Welding in the World
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RESEARCH PAPER

Advances in machine learning for parameters optimisation and in-situ monitoring of wire arc additive manufacturing

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Abstract
Wire arc additive manufacturing (WAAM) demands both real-time monitoring of process stabi-supervised learning for real-time anomility and defects and offline optimisation of process parameters to guarantee part quality and production efficiency. This review critically surveys recent machine learning (ML) techniques for in situ monitoring and parameter optimisation in WAAM, with an emphasis on the integration of ML and bio-inspired optimisation algorithms. In relation to in-situ monitoring, this review examines the roles of supervised and unsupervised learning, as well as advanced deep-learning architectures—such as generative AI and frequency-informed neural networks—in processing welding current and welding voltage, as well as vision-based, audible, acoustic-emission, and thermal imaging data. Furthermore, this paper surveys the latest developments in bio-inspired optimisation models applied to WAAM, discussing how ML-enabled frameworks can enhance sustainability and efficiency metrics in the offline selection of optimal process parameters. The synthesis of insights at the end of each section establishes a structured framework for practitioners, highlights existing research gaps, and outlines strategic directions for future advancements in ML-driven WAAM monitoring and optimisation.

Keywords Arc welding · Additive manufacturing · Wire arc additive manufacturing · Process monitoring · Process optimisation · Machine learning

1 Introduction

Wire arc additive manufacturing (WAAM) is an additive manufacturing technique that utilises an electric arc—generated through well-established welding technologies such as plasma arc welding (PAW) or gas metal arc welding (GMAW)—to melt and deposit metal in a layer-by-layer manner. However, innovations in arc welding technologies, such as double-electrode GMAW (DE-GMAW) [1, 2], are increasingly being explored. Indeed, this approach enables improvements in deposition rates while decoupling them from the heat input generated during the process, with potentially significant impacts on both the mechanical properties and the reduction of production time for large-scale parts. The robotic WAAM process was first proposed in the early 1990 s by Ribeiro and Norrish [3], who demonstrated the feasibility of using arc welding to fabricate metallic prototypes. Since then, WAAM systems have remained relatively unchanged in their fundamental configuration. They typically consist of robotic arms controlled by CAD/CAM software, integrated with welding machines, thereby enabling the production of large-scale metal components. The entire process is summarised in Fig. 1.

WAAM has become a well-established research topic, with over 3000 publications currently available in the literature. Between 1998 and 2017, the field experienced steady, linear growth, with fewer than 80 papers published during that period. However, as illustrated in Fig. 2, recent years have seen an exponential rise in research output. As highlighted by He et al. [4], the early stages of WAAM research, up to around 2013, were largely focused on process

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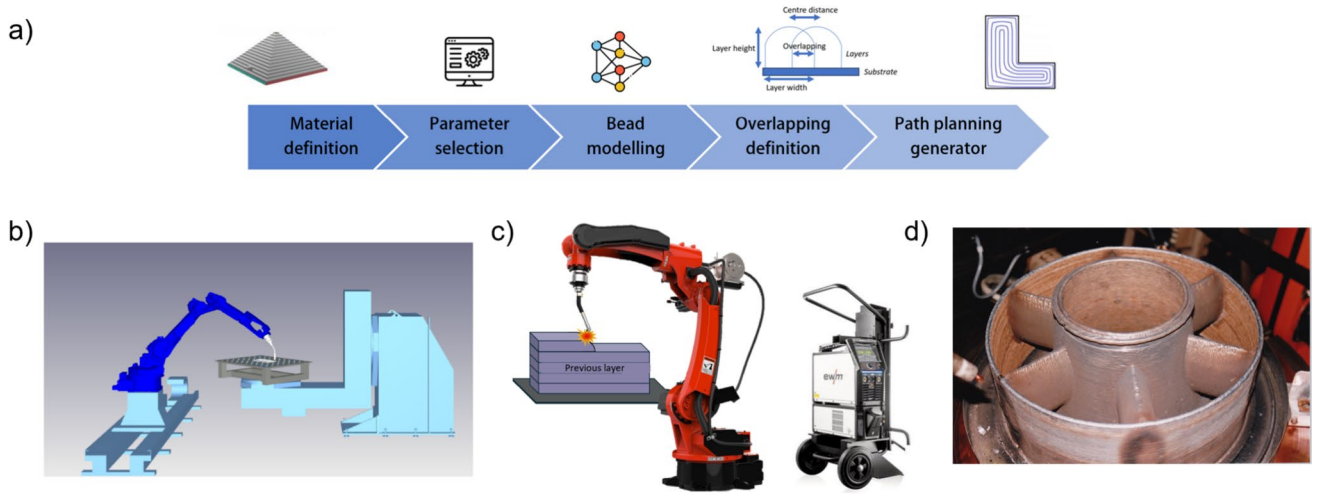

Fig. 1 Overview of the WAAM process: **a** process workflow, **b** example of a robotic system, **c** illustration of the deposition procedure, and **d** example of a final manufactured component

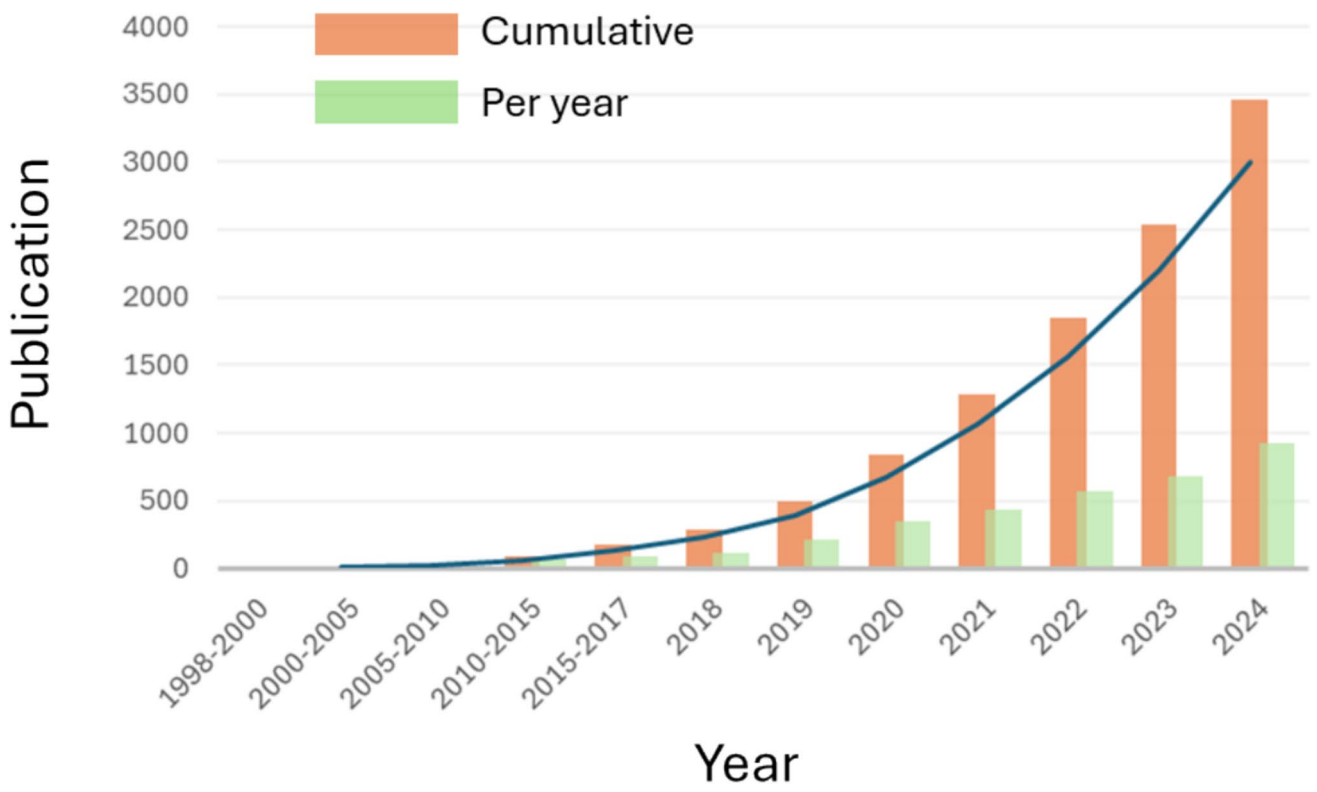

Fig. 2 Number of publications about WAAM technology

development, particularly the optimisation of operational parameters and automation strategies. From 2013 to 2017, the focus shifted towards metallurgical investigations, addressing issues such as defect formation [5–7], mechanical property enhancement [8–11], and bead geometry modelling [12]—key areas underpinning the development of advanced slicing techniques [13, 14]. More recently, attention has increasingly turned towards real-time quality assurance and, notably, the integration of artificial intelligence (AI) for process monitoring, control, and optimisation [15].

The growing interest in the application of AI to WAAM is largely driven by the need to control susceptibility to defect

formation during deposition, owing to the complex underlying physical phenomena involved. Potential defects may include the occurrence of cracks, porosity, geometric deviations, undercutting, and other irregularities. For example, Teng et al. demonstrated that the geometry of individual layers can vary significantly during deposition, even when identical process parameters are employed. Without an integrated process monitoring module, the robotic system may operate with an arc length that is either too short or too long, resulting in inadequate shielding gas coverage, arc instability, or unstable heat input. Furthermore, improper overlap settings or fluctuations in layer width can lead to void formation or even layer collapse. Indeed, the work of Chen et al. [16] demonstrated that proper process monitoring and the consequent feedback control can improve parts quality, representing fundamental modules for new generation WAAM systems. As a result, nowadays AI technologies represent an enabling technology for WAAM systems, and they can be utilised at both the offline and online stages of the process. Offline, AI can serve as an optimisation tool to support process planning and parameter selection. Online, trained machine learning (ML) models can be employed to monitor the deposition process in real time, enabling the detection and diagnosis of anomalies as they occur. Based on these insights, decision support systems can then suggest appropriate corrective actions or, in more advanced configurations, autonomously adjust process parameters to mitigate defects. As explored in this work, AI represents an advanced alternative to traditional methods. Indeed, regarding online in situ process monitoring, several recent studies have compared the monitoring capabilities of AI with the standard statistical process monitoring (SPM) techniques. In particular, the SPM methods rely on Gaussian distribution assumptions to detect out-of-control conditions by monitoring deviations outside control limits defined by $\mu \pm 3\sigma$, where μ is the mean of the controlled variable (e.g., welding voltage) and σ is its standard deviation observed during a high-quality deposition process. Applications of this approach, which can be extended to the WAAM process, can be found in the works of Thekkuden et al. [17], Bancker et al. [18], Cook et al. [19], and Feng et al. [20], who applied control charts to detect weld porosity or shifts in arc stability. While such univariate statistical approaches are simple to implement and attractive for industrial use when only high-quality data are available, they often fail to capture subtle defects, particularly those associated with frequency-domain changes rather than amplitude or mean shifts. In arc-based additive processes, anomalies such as porosity or spatter may manifest as abnormal frequency peaks or elevated spectral energy within specific bandwidths [21], which conventional tools may not reliably detect. Furthermore, with the advent of the Fourth Industrial Revolution, the growing availability of big data and multi-sensor information has highlighted additional limitations of traditional SPM techniques, which struggle to cope with nonlinear, non-Gaussian data and real-time monitoring requirements [22]. These challenges underscore the need for more advanced approaches, paving the way for ML to address the complexity of defect formation mechanisms in WAAM.

Moreover, regarding process optimisation, while traditional approaches based on experimental evidence remain widely adopted in the WAAM field, they are largely limited to manual knowledge-driven parameter tuning through trial-and-error experimentation. Although such methods lack the predictive capabilities and scalability of data-driven approaches, they often reflect valuable, experience-based decisions and enable direct observation under real manufacturing conditions, thereby helping to identify critical parameter sensitivities. Nevertheless, manual tuning is time-consuming, resource-intensive, and limited in its ability to capture complex parameter interactions. By contrast, mathematical models (e.g., data-driven approaches) provide a more efficient means of exploring broader parameter spaces, including those not directly tested in experiments. They facilitate multi-objective optimisation, reduce the experimental burden, and are generally more cost-effective, particularly in industrial contexts.

Therefore, given the growing interest in these techniques, this paper provides a timely review of recent advances in the application of ML to WAAM, with a specific focus on in situ online monitoring and offline process optimisation. While the number of publications in this field is rapidly increasing each year, no comprehensive review has yet consolidated the latest progress in these two crucial areas, especially with a focus more industry-oriented. By systematically tracking and synthesising recent contributions, this work aims to clarify the current state of the art, identify emerging innovations, and outline future research directions that can guide both academic studies and industrial applications.

This paper is structured as follows: Sect. 2 reviews the state of the art of ML algorithms and techniques for data processing, together with bio-inspired optimisation methods, to provide context for readers who may not be familiar with the topic. Section 3 focuses on in situ monitoring, while Sect. 4 discusses process optimisation. The main findings are summarised as bullet points in the Conclusion, emphasising the key takeaways and the remaining open challenges in this evolving field.

2 State-of-the-art of machine learning models and bio-inspired optimisation algorithms employed in welding technology

Machine learning (ML) is a subfield of AI that enables systems to automatically learn patterns from data. ML algorithms are commonly categorised into supervised,

unsupervised, and semi-supervised approaches, as shown in Fig. 3, depending on the availability of labelled data and the strategy used to process it.

In welding applications, for instance, data are typically collected from sensors monitoring signals such as current and voltage. However, ML models are usually not trained directly on the raw signals, but rather on features extracted from them—statistical indicators such as the mean, variance, or shape descriptors such as minimum and maximum values. These features form the input data (commonly denoted as X). A second essential concept in ML is the label (Y), which represents the meaning or classification associated with each data point, or the continuous value in a regression problem (e.g., layer geometry). For example, each input vector—whether it consists of features from time-series signals or pixels from an image—may be labelled by an expert as normal or defective, possibly including additional information such as the type of defect or recommended corrective action. When both X and Y are available, a supervised learning model can be trained to map inputs to outputs and be used for future predictions.

If only the input data X is available (i.e., without labels), then unsupervised learning methods are employed. These aim to discover inherent structures or similarities in the data by applying distance-based metrics (e.g., Euclidean distance) to group similar data points, often using clustering techniques.

