MACHINE LEARNING TECHNIQUES FOR ACOUSTIC DATA PROCESSING IN ADDITIVE MANUFACTURING IN SITU PROCESS MONITORING A REVIEW

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ABSTRACT

There have been numerous efforts in the metrology, manufacturing, and nondestructive evaluation communities to investigate various methods for effective in situ monitoring of additive manufacturing processes. Researchers have investigated the use of a variety of techniques and sensors and found that each has its own unique capabilities as well as limitations. Among all measurement techniques, acoustic-based in situ measurements of additive manufacturing processes provide remarkable data and advantages for process and part quality assessment. Acoustic signals contain crucial information about the manufacturing processes and fabricated components with a sufficient sampling rate. Like any other measurement technique, acoustic-based methods have specific challenges regarding applications and data interpretation. The enormous size and complexity of the data structure are significant challenges when dealing with acoustic data for in situ process monitoring. To address this issue, researchers have explored and investigated various data and signal processing techniques empowered by artificial intelligence and machine learning methods to extract practical information from acoustic signals. This paper aims to survey recent and innovative machine learning techniques and approaches for acoustic data processing in additive manufacturing in situ monitoring.

KEYWORDS: additive manufacturing, in situ monitoring, acoustic, machine learning, data processing

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Introduction

Various additive manufacturing (AM) methods are utilized for manufacturing parts with complex geometries and complicated features that are either unfeasible or highly challenging to produce via traditional manufacturing techniques. This outstanding capability of AM provides substantial design flexibility and facilitates the production of complex parts with marginal added cost compared to subtractive and traditional manufacturing methods (Calta et al. 2018). Laser powder bed fusion (LPBF), directed energy deposition (DED), and wire arc additive manufacturing (WAAM) are among the most popular methods of metal AM (Koester et al. 2018). Fused deposition modeling (FDM), stereolithography (SLA), direct ink writing (DIW), and selective laser sintering (SLS) are the most common AM techniques for polymers (Baechle-Clayton et al. 2022; Lee et al. 2020).

The AM processes not only can cause different mechanical properties for the parts manufactured, but also lead to the potential generation of specific types of discontinuities and defects in AM parts (Koester et al. 2018, 2019b; Taheri et al. 2017). The types of defects in AM parts significantly depend on manufacturing process conditions and type of materials. A summary of defect types, causes of defect generation, and their potential effect on AM parts is presented in Table 1.

Although inspection and quality assessment for the manufactured parts can be done after the production is finished (ex situ), there are several significant challenges in traditional ex situ inspection methods. One of the major challenges of traditional inspection of AM parts is due to the capability of AM techniques to produce complex-geometry components. This is an outstanding capability for AM but makes traditional inspection of AM parts extremely challenging since many available nondestructive testing (NDT) techniques have been developed for simpler geometries (Bond et al. 2019). Another primary concern in post-production or ex situ inspection of AM parts is that AM techniques are used to manufacture many critical, high-valued, or exotic parts. Possible rejection of such unique parts due to unacceptable quality causes a significant loss of time and cost and is not a desirable outcome for industries (Koester et al. 2018c; Taheri 2018). Despite the complexity of the processes in AM, the layer-by-layer deposition of materials allows the measurement and recording of large amounts of data on each layer for statistical process monitoring and quality assessment (Grasso and Colosimo 2017; Koester et al. 2018b).

TABLE 1

A summary of common process-induced defects, their causes, and potential effects on part quality in laser metal additive manufacturing (Herzog et al. 2023)

Defect type	Common causes	Potential effects
Keyhole pores	• Excessive input energy density	• Reduction in mechanical properties • Reduction in fatigue properties
Lack of fusion pores	• Insufficient input energy density	• Reduction in mechanical properties • Reduction in fatigue properties
Gas pores	• Gas entrapped in feedstock • Gas entrained into the melt pool	• Reduction in fatigue properties
Cracking and delamination	• Residual stresses exceeding the local ultimate tensile strength • Insufficient bonding between layers	• Part failure
Deformation	• Residual stresses exceeding the local yield stress	• Conformance failure
Alloy compositional variance	• Improper powder deposition • Differing chemical mobility • Preferential evaporation • Gas incorporation/adsorption	• Inhomogeneous mechanical properties
Balling	• Low/high input energy density • Surface oxidation	• Part/conformance failure • Formation of other defects
Rippling	• Instabilities of layer-to-layer deposition	• Part failure • Production failure
Spatter/particle ejection	• Overheated melt pool • Recoil pressure and melt plume	• Formation of other defects

In situ measurement and monitoring techniques using various sensors and NDT methods have been extensively utilized and studied over the last few years for understanding and predicting the alterations in AM process parameters and, consequently, the quality of the manufactured parts. In situ measurement data obtained over the entire period of manufacturing processes, combined with ex situ material characterization and information from process modeling and simulation, are essential for reducing the time and cost of process development, improving part quality, and minimizing defect formation (Hossain et al. 2022; Koester et al. 2018b).

A large body of existing and rapidly growing literature is devoted to in situ monitoring methods, surveying various in situ monitoring techniques and sensors used for different types of AM processes. High-speed visible imaging (Scipioni Bertoli et al. 2017), thermography (Raplee et al. 2017), and X-ray imaging (Calta et al. 2018) are among the most used methods for in situ process monitoring for AM. Optical-based in situ monitoring methods can monitor process conditions and variations on the surface of the parts but are limited in assessing bulk material behavior. In addition, high-resolution imaging at high scanning velocities requires an external illumination source (Lott et al. 2011). Also, a wide range of magnification may be needed to cover the imaging of the entire melting pool (Lott et al. 2011). Arntz et al. (2018) analyzed the melt flow dynamics of a laser cutting process by in situ high-speed video diagnostics (>100 000 fps). They showed a correlation between fluid dynamics, cutting velocity, and the average roughness of the cut flank (Arntz et al. 2018). In contrast, X-ray-based measurement methods can penetrate the materials and provide valuable information regarding the structure of the part. However, the complexity and cost of the X-ray monitoring technique and availability to most industries and manufacturers for widespread implementation of AM is a significant challenge. On the other hand, acoustic-based techniques have been used historically for a variety of process monitoring and part qualification applications, such as in the welding process, where its rapid solidification phenomena are very similar to the AM process (Taheri 2018). Recent work has investigated the potential application of acoustic emission testing (AET) for AM processes (Koester et al. 2016, 2018a, 2019a).

