Materials Today: Proceedings 46 (2021) 7402–7410

Contents lists available at ScienceDirect

Materials Today: Proceedings

journal homepage: www.elsevier.com/locate/matpr

Intelligent welding by using machine learning techniques

Rishikesh Mahadevan R, Avinaash Jagan, Lakshmi Pavithran, Ashutosh Shrivastava, Senthil Kumaran Selvaraj *

Department of Manufacturing Engineering, School of Mechanical Engineering, Vellore Institute of Technology, Vellore 632014, India

ARTICLE INFO

Article history:
Received 2 December 2020
Received in revised form 22 December 2020
Accepted 29 December 2020
Available online 16 February 2021

Keywords:
Intelligent welding
Friction stir welding
Laser welding
Machine learning
Metal inert gas welding
Plasma arc welding
Tungsten inert gas welding

ABSTRACT

This paper talks about how machine learning techniques can be applied in the welding industry. Machine learning techniques could be used to find solutions to the problems faced by different welding processes and make them even more efficient. The welding processes' efficiency and accuracy have been proved to increase significantly by using machine learning algorithms. Industrial robots trained using artificial intelligence can find solutions to many complex manufacturing industry problems. Many welding processes rely on human expertise while choosing optimum parameters that are quite susceptible to human error and less efficient. To reduce this dependence, robots and automatic systems are trained using neural networks capable of delivering consistent weld quality and improved efficiency. Machine learning is also employed to visualize welding since the visual inspection is critical to determine weld quality. These techniques can also be used to evaluate the causes of various health hazards using regression analysis.

Selection and peer-review under responsibility of the scientific committee of the 3rd International Conference on Materials, Manufacturing and Modelling.

1. Introduction

Machine learning is an A.I. application that gives systems the flexibility to learn and improve through experience mechanically. It has become increasingly popular in many industries, such as the I.T. industry, data security [1], robotics [2], manufacturing, etc. The popularity and use increase as more and more people are becoming aware of the concept [3,4]. The ability to mimic human intelligence and learning provides a significant advantage compared to the conventional means of accomplishing the same task [5]. Its performance improves over time.

As shown in Table 1, Friction stir welding is mainly useful in [6] shipbuilding [7], aerospace industry, and robotics. It is used for the [8] production of large aluminium panels. It is a useful method for joining different materials. Laser welding has been applied in the [9] medical and [10] automotive industries. Resistance welding is used to join coil wires and the joining metals for the assembly of components. Plasma arc welding can be employed in the marine, aerospace, and electronics industries [11]. Its high speed and precise nature help with the increase in efficiency of the process. One of the major problems faced in traditional welding processes is the [12,13] monitoring of quality. There is always the difficulty of radiation due to heat [14,15]. The monitoring of quality, while the welding process is ongoing, is challenging. There are always chances of [16] human error.

This paper illustrates how machine learning techniques are used in various welding processes, which has resulted in a significant increase in their efficiency and accuracy. Problems like quality monitoring [17], skill requirement, time consumption, etc. have been solved using machine learning. Machine learning techniques are [18,19] computer-based, helping overcome human constraints such as [20,21] harmful radiation, high temperature, limited visibility, and [22] accuracy of performing tasks. The problems have been solved quite effectively by the use of machine learning.

2. Literature survey

Welding is one of the initial processes in many industries, such as the automobile industry, robotics industry, marine industry, etc. It is a permanent joint between metals or dissimilar materials. Joining of components is one of the incredibly essential processes in [23] manufacturing. Welding requires [24] highly skilled labour, and hence it is one of the highly paid jobs in the manufacturing sector [4]. The quality of welding processes in a country is essential for its [25] economy. This paper would study some of the welding processes and some of the problems associated with it.

* Corresponding author.
E-mail address: senthilkumaran.s@vit.ac.in (S.K. Selvaraj).

https://doi.org/10.1016/j.matpr.2020.12.1149
2214-7853/
Selection and peer-review under responsibility of the scientific committee of the 3rd International Conference on Materials, Manufacturing and Modelling.

Table 1
Application of different welding processes.

Welding Type	Applications
Friction Stir Welding	Shipbuilding, aerospace industry, robotics
Laser Welding	Medical and automotive industries
Plasma Arc Welding	Marine, aerospace and electronics industries
Resistance Welding	Welding sheet metal, wire, tubes, bars, boxes
Metal Inert Gas Welding	Automotive industry, construction, high production manufacturing
Tungsten Inert Gas Welding	Pipe welding, aerospace, aviation and sheet metal industries

2.1. Tungsten inert gas welding (TIG)

Intelligent attachment systems are slowly replacing welding systems, and robots have made machining processes easier [26]. Weld bead geometry, as shown in Fig. 1 [27,28], dramatically influences the assembly's mechanical properties like strength and [29,30] stress concentration characters [31]. A human-made intelligence TIG welding algorithmic program has been developed to assist and choose the acceptable input parameters which can be used to calculate human data. An automatic TIG welding system uses an associate industrial mechanism to conduct aluminium weld experiments. Controlled method parameters and the resulting weld bead quality measurements are used to make an attachment method dataset [32]. A Gaussian process Regression (GPR) rule has been used to simulate the relationship within the dataset input parameters and output parameters [31]. For a desired thickness of the weld bead, the desired change in attachment current or skill could be expected to handle this method efficiently [33,34]. The use of A.I. in manufacturing will provide solutions to several [35] automation problems faced by the producing department managing advanced techniques.