Supervised learning models, while powerful, can suffer from overfitting, especially when trained on small or imbalanced datasets—i.e., datasets with significantly more examples from one class than another. In such cases, model generalisation becomes poor. To mitigate this, a sufficiently large and balanced dataset is typically required. In scenarios where labelled data are limited or expensive to obtain, two alternative approaches are gaining traction in welding applications:

- Unsupervised learning can be used for soft classification or anomaly detection by clustering the data and assigning new samples to the most similar cluster without requiring predefined input-output mapping.
- Semi-supervised learning, a more recent and promising approach, particularly in welding, allows models to be trained using a small amount of labelled data and a larger set of unlabelled data. A specific case is one-class learning, where the model is trained solely on normal data and then used to detect deviations from this learned behaviour—making it ideal for anomaly detection in quality assurance tasks.

As briefly mentioned, ML models can be classified not only based on the learning approach employed, but also according to the type of prediction task: regression or classification. Common applications of classification models include multi-class classification, where features or images are mapped to specific types of defects, and binary classification, where the output is a value between 0 and 1 representing the probability that a given feature vector belongs to a particular class. Binary classification is frequently used in anomaly detection, where anomalies represent rare or unusual data, often associated with faults in the system. These may correspond to specific or generic defects, without necessarily specifying their exact nature.

With regard to regression tasks, univariate regression involves predicting a single continuous variable—such as penetration depth [23–25] or layer width [26]—while multivariate regression predicts multiple outputs simultaneously [12, 27, 28]. The latter is often used in bead modelling,

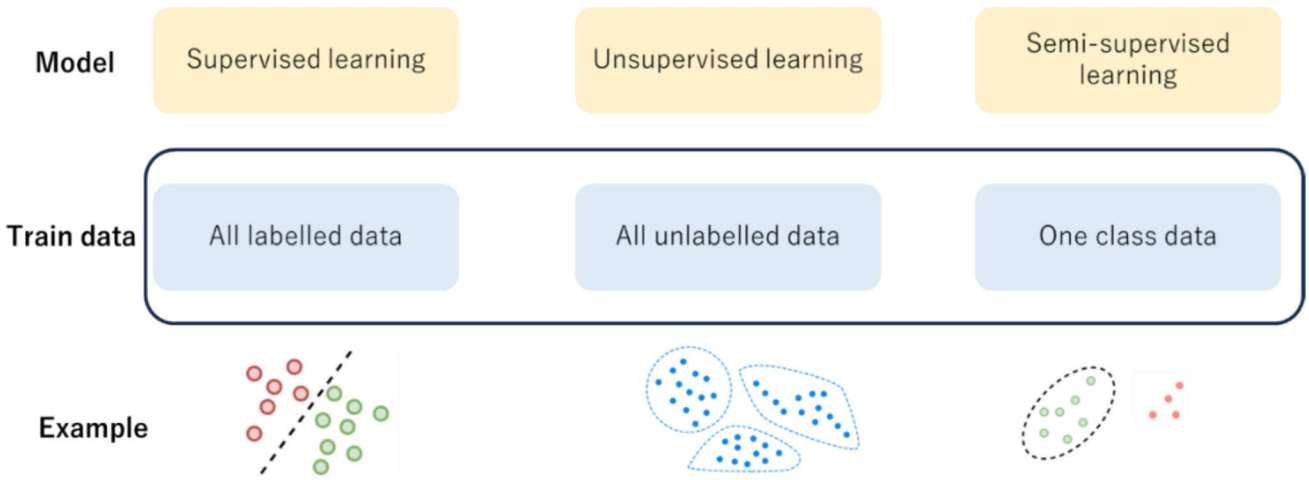

Fig. 3 Difference between supervised and unsupervised learning based on the training data type

which is a critical activity in WAAM. Bead modelling estimates layer geometry (height and width) based on the process parameters, allowing the use of data-driven models to determine optimal overlapping distances—typically around 70% of the layer width [14, 29]—between adjacent passes to ensure proper filling of the part geometry. It also enables the calculation of the number of slices required to fabricate the final component. This is crucial, as identifying the correct starting point for deposition is essential for robot path planning and the generation of robot code, as illustrated in Fig. 4.

However, regression models are not limited to path planning. They can also be integrated into offline data-driven optimisation routines, for instance by employing techniques such as genetic algorithms or reinforcement learning for parameter selection and path planning [30–32]. While the detailed discussion of bead modelling and AI-based path planning lies beyond the scope of this review, the role of regression models in WAAM is highly significant. Therefore, in this section, we present both classification models—typically used for process monitoring—and regression models, which are applied not only in offline optimisation but also, in some cases, for anomaly detection in predictive maintenance frameworks and in the development of digital twins [33].

A digital twin (DT) is a virtual replica of a physical system, capable of accurately estimating process outputs and forecasting future behaviour. Such forecasts can be used to detect anomalies by comparing predicted and actual performance, or to anticipate failures. As shown in Fig. 5, a DT uses all the mentioned models in the cyber-space to elaborate the data and interact with the human via the dashboard in the cognitive layer (visualising the main features extracted and the outcome of monitoring modules and/or suggesting actions via decision support system) and to make action in the configuration layer [34]. Another emerging application is in control system development, which, although still relatively unexplored in welding-based AM, has begun to attract interest. Some recent studies have highlighted the potential of regression models and digital twins for the development of reduced-order models in this context [35–37].

Although the topics presented reflect a general overview of ML applications in welding technologies, two specific subfields of ML remain particularly relevant to this transformative area. The first is deep learning (DL), which encompasses a family of neural network-based architectures, including standard feedforward networks, recurrent neural networks (RNNs)—and their more recent developments such as long short-term memory (LSTM) networks, gated recurrent units (GRUs), and Transformers—as well as convolutional neural networks (CNNs). The latter two are particularly well-suited for processing sequential data or time series and images, respectively. Additionally, a noteworthy subfield of DL is generative artificial intelligence (GenAI), which focuses on generating new data that resembles the

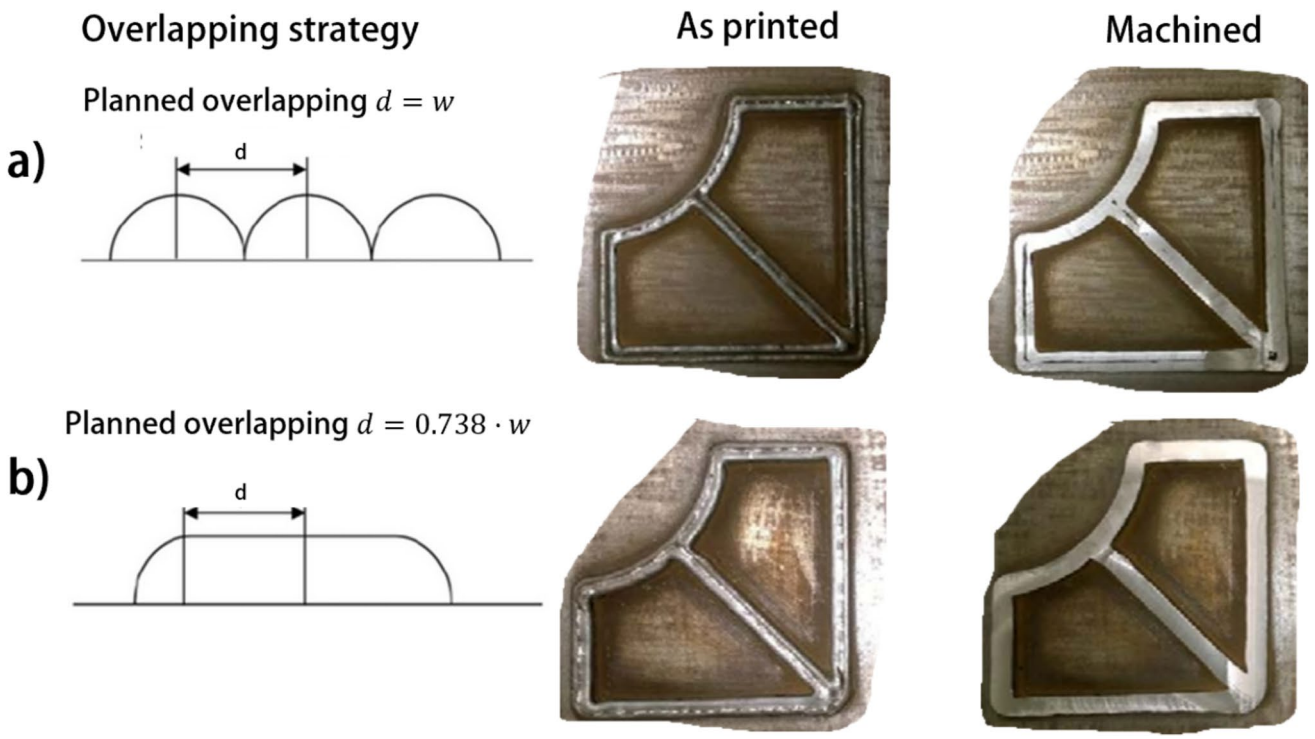

Fig. 4 Importance of correctly predict layer width and the optimal selection of overlapping

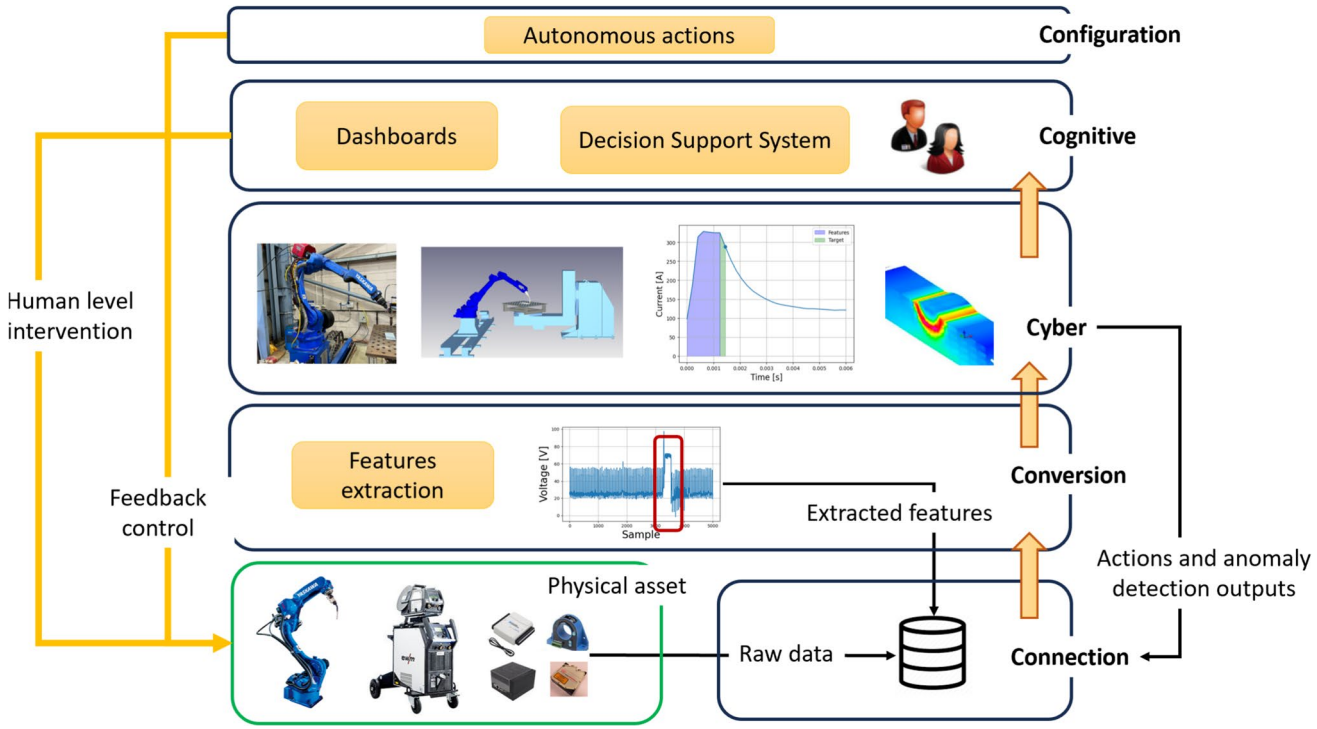

Fig. 5 An example of an ML-based digital twin architecture for a WAAM system

training data. While DL models are often employed as more powerful—even though more complex to train—alternatives to traditional regression and classification algorithms, they offer considerable advantages, especially in handling time series and image data. A more detailed discussion on their specific applications will follow later in this section, prior to the presentation of the state-of-the-art. GenAI, in contrast to traditional DL models that primarily classify or predict, employs models such as generative adversarial networks (GANs) and large language models (LLMs) to synthesise entirely new outputs, including images, text, audio, or even 3D models, based on the data observed during the training. In the context of welding, GenAI models have been applied for data augmentation [38], simulating realistic defect scenarios to enhance classification accuracy in anomaly detection systems, and process modelling [39–41]. In the broader field of additive manufacturing, they have also been used to design optimised component geometries [42], demonstrating the versatility and potential of generative approaches.

2.1 Machine learning models

2.1.1 Regression models

As discussed, both regression and classification tasks can be addressed using ML models. To elaborate, regression analysis is a modelling technique employed to describe the relationship between a continuous dependent variable Y (output) and one or more independent variables X (inputs or features) through a mathematical formulation, as illustrated in Eq. 1, and various optimisation methods (ML techniques) may be employed to estimate the model parameters θ, depending on the complexity of the problem and the nature of the data.

$$Y = f_\theta(X) \tag{1}$$

Linear and polynomial regressions are among the simplest modelling techniques, and are effective when the relationship between the input variables X and the output Y is approximately linear. This implies that each feature is linearly correlated with the target variable and that multicollinearity among the features is limited. In the absence of multicollinearity, these models can employ ordinary least squares (OLS) estimation to compute the model weights in closed form, thereby providing a straightforward analytical solution for the underlying relationship. When multicollinearity is present, however, the estimated weights in a linear regression-based model can become unstable or excessively large. In such cases, regularisation methods such as Ridge regression, which penalise large weight coefficients, can be used to mitigate the issue.