Accordingly, despite the type of sensing and measurement technique used for in situ AM process monitoring, analyzing the recorded dataset to identify, map, and potentially characterize the defects will be the next challenging step. The large dataset size and real-time processing are significant challenges in processing data for in situ measurement (Taherkhani et al. 2022). Artificial intelligence (AI) and machine learning (ML) algorithms can be promising solutions for such problems (Taheri et al. 2022). Researchers have used various supervised (Gobert et al. 2018), unsupervised (Scime and Beuth 2018), and reinforcement learning algorithms (Knaak et al. 2021) for the prediction of defects during AM processes.

AI/ML methods have significant potential to improve the AM processes and the quality of manufactured parts. The necessity of AI/ML integration to AM processes is due to the contemporary need for reduced labor cost and time, digitization in AM, and massive data availability (Kumar et al. 2023). AI/ML can be integrated into different sectors of manufacturing. In design, AI/ML increases acceptance of novel approaches and saves time and resources. In production, application of AI/ML saves time and energy and avoids waste. Finally, smart manufacturing can be interpreted as application of AI/ML in assembly processes to adjust any error in real time. Addin et al. (2007) demonstrated the potential application of ML in material science and design. In their paper, the Naïve Bayes classification is used for deterioration detection in construction. Jin et al. (2020) indicated that an ML model based on real-time camera images and deep learning algorithms can detect different levels of delamination conditions in FDM and determine the tendency of warping before it actually occurs.

This paper aims to survey the application of AI and ML for data processing in acoustic-based in situ monitoring of AM processes. First, an overview of the acoustic emission NDT method for in situ monitoring of AM processes is presented. Then, various AI/ML techniques used by different researchers and the outcome of their analyses are described. The paper concludes with a summary of the discussion, existing challenges, and potential future work.

Acoustic Emission for In Situ Monitoring in AM

Acoustic emission (AE), also known as acoustic emission testing (AET), as a monitoring technology has been explored by several research groups (Koester et al. 2018a; Wasmer et al. 2019; Wu et al. 2016). AE refers to the generation of elastic (mechanical) waves released by materials when subjected to an external impetus, such as raising the gas pressure inside a cylinder, stimulating a given structure will cause deformation inside of it, such as crack growth. Consequently, this will trigger the rapid release of stored strain energy as transient elastic waves, typically from a localized source. Formally, AE refers to both the generation mechanism and the waves themselves (ASTM 2020). Rapid melting and solidification occurring during the AM processes is a significant potential source of elastic waves that AE can hypothetically detect (Morales et al. 2022). Rapid generation of defects, such as cracks or porosity, can also produce elastic waves in the form of AE. A standard AE setup includes a set of piezoelectric transducers coupled to a structure, connected via cables to a monitoring system that performs data acquisition and processing. The data is stored on a computer and can be visualized in real time for further analysis after testing is complete. For the sake of brevity, this paper will not go into further technical details of AE fundamentals (Hossain et al. 2020).

Most AE systems use a hit-based mode, which identifies transient waves in the signal and extracts features from them. A small set of parameters can describe discrete AE, which is digital (Taheri et al. 2013). The most commonly used parameters are rise time, peak amplitude, duration, MARSE (measured area under the rectified signal envelope) energy, and (ring-down) counts, as highlighted in Figure 1. The rise time is the time it takes for the signal to reach its peak amplitude after the first threshold crossing (defined by the operator), measured in microseconds. The duration of the hit is the time measured (usually in microseconds) from the first to the last crossing of the threshold, after which the AE hit will remain below the signal detection threshold, which the user identifies. The duration is often measured in microseconds. Given reflection and other mechanisms in a specimen, AE systems use different timing parameters to compute rise time and duration.

The burst signal energy, or MARSE, is computed by taking the integral over time of the squared electrical signal over its duration. Finally, ring-down counts are the number of threshold crossings of an AE signal. It is another valuable parameter to help distinguish between AE signals and background noise. Combined with other signal features, some or all of these parameters can be correlated with the AM process condition through statistical signal processing and ML techniques and used to identify potential discontinuities in the manufactured parts (Bond et al. 2019; Taheri et al. 2019).

For instance, Li et al. (2021) observed that the AE signals collected over a laser-cladding AM process where cracks exist in the parts have larger amplitude and energy than AE signals collected over a normal cladding process. Hossain and Taheri (2021a) discussed the potentials, limitations, and opportunities of acoustic techniques for process monitoring of AM. In this paper, the authors highlighted the capability of acoustic techniques for volumetric quality identification and adaptability to various manufacturing techniques as the major promising features of acoustic techniques for in situ process monitoring for AM. These abilities have been investigated in various manufacturing processes, including but not limited to AM, by other researchers. Ramalho et al. (2022) showed that the influence of contamination in WAAM can be identified through the analysis of the acoustic spectrum of the process. Ramalho et al. aimed to establish a microphone-based acoustic sensing method for WAAM quality monitoring. WAAM parts were fabricated with