2.2. Friction stir welding (FSW)

It uses the heat generated between the rotating tool and workpiece material through friction to join two workpieces as shown in Fig. 2 [36]. Friction stir welding has several benefits; however, it depends on several complicated physical processes like temperature distribution, material velocities, the proportion of strain, and different physical and chemical parameters [37]. Altercations within the parameters mentioned above might end in forming pits within the element at a location close to the pin's tip [38]. Spaces in the attachment have an effect on properties and the usefulness of the joints. So, a forecasting technique will play a crucial role in reducing voids.

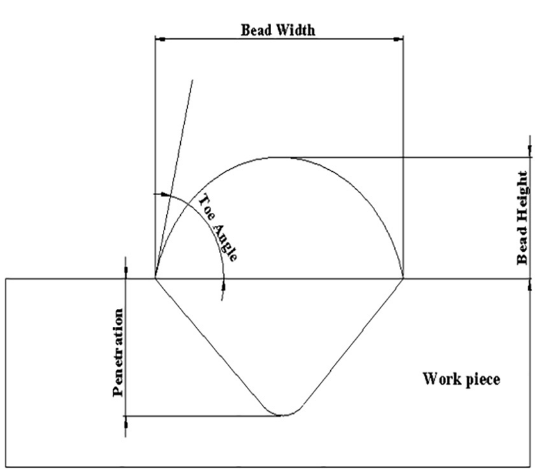

Fig. 1. Weld bead geometry.

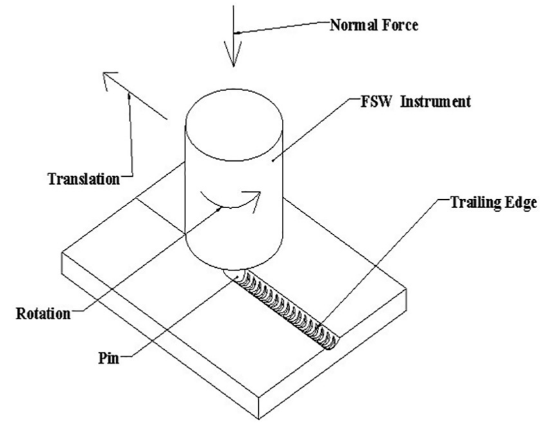

Fig. 2. Schematic diagram of friction stir welding.

2.3. Laser welding

Laser welding is a welding technique used to join pieces of metal or thermoplastics utilizing a laser. The pole gives a concentrated warmth source, thinking about limited, significant welds and [39] high welding rates [40]. The cycle is regularly utilized in high volume applications utilizing mechanization. It is an adaptable cycle, equipped for welding carbon prepares, HSLA prepares, treated steel [41], aluminium, and titanium. [42] The weld quality is high, like that of electron welding [43]. The speed of welding relates to the proportion of power given at this point; what's more, it depends upon the workpieces' sort and thickness. The groundbreaking limit of gas lasers makes them especially proper for high volume applications. It is particularly transcendent in the vehicle business.

2.4. Resistance welding

Resistance welding is done by putting metal parts in contact and joining them by applying heat in the form of an electric current, and thus melting the metal in contact with the joint [44]. The electric current can be supplied to electrodes that also apply clamping pressure or may be induced by [45] an external magnetic field. Some factors as shown in Table 2 are influencing heat or welding temperatures are the proportions of the workpieces, the [82] metal coating or the lack of coating, the electrode materials, electrode geometry, electrode pressing force, electrical current, and length of welding time [46]. However, the equipment required is complex and has a high level of technical maintenance required. It also has a huge capacity and needs a highly skilled single-phase welder [47]. There is a lack of ease, a practical way of carrying out NDT. Intelligent welding systems are being developed to overcome some of these limitations.

2.5. Metal inert gas welding (MIG)

Metal inert gas welding is an arc welding technique that utilizes a solid electrode that is continuously fed, an electric power supply, and a shielding gas comprising of argon or helium or argon-helium mixture [48]. Coalescence required for welding is provided by heating the workpiece with the aid of an electric arc struck between the workpiece and electrode. Higher welding speed [49], greater deposition rate, and less weld contamination make it a compelling option for many applications. But, improper pene-

Table 2
Welding parameters in Resistance Welding.

Welding Parameters
Heating Pulses
Voltage Setting (V)
Welding time (ms)
Electrode force

tration, lack of fusion, and weld profile reduce the quality of weld joint and strength. So, we are going to investigate how machine learning can be used to solve these defects. However, we can reduce these problems with close parameter control.

2.6. Plasma arc welding (PAW)

It is a liquid state welding technique- in which coalescence is generated between a tungsten electrode and a workpiece with the aid of a highly ionized plasma stream. Argon or helium is a commonly used inert gas mixture to provide shielding protection [50]. Close control of the torch and high quality are the significant advantages of plasma arc welding. Heat affected zones and damage is reduced by the advent of the keyhole effect, which is only possible through the precise selection of nozzle-orifice diameter, speed, and current. Uniform welds in thick sections are made possible by the keyhole effect, and it is crucial for producing high-quality welds.

