Journal of

Advanced Manufacturing Science and Technology

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Monitoring Wire Arc Additive Manufacturing process of Inconel 718 thin-walled structure using wavelet decomposition and clustering analysis of welding signal

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Received 1 June 2024; revised 17 June 2024; accepted 24 July 2024; Available online

Abstract

Monitoring is a crucial aspect of modern production systems, especially in additive manufacturing, where instabilities and defects can lead to significant economic losses due to defective components. Consequently, artificial intelligence is increasingly used to monitor processes, enabling machines with self-analysis capabilities to generate stops or provide automatic feedback to operators. In the Wire Arc Additive Manufacturing (WAAM) process, frequency analysis of voltage signals offers an additional method to study signal characteristics, enabling the extraction of features that describe the process state. This study conducted deposition tests of Inconel 718 using the Pulsed Gas Metal Arc Welding process with pre-optimized parameters. Features were extracted by analysing the time-frequency behaviour of welding voltage signals using wavelet decomposition. Subsequently, a Gaussian Mixture Model was employed to identify clusters that define the process state. By utilizing the centroids of these clusters, the process was monitored online by assigning new samples arriving online from the real deposition process to the nearest centroid. This enabled alerts to be generated for an operator or an autonomous decision-making module regarding current state of the WAAM system.

Keywords: clustering; frequency domain; wire arc additive manufacturing; welding; monitoring; Gaussian Mixture Model

1. Introduction

Additive manufacturing (AM) occupies a crucial role in the Industry 4.0 production paradigm[1] enabling the realisation of components with complex geometries that conventional methods find challenging to replicate. Furthermore, AM expedites the prototyping process, thereby decreasing the time to market for new products. Its capacity to minimize waste by utilizing materials only where required also promotes sustainability. Among the AM technologies, Wire Arc Additive Manufacturing (WAAM)[2] has garnered significant attention from the scientific community due to its capability to rapidly construct large metal components. WAAM, as depicted in Fig.1, represents an AM technique rooted in welding principles. In this process, a welding torch is fixed on a motion platform and, utilising a welding equipment, deposits material layer by layer along a predetermined path, defined by a slicer software. This method yields near-net-shape components, which typically undergo post-processing, such as machining, to achieve the final tolerances specified by the project requirements. Nevertheless, WAAM is subject to the presence of defects such as porosity, instabilities, layer collapse, humping and distortion[3]. Thus, a

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Peer review under responsibility of Editorial Committee of JAMST
DOI: 10.51393/j.jamst.2025006

primary objective in this field is the development of monitoring applications capable of real-time defect detection[4,5] and general self-monitoring to identify the process states. These applications aim to halt the production process upon detecting defects to prevent the generation of not compliant parts, which translate into waste generation and higher production costs. In alternative, monitoring application can generate alert or feedback to the operator about process stability. Nowadays, the possibility to use the torch position data coming from the motion platform along the path with the output of the anomaly detection systems, give the possibility to localise potential defects, thereby streamlining and expediting the certification procedure[6]. In fact, the detected anomalies can be used as Non Destructive Evaluation (NDE) targets during the inspection process, which is potentially useful for real-world application, especially for the certification process of large complex shape components.

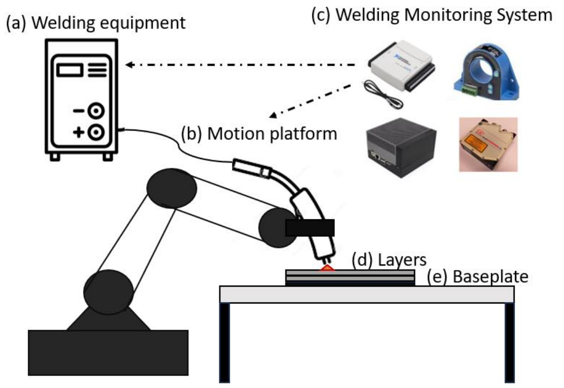

Fig. 1. Wire Arc Additive Manufacturing utilizes an electric arc to selectively melt a wire feedstock, enabling a layer-by-layer deposition to create near-net-shape components. A Welding Monitoring System can be used to collect data from the process and take action based on the data.

Nowadays, the abundance of resources dedicated to the development of AI applications has facilitated the widespread integration of AI across various industrial applications, including modelling[7-9], control[10-12], optimisation[13-16] and monitoring[17-20]. Particularly in monitoring tasks, AI has emerged as a prominent tool, with supervised learning approaches predominantly favoured due to their demonstrated effectiveness and reliability in achieving desired outcomes[21,22]. These approaches leverage labelled datasets to train models, enabling them to accurately identify patterns and make informed decisions based on past observations. As a result, supervised learning methods have become instrumental in enhancing monitoring capabilities across diverse sectors, offering valuable insights, and facilitating proactive decision-making processes. Nevertheless, it is widely recognized that developing supervised learning applications can be resource intensive. Consequently, researchers are increasingly exploring semi-supervised or unsupervised learning approaches as viable alternatives[23-26]. Semi-supervised learning involves gathering data primarily associated with normal behaviour and learning the patterns of normality. Deviations from what the algorithm has learned can then serve as indicators of anomalies. On the other hand, unsupervised learning entails clustering data into meaningful groups and assigning significance to these clusters. Once meaningful interpretations are assigned to the clusters, the data can be labelled accordingly, and this information can subsequently be utilised to develop anomaly detection applications. However, it's important to note that these approaches still face limitations in the current literature, and further research is needed to explore the potential application of these techniques in WAAM process. In Fig.2 are illustrated the different Machine Learning techniques employable in monitoring applications.