Beyond these basic models, more advanced machine learning approaches such as support vector regression (SVR)

and Gaussian process regression (GPR) are widely adopted for handling non-linear regression tasks. SVR is particularly effective in the presence of non-linear correlations and can perform robustly even when the dataset includes outliers, thanks to its margin-based optimisation framework. Compared to polynomial regression, which may overfit and become sensitive to outliers, SVR typically requires fewer data cleaning steps and performs well with smaller datasets. Conversely, GPR provides a Bayesian, non-parametric approach to regression. In addition to point predictions, GPR outputs predictive confidence intervals, making it particularly suitable for applications where uncertainty quantification is essential. Unlike traditional models, GPR does not assume a specific form for the data distribution; instead, it relies on the covariance function (kernel) to model relationships within the data (see Eq. 2).

$$Y = GP\left(m(X), k\left(x, x'\right)\right) + \epsilon_{\sigma} \tag{2}$$

In Eq. 2, m is the mean function, which is often assumed equal to zero, σ is the variance of the Gaussian noise, while $k\left(x, x'\right)$ is the kernel function, in which x and x' are two samples of the dataset, measuring the covariance of the outputs generated by different samples of the train dataset. For this reason, GPR is well-suited to small- to medium-sized datasets, such as those commonly encountered in industrial settings, including welding process modelling. However, the results—particularly the confidence intervals—are sensitive to the choice of kernel, which is typically a combination of different functions, such as linear and radial basis function (RBF) kernels.

2.1.2 Classification models

Although these models are the most commonly employed for regression, other ML models are widely used for multi-class classification, which is typically applied in defect detection. Given the complexity of these tasks—which often involve partitioning the feature space into distinct regions, each corresponding to a specific class—decision tree models and their variants are commonly employed. These include ensembles of decision trees, such as random forests, and boosting algorithms like XGBoost, which are particularly effective for classification problems.

In particular, decision trees recursively split the dataset into subsets based on input feature values, forming a tree-like structure where each internal node represents a decision based on a feature, and each leaf node corresponds to a class label. The tree is constructed by selecting splits that maximise information gain or minimise impurity measures such as Gini impurity or entropy. While decision trees are interpretable and easy to visualise, they are prone to overfitting, especially when the tree grows deep. Therefore, hyperparameter tuning—such as setting the maximum depth and minimum samples required for a split—must be performed carefully. To overcome the limitations of single decision trees, random forests were developed as an ensemble learning method. Random forests build multiple decision trees during training, with each tree trained on a random subset of the data via bootstrapping. Furthermore, at each split, only a random subset of features is considered. The final classification is determined by aggregating the predictions from all trees, typically using majority voting. This ensemble approach significantly reduces overfitting, improves predictive accuracy, and enhances robustness. The difference between decision tree and random forest is illustrated in Fig. 6.

An advanced technique is boosting, which combines multiple weak learners—typically shallow decision trees. Unlike random forests, where trees are constructed independently, boosting trains models sequentially. Each subsequent weak learner, in addition to using the input features, aims to correct the errors made by the previous predictions. A well-known example of this approach is extreme gradient boosting (XGBoost), in which the objective function can be expressed as in Eq. 3, where l is the loss that calculates the error between the predicted values $\hat{y}_i^{t-1}$ from the previous iteration and the true value y_i, considering the output of the t-th decision tree, while $\Omega(fk)$ is the regularisation term for the kth tree.

$$L = \sum_{i=1}^{n} l\left(\hat{y}_i^{t-1} + f_t\left(x_i\right), y_i\right) + \sum_{i=1}^{n} \Omega\left(f_k\right) \tag{3}$$

The regularisation function $\Omega(f)$ for an individual tree is typically defined as in Eq. 4, and it is crucial to prevent overfitting, where T is the number of leaves in the tree, and w_j are the leaf weights.

$$\Omega\left(f_k\right) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{4}$$

Although these decision tree-based models can also be used for regression, as they operate in a similar manner, their regression outputs are often not smooth. Moreover, when the model is complex, they tend to perform poorly on relatively simple data. However, XGBoost has begun to be applied in process modelling tasks, as it can achieve performance comparable to more complex models such as feedforward neural networks [43].

2.1.3 Soft-classification models

As mentioned, supervised learning techniques require large and balanced datasets to perform effectively. However, in

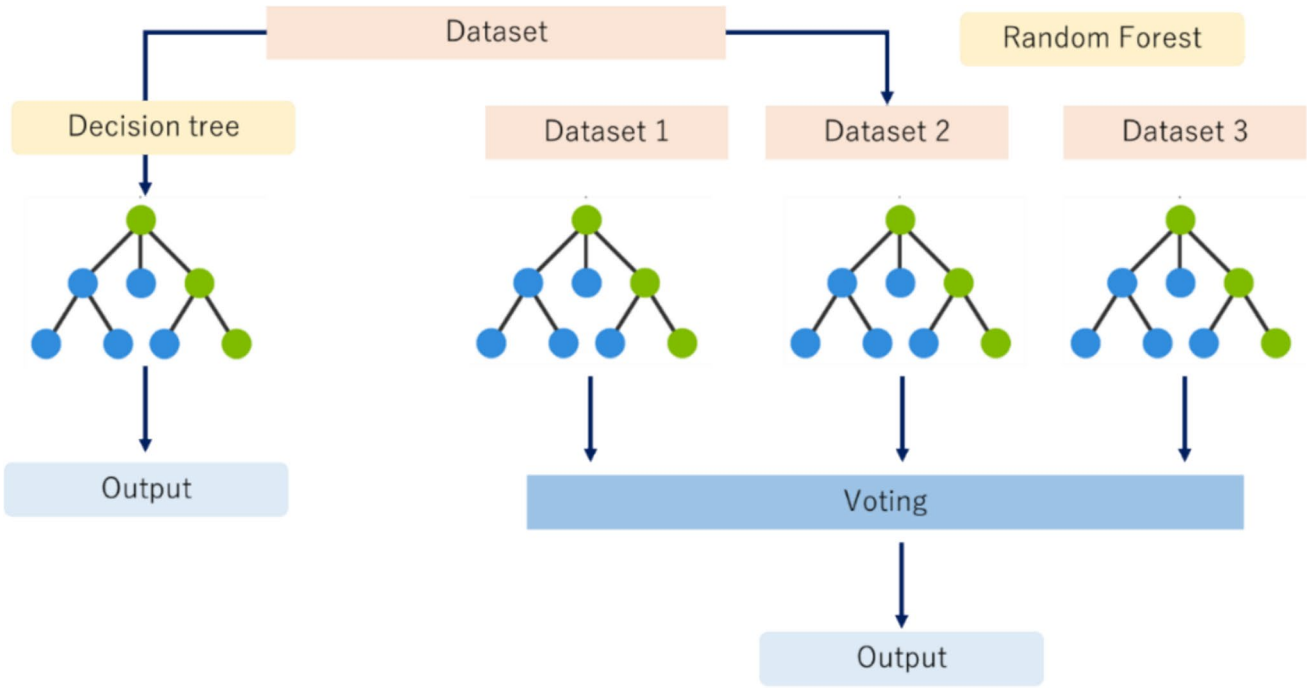

Fig. 6 Schematic difference between the decision tree model and the ensemble of decision trees or the random forest model

industrial settings, collecting sufficient data for classification tasks can be particularly challenging, especially when it comes to defective samples. These are often rare and not available in the quantities needed to train supervised models reliably. Therefore, in such cases, unsupervised learning can be employed to develop soft-classification procedures, enabling the detection or differentiation of patterns without the need for labelled data.

As detailed in [44], if the dataset is partially labelled or has a limited number of samples for each class, clustering can group data points in the feature space based on the similarity of their characteristics. Once clusters are formed, a simple distance-to-centroid method can be used to assign a class label to new samples. This approach, shown in Fig. 7, enables classification in scenarios where traditional supervised learning may be impractical, making it ideal in industrial settings, where data often exhibit a predominance of non-defective samples or suffer from significant class imbalance.

Among the advanced clustering techniques suitable for online process monitoring, K-Means, DBSCAN, and Gaussian mixture models (GMMs) offer a favourable balance between computational efficiency and robust performance. Other methods, such as t-SNE and UMAP, can also be used

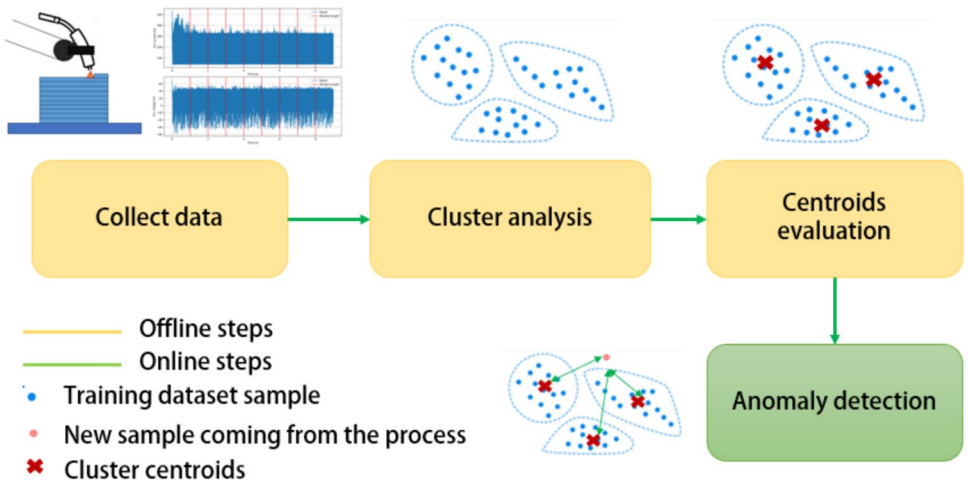

Fig. 7 Clustering approach utilised in [44]

to group and identify clusters; however, due to their high computational cost, their implementation is often impractical for real-time monitoring systems, which typically require response times on the order of 100 ms (depending on the application's timing constraints).

The K-Means algorithm partitions a dataset into k distinct clusters by minimising the within-cluster sum of squares. It operates iteratively by assigning data points to the nearest cluster centroid and subsequently updating the centroids based on the mean position of the assigned points. Due to its simplicity and computational efficiency, K-Means is widely employed in real-time pattern recognition and process monitoring applications. However, its reliance on the Euclidean distance metric and the assumption of spherical clusters with uniform density limit its effectiveness in more complex scenarios. In contrast, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) identifies clusters based on data density, allowing the detection of arbitrarily shaped clusters and the ability to distinguish noise or outliers, without requiring prior specification of the number of clusters. Rather than relying solely on Euclidean distance, DBSCAN identifies the k nearest neighbours around a sample within a specified distance threshold and classifies it as part of a cluster if at least n neighbouring points are found.

An advanced alternative is the GMM [45], which represents the data as a weighted sum of M component D-variate Gaussian distributions, as shown in Eq. 5. Here, x denotes a D-dimensional continuous-valued data vector (e.g., measurements or features), while the covariance matrix Σ and the mean vector μ of the M components are parameterised by λ.

$$p(x|\lambda) = \sum_{i=0}^{M} w_i \cdot g(x|(\mu_i, \Sigma_i) \tag{5}$$

Unlike K-Means, which assigns data points to the nearest cluster centroid, and DBSCAN, which relies on density-based connectivity, GMMs perform probabilistic clustering, assigning data points to clusters based on the likelihood of belonging to each Gaussian component. In contrast to DBSCAN, GMMs assume a parametric form and require the number of clusters to be specified a priori, but are less sensitive to parameter tuning and can handle high-dimensional continuous data more gracefully.

Despite the potential relevance of applying these methodologies to arc-welding in situ process monitoring, such as in WAAM, these techniques remain largely unexplored in this specific field, as will be further discussed in the state-of-the-art section. Nevertheless, it is worth highlighting, even prior to concrete evidence, that their application in industrial contexts holds considerable promise. In particular, industrial datasets often involve highly imbalanced class distributions, where soft classification approaches (as offered by methods such as GMMs or DBSCAN) could be more effective than hard classification techniques. These unsupervised methods are capable of identifying outliers and unlabelled anomalies, mitigating the risk of completely random guesses on unseen data. This is especially important for defect instances that differ from those observed during training—situations where traditional supervised learning models are prone to misclassification. Therefore, integrating such techniques can enhance robustness and adaptability in complex, real-world scenarios.

2.1.4 Anomaly detection models

The aforementioned soft-classification approaches can be particularly useful for identifying clusters and centroids when dealing with unlabelled or small, imbalanced datasets. However, in many industrial scenarios, the only data available are those corresponding to good depositions. This is especially true in practice, as most data are collected during welding procedure qualification, resulting in a large number of samples representing nominal or defect-free conditions. In well-established and experienced industries, defects are rare events, making it even more difficult to collect faulty examples in sufficient quantity. Monitoring in industrial contexts is especially relevant within the scope of welding procedure qualification, where the objective is to certify that a specific machine and set of parameters consistently produce high-quality parts that meet mechanical requirements. In this setting, it is reasonable to develop a product-specific monitoring module aimed at detecting deviations from the expected, nominal pattern. In alignment with recent advances in ICT technologies, such as the internet of things (IoT) and robotic systems, the integration of anomaly detection modules with robot pose information can help identify regions more likely to exhibit anomalies. This approach offers significant advantages over traditional random or statistical non-destructive evaluation (NDE) methods, potentially enabling cost and time savings during qualification procedures. Most importantly, it provides a valuable framework for industrial monitoring in contexts where only limited labelled data are available.

To serve this scope, specialised ML models can be used, such as isolation forest and local outlier factor (LOF).

The isolation forest model is a tree-based method for anomaly detection that operates by recursively partitioning the data, similar in principle to random forests. However, instead of building predictive models, it identifies anomalies based on the number of splits required to isolate a point: the fewer the splits, the more likely the point is an outlier. A different approach, based on local data density, is the LOF, which identifies anomalies by comparing the local density of a point to that of its neighbours. If a point lies in a region of significantly lower density than its surroundings, it is considered an outlier [46, 47].

