Contents

Journal of NDE – Non Destructive Testing and Evaluation

MARCH 2024
Volume 21 - Issue 1

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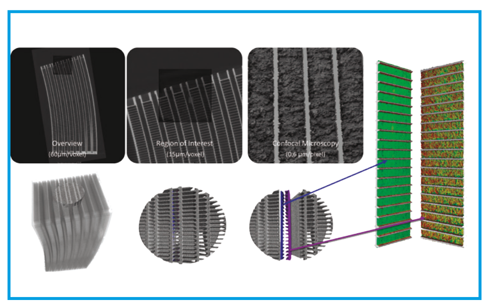

"2D Cross Section CT Scans with increasing resolution of a 3D printed fin and plate heat exchangers."

OBJECTIVE - This Journal of Non Destructive Tesing & Evaluation (JNDE) is published quarterly by the Indian Society for Non Destructive Testing (ISNT) for promoting NDT Science & Technology. The objective of this Journal is to provide a forum for dissemination of knowledge in NDE & related fields. Papers will be accepted on the basis of their contribution to the growth of NDE Science & Technology.

PUBLISHED BY: Mr. Bikash Ghose - Managing Editor, JNDE

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Future of Non-Destructive Testing in the Era of Additive Manufacturing and Machine Learning

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Abstract

Additive manufacturing (AM) methods have become mainstream in many industry sectors, especially aeronautics and space structures, where production volume for components is low and designs are highly customized. The frequency of launching space missions is increasing around the world. Some of these missions are sending landers and rovers to moon, mars, and other planets. Such space structures require numerous parts that are unique in design or are produced in just one or a very small production run. Such parts produced for high stake and very expensive missions require complete confidence in the quality of each part. Characterization of parts manufactured by AM is a significant challenge for many existing methods due to the geometric complexity, feature size in the structure, and size of the part. This paper discusses various challenges in applying current characterization methods to the AM sector. Machine learning (ML) methods are considered promising in materials and manufacturing fields. However, generating the training dataset by creating a large number of parts is expensive and impractical. New methods are required to train the ML algorithms on small datasets, especially for parts of unique geometry that are produced in limited production run such as space structures.

Keywords: *non-destructive testing, additive manufacturing, machine learning, thermal imaging, artificial intelligence.*

1. INTRODUCTION

Manufacturing has gone through three industrial revolutions and is now well into the 4th revolution [1]. The third industrial revolution (IR3) was focused on automation for large-scale production of parts to make them cheaper and widely available. Various kinds of manufacturing machines and methods developed in IR3 enabled production runs from a few thousands to several millions, where economy of scale ensured that the cost of each part decreased as the size of production run increased. Such methods allowed economical production in many sectors at large scales. For example, almost 90 million automobiles were produced around the world in 2023. Most of these cars were produced by a small number of companies of a handful models, which leads to many components to be manufactured in millions of quantities as original and replacement parts. There are many such examples in the industrial production sectors where production runs are in millions. Such large production runs require a complete ecosystem for testing and characterization because testing each component for all desired parameters is impractical and expensive.

The current methods of materials characterization can be divided into destructive and non-destructive methods. These methods work in conjunction with each other to provide the desired parameters that range from microstructure and defects to mechanical properties. These test methods are governed by standards that are developed by technical societies such as American Society for Non-Destructive Testing and American Society for Mechanical Engineers or national boards created by governments of various countries. The focus of the fourth industrial revolution (IR4) on individually customized products manufactured using general purpose machines such as 3D printers has made it difficult to apply the existing principles of materials characterization to these limited production runs. The present article is focused on analysing the role of existing materials characterization methods as additive manufacturing (AM) and machine learning (ML) become mainstream in the manufacturing field and the needs for developing next generation non-destructive testing (NDT) methods incorporating AM and ML for objectives such as defect detection and mechanical property measurements.

2. DIGITAL MANUFACTURING

One of the main thrusts of IR4 is to introduce network connectivity in the entire manufacturing process chain, from the design to manufacturing to materials characterization stages. Even though companies may not connect their printers to internet due to the potential cybersecurity vulnerabilities, they may create an intranet within their company to connect designers to printers [2]. An example of such system is shown in Fig 1, which is called digital manufacturing (DM). The DM system is based on the connectivity and all the steps are based on the flow of data until the physical object is produced on the 3D printer. There are several other manufacturing methods that can also be connected in such a system. For example, toolboxes are available for CNC machines to connect them in a DM system. It is well understood that the development of AM methods will not replace the traditional manufacturing methods, rather they will provide additional options to select the appropriate method based on the part design and material. Over time many other traditional methods will be connected in such data driven networked systems. Hence, DM represents a larger concept of manufacturing system, where actual manufacturing is only one of the many steps and the actual part may or may not be manufactured by AM. The entire DM system can be connected to the same cloud platform.