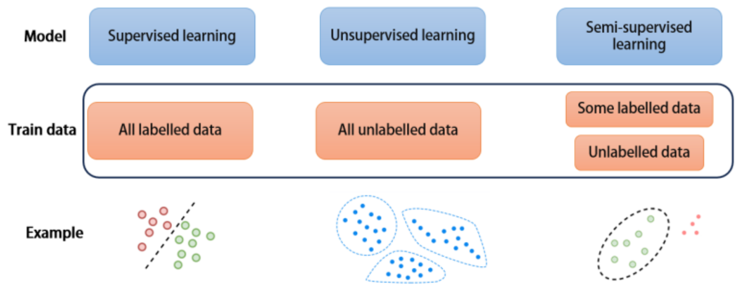

Fig. 2. Machine Learning techniques employable in monitoring applications.

Clustering techniques are fundamental in unsupervised learning, playing a pivotal role in various applications such as pattern recognition, data analysis, and exploration. These methods organise data into coherent groups or clusters based on their similarities, thereby revealing underlying structures within datasets and facilitating insightful interpretation and decision-making. In the context of AM, clustering finds diverse applications, including label generation, identification and rectification of incorrect parameters, and, in more sophisticated systems, anomaly detection[27]. In this work a online monitoring system based on unsupervised machine learning and frequency analysis of welding voltage signals is developed to monitor the production process of Inconel 718 thin-walled structure through

WAAM process.

2. Materials and Methods

2.1. Experimental setup and dataset generation

In the conducted experimental campaign, data were collected while depositing thin-walled structure through the WAAM process, specifically employing Inconel 718 with a wire diameter of 1.2mm and a synergic Pulsed-GMAW waveform welding, illustrated in Fig.3. For the deposition, a Yaskawa MA2010 robotic arm has been programmed and used as motion platform, while the Lincoln PowerWave 500 welding machine is used as welding equipment.

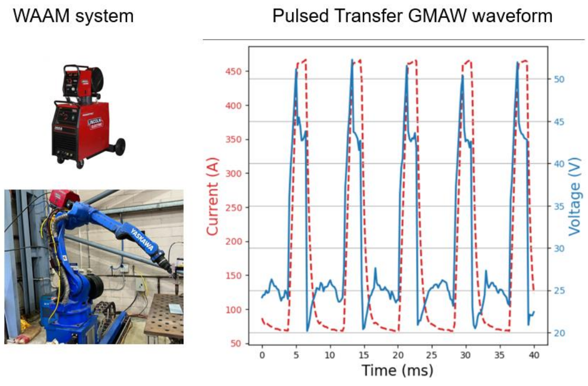

Fig. 3. Experimental setup and waveform welding process employed. Traditional Pulse welding consists of a peak and background current to deposit a molten droplet after each pulse. The waveform, described by parameters like Pulse ramp, tailout and background current, is developed by a welding supplier and allows to deposit of a droplet with a fixed frequency depending on wire material and diameter.

In the thin-walled construction, 25 layers of 100 mm in length have been deposited, maintaining a fixed interpass temperature of 30 degrees. The parameters utilized included well-established parameters such as a wire feed speed of 8.5 m/min, a welding speed of 600 mm/min, and a contact-to-workpiece distance (CTWD) of 15 mm. The synergic line employed for Inconel 718 1.2 mm wire has been developed by Lincoln.

Find the best parameters is complex, since they have to avoid issues like excessive spatter or layer collapse during the deposition. Unlike Gas Metal Arc Welding, where the synergic lines are typically chosen based on the thickness of the plate to be welded, for WAAM no criteria exist, consequently, selecting the parameters relies on experimental experience and existing literature which suggest a starting point. In this study various parameter combinations have been explored, starting with experience-based parameters, and the best parameters presented above have been utilised to print a wall without defects, as shown in Fig.4.

Fig. 4. Wall printed without defects using well-established parameters that have been controlled during the deposition.

To induce anomalies within the dataset aiming to validate the methodology, another wall was deposited with the same parameters, this time without adjusting the CTWD before each deposition. This new layer contains both defect-free and anomalous layers. The introduction of disturbances in the CTWD resulted in anomalies such as spatter generation and porosity, which simulate real-world scenario due to factors such as incorrect path planning, heat accumulation and absence of a closed-feedback controller. Furthermore, the not controlled interpass temperature led into layer collapse, due to a too hot substrate. The experimental set up is summarised in Table 1.