The keyhole geometry as shown in Fig. 3 can be investigated using image processing and evaluating acoustic features to determine the welding property and optimize the parameters to obtain a good quality weld [51].

3. Experimental procedure

We have determined the main problems faced by each welding method through our literature survey. It would investigate how different machine learning techniques can be used to solve the problems faced by each of the welding mentioned above processes. The factors causing the problems have been identified. A literature survey has been done regarding the welding processes and the problems associated with each of them. Methods have been developed to use machine learning to solve these problems. These methods have been explained in the paper. The same procedure as shown in Fig. 4 has been followed for the other types of welding.

3.1. Tungsten inert gas welding (TIG)

The change in the root gap is inevitable and affects the quality of the weld in practical situations [52]. A neural network model can predict the backside dimension and upper height through parameters of the weld and upper form parameters [53,54]. Weld penetration is precisely controlled in mechanized TIG. The dynamic direct model is developed beforehand, and the displaying results broke down. The direct model is then subject to improvisation by fusing a nonlinear operating point shown by an ANFIS

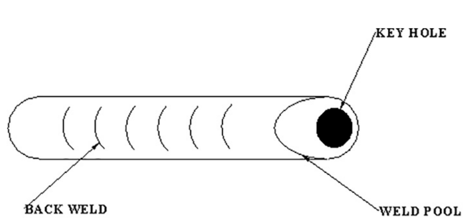

Fig. 3. Schematic diagram of keyhole.

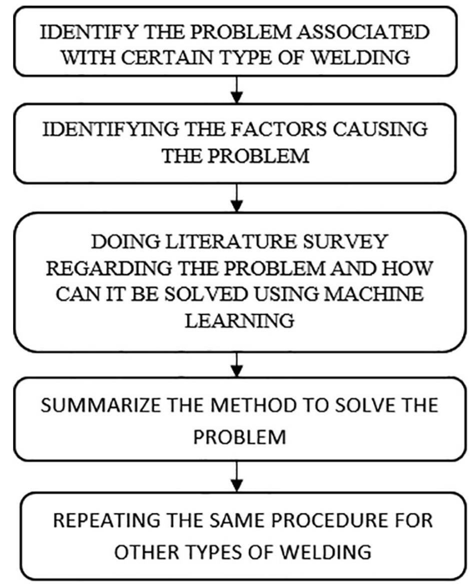

Fig. 4. The flowchart of experimental procedure.

(adaptive neuro-fuzzy inference system). ANFIS model will model human craftsman intelligence with acceptable accuracy of 1.5 delays [55,56]. The resultant model has been compared with the model derived from amateur artisans and used to improvise and control the TIG process [57]. Weld pool dynamics conduct would be checked utilizing each dynamic and inactive vision technique to obstruct circular section light within the picture [58]. Computer vision calculations from latent vision footage have been created to systematically analyze the 3D weld pool calculation's surface calculation [59]. A modern visual double-sided sensing system can imagine the weld pool upper side and backside simultaneously in the frame by illuminating the weld pool with arc lamp emission to get a clear image beneath the base current.

3.2. Friction stir welding

The procedure for the perception of the weld quality in friction stir welding was done through information from prior welds [60,61]. These were made underneath completely different welding conditions by variable speeds of entirely different components. The extended watching framework gives a quantitative measure weld joint than subjective measure area appearance. The relationship between surface properties and rigidity proposes that the weld joint with the sporadic and faulty surface have lower quality. This relationship was used for building up an observation strategy for friction stir welding [62]. ANFIS procedure is utilized to anticipate the quality and strength of friction welded empty line joints with the assistance of an A.I. neural network joined with the standard of formal logic. The extended model is many inputs but a single yield kind of model that utilizes rotatory speed and produces load as information signals. Fuzzy logic that is fundamentally dependent on the ANFIS framework was adaptable and easy to comprehend and will subsequently substitute to the conventional demonstrating strategies. Fuzzy logic permitted the demonstrating and online administration downside to be treated simultaneously.

3.3. Laser welding

Weld surrenders in high voltage circle laser welding cause mediocre weld appearance and exceptionally crumbles the weld quality.[63] A Profound learning algorithmic program dependent on a convolutional neural organization (CNN) was created to watch 3 entirely unexpected connection absconds all through high-power plate laser welding. It utilized a various finder framework with assistant enlightenment (A.I.) visual locator framework, a UVV band visual identifier framework, a spectroscope, and 2 photodiodes, to set up welding status. A filter has been fitted to filter the radiations from the beam and plasma. PCA algorithmic program has also been accustomed to cutting back on the redundancy of information to accelerate the training method. The PCA algorithmic program would be accustomed to improve prediction accuracy [64]. A self-advancing machine with the help of three ML techniques has been used to extract meaningful, low-dimensional options from high-dimensional laser-welding camera information and situation-appropriate welding power [65]. Optical coherence tomography (OCT) permits a quick estimating of the geography inside the cycle zone continuously [66]. It is independent of technique emanations and metal fume or plasma and is assessed and superimposed with the confounded and dynamic marvels inside the cycle zone to make solid inferences concerning the weld crease quality.

