



Energy Efficiency Optimisation in Wire arc Additive Manufacturing of Invar 36 Alloy via Intelligent Data-Driven Techniques

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Abstract

Nowadays, sustainability of manufacturing processes is a major concern which calls for special efforts to reduce their environmental impact and energy consumption. In additive manufacturing, this issue is even more challenging due to the usually high energy demands of these processes. However, in the era of Industry 4.0, machine learning (ML) techniques, combined with metaheuristic optimization algorithms, offer a powerful solution to explore new, unproven combinations of process parameters that better align with sustainability goals of manufacturing. These methodologies can minimize the need for extensive experimental campaigns and provide a valuable decision-making support tool for goal-oriented process parameters optimization. In line with such approach, this research work introduces an intelligent data-driven methodology using ML to optimize wire arc additive manufacturing (WAAM) of Invar 36 alloy considering both the resulting layer geometry and quality as well as the process energy consumption. An experimental campaign involving WAAM deposition of 15 walls made of Invar 36 alloy using a natural dip transfer welding process was carried out. The data acquired from the WAAM experimental tests were used to develop and train an artificial neural network (ANN) which, on the basis of the process parameters, was able to predict the layer geometry, the specific energy consumption and a specified quality score indicative of the presence of defects. The ANN achieved a high accuracy with 100% F2 score for quality classification, 0.4 mm mean absolute error for layer geometry, and 20 J/mm MAE for specific energy consumption. A genetic algorithm (GA) was then used to identify optimal process parameters able to minimize the specific energy consumption while maintaining quality and smoothness of the deposited layer. The experimental validation carried out using the GA-optimized process parameters in the WAAM process confirmed the reliability of the model, resulting in energy-efficient and defect-free walls.

Keywords Wire arc additive manufacturing · Sustainability · Energy consumption · Machine learning · Genetic algorithm

1 Introduction

In recent years, manufacturing technologies have experienced significant advancements, with modern additive techniques emerging alongside traditional subtractive methods,

such as machining and milling. Traditional manufacturing often relies on a subtractive paradigm, where material is removed from a solid block (e.g., using cutting tools [1–3], laser [4, 5] or waterjets [6, 7]) to achieve the desired shape. Alternatively, casting technologies [8, 9] involve flowing molten material into a mould where it solidifies to form a component with the desired geometry. Today, additive manufacturing (AM) has emerged as a transformative technology for modern manufacturing systems. It enables the production of complex shapes with lower overall costs, considering the entire product lifecycle, while promoting a more sustainable and environmentally friendly production paradigm [10]. Additionally, AM facilitates decentralized production, supports mass customization, and enhances supply chain flexibility, making it a key driver of innovation in manufacturing [11]. While AM offers advantages such as a lower buy-to-fly ratio and the possibility to produce

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complex shapes which could not be realised through other conventional technologies, it is usually characterized by higher electrical energy intensity and increased production time compared to traditional subtractive manufacturing processes [12–14]. Therefore, additional efforts are needed to enhance the energy efficiency and quality of AM processes, primarily by focusing on optimizing the process parameters. Among the available metal AM processes, wire arc additive manufacturing (WAAM) [15, 16] is raising increasing interest due to the possibility of producing mid/large-size components with good mechanical properties in a short time thanks to the high deposition rates, commonly in the range of 1–10 kg/h [17].

As illustrated in Fig. 1, WAAM usually employs a robotic welding system to deposit metal in a layer-by-layer manner to fabricate a near net-shape component, which is then removed from the substrate and subsequently machined to meet the part requirements in terms of final geometry and surface finish. Various welding techniques can be utilized for this process [18]; however, research has shown that dip transfer methods (both natural and waveform-controlled [19–21]) are among the most effective ones. As a matter of fact, their lower heat input minimizes distortion and residual stress, thereby improving the mechanical properties of the final product [22].

Since the WAAM process is based on welding technology, the process parameters are those typical of gas metal arc welding (GMAW) [23], namely arc welding current (I), arc voltage (V), welding speed (WS), wire feed speed (WFS) and contact tip to workpiece distance (CTWD). Additional relevant parameters are the interpass temperature [24, 25], the gas flow rate and the torch angle. The

WAAM process parameters can be classified into two main groups: welding process parameters related to the welding machine (welding current, welding voltage and wire feed speed) and external process parameters such as welding speed, contact tip to workpiece distance, torch angle, gas flow rate and interpass temperature, as reported in Table 1.

The above mentioned parameters influence the resulting part quality and adversely affect the produced layer geometry and the power consumption during the WAAM process [26–28]. Specifically, with reference to power consumption (P), both wire feed speed and welding voltage tend to increase power consumption by raising the welding current. In contrast, an increase of CTWD reduces power consumption by reducing the welding current [29]. Welding speed (WS), on the other hand, is closely linked to the Specific Energy Consumption (SEC) index, i.e. the energy needed to deposit 1 mm of material under the employed process parameters, computed as reported in Eq. 1.

$$SEC = \frac{P}{WS} \left[\frac{J}{mm} \right] \quad (1)$$

Moreover, welding speed mainly affects the layer geometry, with a wider layer obtained under a reduced welding speed. Accordingly, the selection of the optimal process parameters for a given application is not a trivial task and needs to take into account the different effects of the several relevant process parameters on the layer geometry and on the process energy efficiency while guaranteeing an acceptable part quality without the presence of defects.