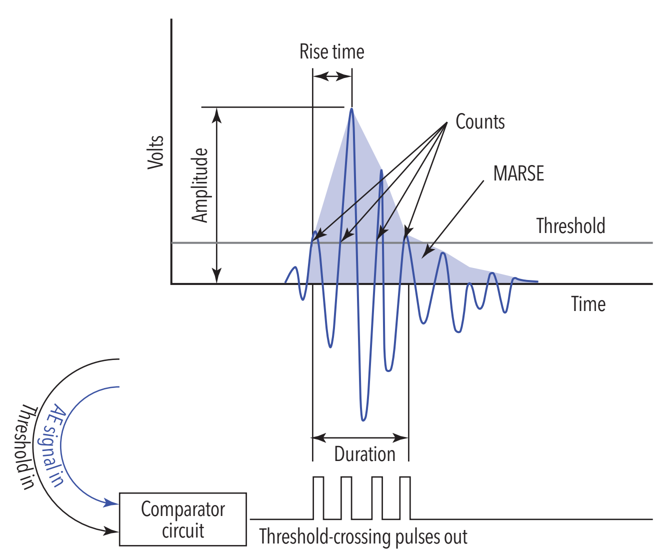

Figure 1. A burst-type AE signal and associated features (from nde-ed.org).

introduced material contaminations in Ramalho et al.'s work, and acoustic signals were recorded during the manufacturing process. Power spectral density (PSD) and short time Fourier transform (STFT) were used to pinpoint the location of discontinuity formation (Ramalho et al. 2022). Active acoustic methods, or ultrasonic, have also been studied for in situ monitoring of the WAAM process. Hossain et al. (2020) designed a fixture to connect an ultrasonic transducer to the build plate of the WAAM system and keep it in constant contact during the manufacturing process. The features extracted from ultrasonic signals showed that there is a detectable difference between the values of root mean square (RMS), root-sum-of-square (RSSQ), and peak magnitude-to-RMS ratio (P2R), which was interpreted as the indication in process deviation from the typical window of WAAM (Hossain et al. 2020). The features extracted from AE signals can be correlated with the AM process condition through statistical signal processing and ML techniques or be used to identify the potential discontinuities in the manufactured parts. Despite the large amount of information that can be extracted from AE signals, challenges exist in interpreting the signals due to the potentially low signal-to-noise ratio (SNR) and significant variation in the magnitude or frequency of the AE signal over the monitoring period of the AM process. The literature discussed previously reveals that AE shows a promising ability to distinguish variations in the operating conditions of AM systems, known as process conditions. The contrast between AM process conditions is the main cause of quality variation and changes in AM parts. Studies have also shown that AE not only distinguishes between contrary AM processing conditions, which potentially cause different types of defects, but also differentiates various levels of defects. As an example, Shevchik et al. (2019) showed that three levels of quality categories of AM parts manufactured by LPBF can be identified by detecting AE signals analyzed by ML techniques. In their study, quality categories are defined as high, medium, and poor corresponding to various levels of porosity of 0.07%, 0.30%, and 1.42%, respectively (Shevchik et al. 2019).

Machine Learning Techniques for Acoustic Data Processing

Massive datasets are ubiquitous across scientific and engineering disciplines in the current era, and this trend can be attributed to the meteoric rise in computing power over the past few decades. Consequently, applying ML algorithms to infer patterns and gain insight from these datasets has become a new mode of scientific inquiry (Brunton et al. 2020). The NDT industry is no exception to this trend, especially for AET.

ML is a subset of AI and is usually divided into three main categories: supervised, unsupervised, and reinforcement learning. Several learning algorithms fall under each of these categories, and in the context of NDT, the fundamental task is to discover or find discontinuities in the specimen of interest.

This section aims to avoid discussing ML jargon for brevity. Instead, this paper will elucidate the workings of selected ML algorithms relevant to AE testing as applied to AM. This paper will explain mathematical concepts with analogies, where necessary, to reach a wider audience.

One of the challenges in AE signal processing is the high level of dependency on human expert participation. However, this could be a major limiting factor when AE is used for in situ monitoring and control of the manufacturing processes. Specifically, this can be an issue when instant and accurate feedback is desired. AE is a data-intensive technology and using ML algorithms to analyze large datasets is of considerable interest to researchers and practitioners. Additionally, utilizing ML algorithms makes the technique more quantitative and less vulnerable to subjective judgments made by technicians and engineers when analyzing AE test data. However, despite the large amount of information that can be extracted from AE signals, challenges exist in interpreting the signals due to the potentially low SNR and a considerable variation in the magnitude or frequency of an AE signal over the monitoring period of the AM process. The forthcoming sections briefly discuss how classifiers using various ML techniques are built to help sort AE data obtained from AE systems in the context of AM. ML methods can handle these situations with reasonable efficiency. However, there are still some challenges associated with various ML techniques that must be resolved.

Supervised Classification of AM Process States

Supervised learning refers to a learning paradigm that requires prior knowledge of the answers to the problem at hand, which implies providing both the input data and the corresponding output labels when training the ML model. The model then learns a pattern to better predict or classify future data based on the knowledge from the examples during training. Supervised learning is analogous to a pupil learning a subject by studying a set of questions and their corresponding answers. Classes of problems that require supervised learning include regression and classification problems.

Neural Networks

This section provides an overview of neural networks, including the differences between artificial neural networks (ANNs), convolutional neural networks (CNNs), spectral convolutional neural networks (SCNNs), reinforcement learning (RL), and support vector machines (SVMs).

ARTIFICIAL NEURAL NETWORKS

ANNs are a commonly utilized ML architecture, modeled loosely on the human brain, mimicking how biological neurons communicate with one another. The perceptron, demonstrated by Frank Rosenblatt of Cornell in 1958, was the first trainable neural network (NN) (Rosenblatt 1958). However, it consisted of only a single layer, as opposed to the modern iteration of neural nets (also known as feedforward NNs), which have multiple layers of neurons (multilayer perceptron, or MLP). Figure 2 shows a sample ANN with one input layer (with five neurons), two hidden layers (each with four neurons), and one output layer with two neurons.