Table 1 Summary of conducted experiments

Experiment	Thin-walled structure printed without defects	Thin-walled structure printed with anomalies
Note	Process parameters have been controlled during the deposition with WFS 8.5 m/min, WS 600 mm/min and CTWD 15 mm at Interpass T of 30°.	Using the same parameters of good deposition experiments, the CTWD and the interpass temperature have been not controlled properly during the building process.
Anomalies	Not present	Excessive spatter Arc suppression Layer collapse

During the deposition process, welding voltage signals have been acquired using an NI-6001 USB device with a high-sample-rate acquisition system operating at 5 kHz. To assess the quality of deposited layer, expert welders participated to the classification procedure via both surface appearance and sound coming from the process. In fact, traditionally the analysis of acoustic emission has been a crucial aspect in the qualification of welds by skilled welding operators. Consequently, the contemporary examination of acoustic emission during welding processes represents a cutting-edge pursuit in defect detection systems, often monitored via microphones[27-30]. Nonetheless, the effectiveness of these methods can be undermined in noisy environments, especially within the audible range of 20 Hz-20 kHz with the employment of microphones. Utilizing a high-frequency system for welding electrical signals such as welding voltage, addresses this challenge by facilitating signal measurement within a narrower bandwidth, thereby reducing environmental noise and enhancing the robustness of the detection method in the frequency bands correlated to droplet transfer to the melting pool, which is related to both layer geometry and process stability. Furthermore, a well-established association between welding signals and acoustic emission exist, as welding signals can indeed be converted into audio signals[31]. Processing these high-frequency signals necessitates the extraction of pertinent features before applying clustering techniques, which employ frequency domain analysis in state-of-the-art methods[32]. Consequently, in this work, a Morlet transform is employed to convert the welding voltage signals into a scalograms using wavelet analysis, which is a visual representation of the energy content of a signal across both time and frequency domains. Then, the frequency bandwidths of interest have been founded and features that describe the frequency response in these bandwidths have been extracted via wavelet decomposition and used to monitor the process.

2.2. Time-frequency domain features extraction

The Morlet wavelet, in Eq.(1), is a complex-valued wavelet function commonly used in wavelet analysis due to its advantageous properties, particularly in capturing both frequency and temporal information simultaneously[33].

$$\psi(t) = \pi^{-1/4} e^{\omega_0 t} e^{-t^2/2} \tag{1}$$

where t represents time, ω_0 denotes the non-dimensional frequency and i represents the imaginary unit.

The Morlet wavelet is characterized by its oscillatory behaviour, resembling a sinusoid wave modulated by a Gaussian envelope. This combination enables it to effectively capture both high-frequency oscillations and transient features within a signal, making it particularly suitable for analysing welding data in this context. To generate scalograms of welding signals, the collected signals have been segmented into 1-second-long windows, each comprising 5000 samples, for a total of 614 samples in the dataset under study. This segmentation is crucial for developing an online approach to online monitoring welding processes. Then the mean value of the time window is removed to remove the contribute of the constant components and a Morlet transform is applied using 256 wavelets across different scales. Fig.5 displays two distinct scalograms associated with normal and anomalous depositions that highlight how the low-frequency content of the signal indicates the presence of anomalous conditions. In fact. the scalogram of the normal deposition process demonstrates a consistent frequency band cantered around 500 Hz, while in the high frequency bands a different and higher contribution can be founded. This approach utilizing scalograms provides a comprehensive view of the welding process dynamics, enabling real-time anomaly detection and monitoring. By leveraging wavelet transform techniques and analysing frequency distributions, subtle deviations from normal operation can be effectively identified, facilitating timely intervention and maintenance. For this reason, a python software package has been developed using libraries such as NIDAQMX for data collection, wavelet[34] and Open CV for data processing and features extraction and SciKit Learn for the clustering analysis.

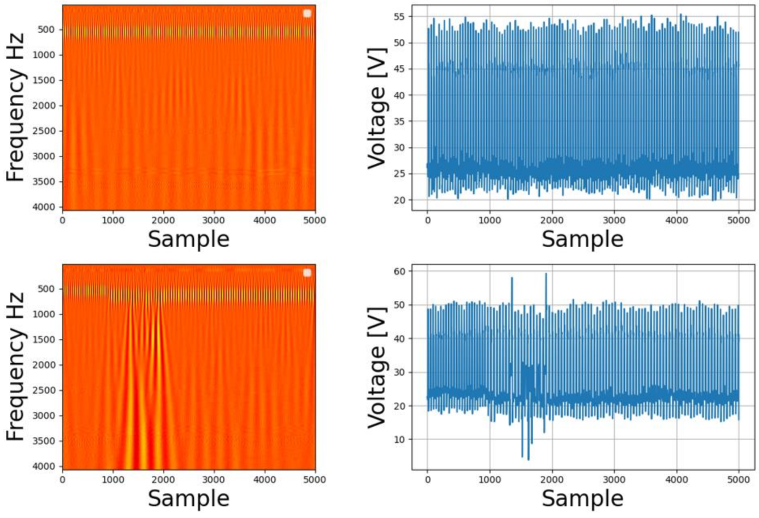

Fig. 5 Scalograms obtained using the Morlet wavelet transform applied to the time series of welding voltage for (a) normal deposition and (b) deposition with anomalies.

To develop the monitoring module for the proposed WAAM system, in this work is proposed a clustering approach that relies on features extracted from time-frequency domain analysis. In particular, a wavelet decomposition using a 2nd order Daubechies wavelet is used to decompose the signal into 2 levels, obtaining the frequency content of the signal in the bandwidths of 0-625 Hz, 625-1250 Hz and 1250-2500 Hz. Energy, variance, skewness, kurtosis and the delta of the coefficient's amplitude have been extracted in the 0-625 Hz and 625-1250 Hz bandwidths for the welding voltage signals, for a total of 10 features for samples.

The extracted features of the training dataset are then normalised in the range of 0-1 to assure that all the features are in the same interval and that the scale of the features do not influence the results of clustering. Obtained the minimum and maximum values on the training dataset, the features of the test dataset are scaled accordingly.