In this framework, the employment of data driven techniques can be highly effective in developing models

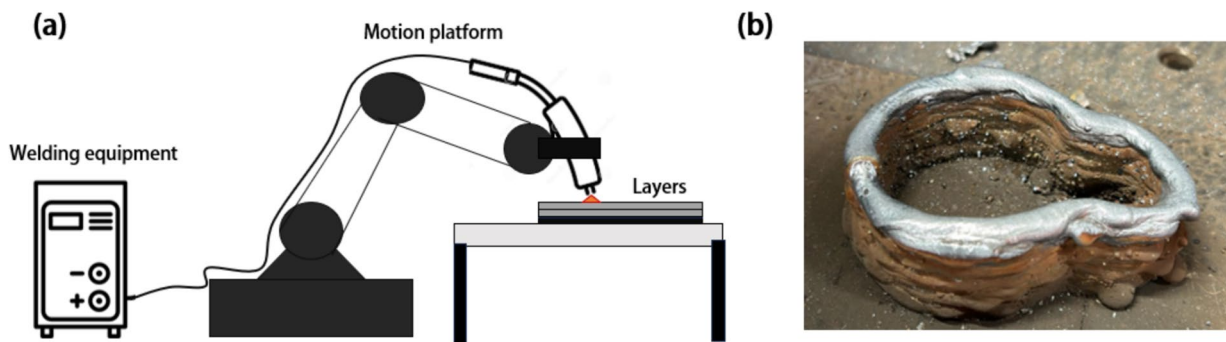


Fig. 1 **a** Main components of a robotic wire arc additive manufacturing system; **b** near net-shape produced component

Table 1 Welding machine and external process parameters

Welding process parameters	Welding current (I)	Welding voltage (V)	Wire feed speed (WFS)		
External process parameters	Welding speed (WS)	Contact Tip to workpiece distance (CTWD)	Torch angle	Gas flow rate	Interpass temperature

designed to optimise the process parameters in a goal-oriented manner. The model-based approach allows to explore the impact of a new combination of process parameters on the process under consideration. Accordingly, AI tools can be utilized to develop a simulation environment supported by regression models such as neural networks and support vector machines (SVM) [30, 31] in which metaheuristic methods such as genetic algorithm [32], reinforcement learning [33] and Particle Swarm Optimisation (PSO) [34] can interact to discover in an automatic manner new sets of process parameters which maximise a goal-oriented function. In the recent literature, Xiong et al. [30] employed neural networks and second order polynomial regression to estimate the layer geometry based on process parameters, while Ding et al. [31] demonstrated the performance obtained by the SVM model and how the “bead modelling” activity is important in the development of the slicer for the WAAM process. These models can also be used in data-driven optimisation techniques. In the work of Tomaz et al. [32], a model obtained via neural networks was used to estimate the bead geometry and penetration during gas tungsten arc welding (GTAW) and a genetic algorithm was used to optimise the process parameters with the aim to maximize the penetration depth. Similar works were performed by Kathersan et al. [34] for fluxed core arc welding (FCAW), with the difference that the authors proposed the usage of PSO to minimize the bead geometry and maximize the penetration depth.

Although the combined employment of these methodologies has been investigated for the optimisation of arc welding processes [35–37], there is still a gap concerning the application of these methodologies to WAAM, where the layer geometry is significantly influenced by the repetitive heat cycles that occur during the part building process [38]. These heat cycles impact the layer geometry, the overall power consumption, as well as the quality of the final part. As a matter of fact, problems such as layer collapse and porosity are more common in WAAM than in GMAW processes. This means that, although some models are available for GMAW processes, additional ones should be developed to model the WAAM environment to be used for the optimization procedure. Despite the importance of this aspect, a significant research gap persists in the field of WAAM. Furthermore, sustainability and energy efficiency goals are often overlooked in arc welding processes, making it difficult to select the optimal parameters that allow achieve the desired layer geometry, as defined by the slicer, while also minimizing heat input and energy consumption during the welding process.

Accordingly, this work aims to address such research gap by developing an intelligent data-driven methodology based on Machine Learning to optimize the WAAM process

considering both the resulting layer geometry and quality as well as the process energy consumption. The study was focused on WAAM of Invar 36 alloy, a material with unique thermomechanical properties that is often used in applications requiring minimal distortions [39] such as the case of aerospace tooling. Despite its industrial relevance, Invar 36 has been relatively underexplored in the literature, with only a limited number of studies focusing on its processing via WAAM. Veiga et al. [40, 41] used a GMAW spray transfer process, while Sood et al. [42] studied the printability of this alloy via different GMAW metal transfer modes, observing that the susceptibility of Invar 36 to ductility dip cracking decreases with a reduction in the heat input, typical of the dip transfer process. Finally, Jiao et al. [43] investigated the CMT process and Fowler et al. [44] employed a STT process, which allows to reduce the heat input and the overall energy consumption. While the presented research works focused on the characterisation of the mechanical properties of the final components realised via WAAM technology, additional studies are necessary to understand how to deposit Invar 36 in GMAW dip transfer mode. As a matter of fact, this process mode allows to reduce both heat input and energy consumption. However, the process parameters must be carefully optimized to ensure the stability of the deposition process and the successful production of components using WAAM. To investigate these aspects, Invar 36 alloy was employed in this research work to deposit 15 walls by ensuring the use of the natural dip transfer process mode during deposition. By analysing the layer geometry and SEC data, a data-driven model was developed, and a Genetic Algorithm was employed to optimize the designed fit function.

The flow chart followed in this study is shown in Fig. 2. After reviewing the literature and identifying the research gap, a WAAM experimental campaign was conducted on Invar 36 to collect data on layer geometry, power consumption, and quality. An energy-reduction fitness function was then designed for WAAM, and a Genetic Algorithm was employed to optimize the process parameters. Finally, the optimized process parameters were applied to produce a new wall, which was used to validate the optimization performance in terms of both part quality (through microscopic analysis) and power consumption reduction.