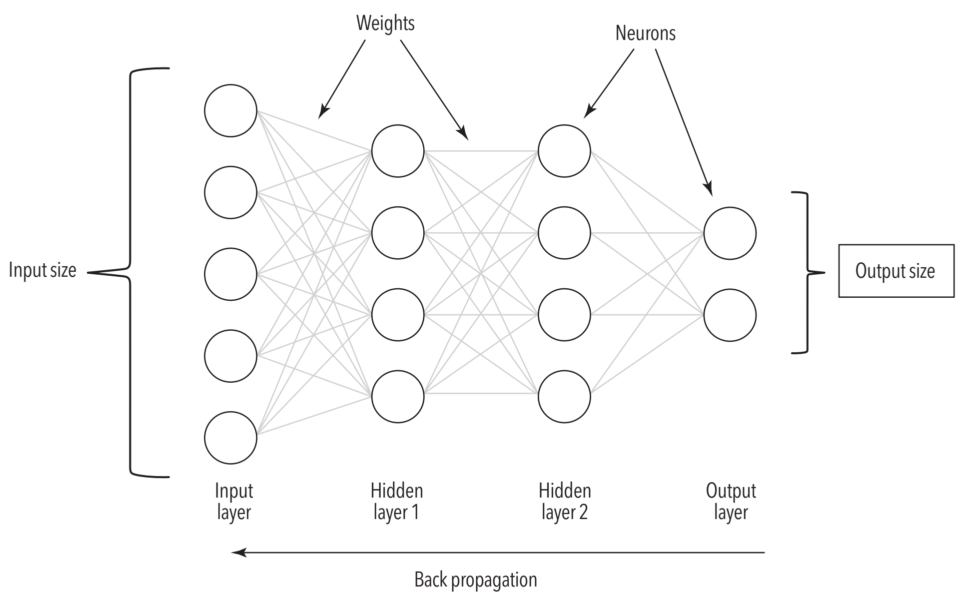

Figure 2. An artificial neural network with various components labeled. The arrow shows the direction of back propagation.

In NNs, weights are coefficients that act as scaling factors for the output of any given layer in an NN. They are the fundamental parameters of an NN, and the aim is to optimize the values of these scalars to minimize the objective (or loss) function during the training phase. Back propagation (also known as backprop for short) is the primary algorithm for performing gradient descent on NNs. It involves performing a forward pass through the network by computing the output value of each node. Then, a backward pass through the network is performed, adjusting the values of the weights in the network.

A weighted linear combination of all its inputs is calculated at each neuron. The inputs to the neurons are multiplied by their corresponding weights and then summed up. The result is then passed through an activation function. The activation function decides if the neuron should be activated or not and, if activated, decides its value. The sigmoid function is one example of an activation function. Training an NN requires defining the objective or loss function, typically the mean squared error (MSE) for regression problems or the cross-entropy loss for binary classification problems (relevant to NDT).

With the rise of more powerful hardware, especially graphics processing units (GPUs), NNs can now be trained faster, requiring less computational hours while simultaneously being "deeper." The "deep" in deep learning simply refers to the depth of layers in an NN, typically in the hundreds and thousands of hidden layers. The use of deep NNs has revolutionized the field of AI and ML, and frameworks such as PyTorch allow engineers in various fields to apply these powerful algorithms to problems in their respective domains of expertise.

CONVOLUTIONAL NEURAL NETWORK

CNNs, also known as ConvNets, are a class of NNs that are exceptionally well-suited for applications involving images and videos, such as image and video recognition, driverless cars, and image classification. Like ANNs, CNNs have an input layer, hidden layers, and an output layer. However, the hidden layers will have one or more convolution layers (hence the name). In conjunction with the convolution layers, CNNs also have pooling layers, and together form a single layer of a CNN. The architecture of a CNN is shown in Figure 3.

The function of the convolution layer is to detect specific features in an image using the convolution operation that utilizes the concept of the inner (or dot) product between two vectors. In a CNN, the convolution operation is executed using a kernel that is the same size as the window of data it operates on. It is important to note that the kernel elements are weights the network learns when trained. The pooling layer is utilized to reduce the spatial dimension of the data, which helps reduce computational costs and makes the network resistant to overfitting. Each convolution layer has a rectified linear unit (ReLU) activation function that converts all negative values to zeros. The fully connected layer is not a characteristic of the CNN and contains an activation function just like an ANN, converting features into class probabilities (in classification problems).

CNNs can process data with a similar grid structure. Local connections, weight sharing, and down-sampling are the main characteristics of CNNs that make them suitable for several types of AE signal analysis. CNN methods are based on the translation invariance of feature extraction and ignore the time correlation of signals. In the case of cyclic NNs, the complex structure and numerous parameters involved in the process make them difficult to optimize and train. Considering these limitations and challenges, research needs to be done to enhance the application of deep learning techniques for AE in situ monitoring for manufacturing processes, specifically in the case of AM. Li et al. (2022) presented a new AE signal recognition method based on a temporal convolution network called acoustic emission temporal convolution network (AETCN) for real-time polymer flow state monitoring in an FDM process.