Then a Principal Component Analysis (PCA) has been conducted to reduce the dataset dimensionality and visualisation purposes. In particular, the PCA has been performed on training data, associated with defect-free deposition, and the same transformation is then applied to test dataset. This because if the features come from the defect-free deposition, it is possible to use the same transformation to effectively represent the data. If they come from a different process, e.g. an anomalous one, the applied transformation emphasises the difference between the features, increasing the anomaly detection capabilities of the proposed unsupervised learning algorithm. In Fig.6 is shown the Pareto diagram of the explained variance in employing 6 components. The Fig.6 shown that 80% of variance is explained using 3 components, while 90% is explained by using 4 components.

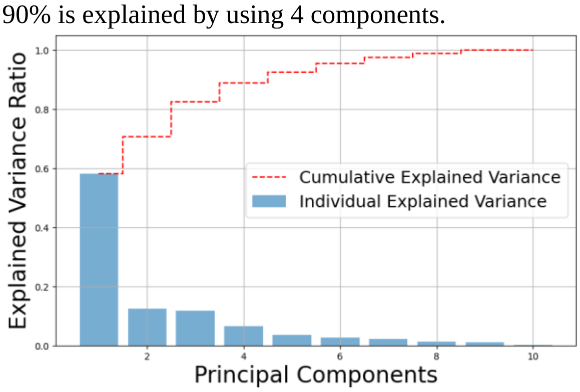

Fig. 6 Pareto diagram of conducted PCA showing that 4 components explain 90% of the data variance.

The samples collected during the experimental campaign are visualised in Fig.7, which highlight the presence of anomalous deposition thar can be detected by a machine learning algorithm, once meaningful features are extracted and reduced to 4 components.

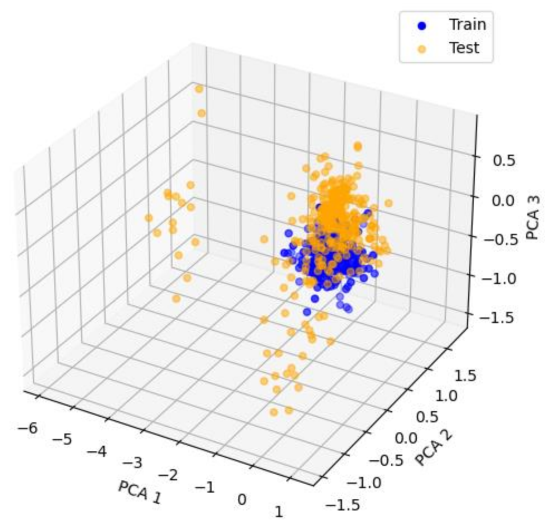

Fig. 7 Principal Components that allow to visualise in the feature space the features extracted in the time-frequency domain.

2.3. Anomaly detection based on clustering in Additive Manufacturing

In machine learning clustering techniques are used to grouping data points into subsets, or clusters, where data points within each subset share similarities. These similarities can be evaluated based different criteria, such as distance metrics, density, or distribution patterns in different algorithms like KMeans, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and Gaussian Mixture Models. Although clustering is primarily used to organise datasets and extracting labels from cluster analysis, it may be employed for anomaly detection, e.g. to detect instabilities and flaws generation in additive manufacturing parts. One effective approach in this case is the centroid and distance-based method. This method involves assigning class labels to data points based on their proximity to cluster centroids. Once clusters have been identified offline, a label can be assigned to each cluster exploring the data in them contained. If one of the clusters present anomalous conditions and a new sample coming from the process is closer to the anomalous cluster, it can be classified as an anomaly. The advantage of this methodology is the possibility to develop an expert system that, employing machine learning, is able to classify anomalies although the data available of anomalous conditions are rare and not balanced in number with normal data, which makes impossible training supervised machine learning algorithms. The methodology proposed in this work is summarised in Fig.8 and consists in four different steps:

- Cluster Formation: Initially, the dataset undergoes clustering and k clusters can be identified based data features.

- Cluster meaning evaluation: Once the clusters have been identified, a label is assigned to each cluster following a clustered-data exploration in which engineering knowledge is used.
- Centroid Calculation: Once clusters are formed and labelled, the centroid of each cluster is computed as the mean of all data points within the cluster.
- Anomaly Identification: Once a new data come from the WAAM process, the distance with respect to identified clusters is computed and it is assigned the label of the closest centroid.

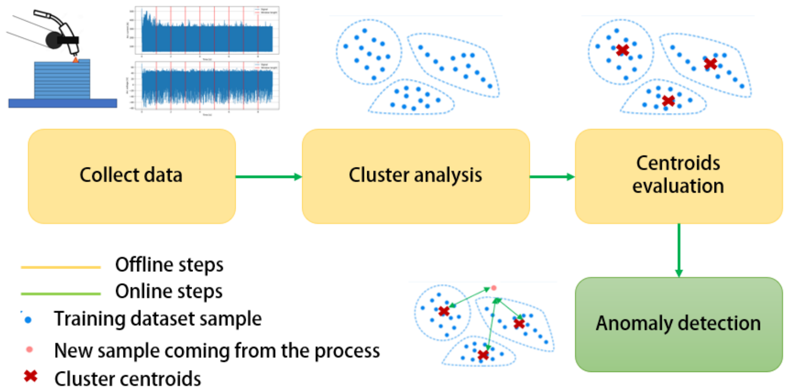

Fig. 8 Proposed methodology for anomaly detection based on clustering analysis and centroid-distance methods.