2 Materials and Methods

2.1 Experimental Setup and Procedure

The experimental setup employed in this research work comprised an Omron Viper s850 robotic arm equipped with a Miller Phoenix 456 welder, as illustrated in Fig. 3. During the experimental campaign, 15 walls, each consisting of

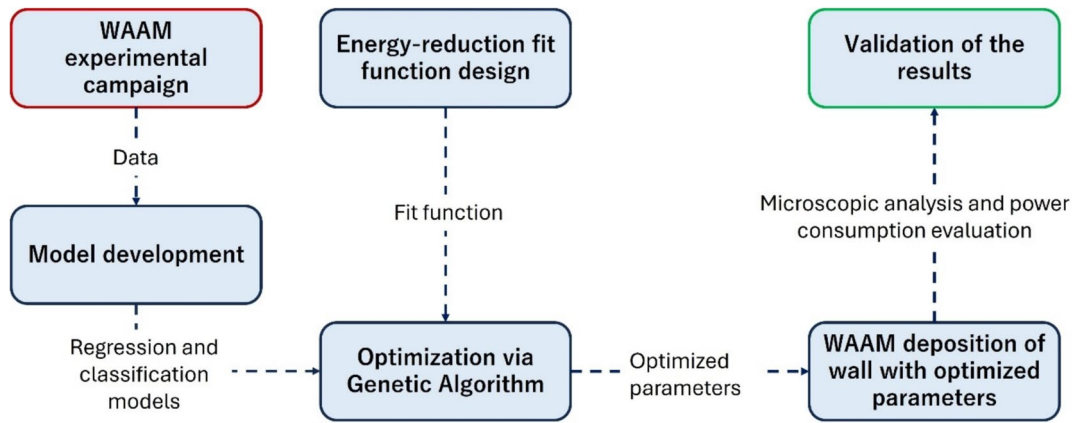
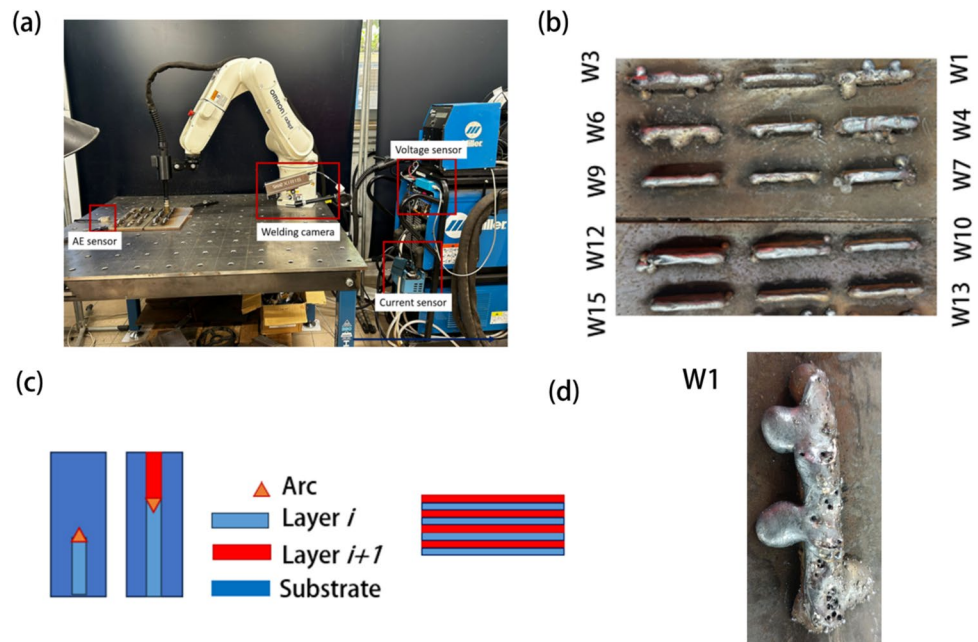


Fig. 2 Overall flowchart of the research work

Fig. 3 **a** Experimental setup; **b** Invar 36 walls realised in the experimental campaign; **c** deposition strategy; **d** example of collapsed layer with internal porosity from W1



10 layers with a length of 60 mm, were deposited using a 1.2 mm wire of Invar 36. The stability of this alloy during WAAM in dip transfer mode was investigated by employing different process parameters following the design of experiments reported in Table 2. During the deposition process, welding current and welding voltage sensor signals were acquired, and a Xiris XVC100 welding camera was employed to capture images of the process. At the end of deposition, some combinations of process parameters led to layer collapse, while others introduced further defects such as excessive spatter or porosity (Fig. 2c, d). Through visual inspection of the deposited layers, a quality score λ was assigned. A score of $\lambda = 0$ indicated good quality of the deposited layer, while $\lambda = 1$ signified the presence of some defects during average wall deposition. The average quality

scores λ for each test of the WAAM experimental campaign are reported in the last column of Table 2. At the end of each layer, both the collected sensorial data and the images captured by the welding camera were used to assess the layer quality and confirm that the transfer mode corresponded to dip transfer. During the walls construction, the contact tip to workpiece distance and the gas flow rate of full Argon were maintained fixed at 13 mm and 16 L/min, respectively, and the cumulative height and width of the walls were measured to collect the data associated to each layer height and width. The average layer height and width values for each test of the WAAM experimental campaign are reported in columns 6 and 7 of Table 2.