3.4. Resistance welding

An intelligent framework is anticipated for changing the amount of current to remunerate the cathode corruption brought about by mushroom impact (the expansion inside the transmitter breadth on account of copper deposition into the spot surface) for welding covered steel. The strategy will be all the more precisely higher by synchronizing extra strategies to channel undesirable commotions [67]. Simulated intelligence procedures are utilized for watching the weld nature of minor scope resistance spot welding measures. The time qualification between the intonation point and the beta point and the comparing amplitude distinction, the declining pace of the bend Vs. and the weld heat Q is the boundaries utilized as info factors for the ANN. The voltage mark may likewise be utilized as a constant no-destructive approach for watching the weld quality.

3.5. Metal inert gas welding

Welding current, gas pressure, and welding speed are the significant parameters responsible for welding hardness and tensile strength in MIG welding [68]. The combinations of these parameters can be suggested for target quality using ANOVA, and these parameters can further be optimized using a Genetic Algorithm. Then a subsequent Artificial Neural Network (ANN) is designed based on experimental results capable of predicting accurate values of hardness and ultimate tensile strength based on the input parameters of gas pressure, welding current, and welding speed.

3.6. Plasma arc welding

Prediction based on the keyhole's acoustic features is made using extreme learning machine techniques that provide excellent regression analysis [69]. Another method is with the aid of a fuzzy neural network [70]. It is designed using Taguchi experiments, which can act as an intelligent decision support system capable of optimizing different weld parameters. Taguchi method is an 8-step optimization method that involves proposal, managing, and analyzing outcomes of matrix experiments to find the best levels of control factors. Electric current, welding speed, inert gas flow, and voltage are the input parameters chosen for designing the network. Welding is one of the initial processes in many industries, such as the automobile industry, robotics industry, marine industry, etc. It is a permanent joint between metals or dissimilar materials. Joining of components is one of the incredibly essential processes in [23] manufacturing. Welding requires [24] highly skilled labour, and hence it is one of the highly paid jobs in the manufacturing sector [4]. The quality of welding processes in a country is essential for its [25] economy. This paper would study some of the welding processes and some of the problems associated with it.

4. Results and discussion

The results obtained after implementing the experiment procedure mentioned in the previous section is discussed in this section

4.1. Tungsten inert gas welding

The intelligent welding techniques for mechanical systems conclude the vision sensing and follow the weld seam. Other factors are the programmed path, pose weld parameters, modeling of knowledge, and real-time intelligent management of welding dynamics, optimizing attachment management manufacturing cell/system, etc. [71]. The technique was checked with dot on-plate and butt-joint welding tests [58]. The dynamic neuro-fuzzy model is projected to stimulate the intrinsic nonlinear fuzzy-based model mechanism that mimics a human welder [72]. Closed-loop control experiments beneath various disturbances have examined the model-based controller's efficiency and strength, and initial conditions and results are quite promising.

4.2. Friction stir welding

The Support Vector Machines [73] is employed for weld segregation of friction stir welding utilizing the features from the [74] surface image, and it's trained with entirely different kernel functions. These can classify defect weld and sensible weld with an accuracy of over 90%. Gap formation conditions are employed using a decision tree, and a Bayesian neural network was expected, employing a set of welding parameters. It produces incredibly correct predictions of the accuracy of over 95%. Since void formation is very undesirable in friction stir welding, neural networks and machine learning algorithms will facilitate the welder and cut back void formation. There is a heap of scope and gap out there in this field. There is an excellent need to implement machine learning techniques to [75] predict process parameters in FSW or FSSW.

4.3. Laser welding

Weld bead geometry optimization using Artificial Intelligence has been carried out for the Al-Mg sheet laser welding. The results given by machine learning and traditional methods have been compared [76]. Different parameters like oxygen pressure, pulse width, pulse frequency, etc. have been compared, and these parameters dictate the process's efficiency. Hence, comparing these parameters from both methods will provide us an insight into the accuracy of the machine learning approach to laser welding [77]. The graph shown in Fig. 5 depicts the various parameters and the percentile difference between the values obtained by both methods.

4.4. Resistance welding

MATLAB code would be accustomed to efficiency to analyze the sound signals' information [78]. The anomaly election model was established for the unbalanced knowledge classification compared with alternative strategies like [79,80] one-class SVM and [81] native outlier issues.

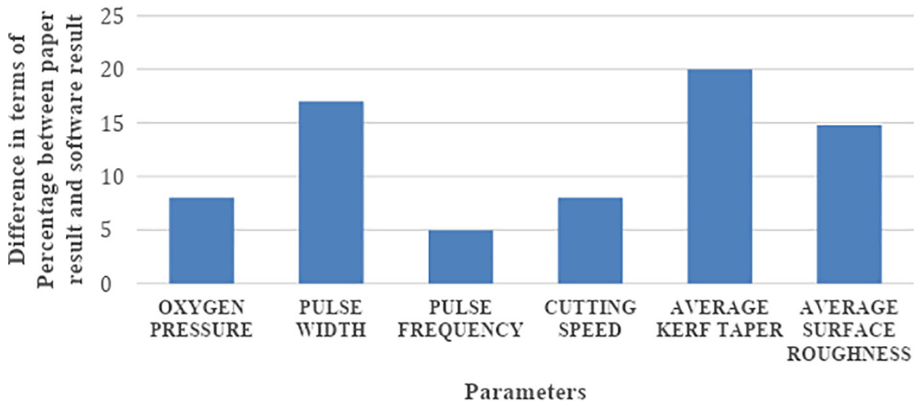

Fig. 5. Graph depicting the accuracy of machine learning in laser welding.