In this work a Gaussian Mixture Model (GMM) algorithm is used to cluster the datapoints collected during the experimental campaign, thanks to its ability to deal with intricate and non-linear data structures[36]. Unlike other techniques like KMeans, GMM represents clusters as probability distributions, allowing for soft assignments of data points to clusters based on the likelihood of belonging to each cluster. GMM assumes that data points are generated from a mixture of several Gaussian distributions, each characterized by its mean, covariance, and weights, which are estimated using the Expectation-Maximization (EM) algorithm[37]. The EM algorithm iteratively refines the parameter estimates until convergence, maximizing the likelihood of the observed data given the model. Although GMM allows for capturing complex data distributions, determining the appropriate number of clusters in a GMM remains a challenging task. The Bayesian Information Criterion (BIC) offers a principled approach to address this challenge by balancing model complexity and goodness of fit.

The BIC method assesses the balance between model complexity and fit quality by adjusting the likelihood function according to both the model's parameter counts and the sample size. By penalising models with more parameters, it promotes simpler models capable of capturing the underlying data structure without overfitting. The ideal number of clusters among the 614 samples contained in the training dataset, denoted as *k*, is determined by minimizing the BIC score across various k values. Furthermore, the evaluation typically caps at 15 clusters to ascertain the optimal value, which is equal to 4 as shown in Fig.9.

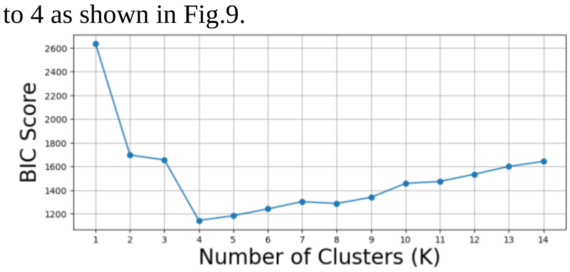

Fig. 9 BIC score used to determine the optimal number of clusters.

The proposed anomaly detection process operates in two distinct steps. Firstly, the normalised features are compared against those obtained from the training dataset. Specifically, if the squared sum of the obtained features exceeds the maximum values observed during training in terms of squared sum, an anomaly is flagged. This step is crucial because skipping it could lead the algorithm to incorrectly assign the sample to a cluster even if it is significantly different. This misassignment can occur when new and previously unseen anomalies arise, differing from those in the test dataset. Secondly, if the sample falls within the acceptable range, it is assigned to the nearest cluster as proposed in Fig.8.

3. Results and discussion

Using the proposed approach, we obtained 4 clusters, the centroids of which are shown in Fig.10. A medoid is defined as the point within a cluster that has the minimum average distance to all other points in the cluster. Medoids can be used to visually represent a characteristic sample of a cluster, as they are actual points within the cluster and minimize the sum of distances to all other points in the cluster. In the following section the medoids of each cluster have been analysed aiming to associate a label to each cluster.

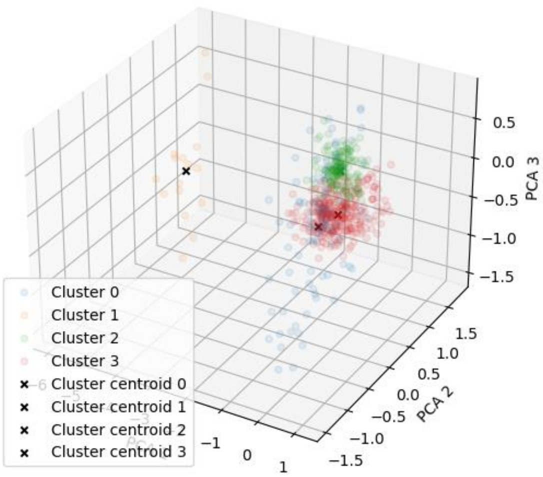

Fig. 10 Results obtained using GMM clustering and centroids used for the anomaly detection task.

3.1. Analysis of cluster 0

The medoid of the cluster 0, which is contained in the training dataset, is shown in Fig.11 for both time series value and associated spectrogram. The constant droplet releasement is characteristic of the synergic pulsed for the selected material. In this cluster follow the 54% of the samples part of this study, which is associated to a normal deposition.

3.2. Analysis of cluster 1

The medoid of the cluster 1 is shown in Fig.12, in which an anomaly associated to the unexpected arc ignition process can be found in a sample contained in the test dataset. More specifically, in this case is possible to notice a change in transfer mode to uncontrolled short circuit and undesired arc ignition associated to low quality deposition. In this cluster follow only the 2% of samples part of this study.

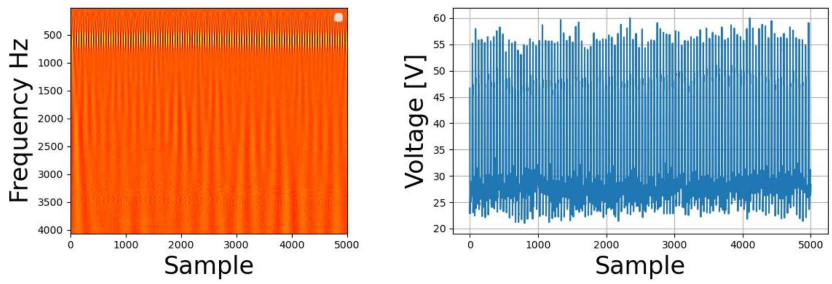

Fig. 11 Spectrogram and time series welding voltage signal of cluster 0 medoid.