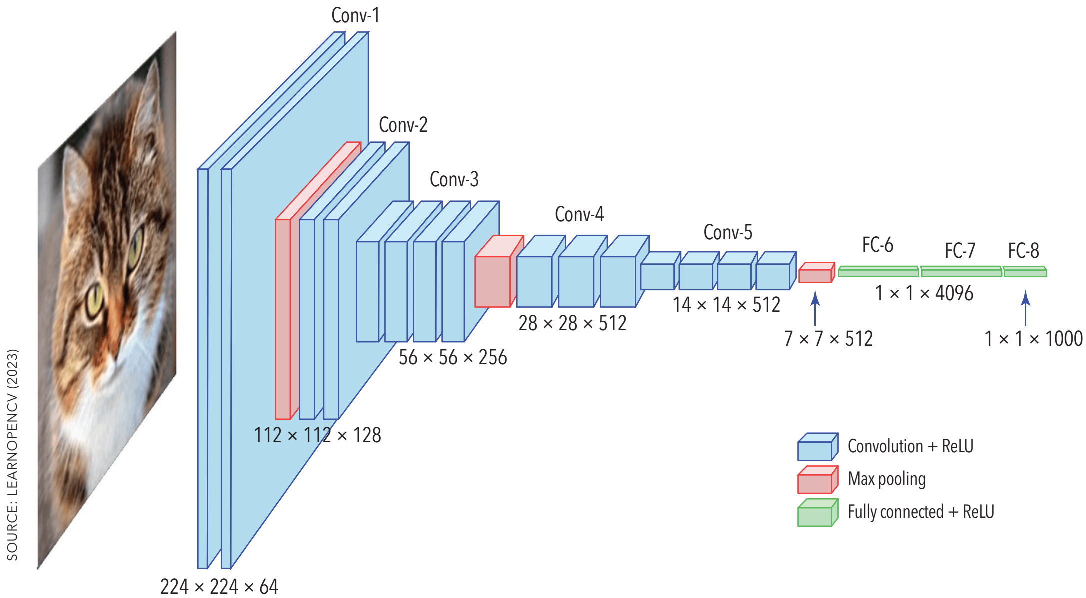

Figure 3. A convolutional neural network (CNN) model.

AETCN uses the dilated causal convolution and dilation convolution as the cornerstone of building a network such that it has both the convenience of convolution and the advantage of using correlation information of time series, so it reduces the intervention of expert knowledge in feature extraction. To obtain information over time in an AETCN, causal convolution is used. In causal convolution, the output prediction Y_t of a time sequence at time t only depends on the timesteps from the sequence X_t and before X_t. The fact that causal convolution cannot see the future data is the main difference with traditional CNN. Figure 4 shows the basic idea of the AETCN and its construction. In the proposed AETCN by Li et al. (2022), to prevent performance degradation and gradient disappearance or explosion in the deep network, a residual network structure was introduced as can be seen by "Resblock" in Figure 4b. Network degradation, gradient explosion, and gradient subtraction can influence the performance of a deep NN, and this effect increases as the network becomes deeper.

The source of elastic waves generated over the AM processes is commonly intermittent, nonstationary, or a time-varying phenomena. This characteristic means that the generated acoustic waves are subject to rapid change in time and frequency. In such a situation, the wavelet transform (WT) can be an efficient method of capturing both time and frequency information of the signals. To address this issue, several researchers used WT for the preliminary signal processing and feature extraction from AE signals recorded from in situ AM process monitoring. Hossain and Taheri (2021a) used WT to decompose the AE signals recorded during the different process conditions in a DED process into various discrete series of sequences over different frequency bands. These segments were then analyzed to identify different process conditions using a CNN. The results show a classification accuracy of 96% and validation accuracy of 95% for different process conditions (Hossain and Taheri 2021a, 2021b).

SPECTRAL CONVOLUTIONAL NEURAL NETWORK

Researchers at Empa, the Swiss Federal Laboratories for Materials Science and Technology, have done extensive work on the application of ML techniques for AE signal processing in AM in situ monitoring and published their approaches in several articles (Masinelli et al. 2021; Shevchik et al. 2018, 2019; Wasmer et al. 2018, 2019). They used a fiber Bragg grating sensor to record the acoustic signals during the powder bed AM process at different intentionally altered processing regimes. The acoustic signals' relative energies were considered the features and extracted from the frequency bands of the wavelet packet transform (Shevchik et al. 2018). Wavelet packet transform can be described as applying a set of filters on a signal, as shown by Equations 1 and 2:

$$(1)\quad \varphi_j(n) = \sum_n h_0(k)\sqrt{M}\,\varphi(Mn-k),\ k \subset Z$$

$$(2)\quad \psi_{ji}(n) = \sum_n h_{m-1}(k)\sqrt{M}\,\psi(Mn-k),\ k \subset Z$$

where

h_0 is a low pass and h_m is a high pass filter,
φ and ψ are the scale and wavelet functions, respectively,
j is a scale,
n is the current sampling point of the digitized signal, and
the parameter m is the total number of filter channels.

A spectral convolutional neural network (SCNN) classifier was developed by Mathieu et al. (2014). It could differentiate the acoustic features of the different quality of AM parts with the different level of porosities. The confidence in classifications varies between 83% and 89%.

