV, such as the track orientation. The original XCTV is in grayscale but can be thresholded to binary in order to label the voids. More details on the XCTV alignment and thresholding can be found in [9,16].

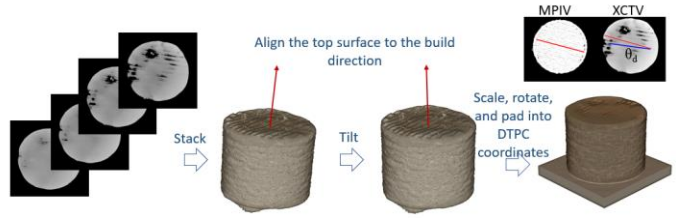

Figure 11: XCTV creation and alignment.

Once the XCTV is thresholded and put into the same scale and coordinates as MPIV, the locations of the voids determined in the XCTV can be mapped directly to their locations in the MPIV. Multi-layer blocks centered around the void location can be ‘cut’ out from the MPIV and used to train a deep learning model to identify the common features in the MPIV tied to these voids. Once a model is trained, it can be used to predict voids directly from the DTPM. This approach is explained in Figure 12. It is different from many existing defect prediction studies; they are either based on layer-wise images [19], or individual MP images [20]. The defect formation in the LPBF process is very dynamic and localized, and there is also much remelting within and between layers. The MPIV creation (Figure 8) takes into consideration the same layer remelting, while the multi-layer blocks retain the cross-layer remelting information.

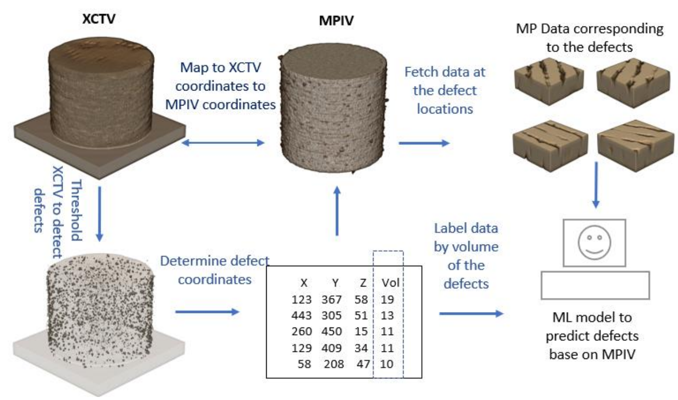

Figure 12: Development of defect prediction ML model.

The DTPC, DTPM, and DTPP have mapped the control, monitoring, and measurement data into the same coordinates through the virtual volumes they created. This mapping is sometimes referred to as data registration. In this digital twin framework, all the data are registered to the time-stepped digital command of the pointwise control. ML models can be developed to connect DTPC to DTPP through DTPM, to predict the build quality directly from the time-stepped digital commands. Meanwhile, the DTPP and DTPM can also be used to optimize the DTPC and DTPD. This is summarized in Figure 13.

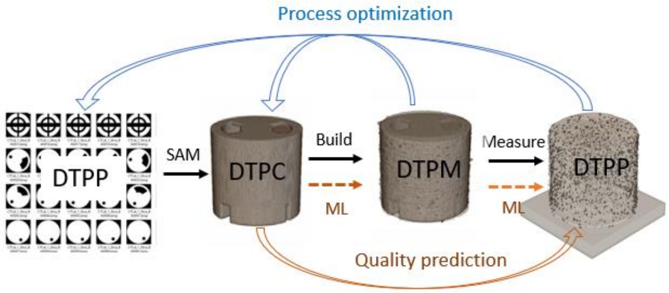

Figure 13: AM quality prediction and process optimization by digital twins.

4. CONCLUSION

An AM digital twin framework is demonstrated. It consists of four components: digital twins of process design, process control, process monitoring, and printed part. Their applications in the AM process control and optimization are demonstrated. A machine-learning based descriptive model for the AM process can be established based on these digital twins, and the process can be continuously improved through the design-control-monitoring-measure cycle. The digital twin framework was developed for AM process control, but can also be applied for certification, data correlation, and quality prediction.

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