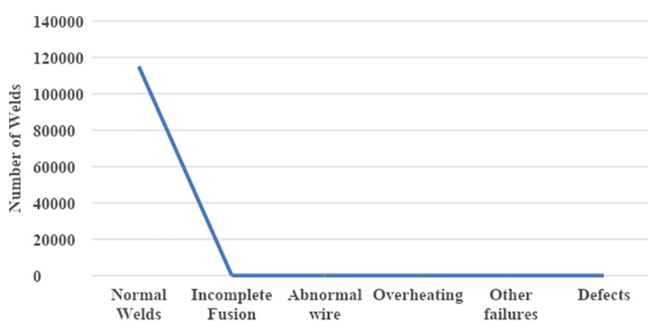

Fig. 6. Graph showing the determination of weld quality and visual testing results estimated manually.

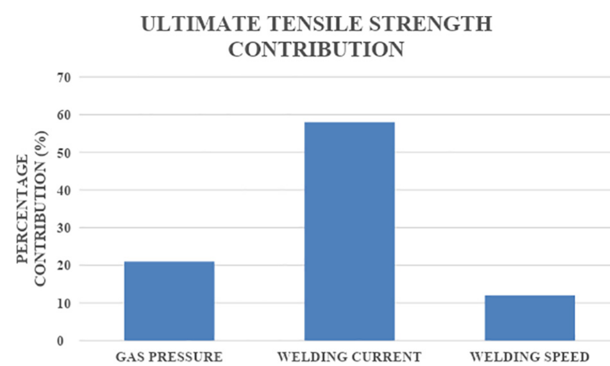

Fig. 7. Graphs showing the contribution of gas pressure, welding current, and welding speed to UTS and hardness.

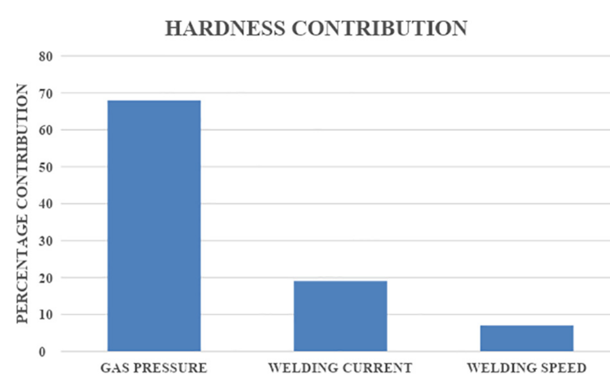

Fig. 8. Graphs showing the contribution of gas pressure, welding current, and welding speed to UTS and hardness.

Fig. 6 shows the result of weld quality and testing manually, which are calculated manually. It is mainly split into 2 classes (normal and abnormal) and the class imbalance causes a massive difference between the minority and the majority. However, it is still crucial and would assist the quality observation of the welding method of enameled wire that is to be manufactured [68]. Overall, it is a practical methodology for internal control such as resistance and power waveforms while also enabling intelligent NDT for defect testing.

4.5. Metal inert gas welding

It is inferred from the results shown in Figs. 7 and 8 [82], that gas pressure is a crucial factor for the hardness of welding, whereas the welding current is a pivotal factor for the tensile strength of welding. Another mathematical tool that can be used to model and analyze a process in which various parameters influence the response of interest to improve the response is Response surface methodology [83]. A set of planned experiments are conducted to obtain an improved response in Response Surface Methodology. So, this methodology can be employed here to determine various experimental values that can be utilized to design an accurate ANN model capable of predicting values of strength and hardness. Further, this same methodology can be adopted for predicting the values of other desired properties like weld profile depending on input parameters [84]. Machine learning can reduce the complexity and uncertainty in output associated with metal inert gas welding.

4.6. Plasma arc welding

A binary sensor system is designed to picture the keyhole from behind the job using the predictions made using extreme learning machine techniques [64,85]. A neural network, which is back-propagating and support vector machine techniques, were also used to construct similar networks, but the extreme learning machine technique was better [73]. This system was able to predict the welding property and optimize the parameters effectively. A fuzzy neural network was designed using the Taguchi method to optimize the parameters like an electric current, welding speed, inert gas flow rate, and voltage [70]. The Taguchi method's main aim is to decrease the difference in output in the existence of unwanted inputs. This intelligent system can also predict the weld's quality, even for a different design of untrained welding parameters, and decrease training time in a back-propagation neural network. Thus, machine learning can significantly improve the plasma welding process and enhance its efficiency.

5. Discussion

The inferences and the merits of using these techniques and the future scope of these techniques in different welding processes mentioned in the previous sections are discussed in this section.

5.1. Tungsten inert gas welding

For tungsten inert gas welding, the feasibility of various processes are checked, and based upon that; machine learning models are developed [52]. Real-time data gathered from numerous welds was filtered and analyzed using intelligent models to predict defects and mimic human accuracy [58]. While rapid welding speed gave better infiltration contrast, the imperfections caused could be covered up through proper camera sensor identification [31,52]. Controllable parameters such as weld speed, arc length, and input current play a massive role in determining the weld's accuracy. In the future, the effects of the heat affected zone and other welding conditions need to be further explored to improve the model's database.