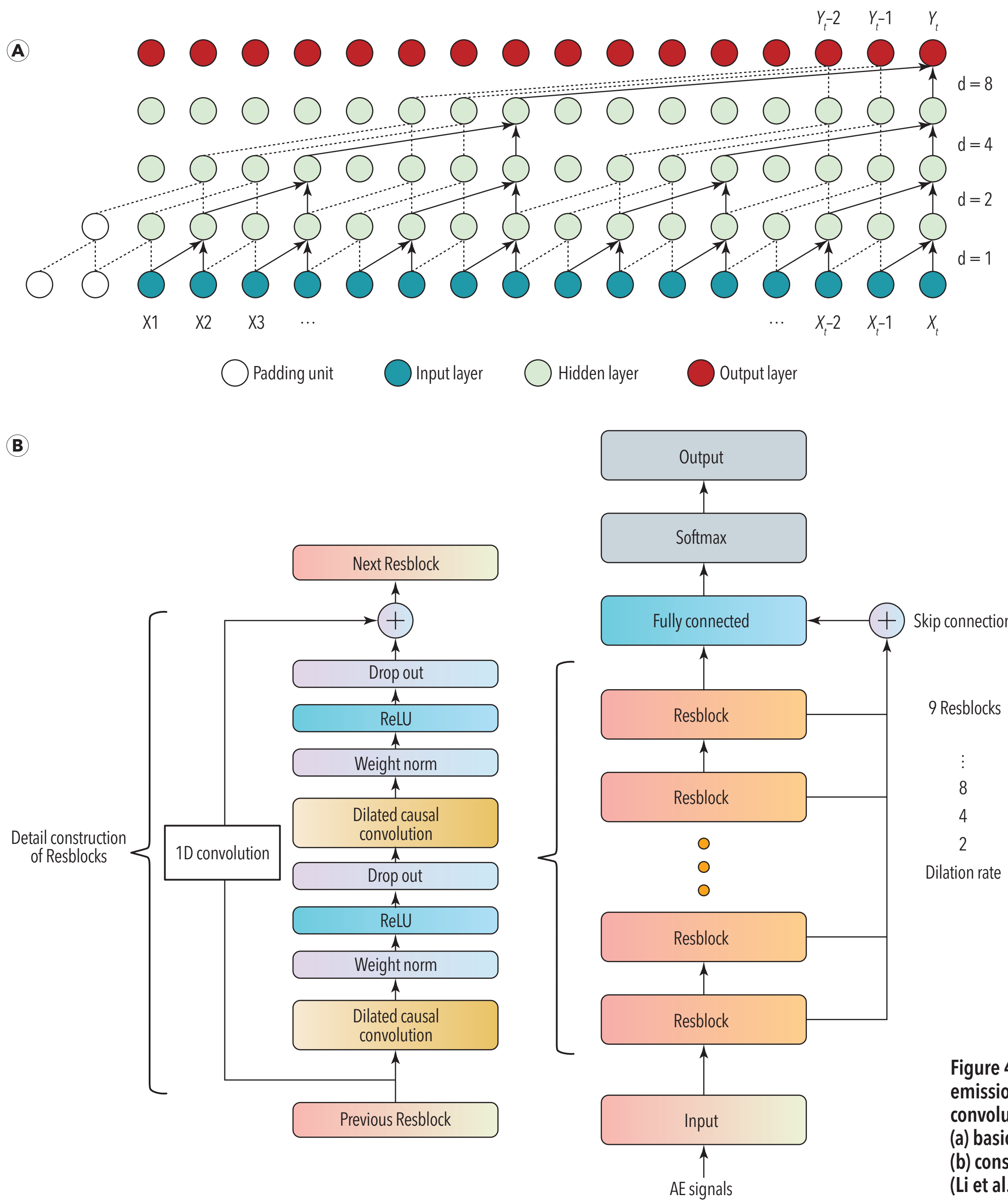

Figure 4. Acoustic emission temporal convolution network: (a) basic concept; (b) construction (Li et al. 2022).

REINFORCEMENT LEARNING

Using the same dataset, the Empa group studied the application of a reinforcement learning (RL) approach to classify different levels of quality for parts manufactured using AM (Wasmer et al. 2019). The RL technique is inspired by the human cognitive capabilities of learning in its surrounding world. In RL, knowledge is acquired through trial and error (or reward and penalty) in an environment by performing the actions and seeing the results of actions (Sutton and Barto 2018). In their approach, a Markovian process is the way of interaction between the RL agent and the environment. The initial state was set to s_0 in the classification process and the algorithm reached the goal s_g by the actions that win the maximum reward. The governing equation for the optimal reward is given by Equation 3:

$$(3)\quad T_\pi(s) = E\left\{\sum_t \lambda R(s_t, \pi[s_t]) | s_0 = s\right\}$$

where

E is the expectation,

the discount factor $\lambda \subset [0,1)$, and $\pi(s_t)$ is a policy that maps the states to the actions, and

R is the space of the rewards.

The confidence level of the RL-based classification in this case (Wasmer et al. 2018) was between 74% and 82%, which shows a slightly lower performance compared to their SCNN approach.

Despite the encouraging results from the SCNN and RL, researchers at Empa empowered their acoustic-based ML approach by verifying the results using high-speed X-ray imaging techniques. Four categories of conduction welding, stable keyhole, unstable keyhole, and spatter were defined in a laser welding experiment and gradient boost with both independent component analysis and with CART were used to classify the different process conditions. 74% to 95% of accuracy was achieved in their assessments (Wasmer et al. 2018).

SUPPORT VECTOR MACHINE

Support vector machines (SVMs) can be used for both classification and regression problems, although typically used for classification. The idea behind the SVM is to find the optimal hyperplane (the hyperplane with the highest margin) that separates the two classes. SVM is fundamentally a binary classifier, and a hyperplane is a decision boundary that separates the two classes. If the dimension of the input data or the number of features is two, then the hyperplane is a line. For a three-dimensional feature space, the hyperplane is a two-dimensional plane.

AE, in combination with accelerometers and thermocouples data, was used by Nam et al. (2020) to train an SVM algorithm for diagnosing health states of the FDM process. The researchers first obtained the RMS values from the AE, accelerometers, and thermocouples data. They applied both linear and nonlinear SVM algorithms to identify the state of the FDM process as healthy or faulty. This research is a good case study of how to use SVMs for studying an AM process with the help of AE. However, it is to be noted that the SVM algorithm is ineffective when the dataset has more noise, which is a downside of using AET.

Unsupervised Classification of AM Process States

Unsupervised learning is a learning paradigm that does not require prior knowledge of the solution to the problem at hand, which implies that specifying the output is not required, or in some cases where such data may not be available. The implications of this approach are that we can learn inherent patterns in the data that we were not privy to; there may be several solutions to the problem; and different results can be obtained each time we run the model. In the following sections, we discuss the application of specific unsupervised learning algorithms to the study of AM using AET.