3. NON-DESTRUCTIVE TESTING APPLIED TO ADDITIVE MANUFACTURING

One of the major benefits of AM is the production of small number or even a single part without having to apply the economy of scale. In addition, a flexible production method like AM can switch between manufacturing parts of different designs without having to change any dies, molds or tooling. The traditional testing scheme based on large production run has many steps, which include sampling of parts based on statistical analysis followed by testing a small number of parts for destructive and non-destructive testing. Usually a number of replicas of a part are tested and statistical analysis is conducted on the data.

3D printers, as well as many other manufacturing platforms such as additive-subtractive hybrid machines, can be heavily instrumented with many different kinds of sensors such as temperature sensors, vibration sensors, acoustic emission sensor, optical cameras, and thermal cameras, among many others as shown in Fig 2. These sensors provide continuous information when the part is being printed. The information obtained from these sensors can be used to verify and print parameters or find a defect while the part is still being printed. Use of optical and thermal cameras has allowed obtaining real time information on defects right at the onset of these defects as the part is still being printed. A comprehensive review of in-situ monitoring methods for subsurface and internal defect detection during additive manufacturing has been published previously [3]. Early detection of parts allows the possibility of implementing intervention to either repair the defect or discard the print early without wasting time and material in completing a defective print. Hence, there is a strong interest in the AM field for applying in-situ NDT methods to improve the process quality and economy. AM equipment based on material extrusion and powder bed processes often either come with many types of sensors already installed or an option to install sensors and cameras.

3.1. Defect Detection in Additive Manufacturing

A significant amount of literature is now available on the use of sensors for process monitoring and control during AM. If the product quality is not satisfactory based on various observation methods, including direct visual observation, observation of camera feed or sensor readings, then the parameter set can be adjusted to improve the quality.

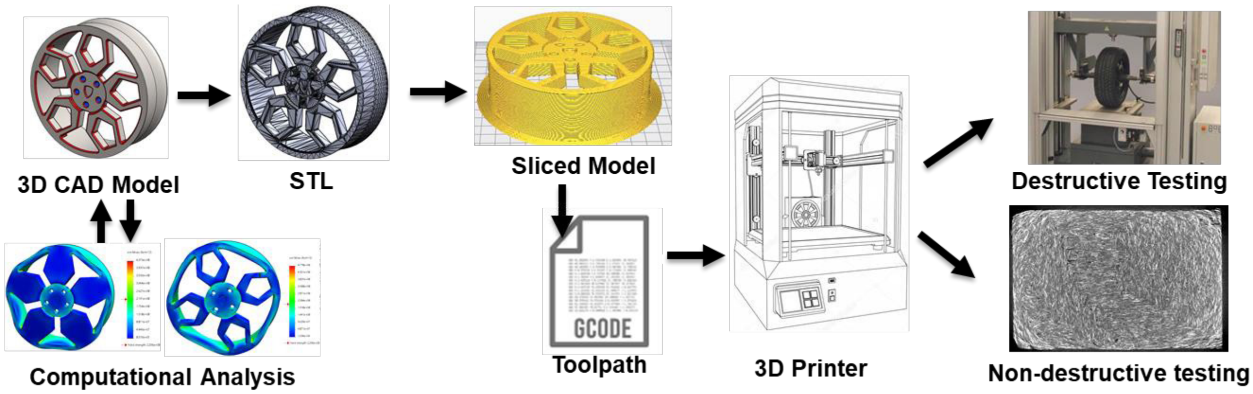

Fig 1. Digital manufacturing process chain that includes all the steps from design to characterization connected and driven by data files.