5.2. Friction stir welding

Temperature distribution, material velocities, the proportion of strain [36], and different physical and chemical parameters influence weld bead geometry and void formation in friction stir welding [38]. The void formation is highly undesirable in friction stir welding and forecasting methods that employ [73] machine learning algorithms to tackle this issue to a great extent. The accuracy of such a forecasting technique is also promising [60]. However, forecasting cannot alone solve the issue of void formation. Machine learning techniques still have a significant role in optimizing process parameters involved in friction stir welding to solve the problems of void formation. So, the scope of machine learning in this domain is huge and needs to be explored [90–94].

5.3. Laser welding

Systems [64] developed from machine learning algorithms captured successive real-time images from high-speed welding and tracked its progress [77]. The main issues encountered were that of control, for which the models used the image data to predict and anticipate further aspects and develop position appropriate welding parameters. It is seen that adding additional dimensional sensors will not affect the systems processing capability and is well within the stipulated time limit [39]. The keyhole area and the weld pool are essential features to be analyzed for further testing and data collection. Other challenges include pre and post-processing quality monitoring and data control to increase the accuracy and conform them to the industrial standards.

5.4. Resistance welding

Electrode degradation or the mushrooming effect is a primary problem of resistance welding that requires precise controlling of the secondary current to eliminate [67]. This was achieved using neuro-fuzzy models that adapted the current to cold welds, thus reducing defects [81]. The heat inputs and positions of the workpiece and operating speed are significant parameters that determine the weld defects [68]. The voltage signature can play a huge role in detecting weld anomalies and an NDT method for small scale resistance welds. So, many of the resistance welding problems can be solved by optimizing and controlling these parameters using different machine learning techniques.

5.5. Metal inert gas welding

In the case of metal inert gas welding, machine learning was used to determine the significant parameters which contribute towards hardness and tensile strength among welding current, gas pressure, and welding speed [68]. Once the main contributing parameters, we can give more attention to that parameter to improve weld property [82]. It is inferred from results that welding current is the significant parameter influencing tensile strength, and gas pressure is the crucial factor for the hardness. Similarly, we need to find solutions to encounter MIG's main problems such as improper penetration, lack of fusion, and lack of control over the weld profile [84]. With the help of more sophisticated machine learning algorithms, these issues can be tackled.

5.6. Plasma arc welding

Keyhole geometry plays a vital role in the quality of weld obtained from plasma welding [51]. Neural networks along with [64] sensor systems were used to optimize keyhole geometry with the control over nozzle-orifice diameter, speed, and current. Results obtained from this system are promising and suggest using similar methods to tackle other issues affecting the weld quality of plasma arc welding. One of the successful methods to control and optimize weld parameters like an electric current [70], welding speed, inert gas flow rate, and voltage mentioned in the results section is using the Taguchi method implemented using neural networks. So, the application of machine learning in plasma arc welding is enormous, and in upcoming years, we require more technology that can improve the quality of weld bead obtained from PAW and also making it cheap and more [24] accessible to low-skilled operators.

5.7. Other applications

Other than the above mentioned six welding process, the use of machine learning in welding can be extended to many more applications [86]. Thermoplastic composite materials have been welded by induction welding using machine learning techniques [87]. Visual Inspection is an important step in monitoring weld quality, and in most cases, it entirely depends on the welder's ability and often susceptible to errors. But, machine learning techniques can also be used in visual inspection to reduce the errors associated with the traditional methods [88]. A portable device was developed using machine learning algorithms, which can provide real-time results of the section and can significantly improve visual inspection. Another method for inspection of welding joints is done through [74,89] ultrasound, which scans the weld and convolutional neural network analysis of the scan and gives the feedback [20]. Welding fumes are harmful and must be dealt with caution. With the help of the bioinformatics model which was developed using machine learning, we were able to understand the relationship between welding fumes and cancer. So, with advanced improvements in machine learning, we will be able to obtain new findings of the dangers and risks associated with different welding processes and how to reduce them.

6. Conclusion

Machine learning is a beneficial method to solve problems faced in welding processes. It can improve the welding process effectiveness as well as the process of quality monitoring. It has helped in being able to detect defects during welding in real-time. Problems that are faced in traditional welding processes have been solved using machine learning. It has been used to forecast the weld bead geometry in TIG welding. The weld quality in friction stir welding has been monitored using data from previous welds which were produced under various welding conditions. Welding defects have been detected in laser welding with the aid of machine learning techniques like neural networks. In GMAW, the weld penetration has been accurately controlled by using a neural network model. The weld quality of the resistance welding process has been monitored using artificial intelligence. The weld properties in MIG welding have been forecasted using artificial neural networks. In plasma arc welding, the parameter optimization was carried out using a fuzzy neural network.

There is significant scope in further research regarding increasing the accuracy of the predictions by artificial intelligence. The algorithms could be made more accurate. The mechanisms could be designed in a better way to facilitate smoother motion that is free of any vibrational or frictional losses. The motion of the camera could be made better by using creative engineering techniques that would minimize the losses to a great extent.

In the future, there are possibilities of the welding industry switching almost entirely to machine learning. The monitoring and prediction processes could become highly accurate. The efficiency would become unmatched by any other traditional welding process and could become completely automated.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The work is supported by School of Mechanical Engineering, Vellore Institute of Technology, Vellore, India.