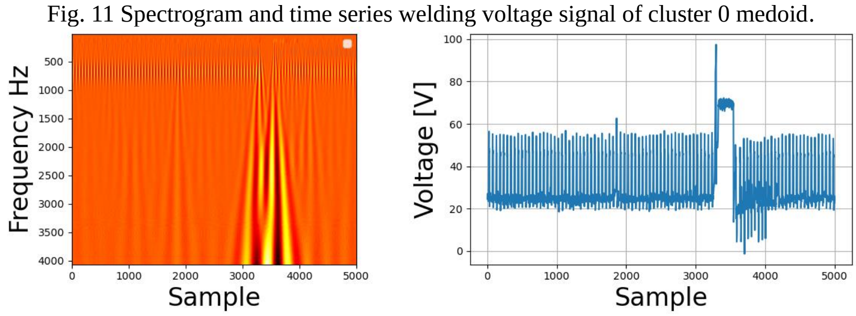

Fig. 12 Spectrogram and time series welding voltage signal of cluster 1 medoid, associated to a deposition under undesired condition.

3.3. Analysis of cluster 2

The medoid of the cluster 2, contained in the training dataset, is shown in Fig.13, in which the deposition process is still stable and no undesired short circuit can be founded. The slightly difference in the frequency content is associated to the building process, which due to heat accumulation introduce acceptable uncertainties during the deposition. In particular, the 33% of the samples of this study follow in this cluster that represent normal deposition with the cluster 0.

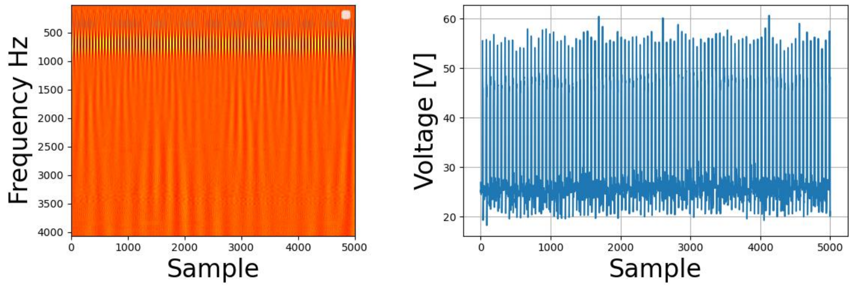

Fig. 13 Spectrogram and time series welding voltage signal of cluster 2 medoid.

3.4. Analysis of cluster 3

Finally in Fig.14 is shown the medoid of cluster 3, contained in the test dataset, in which a process that is diverging from the optimal, although a stable deposition is observed. In this case few undesired short circuits can be detected, which suggest a slight unstable deposition, which should alarm the operator. The 11% of the samples of this study follow inside this cluster.

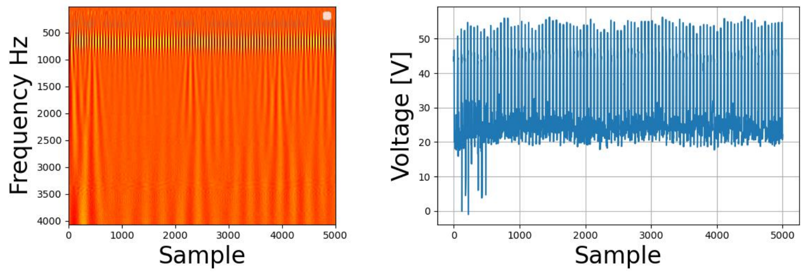

Fig. 14 Spectrogram and time series welding voltage signal of cluster 3 medoid.

3.5. Centroid approach to anomaly detection

Utilising the proposed centroid approach, once the clusters have been identified and labelled, the process can be monitored online with a sample frequency of 1 Hz. In particular, the system equipped with the proposed software module is able to self-diagnosis about its state and can generate alert the operator based on the outputs or stop the process if an anomaly is detected. The thin-walled structure utilised in this work are shown in Fig.15, in which is possible to observe the difference in surface appearance of a good quality and low-quality deposition.

Finally, the proposed software module has been implemented and tested on the last layer of test wall. The results of the proposed clustering method, shown in Figure 16, demonstrated the ability of the proposed approach to monitor the WAAM process. In particular, the arc instability which led into a defect at the beginning of the deposition as shown in Fig.16 has been correctly individuated (as cluster 1) and the operator alerted. Futhermore, undersired short arc (as cluster 3) has been individuated and the operator has been informed about an instability during the deposition process. During the deposition process the welding voltage signal is inside the normality bounds, so no defect has been detected.

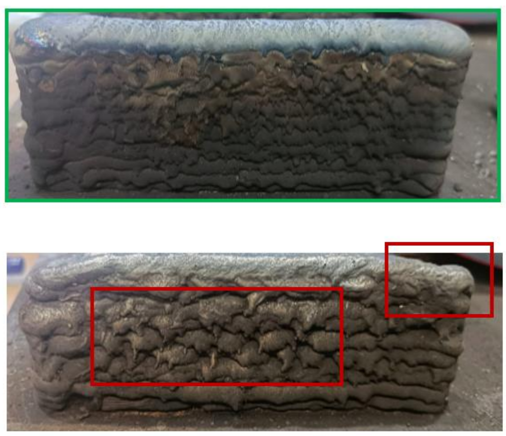

Fig. 15 Thin-walled structures utilised in this work to collect and process data to develop the unsupervised machine learning methodology used to monitor the WAAM process of Inconel 718 parts.