The welding current and welding voltage signals (see Fig. 4) were collected at a sample rate of 5 kHz using a

Table 2 Experimental design

Wall no.	Wire feed speed (m/min)	Welding voltage (V)	Welding speed (mm/s)	Average SEC (J/mm)	Average layer height (mm)	Average layer width (mm)	Average quality (λ)
1	3.5	19	3.2	430.9	1.96	7.7	1
2	4	19	4.5	345.9	1.83	6.3	0
3	3.5	22.5	2.0	867.6	1.76	7.9	1
4	3.5	21	4.0	387.9	1.26	7.8	1
5	3.5	19	4.5	301.3	1.66	6.8	0
6	3.5	20	2.0	754.9	1.94	9.9	1
7	3	19	3.2	401.9	1.93	6.7	0
8	2	20	3.2	294.1	1.36	6.5	0
9	6	19	4.5	432.0	2.13	6.7	0
10	6	21	4.5	503.3	2.25	7.6	0
11	4	22.5	3.2	583.3	2.06	9.9	0
12	3	22.5	4.5	334.9	1.65	6.5	0
13	4	19	4.0	379.1	2.14	6.5	0
14	3	20	4.5	294.1	1.64	6.3	0
15	3	19	4.5	339.3	1.83	7.4	0

NI 6361 acquisition board, allowing to observe the stability of the deposition process and to evaluate the energy consumption in terms of SEC at the end of each deposited layer (Table 3).

In dip transfer based GMAW, an accurate measure of power and energy requires instantaneous measurement of the electrical parameters. As proposed by Joseph et al. [45], the average instantaneous power (P_{AI}) is expressed by Eq. 2.

$$P_{AI} = \frac{1}{N} \int_{t=0}^N V(t) \cdot I(t) dt \quad (2)$$

where $V(t)$ and $I(t)$ are the arc voltage and arc current values over the N samples, respectively. Therefore, from the Welding Speed (WS) parameter, the SEC can be computed for each deposited layer as reported in Eq. 3.

$$SEC = \frac{P_{AI}}{WS} \left[\frac{J}{mm} \right] \quad (3)$$

The average SEC values calculated for each test of the WAAM experimental campaign are reported in column 5 of Table 2.

2.2 Data Driven Approach for Energy Consumption Optimisation

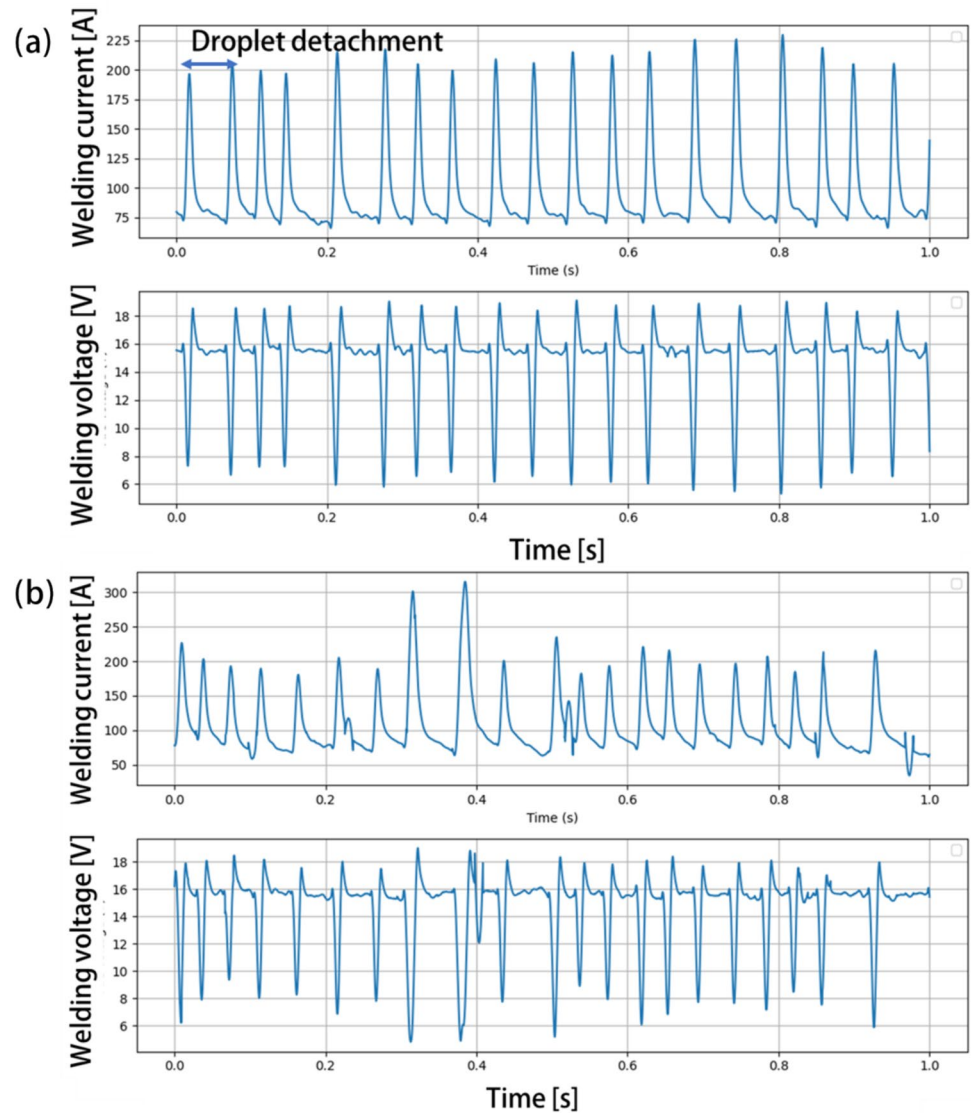
2.2.1 Research Gap

Process optimisation plays a key role in manufacturing engineering, allowing to enhance manufacturing processes with reference to diverse performance indicators. Despite the recent democratization of Machine Learning tools, the procedures adopted in the field of WAAM still primarily rely on experimental evidence, with researchers iteratively adjusting parameters based on empirical observations to improve performance [46]. Zvdoveev et al. [47] employed a combination of 9 process parameters in Pulsed-GMAW and selected the optimal set of parameters among those employed using the Taguchi method. A similar approach was proposed for WAAM by Wani et al. [48], where optimal parameters for carbon steel production were selected among the employed ones by Taguchi method. A more sophisticated approach using models for optimisation was proposed by Panicker et al. [49]. They used FEM analysis to simulate different scenarios and selected the process parameters which reduced the residual stress in simulation. However, the proposed approaches are time- and resource-intensive, often struggling to identify non-intuitive solutions or effectively navigate high-dimensional parameter spaces, which results in acceptable but suboptimal outcomes. Consequently, several researchers in the arc welding field suggested the use