References

[1] M. Rodrigues, M. Kormann, C. Schuhler, P. Tomek, An intelligent real time 3D vision system for robotic welding tasks, in: 2013 9th International Symposium on Mechatronics and its Applications (ISMA), IEEE, 2013, April, pp. 1–6.
[2] C. Chen, N. Lv, S. Chen, Data-Driven Welding Expert System Structure Based on Internet of Things, in: Transactions on Intelligent Welding Manufacturing, Springer, Singapore, 2018, pp. 45–60.
[3] T. Yifei, Z. Meng, L. Jingwei, L. Dongbo, W. Yulin, Research on intelligent welding robot path optimization based on G.A. and PSO algorithms, IEEE Access 6 (2018) 65397–65404.
[4] B. Wang, S.J. Hu, L. Sun, T. Freiheit, Intelligent welding system technologies: State-of-the-art review and perspectives, J. Manuf. Syst. 56 (2020) 373–391. https://linkinghub.elsevier.com/retrieve/pii/S0278612520301102.
[5] Q. Wang, Y. Cheng, W. Jiao, M.T. Johnson, YuMing Zhang, Virtual reality human-robot collaborative welding: A case study of weaving gas tungsten arc welding, J. Manuf. Processes 48 (2019) 210–217. https://linkinghub.elsevier.com/retrieve/pii/S1526612519303330.
[6] D. Sanders, G. Tewkesbury, D. Ndzi, A. Gegov, B. Gremont, A. Little, Improving automatic robotic welding in shipbuilding through the introduction of a corner-finding algorithm to help recognise shipbuilding parts, J. Mar. Sci. Technol. 17 (2) (2012) 231–238. http://link.springer.com/10.1007/s00773-011-0154-x.
[7] D.A. Sanders, Z. Rasol, An automatic system for simple spot welding tasks, Total vehicle technology: Challenging current thinking, 2001, pp. 263–272.
[8] D. Laha, Ye Ren, P.N. Suganthan, Modeling of steelmaking process with effective machine learning techniques, Expert Syst. Appl. 42 (10) (2015) 4687–4696. https://linkinghub.elsevier.com/retrieve/pii/S0957417415000457.
[9] J. Stavridis, A. Papacharalampopoulos, P. Stavropoulos, A cognitive approach for quality assessment in laser welding, Procedia CIRP 72 (2018) 1542–1547. https://linkinghub.elsevier.com/retrieve/pii/S2212827118302762.
[10] F. Echtler, F. Sturm, K. Kindermann, G. Klinker, J. Stilla, J. Trilk, H. Najafi, in: Virtual and Augmented Reality Applications in Manufacturing, Springer London, London, 2004, pp. 333–360. http://link.springer.com/10.1007/978-1-4471-3873-0_17, https://doi.org/10.1007/978-1-4471-3873-0_17.
[11] Y. Matsui, Y. Iizuka, M. Suzuki, E. Urahata, T. Inoue, S. Kumazawa, M. Oka, Development of an ultrasonic phased array testing system that can evaluate quality of weld seam of high-quality ERW pipes, in: International Pipeline Conference, vol. 45134, American Society of Mechanical Engineers, 2012, September, pp. 65–72.
[12] C.J. Arizmendi, W.L. Garcia, M.A. Quintero, Automatic welding detection by an intelligent tool pipe inspection, in: Journal of Physics: Conference Series, vol. 628, No. 1, IOP Publishing, 2015, p. 012082.
[13] W. Zhang, Evolution of computer simulation and optimization with potential for machine learning and artificial intelligence.
[14] C.A. Escobar, R. Morales-Menendez, Machine learning techniques for quality control in high conformance manufacturing environment, Adv. Mech. Eng. 10 (2) (2018), 1687814018755519.
[15] S.W.E.T.H.A. Danthala, S.E.E.R.A.M.S.R.I.N.I.V.A.S.A. Rao, K.A.S.I.P.R.A.S.A.D. Mannepalli, D. Shilpa, Robotic Manipulator Control by using Machine Learning Algorithms: A Review, Int. J. Mech. Prod. Eng. Res. Develop. 8(5) (2018) 305–310.
[16] Y. Liu, Virtualized Welding Based Learning of Human Welder Behaviors for Intelligent Robotic Welding, 2014.
[17] E. Kamar, S. Hacker, E. Horvitz, Combining human and machine intelligence in large-scale crowdsourcing, AAMAS 12 (2012) 467–474.
[18] D. Dubey, U.K. Dewangan, M. Soni, M.K. Narang, An Investigation of Application of Artificial Intelligence in Robotic, 2019.
[19] W. Hou, D. Zhang, Y. Wei, J. Guo, X. Zhang, Review on Computer Aided Weld Defect Detection from Radiography Images, Appl. Sci. 10 (5) (2020) 1878.
[20] M.A. Hossain, S.M. Saiful Islam, J.M.W. Quinn, F. Huq, M.A. Moni, Machine learning and bioinformatics models to identify gene expression patterns of ovarian cancer associated with disease progression and mortality, J. Biomed. Inform. 100 (2019) 103313. https://linkinghub.elsevier.com/retrieve/pii/S1532046419302321, https://doi.org/10.1016/j.jbi.2019.103313.