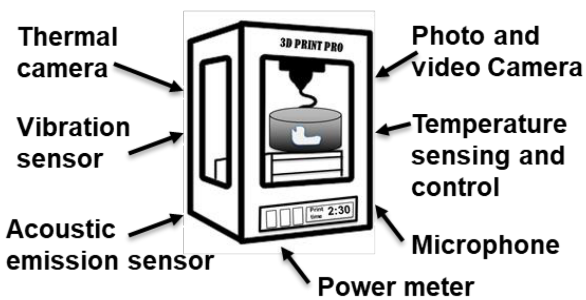

Fig 2. An example of many sensors that can be mounted in a material extrusion 3D printer.

In addition, determination of defect type, location, size and orientation are important for a manufactured part. Optical and thermal cameras have been widely used for monitoring of in-process print quality of individual layers in AM [4, 5]. An example of the use of optical and thermal cameras in a fused filament fabrication (FFF) 3D printer is shown in Fig 3. The results of defects detected from such methods have been compared with those from other methods such as ultrasonic imaging [6]. Post-manufacturing NDT methods such as ultrasound, radiography and CT-scan have been used for defect detection in AM parts [7, 8]. However, quality determination and defect detection during the manufacturing process itself can make this process significantly faster and cheaper.

3.2. Embedded Feature Detection and Recognition

The undesired features occurring inside the structure of a part are usually defects in traditional manufacturing methods. However, a unique feature of AM compared to the most other manufacturing methods is the capability of embedding features deliberately inside the structure of a part due to the layer-by-layer construction process. Fig 4 shows an example of a QR code embedded inside a part. The code can be embedded either in one layer or segmented in a number of slices and each slice can be embedded in a different layer for making it difficult to decode it [9, 10].

Non-destructive imaging methods are required to read such embedded codes without having to section the part. There are several challenges in reading the embedded codes intended for product identification or authentication. These codes are usually designed considering the minimum printable feature size of a particular 3D printing method so that their presence does not compromise the microstructure. It is known that the information can be lost in STL conversion or slicing of the part if the STL resolution or the slice thickness are not appropriately selected to preserve the required information. A variety of methods such as radiography, CT-scan and ultrasonic imaging can be used to read the embedded codes. Among these techniques, ultrasound has the lowest resolution and can read larger size codes, while CT scan and radiography are able to read the individual features that are in the range 5-10 μm or even finer, depending on the material type, feature orientation and scan settings.

In addition to embedding information inside the part structure, sensors are also embedded to monitor temperature, strain, or many other parameters in the additively manufactured parts and it is required to extract the data from these sensors without having to damage the part [11]. NDT methods can help in locating such embedded sensors and preserving them.

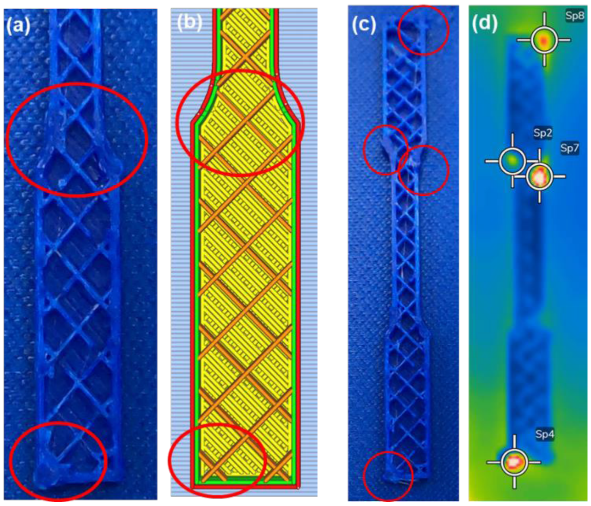

Fig 3. (a) An image captured from optical camera compared with the (b) digital twin to find defect. (c) An image obtained from optical camera compared with an image obtained from (d) thermal camera for finding defects in sub-surface region.

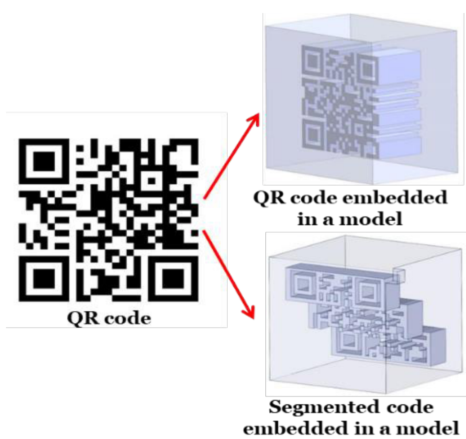

Fig 4. AM allows embedding information inside a part. The information can be embedded either in one layer or in multiple layer. Non-destructive imaging methods are required to read the embedded information.