Table 3 Hyperparameters of the proposed genetic algorithm used for the optimization

Parameter	Population size	Generations	Ini. crossover rate	Ini. mutation rate	Ini. mutation gain	Beta
Value	50	100	0.6	0.6	0.05	1.5

Fig. 4 Acquisition of welding voltage and current signals at 5 kHz during **a** stable deposition and **b** unstable deposition



of data-driven techniques for process optimization. Authors like Tomaz et al. [32] used a neural network to estimate the bead geometry during TIG welding and a GA to optimize the parameters to obtain higher penetration. However, none of the existing works in the literature considered WAAM power consumption in their optimization algorithms and, as a result, no suitable fitness function has ever been proposed to this aim.

2.2.2 Fit Function Design

The objective of the optimization problem, such as the minimization of power consumption, is defined by the fitness function. As previously mentioned in the introduction section, parameters like wire feed speed and welding voltage are closely related to arc voltage and current, directly influencing power absorption and the associated costs. However, the optimization process is complex, as various trade-offs must

be considered. For instance, while reducing welding speed can lower SEC, excessively low speeds can lead to defects such as humping or poor melting pool shielding. Similarly, while decreasing wire feed speed may reduce power consumption, if wire feed speed is set too low or used with a high welding speed, it can cause issues like balling and other defects. Additionally, if welding voltage and welding speed are not properly balanced, lowering wire feed speed may lead to defects such as arc instability, excessive spatter and porosity.

This means that, during the optimisation, it is crucial to consider also the combinations of process parameters which can lead to defective parts. Therefore, the environment model used for process parameters optimisation should take into account both regression and classification problems. The regression problem to estimate SEC and layer geometry and the classification problem to predict anomalous

conditions. Specifically, if the process parameters are related to a deposition without any anomaly, the fit function needs to be evaluated, otherwise the proposed set of process parameters should be neglected. The study of Xia et al. [50] highlighted that increasing the welding speed or reducing the wire feed speed can be beneficial from a surface roughness perspective. Consequently, the agent employed for the optimization should encourage to use a higher welding speed, reducing the deposition time and the surface roughness, and at the same time to use a lower wire feed speed, but should avoid the occurrence of defects due to the inconsistency of process parameters. Moreover, the agent has the goal to reduce the ratio between the layer width and layer height. This allows to reduce the number of passes—since a greater layer height reduces the number of layers needed to produce a component—and to have a smooth layer. Therefore, considering all these factors, the fit function reported in Eq. 4 was developed and utilized. This fit function aims to maintain the layer geometry as smooth as possible, meanwhile reducing the SEC. In this equation, λ represents the quality score (with $\lambda = 1$ representing a combination of parameters leading to anomalies), WFS and WS are the wire feed speed and the welding speed, while h and w are the layer height and width. β is an hyperparameter which allows to change the weight of the two terms of the optimization procedure.

$$f(SEC, WFS, WS) = \begin{cases} -\beta \cdot \frac{SEC}{SEC_{max}} - \frac{\beta}{2} \cdot \left(\frac{WFS}{WFS_{max}} - \frac{WS}{WS_{max}} \right) - \frac{\beta}{2} \left(\frac{w}{w_{max}} \cdot \frac{h_{max}}{h} \right), \lambda = 0 \\ -4\beta\lambda = 1 \end{cases} \quad (4)$$

2.2.3 Continuous Genetic Algorithm

Among the various metaheuristic optimization algorithms that can be used to maximize this fitness function, the Genetic Algorithm (GA) stands out as a powerful technique inspired by Darwin's theory of evolution [51]. It is designed to find optimal solutions without relying on gradients or the differentiation of cost functions. Although typically applied to discrete parameter combinations, the GA can be adapted for continuous variables by appropriately adjusting the evolutionary processes of selection, crossover, and mutation to iteratively refine candidate solutions. This allows to better search in the parameters space aiming to find better solutions.

To achieve this, the initial generation parameters were sampled using a Gaussian distribution. Each parameter was scaled within its minimum and maximum values, mapping the range from 0 to 1. This allows for simple multivariate sampling to populate the initial generation. The crossover operator remained unchanged, consisting in randomly sampling two parameter values and exchanging their positions. Mutation was used to introduce perturbations by adding white noise with a fixed standard deviation σ , ensuring

diversity in the continuous search space. Both crossover and mutation rates were gradually reduced through a linear decrement, transitioning the algorithm from exploration to exploitation as it converges on an optimal solution.

2.3 Environment Model and Optimization Hyperparameters

To develop the model of the environment, an Artificial Neural Network (ANN) was employed to predict the layer geometry and the SEC index using regression layers fed with the process parameters and the number of deposited layers. Then, the process parameters and the estimated SEC and layer geometry values were concatenated and used as inputs to the binary classifier part of the ANN model to assess the quality of the process parameters in terms of λ score. The ANN architecture used to develop the model of the environment, including the regression branch, the concatenation layer and the classification branch, is illustrated in Fig. 5.