2.2 Deep learning models

As previously mentioned, DL represents a family of models built around the concept of the artificial neuron. A neuron performs a linear combination of its inputs (denoted by weights, typically represented as θ), which is then processed through a non-linear activation function$g(\cdot)$. A neural network consists of an ensemble of neurons arranged in layers, where the output of one layer becomes the input to the next. This layered structure allows the network to model highly non-linear relationships and approximate any continuous function given sufficient depth and complexity. The parameters of the network are initially set at random and are iteratively updated through the backpropagation algorithm, a gradient-based optimisation method computed with respect to a chosen loss function. The initialisation procedure plays a crucial role during training, as the performance of the model can vary significantly depending on the starting point of the optimisation. Due to the non-convex nature of the loss landscape, gradient-based methods may converge to different local minima, and a poor initialisation can hinder the model's ability to reach an optimal solution [48]. Importantly, the architecture of a neural network remains largely the same whether it is applied to classification or regression tasks. The key differences lie in the mathematical formulation of the loss function and the activation function used in the output layer, which are adapted according to the specific objective of the task.

For regression tasks, the mean squared error (MSE) loss function is typically used, enabling the network to minimise the discrepancy between predicted continuous values and the true target values. The output layer in such cases commonly employs a linear or ReLU activation function, allowing the model to produce a broad range of continuous outputs. In contrast, classification tasks usually adopt the cross-entropy loss function, which quantifies the divergence between predicted class probabilities and actual labels. The output layer of a classification network generally utilises a sigmoid activation function for binary classification, or a softmax activation function in the case of multi-class problems, thereby converting the raw outputs into interpretable probability distributions over the classes.

Beyond these standard learning frameworks, the performance and generalisation capabilities of neural networks can be further enhanced through the inclusion of additional regularisation terms in the loss function. These regularisation terms serve to constrain the learning process, guiding the model towards more physically plausible or application-specific solutions, in which the human knowledge of the problem can help to improve the performance. One notable approach is frequency-informed learning or frequency-informed neural networks (FINN), in which the regularisation depends on the frequency-domain characteristics of the output. This is particularly beneficial in contexts such as signal processing or time-series modelling, where the spectral content of the prediction carries critical information. By penalising discrepancies in the frequency domain—often through measures such as the difference in power spectral density or Fourier-transformed outputs—the network is encouraged to learn patterns that are not only accurate in time but also in frequency [49].

Another emerging paradigm is physics-informed learning or physics-informed neural networks (PINN), where the regularisation term encodes known physical laws or relationships that govern the system under study (typically the residuals of the PDE). In this framework, the neural network is trained not only to fit the data but also to respect the underlying physics—such as conservation laws, differential equations, or boundary conditions [50].

In addition to standard neural networks, the same architecture can be adapted for both regression and classification tasks by leveraging convolutional neural networks (CNNs) for image data (employed for both defect detection and soft sensing in welding [51–53]) and long short-term memory (LSTM) networks for time series signals [54] or a mix between both [55]. In this case, the basic neuron—responsible for performing a linear combination through a matrix product—is replaced by a convolutional operation in the context of CNNs. This mathematical operation, which closely aligns with filtering in signal processing (for 1D convolutions) and classical computer vision techniques (for 2D convolutions), involves a kernel (of size n or $n \times n$) that is applied across the input data (image or time series) using a sliding window. Regarding LSTM networks, the key concept is to augment the standard neuron with feedback connections—specifically by incorporating the outputs from previous time steps as additional inputs. This architecture allows the network to learn temporal dependencies in sequential data. For further technical insights and mathematical formulations, the authors recommend consulting the cited references.

2.3 GenAI models

The aforementioned features can be extracted from time series data and processed using a feedforward neural network, or the raw time series can be used directly with a 1D-CNN or a recurrent-style network. Similarly, image-based data can be processed using CNNs. These approaches represent some of the most advanced techniques currently applied in the monitoring of welding technologies, as will be discussed in the following section. However, recent developments in network architecture design—such as novel neuron compositions and modified learning frameworks—have enabled new possibilities, characteristic of generative artificial intelligence (GenAI).

The simplest architecture that can be classified as weak GenAI is the Autoencoder, illustrated in Fig. 8. This architecture consists of a nonlinear transformation of the input into a

latent space (using an encoder) and a subsequent reconstruction from this space (using a decoder). It qualifies as GenAI because, once a latent vector is generated, it can be decoded to produce data similar to those in the original training dataset. Although this fundamental concept supports GenAI, autoencoders are predominantly applied for dimensionality reduction, functioning similarly to nonlinear principal component analysis and anomaly detection tasks. For anomaly detection, the reconstruction error that is used to optimise the weights of both the encoder and decoder serves as a metric, since if an input vector significantly differs from the training data, the resulting high reconstruction error can effectively indicate an anomaly.

However powerful, conventional autoencoders suffer from a fundamental limitation: the latent space is unconstrained, which frequently leads to overfitting and poor generalisation when presented with novel inputs. In practice, this unregularised bottleneck makes it difficult for the model to generate truly new, realistic samples, since the latent vectors are merely arbitrary numerical codes, lacking any guarantee of continuity or meaningful structure. Variational autoencoders (VAEs) remedy this by imposing a probabilistic framework on the latent representation. In a VAE, the encoder outputs parameters of a Gaussian distribution (mean and variance) rather than a single point, and the loss function incorporates a Kullback-Leibler (KL) divergence term. This KL regularisation forces the learned latent distribution to approximate a standard normal, structuring the latent space so that contiguous regions correspond to semantically similar outputs. Consequently, sampling from the VAE's latent space becomes straightforward, allowing for true generative capability. Generative adversarial networks (GANs) constitute the most significant recent advance in generative modelling (see Fig. 9). A GAN comprises two neural networks trained in opposition: a generator, which synthesises candidate data samples, and a discriminator, which endeavours to distinguish real data from generated "fakes." During training, the generator seeks to minimise the discriminator's ability to tell genuine from synthetic, while the discriminator simultaneously maximises its classification accuracy—this adversarial dynamic drives both networks to improve. Unlike VAEs, which tend to produce somewhat blurred outputs due to their reconstruction objective, GANs can generate highly realistic, sharp samples by directly optimising for indistinguishability.

2.4 Bio-inspired optimisation algorithms

In advanced manufacturing environments, the efficient selection of process parameters—such as wire feed speed, welding speed, and CTWD—can be cast as a high-dimensional optimisation problem. Bio-inspired algorithms, notably genetic algorithms (GAs) [56] and particle swarm optimisation (PSO) [57], have proven highly effective in this context by emulating natural principles of evolution and collective behaviour.

A GA represents each candidate solution as a chromosome, defined as an ordered vector of real-valued genes corresponding to individual process parameters. After initialising a diverse population of chromosomes within permissible parameter bounds, each candidate is evaluated by a pre-trained ML surrogate (or digital twin, for example using the models developed by regression). The model takes in input the parameter vector and predicts performance metrics—such as bead geometry or energy consumption as will be discussed later in this work—which are then aggregated into a single fitness score. Subsequent selection preferentially preserves higher-scoring chromosomes for reproduction. Crossover operators recombine parental sub-vectors, while mutation perturbs individual genes, maintaining diversity and preventing premature convergence. Iterating through fitness evaluation, selection, crossover, and mutation drives the population steadily toward near-optimal parameter sets.

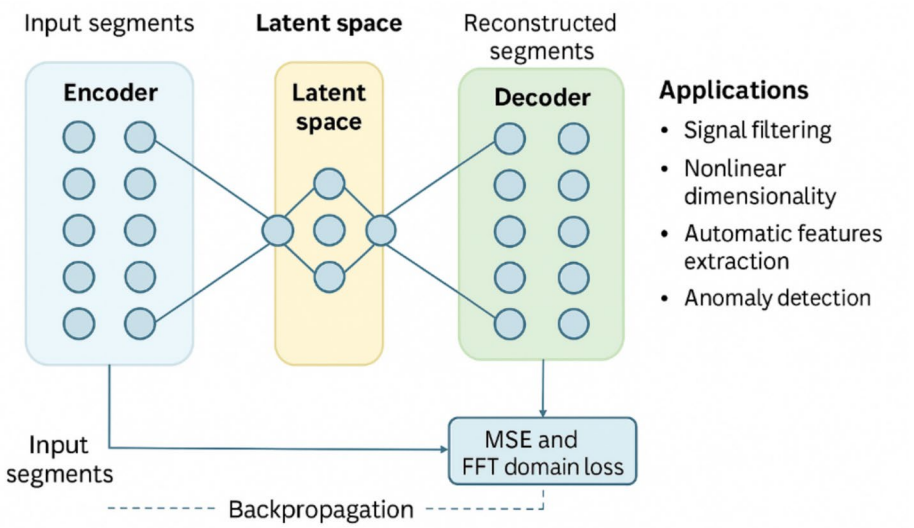

Fig. 8 Example of an autoencoder structure highlighting typical applications and the loss function, which may utilise either standard MSE or frequency-domain/physics-informed criteria

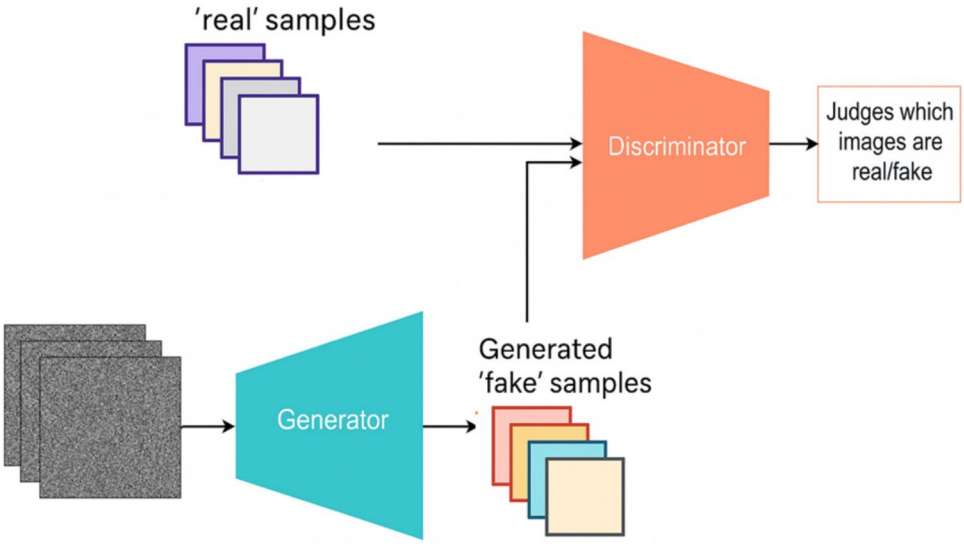

Fig. 9 Example of a GAN, which consists of 2 networks trained in an adversarial manner

PSO offers an alternative paradigm based on the flocking behaviour of birds. Here, each particle embodies a candidate parameter set and carries a velocity vector that dictates its trajectory through the search space. At every iteration, the m model edicts each particle's fitness, and the particle updates its velocity according to three influences: its own personal best position to date, the swarm's global best, and an inertia term that balances exploration against exploitation. Random factors introduced at each step prevent stagnation. The updated velocity is applied to adjust the particle's position—i.e., the process parameters—and the cycle repeats until the swarm converges on an optimal or near-optimal solution. The integration of ML models with bio-inspired optimisers (e.g., GA or PSO) is illustrated in Fig. 10.

In welding, this combined approach holds significant promise for uncovering novel process-parameter combinations that have yet to be explored but may yield superior performance. By pairing GA or PSO with rapid ML-based evaluations, engineers can navigate complex, non-convex process landscapes and pinpoint parameter sets that deliver robust, high-quality results—without the need for costly, gradient-based optimisation routines. Instead, the overall objective is encapsulated in a well-defined fitness function, enabling the optimiser to seek global optimality even in the absence of differentiable models.

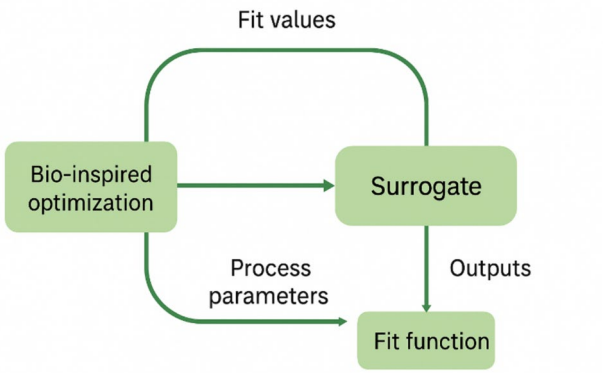

Fig. 10 Schematic of ML-based bio-inspired optimisation. Candidate process-parameter vectors (GA chromosomes or PSO particles) feed into the ML model, whose outputs are evaluated by a fitness function and looped back to guide the optimiser toward improved parameter combinations

3 State of the art for ML-based in situ monitoring

In-situ monitoring of welding processes typically uses optical, electrical, and acoustic-based monitoring to yield a comprehensive real-time picture of arc behaviour and weld quality. Infrared and thermal cameras collect both the dynamic droplet transfer and localised temperature fields of the melt pool, enabling precise feedback about the actual heat input and detection of anomalous cooling rates. Moreover, hall-effect sensors record instantaneous welding current and welding voltage, tracking arc length fluctuations, enabling, in their frequency spectral content, the detection of instabilities such as unstable short-circuit events. Finally, piezoelectric acoustic sensors mounted on the workpiece or microphones detect sound emissions from droplet transfer and phase transformations, enabling the detection of early pore formation or crack initiation below the surface.

3.1 Welding signals

3.1.1 Feature extraction

Regarding monitoring with welding current and voltage sensors, it is essential to capture the temporal dynamics of the process by segmenting the raw signals into short windows, typically ranging from 0.2 to 1.0 s in duration (T). Once the signals are acquired from the process, e.g., by depositing wall structures or more complex components, these time-domain signals can be transformed into more meaningful information, which represents in a low-dimensional space the main characteristics of both signals. An easy way to process these signals is to extract statistics from them, such as mean values and standard deviation, which together describe skewness and kurtosis, the mean heat input and its variability during the considered window (which is associated with a precise portion in the space equal to $WS \cdot T$). Furthermore, supplementary waveform features—for instance, the window's maxima and minima—offer insight into the transient peaks and possible arc instabilities. These feature vectors are then utilised as inputs to ML classifiers for real-time process evaluation, once each windowed segment has been meticulously labelled based on destructive testing, deposition surface morphology and a welding knowledge base derived from signal-shape analysis.