3.3. Mechanical Property Measurement During Manufacturing

Mechanical properties of the manufactured parts need to be measured to ensure their quality. In the current practice the mechanical properties are measured only after the part is manufactured and taken off the built plate. However, this approach has several limitations. The first limitation is that if there is a defect in the part then the detection of a defect during the manufacturing process itself by a camera would inform about the defect but is not able to determine the level of mechanical property loss. In such a situation, researchers have considered several options, which include conducting finite element analysis with a defect in the structure to assess the reduction in mechanical properties. However, the methods to directly measure the mechanical properties of an object during the manufacturing process are currently unavailable. Enhancing the capabilities of NDT methods for mechanical property measurement is extremely important for AM methods. NDT methods such as ultrasound have shown capabilities of measuring Young's modulus from the measured wave velocity and attenuation inside a specimen [12, 13], however, application of such methods inside the print chamber of a 3D printer is very challenging because it needs air coupling and the temperature is high inside the build chamber.

4. MACHINE LEARNING IN MANUFACTURING

ML methods are now widely used in materials and manufacturing research. The field of new material development has particularly benefited from machine learning methods where trained algorithms can be used to identify promising compositions from a large number of possible compositions [14]. In manufacturing domain, ML methods have been very helpful in optimizing the process parameter sets containing hundreds of parameters involved in AM methods. The specific challenges involved in using NDT methods in AM and DM ecosystems are described below.

4.1. Machine Learning Challenges in Additive Manufacturing

Optical and thermal cameras have now become an integral part of 3D printers. These cameras can be configured to obtain images at regular intervals, which could be one image per layer or images obtained at a set time interval. In large dimension parts the imaging methods may acquire hundreds to thousands of images in each build. Processing of such large number of images manually in a reasonable amount of time is impossible. ML methods have provided a powerful tool in analysing these images for detection of defects and anomalies compared to the more traditional batch processing methods. However, there are numerous challenges in applying the ML methods to AM at the production scale level.

The images acquired from the built plate often required substantial pre-processing. Even if the lighting is well adjusted before the start of the print, the increasing height of the print in many 3D printing methods creates shadow effects and other imperfections in the images. Hence, the acquired images often require contrast correction, brightness correction, cropping of the image to obtain only the desired region and other image enhancement steps. In addition to fine tuning parameters for each of these corrections, the large size of the database is still a challenge for processing the images in real time for defect detection so that possible interventions can be implemented. The image data set can be processed using compression methods or filters to reduce the size of these images without compromising the features that need to be identified. Fig 5 shows an example where a Laplacian filter is applied to an optical image to reduce its size, which has also increased the clarity of the image for featured detection. While a large number of images are obtained during a single build, the use of AM methods for producing unique or low production run parts makes it difficult to generate a large training data set to train the ML algorithm. Innovative methods are required for training of such algorithms. As one of the possibilities, the digital twin of the part is always available that can be compared with the acquired images to identify deviations from the design and label them as anomalies generated during manufacturing. The data acquired from multiple channels such as optical camera and thermal camera can be compared to improve the accuracy of feature detection.

4.2. Machine Learning Challenges in Digital Manufacturing

As depicted in Fig 1, the DM ecosystem comprises of a number of steps that start from the part CAD model development, toolpath development, and part manufacturing. Ideal DM process will include sharing the data from each step to the same database and using this database to train ML algorithms that can predict the part quality and also drive the part design development based on the data obtained from the previous builds.

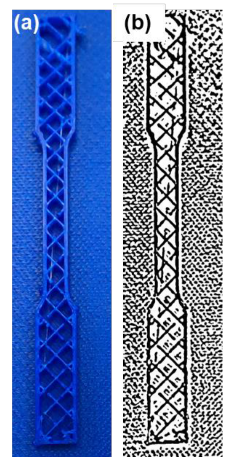

Fig 5. (a) Optical image of a specimen while it is being 3D printed and (b) Laplacian of the image showing improved brightness, contrast and feature details.