A schematic illustration of the data-driven optimization methodology is shown in Fig. 6. First, the GA optimizer generates the process parameters. Afterwards, the environment model, including both regression and classification, estimates the layer geometry, the SEC and the quality label. Then, this information is used to evaluate the fit function

associated with these parameters and the GA elaborates a new generation of process parameters based on the best solutions of the previous generation.

3 Results and Discussion

3.1 Results of the Environment Model

The architecture of the proposed ANN consists of two branches: one for estimating layer geometry and specific energy consumption based on the process parameters, and the other for anomaly detection, which uses as inputs both the process parameters and the ANN regression branch output. To update the network weights during training, the Adam optimization algorithm was employed using a learning rate of 0.00078 and 2500 epochs with a batch size equal to the number of training data. The procedure to manage gradient computation from the two branches of the same ANN involved first calculating the regression loss and its gradients, and then computing the classification loss and its gradients. The optimizer then updates the model parameters based on the accumulated gradients from both tasks.

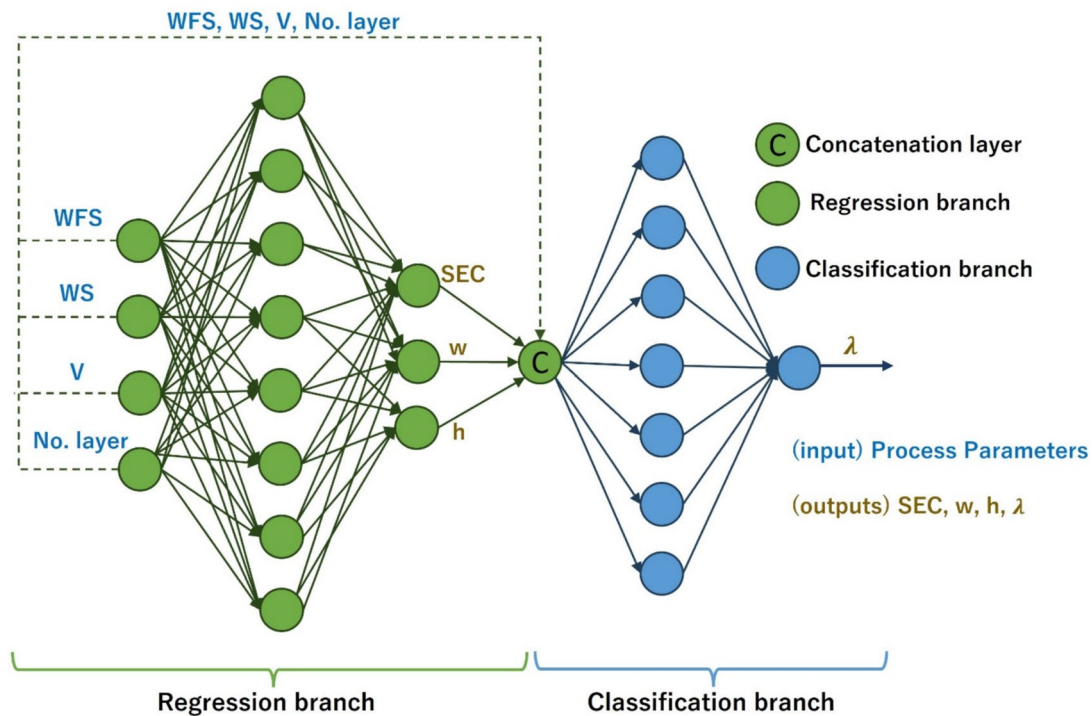


Fig. 5 Illustration of ANN used as environment model consisting of both regression and classification branches

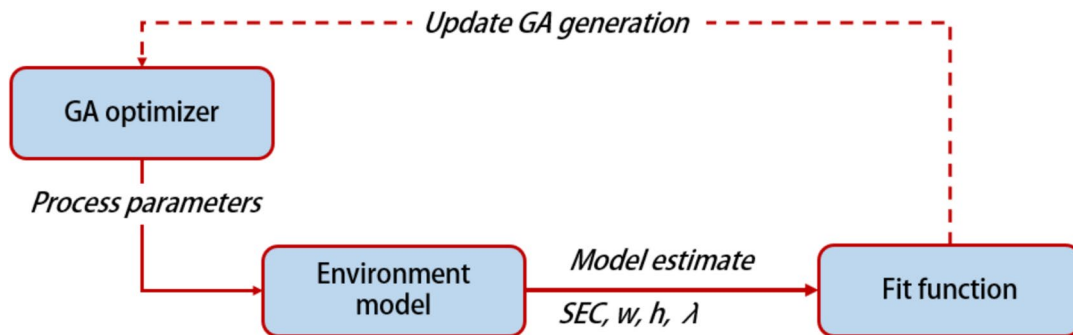


Fig. 6 Scheme of the proposed data-driven optimization methodology

PyTorch's `retain_graph` function was used to allow multiple backward passes, retaining the intermediate values needed for later gradient calculations. Without this, PyTorch would release the computation graph after the first backward pass, preventing the second backward pass (for the classification task) from functioning correctly.

The regression branch consists of two hidden layers with 8 and 3 neurons, respectively, and uses sigmoid activation functions. After concatenating the regression output with the process parameters, a shallow hidden layer with a sigmoid activation function is used to combine these inputs, operating similarly to logistic regression. The output of the model is normalized within the range $[0,1]$, with

the Y dataset (including layer height, layer width, layer SEC, and anomaly score) scaled using a `MinMaxScaler` from the `scikit-learn` library. The model is trained using the mean squared error (MSE) loss function on 70% of the samples collected during the experimental campaign, and its performance is validated on the remaining 30%. The final mean absolute error (MAE) on the test dataset was 0.46 mm for layer width, 0.25 mm for layer height and 29.5 J/mm for SEC. Figure 7a shows the loss function trend vs the number of epochs for the training and validation dataset, while Fig. 7b shows the regression plot obtained on the validation dataset for layer width, layer height and SEC.