Beyond time-domain analysis, time-frequency techniques [21] can reveal localised spectral characteristics and global energy content. For example, a multi-level discrete wavelet transform (DWT) decomposition isolates specific bandwidths, enabling the computation of band-limited energy, entropy, or higher-order statistics within each bandwidth. Alternatively, a fast Fourier transform (FFT) over each window yields global spectral features—such as total signal energy, dominant frequency (the frequency with maximum amplitude), and spectral centroid—which reflect the periodicity and stability of the welding arc. It is worth noting—particularly for welding signals—that, given the inherently data-driven nature of ML-based process monitoring, the feature-extraction stage is the principal performance driver. Despite this, there is no universally optimal processing pipeline; rather, performance hinges on selecting descriptors matched to the material behaviour and process regime. For example, frequency-domain features contribute little in spray-transfer welding yet are critical under waveform-controlled conditions. Moreover, in current-controlled waveform welding, welding voltage is often more informative than welding current [58]. Despite this, combining features from current and voltage channels typically results in a high-dimensional input space, with ten to ninety features per sample depending on decomposition levels, and the selection of statistical, shape, and spectral descriptors. Dimensionality-reduction techniques (e.g., principal component analysis) or feature-selection algorithms (e.g., recursive feature elimination) may also be applied to retain the most informative features, reduce computational burden, and improve the robustness of downstream machine-learning models. Moreover, as previously noted, knowledge-based feature selection—informed by process physics and the welding process selected—is crucial to improving the performance and reliability of ML algorithms. Although it is possible, DL models can be used to automatically select the most important features, reducing the manual feature engineering activity as well as reducing the computational time. A schematic workflow is illustrated in Fig. 11.

3.1.2 ML models employed for process monitoring

Once features are extracted from each signal segment, they can be fed into various ML models in either supervised or unsupervised modes. Prior research has shown that analysing welding signals in this way can effectively detect defects such as excessive spatter, humping, arc shift—which may cause layer collapse through geometric deviation in the arc—and porosity. Since most defects are linked to the incorrect heat input, additional faults like microstructural anisotropy or cracking—caused by improper heat input—can also be identified by welding signals processing. These defects often elude detection when only mean signal values are considered, so time-frequency domain analysis is now widely employed to uncover disruptive behaviours in the frequency spectrum, such as energy inconsistencies and shifts in the dominant frequencies.

In state-of-the-art approaches to welding-signal analysis, a variety of models have been applied. For example, Li et al. [59] employed a support-vector machine (SVM) classifier on time-domain features from a cold metal transfer (CMT) WAAM process, whereas Mattera et al. [60] evaluated several algorithms—including random forests, neural networks, logistic regression, and decision trees—using both time and time-frequency domain features from a standard short-circuit Gas Metal Arc-AM process. Although all these methods reported anomaly-detection accuracies of around 90 per cent or higher, class imbalance remains a challenge. When framing anomaly detection as a binary problem—i.e., identifying any defect type—authors have shown that semi-supervised techniques such as isolation forest or local outlier factor can be effective. Alternatively, GMMs operating in an unsupervised mode can surpass certain supervised techniques by flagging outlying behaviour directly within the feature space. In a related study, the authors in [44] employed GMMs as a soft-classification tool: after extracting only time-domain features from a Pulsed-GMAW process, they demonstrated that each Gaussian cluster corresponds to a distinct system state. Crucially, their findings highlight that in tightly controlled deposition processes—such as synergic welding

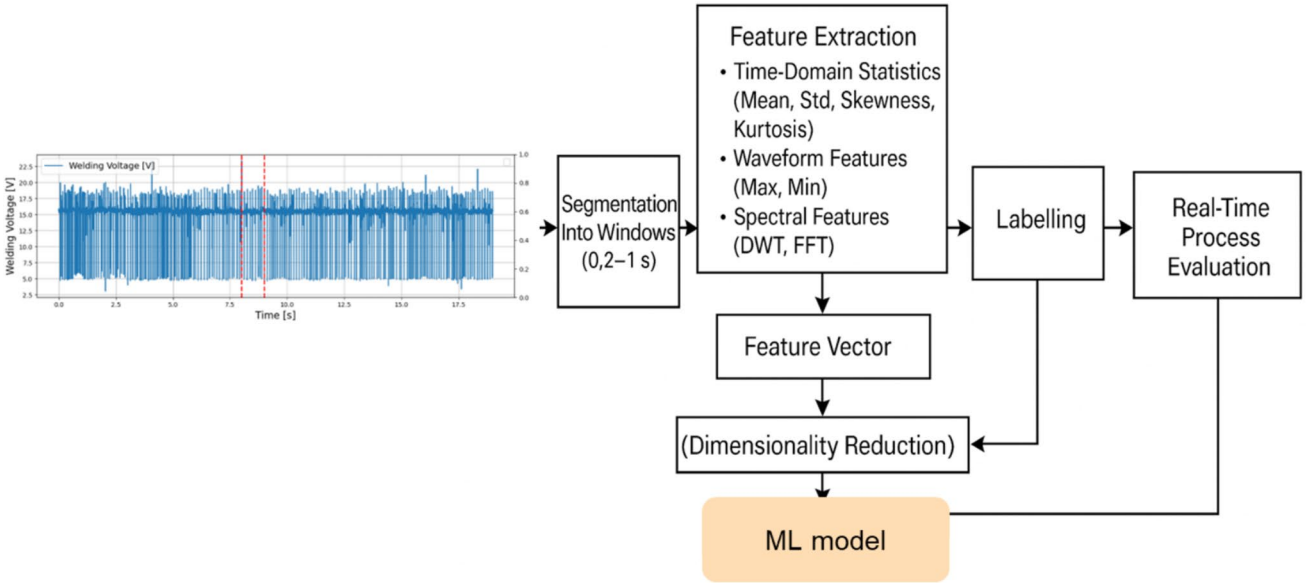

Fig. 11 Schematic view of the workflow for the development of an in-situ monitoring software

methods (whether pulsed GMAW or alternatives like CMT or surface tension transfer)—frequency-domain features afford superior separation of operational states compared with time-domain statistics alone.

State-of-the-art approaches have begun to exploit DL in semi-supervised or unsupervised anomaly-detection systems for Pulsed GMAW [61] and STT processes [62]. For example, time-series welding signals can be converted into spectrograms, which are then analysed by CNNs to identify anomalies. Although this technique is more commonly applied to audio signals—where the high sampling frequency yields large data volumes—its application to welding signals has delivered promising results, with detection accuracies exceeding 90%, significantly outperforming purely time-domain methods. Convolutional autoencoders have also been employed to learn a compact latent representation of the signal and flag deviations via reconstruction error, often in tandem with algorithms like isolation forest. The most advanced solution reported to date is the Frequency-Informed Convolutional Autoencoder (FICA) [49], which integrates explicit time-frequency feature extraction into the autoencoder architecture with a frequency regularisation. FICA not only reconstructs inputs with high fidelity but also generates robust latent features for anomaly detection. Nevertheless, the broad generalisability of these GenAI models remains a challenge, and recent work suggests that hybrid architectures—or supplementary modules tuned to monitor reconstruction errors and latent-space distributions—are required to further enhance performance.

As is noticeable, the most trendy idea is to use feature extraction—whether manual or automatic—followed by ML models, with unsupervised approaches often more interesting for industrial cases. However, regression analysis can also be applied to detect anomalies, leaving room to investigate its suitability for soft classification problems as well. An example is the works [54, 63], in which the authors proposed LSTM models to forecast future process values using only normal deposition data. Based on the error between the digital-twin forecast and the actual value, an anomaly score can be derived, achieving close to 90% performance with a threshold-based method on the estimation error. Alternatively, feeding the estimation errors of both welding current and welding voltage into another ML model can also detect anomalies, using the former for single-sensor scenarios and the latter for multi-sensor monitoring applications. In any case, these approaches demonstrated superior performance compared with classical control charts based on SPM methods. A visual illustration that summarises all the proposed approaches in the literature is shown in Fig. 12.

3.1.3 Additional discussions

A comprehensive comparison of supervised, unsupervised, and advanced deep-learning architectures for single-process monitoring using these sensors has been carried out in the previous sub-sections. It is therefore clear that novel deep-learning models or multimodal monitoring strategies offer promising directions for future research. Indeed, while SPM methods often achieve performance levels below 70% [61, 63], ML approaches demonstrate substantially higher accuracy, frequently exceeding 90%

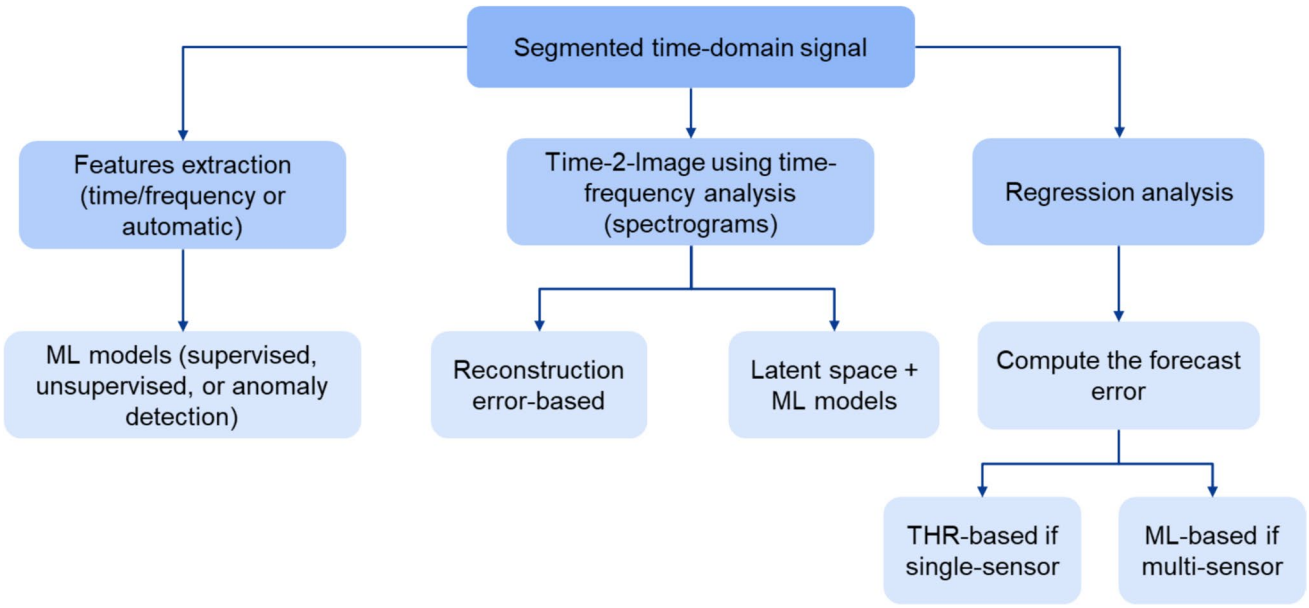

Fig. 12 Visual summary of state-of-the-art methods in welding voltage and welding current signal process for in-situ monitoring applications based on ML

when supervised learning is employed. However, their main drawback lies in the requirement for large, balanced, and well-labelled datasets. By contrast, advanced techniques such as frequency-based feature extraction or unsupervised learning strategies—similar to SPM in that they rely solely on normal data for training—can achieve competitive, though typically slightly lower, performance in recognising out-of-control samples. Further improvements may be attained through multimodal sensor fusion. For example, efforts to exceed the current 90% accuracy benchmark could improve the practicality and applicability of these methods in standard qualification procedures. Furthermore, a significant application of these sensor signals in process monitoring lies in their capacity to estimate layer geometry without recourse to more complex instruments such as laser scanners or cameras. Although Mu et al. [64] have reported encouraging results, further refinement is required to deliver reliable feedback estimates of layer geometry to control systems. Realising this capability would enable the creation of a fully integrated monitoring solution based exclusively on these cost-effective sensors. Accordingly, multi-modal in situ monitoring using such sensors represents a valuable new research direction in process monitoring.

3.2 Audible signals

Similar principles applied to welding signals can also be extended to other types of time-series data, such as acoustic signals captured by microphones. Historically, welders have relied on their senses—particularly vision and hearing—to adjust process parameters in real time; modern monitoring systems emulate these human observations by using both optical and audio signals for online process control. Notably, Chabot et al. [65] and Kershaw et al. [51] conducted foundational work demonstrating that microphone or image-acquired signals carry rich information about the welding arc and molten pool dynamics. Specifically, in relation to audible signals, their studies showed that frequency-domain analysis of these acoustic time series enables accurate estimation of process variables like CTWD, while other works show reliable detection of defects, including porosity, spatter, arc shifts, and contamination, by using those signals and frequency-domain analysis [66–68]. Subsequent research has further validated the use of acoustic signatures for real-time defect detection and process monitoring, opening new avenues for non-intrusive welding quality control.

3.2.1 Features extraction

While voltage and current sensors offer well-established pathways for signal interpretation, the analysis becomes more complex when dealing with high-frequency signals such as those originating from conventional microphones. These sensors typically operate at significantly higher sampling rates and can be analysed both in the time and frequency domains. However, signals captured via microphones are often highly contaminated by noise.

As a result, time-domain analysis (e.g., computing signal energy or statistics) may yield misleading outcomes due to the strong influence of ambient noise. Therefore, for such signals, frequency-domain analysis is generally preferred. Standard approaches include extracting the power spectral density (PSD) or computing energy and statistical descriptors within defined frequency bands that are believed to correspond to specific aspects of the welding process [69].

3.2.2 ML models employed for process monitoring

Building on this idea, Souvori et al. [70] extracted features automatically by applying Principal Component Analysis (PCA) directly to time-domain signals, as well as frequency-domain features using Mel-frequency cepstral coefficients (MFCCs). They then evaluated several supervised classifiers—such as Support Vector Machines, random forests, and neural networks—to detect surface and geometric defects in layered deposits. However, for real-time monitoring, the very high sampling rates (often around 100 kHz) result in prohibitively large, high-dimensional datasets. To address this, many researchers convert the raw time series into spectrogram images, reducing dimensionality while preserving temporal-spectral information. CNNs trained on these spectrograms have proven effective at identifying porosity and other deposition defects within selected time windows, offering a practical solution for continuous, automated welding process inspection [71].