CLUSTERING BY FAST SEARCH AND FIND OF DENSITY PEAKS

The clustering by fast search and find of density peaks (CFSFDP) approach was used by Liu et al. (2018) to identify the FDM process state. Liu et al. used reduced feature space dimension by combining both time and frequency domain features and then reducing them with the linear discriminant analysis for their work. Consequently, CFSFDP, as an unsupervised density-based clustering method, is applied to classify and recognize different machine states of the extruder (Liu et al. 2018). Density-based clustering methods such as CFSFDP used by Liu et al. update the clusters iteratively without grouping the data. This approach is contrary to distance-based clustering methods such as hierarchical and partitioning algorithms like k-means. As a result of using CFSFDP, the FDM machine states were identified within a much smaller feature space, which helps to reduce the computational cost of classification and state identification. Liu et al.'s work declared that reducing dimension in feature space remarkably improves the efficiency of state identification. For dimensionality reduction, the operator part of the algorithm can be customized by linear discriminant analysis.

K-MEANS CLUSTERING

The k-means clustering algorithm is one of the most widely used algorithms due to its flexibility and ease of implementation. It is an unsupervised learning algorithm, a class of ML algorithms that can find patterns within a dataset without being explicitly told what the underlying mechanism is or might be. The only user-defined parameter required to train a k-means clustering algorithm is the number of clusters, *k*. Figure 5 shows an example of two clusters, with optimal locations of centroids represented by triangles.

The algorithm works as follows:

1. The user defines the number of clusters, *k*, and a corresponding number of cluster centroids (or means) are randomly chosen.
2. Each observation (or point) in the dataset is assigned to one of the clusters, based on its distance from a given centroid. There are several metrics used in ML to compute distances, but a commonly utilized measure is known as the Euclidean distance.

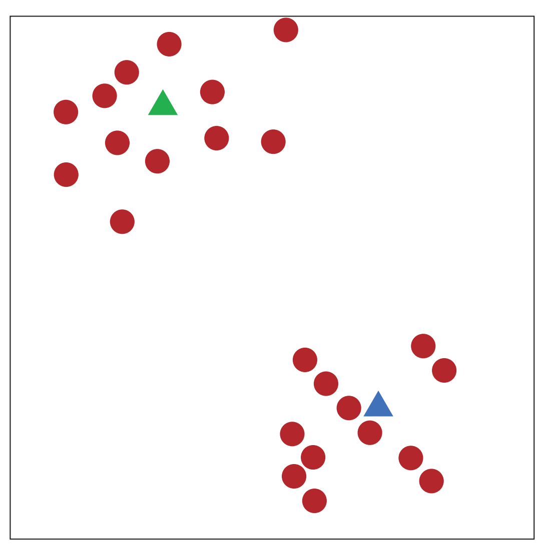

Figure 5. Setup for a k-means clustering algorithm.

3. The centroid locations are recomputed based on the assignment of data points in the previous step.
4. The process repeats, until one of the following conditions is met: (a) the centroid locations are stable; (b) the data points do not change clusters; or (c) the maximum number of iterations has been reached.

An application of the k-means clustering algorithm to the in situ monitoring of an AM process using AET is found in Taheri et al. (2019). In this study, acoustic signatures were used for in situ monitoring of the DED AM process where the deposition was performed with the machine operating in five different states. These states included "control," under which there was just powder spray, and "baseline," under which there were no active deposition activities, as well as optimum (normal) process, low laser power, and low powder feed.

Dominant features of acoustic signatures in both the time and frequency domains were identified and extracted from the acoustic signatures for all process conditions. The k-means clustering algorithm was applied to classify different process conditions, as shown in Figure 6. Correlations were demonstrated between metrics and various process conditions, which showcase the capability of AE for in situ monitoring of the AM process. Clear isolation of the baseline condition, at which no active deposition or laser-powder interaction occurs, shows that basic acoustic response of the AM system is distinct from when active manufacturing is happening. The next observation is related to the optimum settings (C1) versus powder feed only (CO) conditions. However, a separation of C1 and CO clusters was observed for C1 and CO, but the smaller isolation of clusters and larger overlap of cluster data could be an indication of significant influence of laser-material interaction compared to system and material characteristics. Last but not least, comparison of the conditions where manufacturing processes are happening (C1, C2, and C3) is interpreted as the indication of AET for separation of manufacturing processes and significant influence of laser-material interaction in AM processes.

Summary and Conclusions

Acoustic techniques are proven methods for many traditional inspection and quality monitoring applications. Due to the promising capabilities of acoustic methods for nondestructive inspection and monitoring of many kinds of processes, they have been identified as an auspicious candidate for in situ measurement and monitoring for AM processes. Two major reasons impede the application of acoustic techniques for in situ monitoring in AM processes. First is the quite low SNR due to the high sensitivity of acoustic sensors to environmental noise, which is the case in AM processes. The second is interpreting the signals to identify a correlation between the acoustic signals and the actual events. Various sensors and sensing approaches have been used to enhance the low SNR, such as using noncontact acoustic measurement via microphone or laser. Researchers have also utilized fiber-optic sensors to improve acoustic signal detection, which provides a new way of improving signal recording for in situ monitoring. Advanced signal processing techniques were used to perform data preparation, such as noise reduction and band filtering, to address the data processing and interpretation challenge. Consequently, ML algorithms have been adapted in different formats to extract and analyze the features of acoustic signals effectively. These algorithms showed an effective way and significant improvement in analyzing acoustic signals under different conditions for in situ process monitoring of AM and provide a promising pathway for the manufacturers to implement acoustic techniques for monitoring and maintaining the quality of products. Sensor integration into the AM system, detection scheme, and SNR are the existing major gaps and barriers in acoustic-based in situ monitoring of AM processes