4.2.1. Nature of Different Data Stream

The significant challenge in developing the database backbone for the entire DM is that the data obtained from various steps are in several different formats which are not compatible with each other in the same machine learning algorithm. For example, the CAD programs provide output as proprietary format CAD files, the process parameter data from 3D printers can include images as well as time and frequency domain data streams. Different types of ML algorithms are available to effectively handle the data coming in such different formats. New algorithms or ML methods are required to integrate all types of data streams on one platform and conduct the part design from the information generated in the previous build.

A number of different ML algorithms are available. Many of these algorithms are designed to work efficiently with different type of data streams. For example, convolutional neural networks (CNN) are a class of deep learning algorithms that are used for classification and object identification in images (Fig 6a). Recurrent neural networks (RNN) are widely used for time series data (Fig 6b).

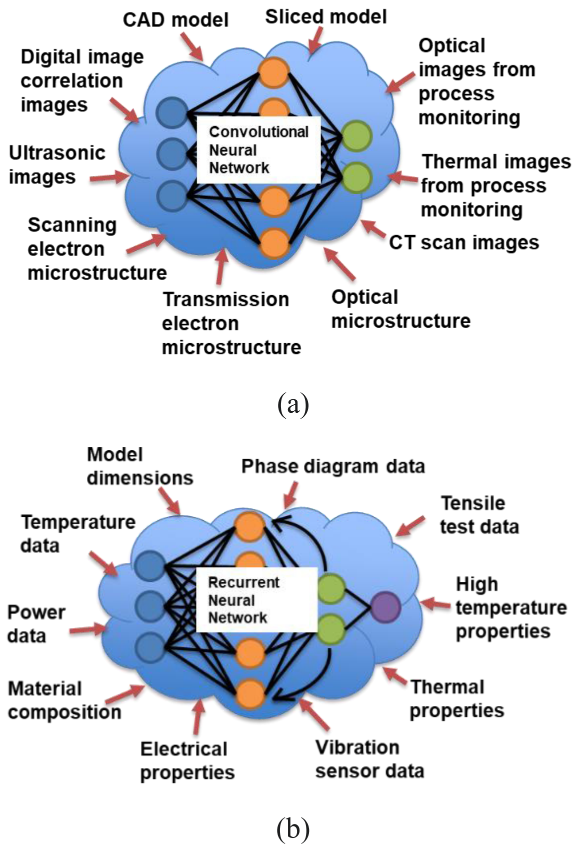

Fig 6. (a) A convolutional neural network with various possible input image streams and (b) a recurrent neural network with possible input data streams.

There are many other neural networks available that specialize on different types of data. Once the CNN and RNN are trained with the available data on processing conditions, raw material properties, material microstructures, mechanical properties and destructive and non-destructive testing data, their outputs need to be designed carefully to provide useful synergistic information to improve the process or the material.

The Industry 4.0 roadmap aspires to develop ML platforms that can host such a variety of data streams, process them and then use the output to drive the manufacturing innovation automatically by making decisions about the design modification, process improvement and product quality assessment. This automated manufacturing cycle coupled with the customized design of each product eliminates the possibility of destructive testing and can only be sustained by implementing the next generation NDT methods as integral part of the system.

4.2.2. Challenges Related to Training Dataset Size

ML methods require large datasets to train the model. One of the limitations in material field is that manufacturing and testing a large number of specimens is very expensive. This is especially a challenge when unique products are being manufactured in small production runs. Innovative methods are required to generate large data sets that can train the ML models from a very small number of specimens. Fig 7 demonstrates one possibility where a CT scan dataset is used to generate a large number of images from the scan of a single specimen [15, 16]. This example shows in Fig 7a a reconstructed 3D model of a composite specimen having about 100 image slices. Fig 7b shows a single image slice where the fiber directions can be observed in a 3D printed specimen. This one image is sectioned into a grid of 18×18 sub-images in Fig 7c. Finally, each of the sub-images can be rotated by 360° angle at a step of 1° rotation. This kind of expansion scheme can generate over 11.66 million images from a single CT scan data set and can be used for training a ML model to identify the direction of fibers in the microstructure of a composite material. The number of images that can be sub-sectioned from a full image depends on the resolution and size of the features of interest. Image compression methods can be applied to reduce the size of the database and make the process faster.

Other methods of expanding the datasets may include using theoretical models to generate parametric plots and the data can be used to train the models. Finite element analysis, molecular dynamic analysis and multi scale models can be used for appropriate problems to generate data at different length scales to train the ML model. In many cases, the ML models are limited to conduct interpolation within the parameter ranges used for training the model. Nonetheless, ML models have been utilized to identify the material compositions that are promising for various applications or for predicting the properties of materials of certain compositions.