3.2.3 Main limitations

Although numerous studies have demonstrated the offline processing of high-dimensional acoustic data [68, 69, 72]—particularly due to the low cost and non-invasive potential offered by this sensing modality—the number of approaches capable of real-time, in situ monitoring remains limited. In particular, applications leveraging advanced frameworks—such as FINN implementations, unsupervised learning techniques, or generative AI models—have yet to be explored extensively. This gap likely stems from the intrinsic complexity of high-frequency time series and the challenges in developing computationally efficient algorithms capable of low-latency inference. Addressing these obstacles will be critical for the deployment of next-generation, intelligent welding monitoring systems based on microphone data. Moreover, it would be beneficial to explore the potential for detecting defects beyond those identifiable using conventional welding signals, first evaluating single-sensor solutions and then progressing to the previously mentioned multimodal, multi-sensor fusion approaches.

3.3 Vision sensing

3.3.1 Data processing procedure

Imaging has long been widely employed in various AM processes [73, 74]; vision-based monitoring is broadly accepted because visualising the underlying physical phenomena is fundamental to process control. This is especially true for arc-welding-based AM: in welding, cameras are used both for feedback control—by extracting geometric information about the arc shape to adjust process parameters [75–77]. Key defects such as spatter, layer collapse, and incorrect energy input or metal transfer can be detected by camera systems; these remain the most common deposition faults, even when parameters are correctly chosen, due to the complex transfer mechanisms discussed above. This issue is particularly pronounced in WAAM, where geometric fluctuations are greater than in powder-based processes (the latter being inherently more stable in the absence of an arc). Moreover, typical defects that occur during the production of overhead or overhanging structures can be detected by vision systems [78–80]. Nevertheless, subtle defects—such as micro-porosity, grain-boundary cracks, and improper microstructure—are more challenging to detect with vision alone because they are closely tied to the local energy input. These conditions are often more readily inferred from process measurements (e.g., welding voltage/current signals) than from welding pool images and can be detected using a more expensive thermal camera.

Moreover, the use of vision systems for welding process monitoring presents unique challenges from a software perspective due to the complexity and variability of the acquired images. These images are often affected by noise originating from arc intensity and are highly dependent on the camera positioning, which can hinder the extraction of meaningful, physically interpretable features. From these processed images, simple physics-informed features—such as arc intensity (approximated through the sum of the white pixels), energy, and standard deviation—can be extracted. These metrics are related to the arc behaviour and can serve as input variables for monitoring models.

Nevertheless, such features fail to capture the full complexity embedded within image data, hindering the possibility of detecting other defects like humping and layer collapse. For this reason, computer vision techniques, and more recently ML-based methods, are increasingly employed to process welding images.

3.3.2 Welding pool images

Most early work has treated real-time WAAM monitoring as an image-classification problem. Researchers first extract regions of interest (ROIs) around the melt pool or deposition

zone—e.g., immediately behind the torch to capture layer collapse, metal transfer instabilities, and arc shape changes caused by spatter or incorrect heat input—and then feed each ROI into a CNN. By fine-tuning pre-trained architectures on these ROIs, studies have achieved high accuracy in detecting common defects [81]. For example, Xia et al. [82] applied a customised CNN classifier to distinguish stable from unstable transfer modes; however, they reported that thousands of manually labelled frames were required to reach satisfactory performance, making large-scale industrial deployment prohibitive.

To alleviate the annotation bottleneck, more recent efforts have borrowed from the welding-signal community and explored semi-supervised or unsupervised learning. In particular, CAEs have been trained on "normal" deposition sequences so that reconstruction error can flag anomalous frames (e.g., layer collapse, excessive spatter) without explicit labels [83]. Others incorporate temporal cues—treating the video stream as a sequence and learning spatiotemporal embeddings—to better capture transient instabilities in the melt pool [84].

While autoencoder-based anomaly detection avoids the need for extensive labelling, it often struggles to detect subtle defects: small spatter events or slight deviations in pool geometry may produce only marginal reconstruction errors, leading to false negatives due to generalisation. Overcoming these limitations will likely require richer feature representations—combining unsupervised deep embeddings with additional statistical descriptors of pool shape or dynamics—and hybrid models that fuse CNN-based feature extraction with lightweight classifiers (e.g., one-class SVM, isolation forests) or graph-based temporal models. Such hybrid pipelines could retain the low-label benefits of unsupervised learning while boosting sensitivity to subtle anomalies, paving the way toward robust, real-time vision control in industrial WAAM systems.

3.3.3 Thermal images

In addition to standard visual cameras—often equipped with narrow-band filters centred on 660 nm to suppress arc-light noise and reveal the melt pool—thermal cameras have been adopted for in-process monitoring, since temperature and cooling rate are critical determinants of mechanical properties. However, the need to adjust emissivity values, which vary during metal phase transformations, renders thermal measurements unstable, complex, and not yet fully robust [85]. This is a central topic in thermal imaging monitoring, with new methods based on DL for emissivity correction [86], and the development of thermal/imaging feedback control of process parameters for layer geometry consistency [87]. Although thermal imaging has long been used to estimate weld penetration depth [88] and layer geometry [89–91] through image processing—and holds great promise for developing high-quality monitoring predictors based on thermal history (e.g., cooling time and microstructure evolution)—to the authors' knowledge, no such studies have yet been reported for WAAM. However, research teams focused on WAAM can draw valuable inspiration from advances in other AM processes, such as those in laser powder bed fusion. For instance, Ho et al. [92] demonstrated the possibility of detecting porosity of different sizes by processing the thermal images collected during the deposition process with advanced CNN models. Despite its promise, thermal-imaging-based in-situ monitoring remains a complex challenge in other AM processes for the reasons outlined above. Nevertheless, it represents a concrete avenue for future research across AM—particularly given the very limited application of ML to real-time thermal data. At the same time, the high cost of infrared equipment means that any cost-benefit trade-off must be carefully evaluated. Since no studies to date have explored this approach in WAAM, a thorough economic assessment and comparison with alternative sensing modalities will be an important task for future work.

3.3.4 Main limitations

Despite their proven effectiveness in process monitoring, vision-based sensing systems, such as welding and thermal cameras, present several important limitations. A first drawback relates to camera positioning, which often restricts the robot's working volume and can compromise the field of view and therefore the performance of the monitoring. Indeed, as shown in Fig. 13, the mounting position of the camera strongly influences the types of defects that can be detected.

Moreover, temporal resolution represents another critical issue, since standard sampling rates, typically around 30 Hz, are often insufficient to capture rapid dynamic events such as incorrect droplet transfer, thereby reducing the reliability of defect detection. On the other hand, excessively high sampling rates can hinder the application of deep learning models, as the inference time, determined by image and model size, may exceed the interval between two consecutive image acquisitions.

Thermal cameras, while offering the potential to estimate defects [94], thermal history, cooling rates, and even microstructural evolution, suffer from strong sensitivity to the emissivity parameter [85], which varies with temperature and requires additional calibration efforts to ensure accurate measurements [86]. Cost further represents a major constraint, as welding cameras can reach several tens of thousands of dollars (around 30 k), while thermal cameras often exceed 60 k, making them significantly more expensive than alternative sensing modalities such as welding signals (around thousands of dollars) or acoustic emissions. Finally, a major gap in the literature is the lack of systematic

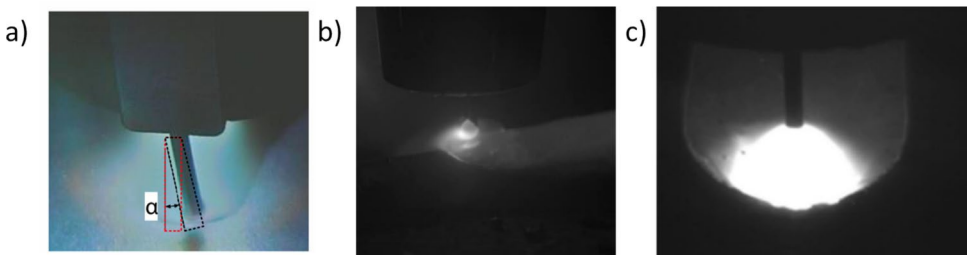

Fig. 13 Welding images captured from different camera mounting positions: **a** front view [93], **b** lateral view, and **c** upper view

comparisons between camera-based monitoring and other sensing approaches using the same datasets, which leaves unclear whether the superior cost of vision systems is justified by a proportional improvement in monitoring performance. These limitations highlight the need for multimodal sensor fusion, where vision data are integrated with lower-cost sensing modalities to achieve more reliable and cost-effective process monitoring.

3.4 Acoustic emission

In addition to before mentioned sensors, recent advancements in acoustic detectors have provided a foundation for better adaptation of this technology into various production processes, particularly materials processing by laser and arc. In particular, since acoustic sensors have been used as a cost-effective alternative to optical monitoring systems, nowadays new opportunities can be considered by the advancement of Acoustic emission (AE) monitoring, since it can be employed using either contacting or non-contacting sensors. In fact, they represent an alternative to conventional microphones available on the market that can measure up to 100 kHz, including the advanced ultrasound sensors. The narrow band limitation of these microphones limits their application in noisy industrial environments, as the majority of the background signal could be dominant in the measured signal thus hiding the process signal and making it difficult to analyse the signal with high reliability and less error.

Conventional contacting sensors (see Fig. 14) measure structure-borne emission from the process. They work based on mechanical parts such as membranes or deformable piezoelectric, and they are limited due to their design limitations. Furthermore, the fact that they need physical contact with the workpiece limits their applications in fully automated industrial environments. On the other hand, the state-of-the-art optical microphones, free from any mechanical parts, are based on Fabry-Pérot etalons which can measure air-borne emission up to 2 MHz frequency bandwidth. Moreover, there is no requirement for any contact with the workpiece. This advancement has boosted the adaptation of the microphones into industrial processes. Despite these advancements, there are no specific works which employ these sensors in WAAM for in-situ monitoring.

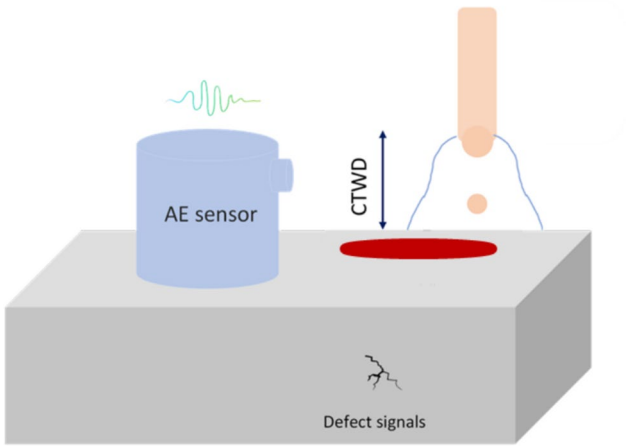

Fig. 14 Example of contact-based AE sensor in arc welding process

Nevertheless, one important aspect of any production process is to stabilise its process parameters in order to achieve the final required quality. This means monitoring the process parameters is of importance in today's in-situ monitoring systems as it provides the ability to address any deviation from the optimised parameters during the process. This can be done with air-borne optical microphones due to their higher frequency bandwidth and higher sensitivity than conventional microphones. Considering other works in the field of welding, and mentioned in the previous sections, according to a study by [95], deviation from optimised parameters in laser welding can be easily picked up by microphones, as shown in Fig. 15. A stable and optimised process will present a stable and calm AE signal, as depicted in Fig. 15a, whereas any defects related to the process parameters could impact the signal and reveal higher frequency disruption in the AE signal (Fig. 15a, b, and c).

However, the ability to measure higher frequency bandwidth is particularly important since it has been reported that cracks usually result in higher frequency emissions (up to 200 kHz) in welding, additive manufacturing, and generally in laser and arc materials processing. This adds to the importance of optical microphones as they can measure higher frequencies, thus revealing more detailed info about the process. For example, in a study by [96, 97], the ability to detect cracks in

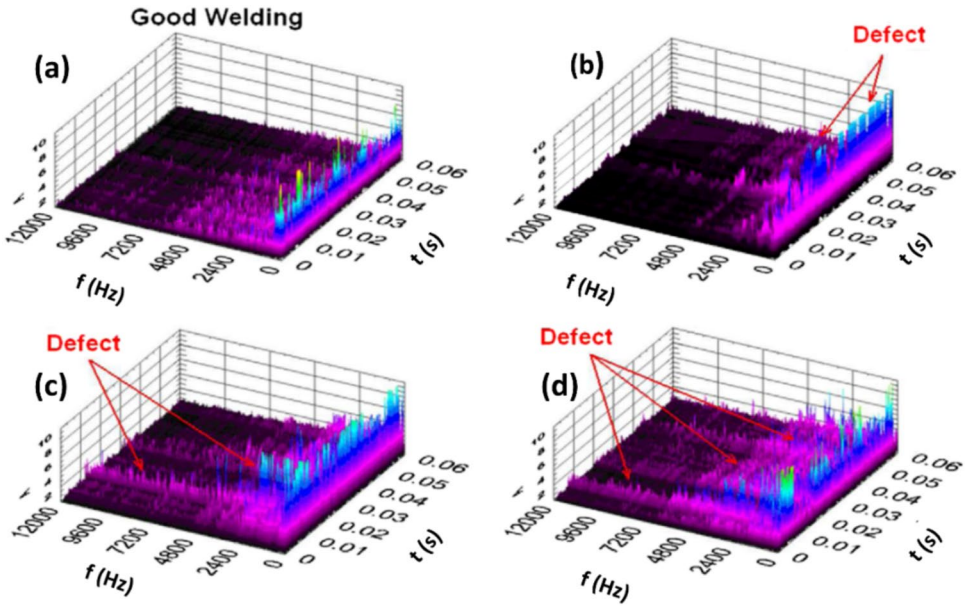

Fig. 15 AE signal analysis for defect detection. Stable and good quality weld (**a**) welding disruption by defects related intensity variation (**b**) welding disruption by defects related to frequency variation (**c** and **d**)

the laser metal deposition (LMD) process was demonstrated. The study concluded that the cracks are expected to produce high frequency signals (higher than 350 kHz). In other studies, the transition from stable conduction mode laser welding to unstable keyhole mode was captured using an optical microphone. Stabilising the welding process through process parameters optimisation has been an important aspect of welding and additive manufacturing, and optical microphones have the potential to provide a robust tool to achieve this goal. The application of optical microphones could be expanded in other processes such as WAAM, in which crucial process parameters and their stability during the process could be monitored. For example, Ramalho et al. [72] studied the effect of oil contamination on the acoustic signature during the WAAM process and compared the data with a conventional microphone. The study concluded that the optical microphone provided much higher resolution data in which some process characteristics of the WAAM process reached 500 kHz and were clearly captured and distinguished from the background noise. However, as mentioned, studies are very limited in this area, and more research needs to be done in order to further improve the adaptation of optical microphones in the production process as a real-time monitoring tool. Moreover, developing ML algorithms to analyse acoustic emissions and, more importantly, to correlate the data with defects within the process is of great interest and requires more investigation to fully adopt AE in the production process.