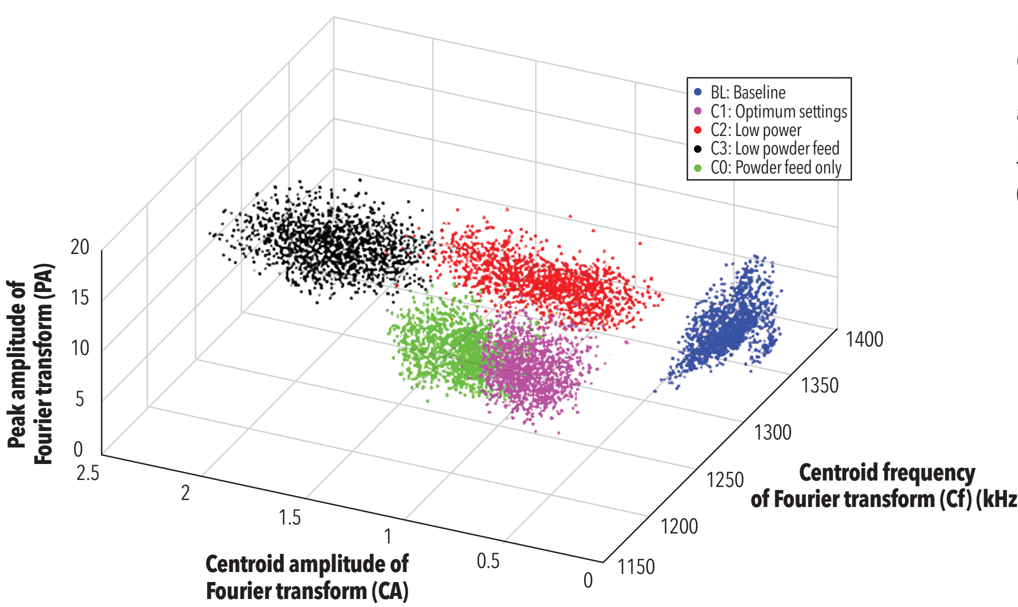

Figure 6. A three-dimensional graphical representation of the additive manufacturing process condition using three spectral features (Taheri et al. 2019).

and parts. Future direction and recommendations of research in this field include improving SNR by reducing undesired influence of environmental and systems factors, integration of complementary monitoring techniques such as X-ray to facilitate subsurface defect monitoring, and surface-sensitive optical detection approaches. Integrating other measurement techniques with AET in a combined approach reduces signal deviations caused by other variations in the process and improves the reliability in detecting process abnormalities that lessen the quality of the AM components. Lastly, a comprehensive study on an inclusive model of effect, optimization, and sensitivity of multiple process parameters on the final AM part quality is required for successful implementation of this technique in the AM industry.

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REAL-TIME AI-DRIVEN INTERPRETATION OF ULTRASONIC DATA FROM RESISTANCE SPOT WELD PROCESS MONITORING FOR ADAPTIVE WELDING

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ABSTRACT

Adaptive resistance spot welding systems typically rely on real-time analysis of dynamic resistance curves and other indirect measurements to estimate weld progress and guide adaptive weld control algorithms. Though efficient, these approaches are not always reliable, and consequently there is a need for improved feedback systems to drive adaptive welding algorithms. As an alternative, an advanced in-line integrated ultrasonic monitoring system is proposed, with real-time weld process characterization driven by artificial intelligence (AI) to create actionable feedback for the weld controller. Such a system would require real-time ultrasonic data interpretation, and for this a solution using deep learning was investigated. The proposed solution monitors the ultrasonic data for key process events and estimates the vertical size of the weld nugget proportional to the stack size throughout the welding process. This study shows that adaptive welding using ultrasonic process monitoring backed by AI-based data interpretation has immense potential. This research highlights the importance of nondestructive evaluation (NDE) in the zero-defect manufacturing paradigm.

KEYWORDS: resistance spot welding, ultrasound, artificial intelligence, deep learning, NDE 4.0

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Introduction

Zero-defect manufacturing (ZDM) has been a dream for decades (Psarommatis et al. 2022, 2023). With respect to many manufacturing processes, this dream is considered within reach given the novel technologies that should be ubiquitous in an idealized Industry 4.0. Unfortunately, however, Industry 4.0 is not yet fully realized and thus the realization of ZDM suffers as well (Psarommatis et al. 2022). Though some requirements of Industry 4.0 are increasingly fulfilled (e.g., big data production, storage, and analytics; increased connectivity and Internet of Things; industrial automation), its full realization requires NDE 4.0 (Meyendorf et al. 2017). For example, NDE 4.0 is a prerequisite for Industry 4.0's widely unfulfilled key requirement of decentralized and autonomous decision-making (Escobar et al. 2021). Fulfillment of these requirements with respect to manufactured products and joining processes is promised by NDE 4.0 through (a) the automation of nondestructive inspections; (b) the automated, consistent, generalized, and accurate interpretation of inspection data; and (c) the resultant characterization of manufactured products, which would be used to inform downstream decision-making without human intervention.

Resistance spot welding (RSW) is a manufacturing process for which the ZDM dream is potentially within reach. Many industries heavily rely on RSW joints including automotive, aerospace, rail, and military. RSW is a favorable joining method in many cases because it is inexpensive to perform, has a fast cycle time, maintains integrity of the joined sheets, has minimal added weight and volume, is highly adaptable, is robust, and is generally amenable to nondestructive evaluation (NDE) (El-Banna 2006). However, across all industries, novel materials are increasingly being developed and incorporated into manufactured products (Perez-Regalado et al. 2013). For example, in the automotive industry—which uses RSW approximately 5000 to 7000 times per vehicle—increasing vehicle electrification imposes new engineering challenges with respect to safety, lightweighting, and weight distribution (Dugmore 2021). Consequently, there is an increasing use of novel lightweight and high-strength materials (e.g., advanced high-strength steels and aluminum alloys), as well as dissimilar-material joints, which pose new challenges for RSW (Dugmore 2021). Thus, there is an increasing demand for solutions that enable ZDM of RSW.