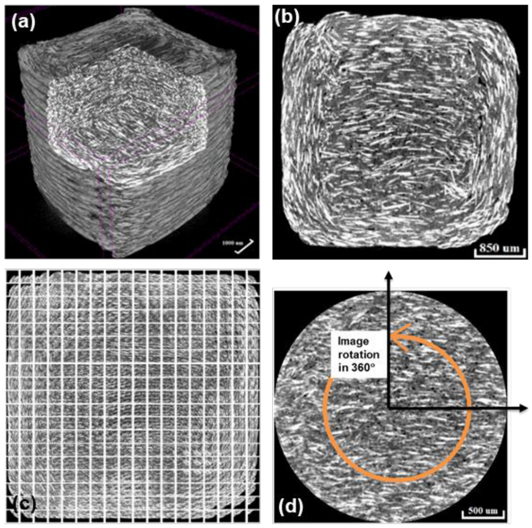

Fig 7. (a) A convolutional neural network with various possible input image streams and (b) a recurrent neural network with possible input data streams [15].

5. ROADMAP FOR NDT FOR INDUSTRY 4.0 AND BEYOND

The industry 4.0 framework of DM requires seamless connectivity among all parts of a manufacturing process and supply chain. As sensors are integrated in every part of the manufacturing process and the data acquired from these sensors are used to determine the influence of processing parameters on the part quality, it is of critical importance that the information obtained from the NDT methods is interpreted in terms of the mechanical properties of the manufactured parts. Search relations are currently missing for most of the methods in the published literature. Although ultrasound has shown limited use in measuring the Young's modulus of metallic materials, high wave damping in the polymer materials makes it difficult to apply the same framework for calculating the Young's modulus of polymeric materials. Accurate prediction of Young's modulus of polymeric materials requires expanding the existing framework to soften materials to account for their viscoelastic nature and high damping.

While research continues in extending the capabilities of NDT methods to measure the mechanical properties of different types of materials, meanwhile, it is of immediate interest to find new methods to reduce the traditional test matrix so that fewer parts are needed for destructive and non-destructive testing. Traditional test matrices require testing at least five replica specimens for each test to obtain their properties over a wide range of parameters such as temperature strain weight frequency and environmental conditions. The existing NDT methods do not guarantee detection of every defect in the specimen and have their own limitations [17], which now need to be interpreted in terms of AM process. New methods are being developed that can provide cross-correlation between the properties under different kinds of loading and environmental conditions so that only a few specimens are tested to obtain properties over a wider range [18].

It is also important to consider the skillset that will be required in the NDT professionals as the testing methods and requirements change in the industry 4.0 framework. It is expected that increased automation combined with machine learning methods will lead to automatic data acquisition and processing. In such case, the personnel involve in this process will have different roles ranging from only maintaining the equipment to decision making based on the processed data provided by the system. Eventually the decision making may also be taken over by the trained ML algorithms when enough confidence in their capability is reached. Development of new NDT methods for industry 4.0 environment, where these methods can be implemented in or alongside the manufacturing machines, well remain as a major priority and an area of growth. It is likely that the imaging and image processing skills will gain more prominence in the NDT field in the coming years.

6. CONCLUSIONS

The industry 4.0 framework is now firmly established in manufacturing sector where it is leading to a revolution by connecting the machines, implementing sensors for acquiring data and developing machine learning methods to process the data automatically. The role of NDT methods is enhanced in such manufacturing environment where data obtained directly from the manufacturing machines needs to be interpreted in terms of embedded defects or mechanical properties of the manufacture parts. It is expected that the industry 5.0 framework will include a more human centric approach where individuals involved in the process will move to higher level roles such as new method development, supervision of the system, and decision making based on the sensor and ML algorithm outcomes. To prepare for such future, not only development and deployment of new NDT methods is required but also preparing a trained workforce is essential. As the machines and processes become more and more connected, there will be additional requirements such as cybersecurity [19], which are not yet of focus in this field. However, such requirements will play a central theme in the next industrial revolution.

ACKNOWLEDGMENTS
This work is supported by the US National Science Foundation award CNS#2234973. The opinions presented in this article are those of the author, not of the funding agency.

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