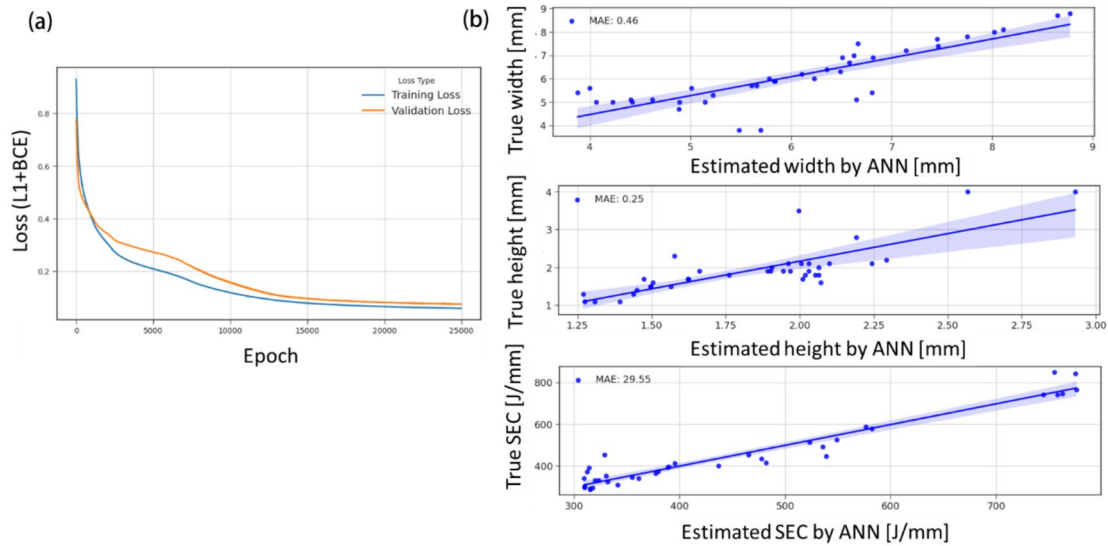


Fig. 7 **a** The MSE loss function during training for training and validation data **b** the result regression plot on validation data

An anomaly is detected when the anomaly score exceeds 0.5. To assess the performance, the Precision, Recall, and F2 score metrics were used, as defined in Eqs. 5–7. Here, TP (true positives) represents the correctly identified anomalies, FP (false positives) denotes false alarms, and FN (false negatives) refers to missed anomalies. On the test set, the model achieved optimal performance with an F2-score of 100%, a precision of 100% and a recall of 100%, indicating that no anomalies were missed and no false alarms occurred.

$$p = \frac{TP}{TP + FP} \quad (5)$$

$$re = \frac{TP}{TP + FN} \quad (6)$$

$$F2score = \frac{(1 + \beta^2) \cdot p \cdot re}{\beta^2 \cdot p + re} = \frac{5p \cdot re}{4p + re} \quad (7)$$

3.2 Optimization Results and Discussion

The hyperparameters of the GA were configured with a population size of 50 and crossover and mutation rates set to 0.6. The optimization process continued for 100 generations, utilizing a mutation gain of 0.05 to introduce white noise, enabling the exploration of new parameter combinations. The hyperparameters of the proposed GA used for the optimization are summarized in Table 2.

Following the optimization procedure, the algorithm yielded the following optimized process parameters: a wire feed speed of 3.8 m/min, a welding voltage of 20 V, and a

welding speed of 4 mm/s. To validate the methodology and evaluate component quality and model performance, a new wall consisting of 30 layers with a length of 100 mm was constructed using the GA optimized process parameters. The wall, shown in Fig. 8, exhibited no defects, such as excessive spatter or porosity. The average layer width and height were 7 mm and 1.9 mm, respectively, with an average specific energy consumption (SEC) of 334.4 J/mm. The model accuracy was confirmed by the MAE values, which were equal to 0.5 mm for layer width, 0.01 mm for layer height, and 30 J/mm for energy consumption. These results are closely aligned with those obtained on the validation dataset used during training.

By comparing the results with the best values achieved in wall 5, characterised by a SEC of 294 J/mm, a layer height of 1.36 mm and a layer width of 6.3 mm, yielding a fit function of -1, it was observed that the optimized process parameters, with a SEC of 334 J/mm, a layer height of 1.9 mm and a layer width of 7 mm, achieved a significantly improved fit function of 0.97. The optimized process parameters allow to reduce the number of passes required to produce a component as the layer height is 40% higher (e.g., for a 100 mm high component around 53 passes are needed instead of 74) and maintain a low energy consumption during the deposition process, without generating defects which could reduce the final mechanical properties of the component.

Using the proposed methodology, it is possible to produce a component with reduced energy consumption and shorter overall production time by optimizing layer height while simultaneously achieving a smooth layer surface. Compared to existing literature, the proposed approach demonstrates how a green manufacturing paradigm can be realized by