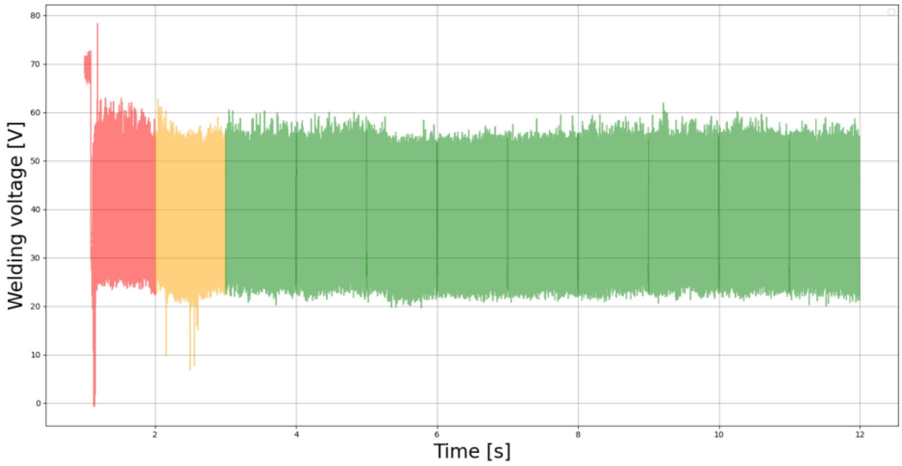

Fig. 16 Results of the proposed monitoring methodology based on clustering and unsupervised machine learning in detecting the WAAM states during the deposition and in identifying anomalies.

4. Conclusions

In this work, an experimental campaign was conducted involving the deposition of a thin-walled structure in Inconel 718 using WAAM technology. The voltage signal was acquired from a defect-free process and another in which various instabilities were introduced to simulate real-world scenarios. A time-frequency study of segmented signals of 1-second length demonstrated that important information regarding the processing state can be found in the low-frequency bands between 300-1500 Hz. A wavelet decomposition was thus utilised to extract features in the frequency bands of 0-625 and 625-1250 Hz, which were then used in a Gaussian Mixture Model clustering algorithm, leading to the identification of 4 clusters. After visualising the medoids of each cluster, a label was assigned to each cluster, using surface appearance and welding sounds of samples present in each cluster. The proposed algorithm enables online process monitoring since every second, a new sample is analysed in the time-frequency domain and assigned an anomaly label or a state label of the process, using the obtained clusters as reference. A final application of this capability is then showed to remark the performance of the proposed methodology. In fact, the potential introduced by this methodology can allow intelligent production systems to provide online feedback to operators regarding the state of the deposition and halt the process if an anomaly is present or highlight it, along with the tool centre point information of the robot, for potential post-processing non-destructive tests as support for the certification of the part produced via AM technology.

Acknowledgements

The INVITALIA Project on NEMESI and POR Campania FESR 2014/2020 Project TOP are gratefully acknowledged for their support to this research work. We acknowledge the Facility for Intelligent Fabrication laboratory of University of Wollongong and their research group for providing equipment and support throughout this research.

References

1. Dilberoglu UM, Gharehpapagh B, Yaman U, et al. The role of additive manufacturing in the Era of Industry 4.0. *Procedia Manuf.* 2017;11:545-554.
2. Norrish J, Polden J, Richardson I. A review of wire arc additive manufacturing: development, principles, process physics, implementation and current status. *J Phys D Appl Phys.* 2021;54(47):473001.
3. Wu B, Pan Z, Ding D, et al. A review of the wire arc additive manufacturing of metals: properties, defects and quality improvement. *J Manuf Process.* 2018;35:127-139.
4. Xia C, Pan Z, Polden J, et al. A review on wire arc additive manufacturing: Monitoring, control and a framework of automated system. *J Manuf Syst.* 2020;57:31-45.
5. Mattera G, Nele L, Paolella D. Monitoring and control the Wire Arc Additive Manufacturing process using artificial intelligence techniques: a review. *J Intell Manuf.* 2023. doi: 10.1007/s10845-023-02085-5.
6. Mattera G, Polden J, Caggiano A, et al. Anomaly detection of wire arc additively manufactured parts via surface tension transfer through unsupervised machine learning techniques. *17th CIRP Conference on Intelligent Computation in Manufacturing Engineering*. 2023.
7. Mu H, He F, Yuan L, et al. Toward a smart wire arc additive manufacturing system: A review on current developments and a framework of digital twin. *J Manuf Syst.* 2023;67:174-189.
8. Mu H, He F, Yuan L, et al. Online distortion simulation using generative machine learning models: A step toward digital twin of metallic additive

manufacturing. *J Ind Inf Integr.* 2024;38:100563.

9. Xia C, Pan Z, Polden J, et al. Modelling and prediction of surface roughness in wire arc additive manufacturing using machine learning. *J Intell Manuf. 2022*;33(5):1467-1482.

10. Mu H, Polden J, Li Y, et al. Layer-by-layer model-based adaptive control for wire arc additive manufacturing of thin-wall structures. *J Intell Manuf.* 2022;33(4):1165-1180.

11. Xia C, Pan Z, Polden J, et al. Model predictive control of layer width in wire arc additive manufacturing. *J Manuf Process.* 2020;58:179-186.