3.5 Multi-modal monitoring via sensor fusion

Given the complementary nature of the features extracted from different sensing modalities—such as voltage, current, acoustic emission, microphone signals, and vision systems—a promising strategy for comprehensive process monitoring involves their combined use through sensor fusion, since each sensor provides a unique perspective on the process. By integrating these heterogeneous sources of information, it becomes possible to exploit the strengths of each sensor while mitigating individual limitations. Feature-level fusion, in particular, allows the construction of enriched input vectors, Sensor Fusion Pattern Vector (SFPV), in Eq. 6, that incorporate both physically interpretable descriptors (e.g., mean voltage, arc energy, power spectral densities) and high-dimensional latent features derived from AI-based processing of acoustic and visual data.

$$SFPV = [F_{current}, F_{voltage}, F_{acoustic}, F_{camera}] \tag{6}$$

This multi-modal representation enhances the system's ability to detect anomalies, track quality indicators, and even estimate physical quantities that may not be directly measurable by a single sensor. In this context, ML algorithms can be trained to identify patterns across fused data, improving both robustness and generalisability of monitoring systems in real-world welding scenarios. A recap of the different features that may be extracted from the different sensors is reported in Table 1.

Beyond simple feature concatenation and filter-based selection, stacked deep-learning ensembles—in which complementary networks are combined through early/late fusion or meta-learners—can deliver significant gains by capturing cross-modal dependencies and higher-order structure in the data. However, such architectures remain underdeveloped; to the authors' best knowledge, no well-validated, industry-ready deployments in WAAM have yet been reported. That

said, early evidence is emerging in arc-welding applications [98, 99], and a responsible pathway exists to extend these approaches to WAAM.

3.6 Summary of the emerging trends, challenges and future perspectives

As discussed, intelligent in situ online monitoring in WAAM has gained significant attention, with an increased number of publications between 2021 and 2025. As discussed, an emerging trend is the shift towards unsupervised and semi-supervised ML methods, which partially solve the challenges of data labelling and enhance anomaly detection accuracy. Additionally, a focus on integrating multiple sensor data (with typical acquisition frequencies in Table 2), frequency analysis, and deep learning models, such as Convolutional Autoencoders, is becoming prevalent for real-time process monitoring and defect detection, especially for time-series signals, given the impact of deposition stability on defect generation.

Moreover, these practical innovations are opening the possibility of employing AI and online monitoring for part qualification. If anomalies with respect to qualified data can be reliably identified with high accuracy, and if anomaly detection tools are further integrated with feedback controllers, this approach could represent a game changer in the field of certification, advancing beyond process monitoring towards data-driven decision-making. Despite this, several critical research gaps remain, which continue to limit the development of standardised and robust monitoring frameworks. However, there is considerable scope for future investigation. Below, we highlight several areas where further research is needed to enhance the effectiveness and reliability of online monitoring in WAAM processes based on the current review:

- *Sensor placement and signal integrity*: While the positioning of voltage and current sensors is well established, the placement of other sensor types, such as AE sensors (see Fig. 16) and microphones, is far more complex. The distance and angle relative to the deposition area can significantly influence signal quality, yet there is a lack of systematic studies exploring optimal placement strategies. As with microphones, small variations in positioning can lead to substantial changes in the data captured, potentially impacting the reliability of the extracted features.
- *Data processing for high-frequency sensors*: Unlike electrical signals—whose high- and low-frequency components often carry interpretable meanings related to process stability or defect formation—or welding camera images, which have been extensively studied, AE and microphone signals lack a consistent theoretical framework for interpretation. There is currently no consensus from scientific community on standard frequency ranges or feature types for these sensors. Although promising correlations have been observed between high-frequency signals and welding defects such as porosity and hot cracking, the underlying physical mechanisms remain poorly understood. This limits the generalisability and repeatability of findings across different setups.
- *Non-visual estimation of CTWD and of the layer geometry:* Contact Tip to Work Distance (CTWD) and layer geometry are critical parameters in arc-based additive manufacturing, directly influencing process stability and final part quality. While these parameters are typically measured using visual sensors, non-visual estimation

Table 2 Sensors and typical acquisition frequencies used in online process monitoring

Sensor	Sample rates
Welding current	2–5 kHz (up to 1 MHz)
Welding voltage	2–5 kHz (up to 1 MHz)
Welding camera	30 Hz–10 kHz (up to 10 MHz)
Acoustic emission	100 kHz–1 MHz
Microphone	20–100 kHz
Thermal camera	30–120 Hz

Table 1 Features that can be extracted from the different sensors. *FFT refers to the fast Fourier transform, DWT to the discrete wavelet transform, and STFT to the short-time Fourier transform

Sensor	Time domain	Frequency domain
Welding current Welding voltage	Mean, standard deviation, kurtosis, skewness	From FFT* or DWT*, with statistics extracted in specific frequency bandwidths
Welding camera Thermal camera	Physical features: Image binarisation and sum/standard deviation of white pixel (Arc energy); in alternative, automatic features extracted via Convolutional AutoEncoders	
Microphone Acoustic emission	Mean, standard deviation, kurtosis, skewness	From FFT* or DWT*, with statistics extracted in specific frequency bandwidths; power spectral density

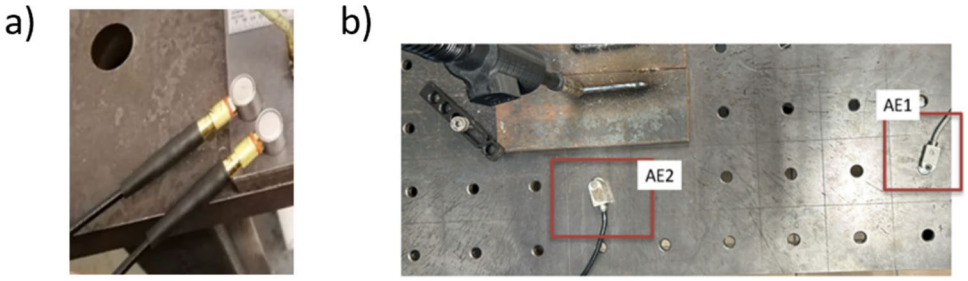

Fig. 16 AE sensors mounted a on top of the substrate plate [100] and b in different positions on the working table [101]

methods remain largely unexplored. From the authors' perspective, developing soft-sensing approaches to estimate CTWD and layer geometry could significantly reduce system complexity and avoid the spatial constraints introduced by camera-based setups. Such methods would be particularly advantageous in industrial environments, where visual systems can restrict the robot's working envelope and increase maintenance requirements. Moreover, non-visual estimation techniques could enable closed-loop feedback control strategies, enhancing process adaptability and reliability.

- *Multi-sensor fusion*: Current approaches to multi-sensor fusion often rely on simple feature concatenation prior to model input. However, this may not effectively exploit the complementary nature of different sensing modalities. Advanced architectures such as hybrid CNN-LSTM or CNN-ANN models offer the potential to process image-based and time-series data in parallel, enabling more nuanced feature extraction. Additionally, converting time-series data into time-frequency representations (e.g., spectrograms via STFT or CWT) and integrating them as additional image channels could enhance the performance of image-based models. Nevertheless, the lack of standard practices for such fusion strategies remains a barrier to implementation.
- *AE-based monitoring*: Research on using AE sensors for online process monitoring during production is still limited. These sensors offer practical advantages—they can be easily mounted on the worktable and are generally less sensitive to ambient noise compared to microphones. However, their use requires high-frequency data acquisition, which significantly increases computational demands.
- *Comparative analysis of sensor data and materials*: The selection of optimal sensors and data processing methods remains an open challenge. Most studies apply their techniques to different datasets and materials, making it difficult to establish consistent best practices. It is particularly hard to determine which features are most relevant depending on the process, material, or sensor used. As a result, systematic comparisons of individual sensors in terms of accuracy, robustness, and reliability in real-world conditions are still lacking, hindering the identification of the most effective monitoring strategies for welding processes.

4 State of the art for bio-inspired ML-based optimisation

Nowadays, a wide range of welding technologies is available and applicable to the manufacturing of various materials. The presence of embedded control systems capable of maintaining stable process parameters plays a critical role in ensuring repeatability and consistency. Moreover, modern welding equipment often integrates synergic lines or one-knob controllers, enabling user-friendly operation by automatically coordinating parameter combinations to avoid typical defects such as unstable arcs, arc extinction, or excessive spatter due to incorrect settings (e.g., wire feed speed mismatched with voltage). Moreover, advances in welding technology, like surface tension transfer (STT™) and cold metal transfer (CMT™), further improve the quality of WAAM parts.

However, it must be noted that these synergic lines and default parameter sets are typically designed for general-purpose welding tasks and not for achieving application-specific objectives, especially in relation to AM. When aiming for specific outcomes—such as reducing surface roughness, minimising the buy-to-fly ratio, tailoring microstructural features, enhancing mechanical properties, or lowering energy consumption—manual fine-tuning of process parameters becomes necessary. This often involves expert intervention and extensive experimentation, even for skilled welding professionals. In relation to WAAM, process optimisation can be used to refine both process parameters and tool paths [13, 102], with the aim of maximising goal-oriented objectives [103]. The application of process optimisation within the context of wire arc additive manufacturing (WAAM) remains relatively recent. A Scopus query using the terms ("WAAM" OR "Wire Arc Additive Manufacturing" OR "Gas Metal Arc Additive") AND "optimisation" returned 331 papers published since 2014, when limiting the search to English-language research articles and conference proceedings. The majority of these works focus on the optimisation of process parameters to improve mechanical

properties, layer geometry, and energy efficiency and reduce parts distortion. From the conducted literature review, three main approaches to optimising the WAAM process can be identified: traditional methods based on experimental evidence, statistical tools, and, more recently, the use of AI. In the following, we briefly present examples of traditional and statistical optimisation methods, before proceeding to a more in-depth analysis of AI-based approaches in this context.

4.1 Traditional optimisation methods and their limits

While formal optimisation techniques offer systematic approaches to process improvement, traditional optimisation based on experimental evidence remains a valuable and widely adopted practice in the WAAM field. The literature analysis revealed that several studies refer to optimisation even in the absence of mathematical models or algorithmic techniques, instead relying on manual tuning of process parameters through trial-and-error experimentation. For example, Li et al. [104] compared various post-processing heat treatments for 91 grade steel with different homogenisation times and found that a duration of 2 h yielded better results. However, no formal optimisation procedure was employed, and the conclusions were based solely on experimental observations. In another example, Wu et al. [105] introduced arc oscillation as a technique to improve, and then optimise, the corrosion properties of Ti6Al4V produced via WAAM, comparing the result with the standard fabrication technique. Vazquez et al. [106] studied the effect of substrate cooling and different interpass time on the mechanical properties of ER5356 produced via CMT, finding a manually optimal value of 140 °C. In [107] the authors compared the effect of active cooling on improving the microstructure of magnesium alloy components produced using CMT-based WAAM. Finally, in [108] Sabancı et al. conducted an experimental campaign to investigate the influence of process parameters on the mechanical properties of ER5554 alloy using CMT technology. The study identified optimal parameters such as a wire feed speed of 0.5 m/min and a welding speed of 7.5 m/min. Although traditional optimisation lacks the predictive capabilities and scalability of data-driven methods, it often reflects valuable, experience-based decisions. These approaches allow for direct observation under real manufacturing conditions, aiding the identification of critical parameter sensitivities. However, manual tuning is time-consuming, resource-intensive, and limited in its ability to handle complex interactions. In contrast, mathematical models offer an efficient means of exploring broader parameter spaces, also those not tried in the experimental campaign. They help reduce the number of experiments, make it easier to optimise for multiple goals, and are more cost-effective—especially in industrial use. So, while traditional methods are still useful, using models is key for making WAAM more efficient and scalable.

4.2 Statistical tool-based optimisation

As an alternative to traditional trial-and-error approaches and manual tuning of process parameters, some authors have proposed the use of statistical and mathematical methods for optimisation. These methods are particularly valuable because they allow for the systematic identification of optimal process parameters by observing the relationships between input parameters (factors) and the output response (Y). One of the most commonly employed techniques for process optimisation is response surface methodology (RSM). The RMS methodology is simple yet effective: once a quadratic model is found that describes the relationship between the dependent variable (Y) and the independent variable or factors (X), it allows for the maximisation and/or minimisation of the response using basic derivative techniques, such as steepest ascent [109]. For instance, Le et al. [110] employed an RSM to optimise a short-circuit-based WAAM process using 308L stainless steel with the objective of maximise layer width and height while minimising heat input. In other works, such as in [111] for natural GMAW of ER5356, researchers used other statistical tools like the Taguchi method for optimisation of an index called "bead-appearance". The usage of RSM or Taguchi method is a common way in the field of WAAM, with several examples of similar methodologies, as reported in [112–117].

Although classical statistical methods like RSM and the Taguchi method offer efficient frameworks for experimental design and optimisation, they exhibit notable limitations in handling complex real-world systems. RSM relies on low-order polynomial models, which restrict its ability to accurately represent nonlinear behaviours, and its effectiveness is limited to local approximations near the experimental region. Moreover, its scalability is reduced by the exponential growth in the number of required experiments as the number of variables increases. On the other hand, the Taguchi method is best suited for discrete input factors and assumes minimal interaction between them, performing poorly in systems with significant nonlinearity or interdependent variables. Therefore, for complex and high-dimensional problems, more scalable and adaptive modelling approaches are needed. An example of an alternative solution is reported in the work of Lee in [118]. The author employed a GPR model for CMT-WAAM of 316L stainless steel and applied sequential quadratic programming (SQP) to optimise a simplified mathematical objective function. The goal was to identify a combination of process parameters—including welding speed (WS), wire feed speed (WFS), and interpass temperature—that minimised height variation and other geometrical deviations, using the predictions obtained

from the GPR model. In gradient-based optimisation methods, it is important to formally and mathematically describe the cost function, which should be differentiable. Additionally, the constraints are typically assumed to be linear and soft. However, alternative approaches enabled by AI, such as the mentioned GA and PSO, allow for the optimisation of functions without the need for a differentiable cost function.