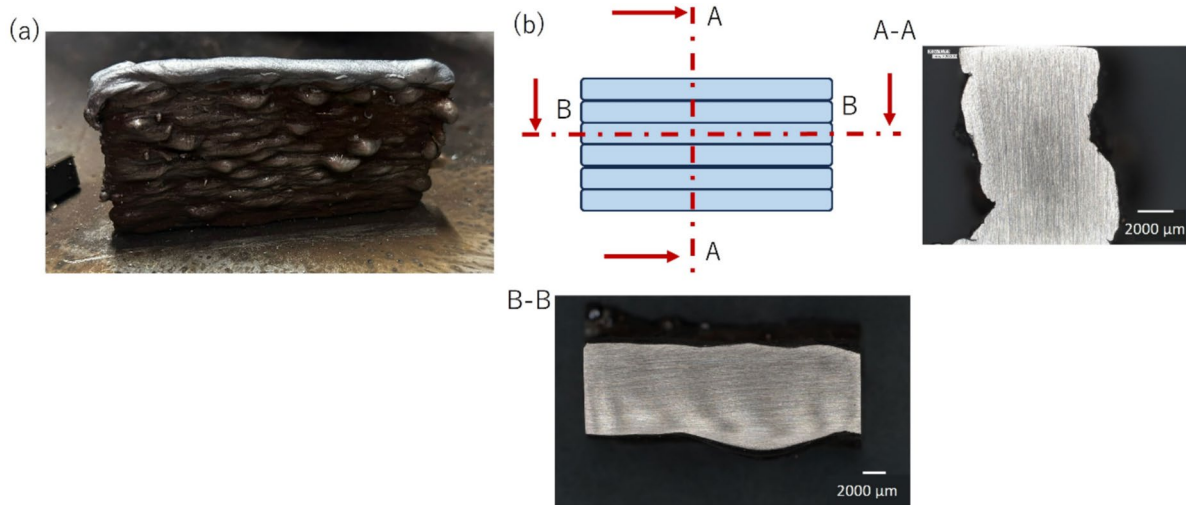


Fig. 8 **a** Wall printed using optimized process parameters. **b** Sections of the wall examined under a Keyence VHX microscope, revealing no defects that could compromise component quality

addressing goal-oriented scenarios through the integration of advanced data-driven AI tools, such as neural networks and genetic algorithms. These tools, when applied to a well-structured dataset that encapsulates prior knowledge of alloy behaviour in the WAAM process, enable innovative solutions, allowing to produce optimized defect-free parts. Despite the widespread use of AI in manufacturing, achieving impactful results requires integrating these tools in the proper way. This methodology emphasizes this synergy, allowing the process parameters and robot path planning to be automatically generated based on user-defined goal functions and predicted layer geometry. This approach, which outlines the development of an energy-optimized fitness function for WAAM, offers significant potential to advance modern manufacturing systems. It moves beyond the traditional "experimental evidence" or only "high-performance" methodologies commonly found in the literature, providing a more comprehensive and goal-driven framework.

Finally, to discuss the limitations of the proposed methodology, it can be observed that the optimization results strongly depend on the accuracy of the model. Achieving better results in optimization requires the development of more robust and accurate predictive models that can more effectively estimate the actual values. In this case study, the model tended to underestimate both the layer width and SEC values, leading to an optimized fit function that is lower in simulation compared to the one observed in the real case. Nevertheless, the methodology demonstrated to be capable of providing an improvement over the experimental results, indicating its potential when appropriately adjusted to suit the available data. While studies in the literature often employ experimental campaigns with limited process parameter combinations—particularly in welding processes,

where full factorial experiments can lead to unstable deposition processes and minimal variations in results due to small parameter changes—it is also evident that more extensive experimental campaigns are necessary. This is especially true for AM, where factors such as the interpass temperature significantly influence the layer geometry. Although this research work incorporated the effect of the interpass temperature through the number of layers, more precise modelling would require explicit consideration of this physical variable and could lead to further improvements of the modelling and optimization results.

4 Conclusion

Sustainability has become a key concern in manufacturing, underscoring the need to optimize processes to reduce environmental impact, with energy consumption being a major contributing factor. In this research work, a data-driven methodology based on artificial intelligence was proposed to optimize wire arc additive manufacturing (WAAM) taking into account energy efficiency together with layer quality and geometry. This approach enabled the identification of new process parameters that better align with goal-oriented objectives compared to those observed during the experimental campaign. In this work, 15 walls of Invar 36 alloy were deposited via WAAM using a natural dip transfer welding process, and data on specific energy consumption, layer geometry and quality were collected at the end of each layer deposition in a multi-layer deposition process. A two-branch Artificial Neural Network (ANN) architecture was developed to model the environment with the aim to use it during the optimization procedure. One branch was used to predict

layer geometry and specific energy consumption (SEC) based on process parameters and layer number, while the other branch was utilized to estimate the layer quality scores. The ANN achieved robust performance, with an F2 score of 100% for classification, a mean absolute error (MAE) of 0.4 mm for geometry predictions and a MAE of 20 J/mm for SEC. Using this trained model, a genetic algorithm (GA) was employed to search the parameter space for an optimal solution able to reduce the SEC while ensuring a flat deposited layer in a stable deposition process. The optimized parameters were then validated experimentally by depositing a new wall with the optimized parameters, namely 3.8 m/min of wire feed speed, 4 m/min for welding speed and 20 V of welding voltage. The geometry and SEC values closely matched the predictions and the analysis of the obtained wall using a confocal microscope showed the absence of defects, demonstrating the reliability of the developed methodology and its potential to enhance WAAM process efficiency while reducing environmental impact. Future work will focus on integrating the developed optimization procedure into slicer software, providing users with guidance on how to automatically apply the optimized parameters during part generation, enabling a fully automated workflow from slicing to production. Additionally, future efforts will be directed towards incorporating the interpass temperature directly into the model to enhance its predictive performance, as this factor could lead to even more optimal solutions.

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Data availability Data are available upon request to the corresponding author.

Declarations

Conflict of interest The corresponding author Giulio Mattera declares to accept responsibility for all statements listed below: all authors have given their contribution in the drafting of this original paper; all authors concur with the submission; I have taken the consent from all co-authors before publishing the present article; the manuscript has not been submitted to another journal and will not be published elsewhere within one year. No funding for the studies in the manuscript exist; all authors have no financial/commercial conflict of interest of any kind to disclose.

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