12. Mattera G, Caggiano A, Nele L. Optimal data-driven control of manufacturing processes using reinforcement learning: an application to Wire Arc Additive Manufacturing. *J Intell Manuf.* 2024.

13. Mattera G, Caggiano A, Nele L. Reinforcement learning as data-driven optimization technique for GMAW process. *Welding in the World.* 2023;68:805-817.

14. Lee DY, Leifsson L, Kim JY, et al. Optimisation of hybrid tandem metal active gas welding using Gaussian process regression. *Sci Technol Weld Join.* 2020;25(3):208-217.

15. Katherasan D, Elias JV, Sathiya P, et al. Simulation and parameter optimization of flux cored arc welding using artificial neural network and particle swarm optimization algorithm. *J Intell Manuf.* 2014 ;25(1):67-76.

16. Deswal S, Narang R, Chhabra D. Modeling and parametric optimization of FDM 3D printing process using hybrid techniques for enhancing dimensional preciseness. *Int J Interact Des Manuf (IJIDeM).* 2019;13(3):1197-1214.

17. Li Y, Pan Z, Han T, et al. A defect detection system for wire arc additive manufacturing using incremental learning. *J Ind Inf Integr.* 2022;27:100291.

18. Xia C, Pan Z, Li Y, et al. Vision-based melt pool monitoring for wire-arc additive manufacturing using deep learning method. *Int J Adv Manuf Technol.* 2022;120(1-2):551-562.

19. Caggiano A, Mattera G, Nele L. Smart tool wear monitoring of CFRP/CFRP stack drilling using Autoencoders and Memory-Based Neural Networks. *Appl Sci (Basel).* 2023;13(5):3307.

20. Caggiano A, Napolitano F, Teti R, et al. Advanced die sinking EDM process monitoring based on anomaly detection for online identification of improper process conditions. *Procedia CIRP*. 2020;88:381-386.

21. Zhang T, Xu C, Cheng J, et al. Research of surface oxidation defects in copper alloy wire arc additive manufacturing based on time-frequency analysis and deep learning method. *J Mater Res Technol*. 2023 Jul;25:511-521.

22. Alcaraz JYI, Foqué W, Sharma A, et al. Indirect porosity detection and root-cause identification in WAAM. *J Intell Manuf*. 2023;35:1607-1628.

23. Song H, Li C, Fu Y, et al. A two-stage unsupervised approach for surface anomaly detection in wire and arc additive manufacturing. *Comput Ind*. 2023;151:103994.

24. Mishra A, Dasgupta A. Supervised and unsupervised machine learning algorithms for forecasting the fracture location in dissimilar friction-stir-welded joints. forecasting. 2022;4(4):787-797.

25. Wang J, Sanchez J, Ayesta I, et al. Unsupervised machine learning for advanced tolerance monitoring of wire electrical discharge machining of disc turbine fir-tree slots. *Sensors (Basel)*. 2018;18(10):3359.

26. Reisch R, Hauser T, Lutz B, et al. Distance-based multivariate anomaly detection in wire arc additive manufacturing. 2*020 19th IEEE International Conference on Machine Learning and Applications (ICMLA)*. 2020.p.659-664.

27. Rahman MA, Jamal S, Cruz MV, et al. In situ process monitoring of multi-layer deposition in wire arc additive manufacturing (WAAM) process with acoustic data analysis and machine learning. *Int J Adv Manuf Technol*. 2024;132:5087-5101.

28. Surovi NA, Soh GS. Acoustic feature based geometric defect identification in wire arc additive manufacturing. *Virtual Phys Prototyp*. 2023;18(1): e2210553.

29. Gourishetti S, Feng P, Zhou W, et al. D7.2 - arc welding process monitoring using neural networks and audio signal analysis. In: *Lectures D7-Al Approches in Measurement*. 2023.p.249-250.

30. Rohe M, Stoll BN, Hildebrand J, et al. Detecting process anomalies in the GMAW process by acoustic sensing with a Convolutional Neural Network (CNN) for classification. *J Manuf Mater Process*. 2021;5(4):135.

31. Čudina M, Prezelj J. Evaluation of the sound signal based on the welding current in the gas—metal arc welding process. *Proc Inst Mech Eng C J Mech Eng Sci*. 2003;217(5):483-494.

32. Mattera G, Polden J, Nele L. A time-frequency domain features extraction approach enhanced by computer vision for Wire Arc Additive Manufacturing monitoring using Fourier and Wavelet transform. *J Adv Manuf Syst*. 2024.

33. Lin J, Qu L. Feature extraction based on Morlet wavelet and its application for mechanical fault diagnosis. *J Sound Vib*. 2000;234(1):135-148.

34. Lee G, Gommers R, Waselewski F, et al. PyWavelets: A Python package for wavelet analysis. *J Open Source Softw*. 2019;4(36):1237.

35. Ismail MF, Jaafar TR, Che Pin N, et al. Sobel operator for edges detection in surface texture analysis. *J Teknol*. 2015;76(10).71-74.

36. Deeva I, Bubnova A, Kalyuzhnaya AV. Advanced approach for distributions parameters learning in Bayesian Networks with Gaussian Mixture Models

and Discriminative Models. *Mathematics*. 2023;11(2):343.
37. Xie Y, Wu D, Qiang Z. An improved mixture model of Gaussian Processes and its classification expectation–Maximization Algorithm. *Mathematics*. 2023;11(10):2251.