4.3 Innovative bio-inspired optimisation techniques

As mentioned, AI-based bio-inspired optimisation techniques can be applied to optimise the WAAM process by accounting for its specific characteristics, thereby enabling the development of new data-driven synergies tailored to this technology. These methods are particularly well-suited to handling nonlinear and complex constraints through heuristic approaches. Their flexibility allows the objective function to be defined in a more general manner, thereby simplifying the optimisation of high-dimensional and continuous problems.

To conduct a detailed analysis of the data-driven optimisation procedures employed in the field of WAAM, a more detailed Scopus query was utilised for this research: ("WAAM" OR "Wire Arc Additive Manufacturing" OR "Gas Metal Arc Additive Manufacturing") AND "optimization" AND ("intelligent systems" OR "smart manufacturing" OR "genetic algorithm" OR "particle swarm optimization" OR "PSO" OR "whale optimization"). By limiting the search to relevant topics from journal articles and conference proceedings in English, only 9 papers were identified. As a demonstration of the growing importance of this topic in the field of WAAM, Fig. 17 illustrates the increasing trend of this research, with the first paper published in 2020.

From the analysis of the literature, a scheme has been introduced in which a data-driven regression model is used to establish a relationship between the process parameters and the output, with both the process parameters and model estimates utilised in the computation of the fitness function. In Ma et al. [119], the authors proposed a linear model to correlate process parameters, such as mean welding current, welding voltage, and welding speed, to the bead geometry of ER308 in a standard welding process, and employed a GA to find the optimal parameters that maximise the ratio of bead width to height.

In another study, Zhang et al. [120] developed a polynomial model to represent surface roughness and porosity percentage in a CMT-WAAM process, and employed the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to optimise the process parameters with the aim to minimise both. In [121], the authors used PSO to reduce the heat input, and maximise the width-to-reinforcement ratio, once a polynomial model was established between process parameters and response variables. Zhu et al. [122] proposed a neural network model capable of more effectively capturing the non-linearity between process parameters, surface roughness, percentage of porosity, and bead geometry [12], with the aim of minimising the surface roughness in CMT-WAAM of ER4043. As another notable optimisation technique in path planning, Kumar et al. [123] employed GA to minimise the sum of void (VP) and post-processing (PP) material volumes, with the output representing the overlap between passes. Similarly, recently Wang et al. [124] proposed the employment of NSGA-II. In another work, Mamedipaka et al. [125] demonstrated that NSGA-II optimised parameters demonstrated improved mechanical properties with respect to RSM. Recently, the sustainability of the process has become an increasingly important consideration.

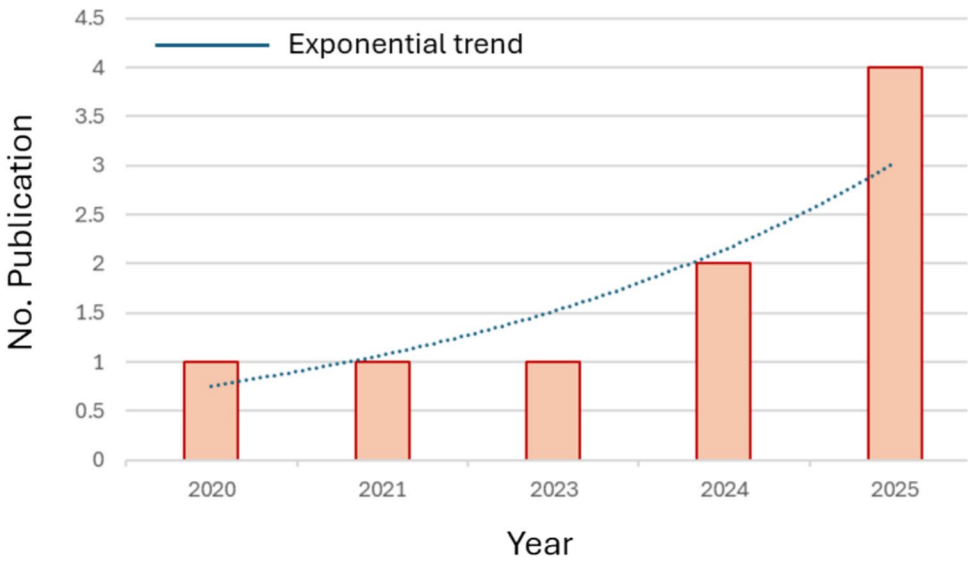

Fig. 17 Number of Publications per year about intelligent optimisation of WAAM process

Therefore, in addition to reducing surface roughness—with the potential to minimise the post-processing operations required to achieve the final geometry—energy-related aspects should also be taken into account. For example, Le et al. [126] applied a Gaussian process regression in conjunction with a Non-dominated Sorting Grey Wolf Optimisation (NSGWO) algorithm to optimise the deposition of Inconel 625, specifically minimising the layer height-to-width ratio. This strategy enables the use of wider layers to accelerate internal geometry filling while simultaneously reducing energy consumption, since this was part of the fitness function. In a related investigation, instead of manually constraining the search space, the authors introduced a hybrid regression-classification neural network to predict both geometric outcomes and energy usage [127]. This network effectively identifies process-parameter sets that achieve high-quality deposition with minimal energy input.

In their most recent WAAM studies, the authors fabricated demonstrator samples to validate the efficacy of the optimised process parameters, underscoring both the novelty and high potential of this research direction. Although existing fitness functions have been adapted from welding applications, WAAM presents unique considerations. First, mechanical properties are intrinsically linked to the heat input, so future models should explicitly correlate process parameters with metallurgical and performance outcomes. Incorporating more sophisticated constitutive or microstructure-aware models into the optimisation loop would further strengthen the integration of these tools in WAAM. Beyond mechanical performance, additional objectives—such as distortion, micro-porosity distribution, crack initiation and length, and surface roughness—should be included in multi-objective optimisation studies. While quantifying these features requires more intensive experimental and microstructural analysis, doing so will yield a richer fitness landscape and more robust parameter sets. Moreover, different optimisation algorithms may converge on distinct "optimal" solutions; ensemble approaches (for example, agent-based voting among candidate solutions with partially overlapping fitness functions) could reconcile these differences and improve overall reliability. Finally, the application of reinforcement-learning techniques offers a promising, data-driven route to adaptive parameter tuning in dynamic build environments.

Looking ahead, a critical frontier lies in balancing build time, energy consumption, and environmental impact. By integrating life-cycle assessment metrics—such as global warming potential [128]—into a comprehensive fitness function, it becomes possible to optimise for production speed, energy efficiency, and green credentials simultaneously. Novel formulations of multi-objective and adversarial fitness functions are required. For example, the function defined in Eq. 7 can be specialised for WAAM, where

- f_1 represents the primary build objective, such as maximising the width (w) and the height (h);
- f_2 captures sustainability targets, such as minimising energy consumption E, surface roughness (S), GWP and defect rates (d);
- f_3 quantifies mechanical performance, for example measuring deviation from the desired material properties (P_{ref}) and the estimated one ($\widehat{P}$).

$$F = w_1 f_1[\max(w;h)] + w_2 f_2[\min(E,S,GWP,d)] + w_3 f_3[\min\left(P_{ref} - \widehat{P}\right)] \tag{7}$$

Embedding these ML-driven, multi-objective optimisers within slicing software would create a new paradigm of goal-oriented build-path planning, enabling practitioners to trade off competing objectives in real time and to extend these advances to other additive manufacturing processes.

4.4 Summary of the emerging trends, challenges and future perspectives

In this section, we analysed the state of the art in optimisation procedures. We first discussed the main limitations of traditional manual optimisation based on experimental evidence, followed by the improvements introduced through statistical tools such as RSM. Furthermore, we addressed the limitations of these statistical approaches and highlighted some of the most innovative research in the field, including the application of GA and PSO. A summary of the state-of-the-art is reported in Table 3. These advanced methods have demonstrated the potential to achieve enhanced performance, as reported in several studies. Nonetheless, from the authors' perspective, certain limitations remain and should be further addressed in future research within this field, such as:

- *Optimisation based on energy consumption and sustainability*: Although the current trend is to incorporate sustainability considerations into process optimisation, to date, only one study has specifically addressed this issue using data-driven approaches. New datasets, as well as appropriately designed fitness functions, must be developed to support this direction. These new multi-objective fitness functions tailored to the WAAM process are needed. These should aim to find an optimal trade-off between performance and sustainability—reducing the number of passes, minimising energy consumption, while simultaneously enhancing mechanical properties and reducing undesirable surface roughness.
- *Optimisation based on residual stresses:* Two important aspects remain largely unaddressed in current optimisation frameworks: residual stresses and the influence of toolpath strategies on final part distortion. The integra-

Table 3 Review of intelligent process optimisation applications

References	Methodology
[119]	Polynomial regression and GA maximise the ratio of bead width to height
[120]	Polynomial model and NSGA-II for surface roughness optimisation
[121]	Polynomial model and PSO for reducing the heat input, and maximising of the width-to-reinforcement ratio
[122]	Neural network and GA for surface roughness optimisation
[123, 124]	Polynomial regression and GA or NSGA-II for void minimisation in path planning
[125]	Polynomial regression and RSM and NSGA-II for optimise of the width-to-reinforcement ratio and surface roughness
[126]	Gaussian process regression NSGWO for surface roughness and energy consumption optimisation
[127]	Neural network and GA for energy consumption optimisation

tion of these factors into the optimisation process is crucial.

- *Integration of optimisation procedures within slicer software*: The implementation of such optimisation techniques within slicing software should be more thoroughly studied and developed. Doing so could enable users to apply goal-oriented optimisation of parts through AI-based approaches. This is especially important given that path planning governs critical parameters such as overlap, the extent of re-heating, and thermal distribution.
- *Enhancing decision-making and optimisation using reinforcement learning*: Finally, as techniques like reinforcement learning have shown promising results in addressing continuous action space problems in arc welding, their application to WAAM optimisation should also be explored in future research. In summary, several challenges still exist, and numerous opportunities for impactful research remain—particularly when these efforts are aligned with sustainability goals.

5 Conclusions

This paper has examined recent advances in machine-learning (ML)-enabled in situ monitoring and process-parameter optimisation in wire-arc additive manufacturing (WAAM), offering an updated literature review and presenting key signal-processing models. By distilling complex concepts into a practical framework, it may guide welding practitioners and software developers alike towards effective implementation strategies. Synthesising the evidence reviewed in this work, we can list the following principal conclusions:

- The analysis of welding current and voltage signals, valued for their standardisation, cost-effectiveness and non-intrusiveness, has demonstrated the potential of both supervised and unsupervised learning techniques—augmented by generative-AI (GenAI) and frequency-informed neural networks (FINN)—to achieve accuracies approaching 90%. Although it is a well-researched topic, refinement in accuracy can be reached by the integration of multi-modal and multi-sensor monitoring approaches. Moreover, the possibility of solving the challenge of real-time, cost-effective layer-geometry estimation with those sensors promises to bridge this gap and to enable closed-loop feedback control, a mandatory next step towards AI-based certification of the parts.
- As discussed, vision-based monitoring remains the predominant method for defect and anomaly detection, but its reliance on fully supervised convolutional neural networks incurs significant labelling overheads and can overlook subtle irregularities. The emerging trend towards semi-supervised and unsupervised feature learning, combined with lightweight classification models, offers a route to reduce annotation burdens and to enhance sensitivity to unseen defects.
- Regarding the audio-based methods, while demonstrating their effectiveness offline, they demand computationally efficient algorithms for adoption in industrial online monitoring. Therefore, few works explored the possibility of employing this sensor (the microphone) for in situ monitoring, opening several research possibilities in relation to the application of state-of-the-art methods like unsupervised learning and complex GenAI methods.
- Thermal imaging, despite its potential disruptive impact for in-situ process monitoring, remains unexplored in WAAM. Similarly, acoustic-emission sensing, with its acute sensitivity to micro-cracking, has yet to be harnessed in a machine-learning context either. Developing comprehensive AE/thermal signature ML-based monitoring could deliver earlier and more precise detection of micro-defects than currently employed sensors. A further critical step is to quantify the suitability of each sensor modality for detecting particular defect types. However, adoption is hampered by uncertainties in emissivity calibration for thermal monitoring, by the still limited understanding and exploitation of acoustic-emission

(AE) signals, and by the computational burden of real-time processing of high-rate data streams (> 100 kHz).

- Current literature offers inadequate data on direct comparisons of single-sensor versus multi-sensor monitoring, leaving practitioners without guidance on optimal sensor selection. Establishing standardised benchmarking protocols to evaluate sensors against diverse defect classes will fill this gap and inform cost-effective, application-specific monitoring strategies. Given that most algorithms are data-driven, performance is strongly dataset-dependent, which hampers like-for-like comparisons; consequently, broader, standardised evaluations on shared benchmarks are required before making credible generalisation claims about the implications of ML monitoring for practical integration into industrial systems and practice.
- Finally, an important topic not addressed in previous reviews is parameter optimisation. In particular, bio-inspired optimisation techniques show considerable promise when coupled with ML. Accordingly, this review examines both traditional and innovative, goal-oriented strategies for parameter selection, demonstrating how they can reduce the number of required experiments—thereby saving time and cost—while maintaining, or even improving, process performance.
- Recent studies have demonstrated the use of regression analysis to build reduced-order models that capture complex relationships between process parameters and performance metrics (layer geometry, porosity dimension, energy consumption and quality scores), enabling efficient parameter searches.
- However, further research is needed to design goal-oriented fitness functions that internalise green-manufacturing criteria—such as specific energy consumption, carbon footprint, and LCA-derived impacts—alongside classical constraints on mechanical properties and micro-defect tolerances, and to develop new multi-objective optimisers accordingly. Extending these frameworks with reinforcement learning and constrained/robust formulations could improve adaptability and deliver efficient, sustainability-aligned process settings. Potentially, the same optimisation pipelines could also be leveraged to develop WAAM-oriented "synergic lines"—data-driven parameter maps tailored to alloys, transfer modes, and geometries—thereby modernising classical welding practice for additive manufacturing.

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Declarations

Competing interests The authors declare no competing interests.

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