[21] K. Anand, S. Elangovan, C. Rathinasuriyan, Modeling and prediction of weld strength in ultrasonic metal welding process using artificial neural network and multiple regression method, Mater. Sci. Eng. Int. J. 2 (2) (2018) 40–47.
[22] L. Monostori, A.I. and machine learning techniques for managing complexity, changes and uncertainties in manufacturing, Eng. Appl. Artif. Intell. 16 (4) (2003) 277–291.
[23] X. Zhan, W. Ou, Y. Wei, J. Jiang, The feasibility of intelligent welding procedure qualification system for Q345R SMAW, Int. J. Adv. Manuf. Technol. 83 (5-8) (2016) 765–777. http://link.springer.com/10.1007/s00170-015-7295-8.
[24] Y.K. Liu, W.J. Zhang, Y.M. Zhang, A tutorial on learning human welder's behavior: Sensing, odelling, and control, J. Manuf. Processes 16 (1) (2014) 123–136.
[25] W.C. Higgins, U.S. Patent No. 5,376,766, U.S. Patent and Trademark Office, Washington, DC, 1994.
[26] A. Mayr, M. Weigelt, M. Masuch, M. Meiners, F. Hüttel, J. Franke, Application Scenarios of Artificial Intelligence in Electric Drives Production, Procedia Manuf. 24 (2018) 40–47. https://linkinghub.elsevier.com/retrieve/pii/S2351978918305237.
[27] I.S. Kim, J.S. Son, C.E. Park, I.J. Kim, H.H. Kim, An investigation into an intelligent system for predicting bead geometry in GMA welding process, J. Mater. Process. Technol. 159 (1) (2005) 113–118. https://linkinghub.elsevier.com/retrieve/pii/S0924013604007873.
[28] J. Mathew, J. Griffin, M. Alamaniotis, S. Kanarachos, M.E. Fitzpatrick, Prediction of welding residual stresses using machine learning: Comparison between neural networks and neuro-fuzzy systems, Appl. Soft Comput. 70 (2018) 131–146. https://linkinghub.elsevier.com/retrieve/pii/S1568494618302801.
[29] P. Rodriguez-Gonzalvez, M. Rodriguez-Martin, Weld Bead Detection Based on 3D Geometric Features and Machine Learning Approaches, IEEE Access 7 (2019) 14714–14727. https://ieeexplore.ieee.org/document/8604036/.
[30] Y. Lu, M. Rajora, P. Zou, S.Y. Liang, Physics-embedded machine learning: case study with electrochemical micro-machining, Machines 5 (1) (2017) 4.
[31] S.A. Huff, TIG welding skill extraction using a machine learning algorithm, 2017.
[32] Q. Wang, W. Jiao, P. Wang, YuMing Zhang, A tutorial on deep learning-based data analytics in manufacturing through a welding case study, J. Manuf. Processes (2020). https://linkinghub.elsevier.com/retrieve/pii/S1526612520302668, https://doi.org/10.1016/j.jmapro.2020.04.044.
[33] H. Ates, Prediction of gas metal arc welding parameters based on artificial neural networks, Mater. Des. 28 (7) (2007) 2015–2023. https://linkinghub.elsevier.com/retrieve/pii/S0261306906002081.
[34] S. Penttilä, P. Kah, J. Ratava, H. Eskelinen, Artificial Neural Network Controlled GMAW System: Penetration and Quality Assurance in a Multi-Pass Butt Weld Application, Int. J. Adv. Manuf. Technol. 105 (7-8) (2019) 3369–3385. http://link.springer.com/10.1007/s00170-019-04424-4.
[35] R.T. Martinez, S.C.A. Alfaro, Data Analysis and Modeling Techniques of Welding Processes: The State-of-the-Art, Welding, IntechOpen, 2020.
[36] Y. Du, T. Mukherjee, T. DebRoy, Conditions for void formation in friction stir welding from machine learning, npj Comput. Mater. 5 (1) (2019) 1–8.
[37] W. Cai, G. Daehn, A. Vivek, J. Li, H. Khan, R.S. Mishra, M. Komarasamy, A state-of-the-art review on solid-state metal joining, J. Manuf. Sci. Eng. 141 (3) (2019).

[38] K. Schrickera, M. Glasera, J.P. Bergmanna, Applied machine learning for predicting the weld seam geometry based on the example of laser-assisted metal-plastic joining.
[39] C. Knaak, G. Kolter, F. Schulze, M. Kröger, P. Abels, Deep learning-based semantic segmentation for in-process monitoring in laser welding applications, in: Applications of Machine Learning, vol. 11139, International Society for Optics and Photonics, 2019, September, pp. 1113905.
[40] D. You, X. Gao, S. Katayama, WPD-PCA-Based Laser Welding Process Monitoring and Defects Diagnosis by Using FNN and SVM, IEEE Trans. Ind. Electron. 62 (1) (2015) 628–636. https://ieeexplore.ieee.org/document/6803929.
[41] M.P. Satpathy, S.B. Mishra, S.K. Sahoo, Ultrasonic spot welding of aluminum-copper dissimilar metals: A study on joint strength by experimentation and machine learning techniques, J. Manuf. Processes 33 (2018) 96–110. https://linkinghub.elsevier.com/retrieve/pii/S1526612518303682.
[42] C. Knaak, U. Thombansen, P. Abels, M. Kröger, Machine learning as a comparative tool to determine the relevance of signal features in laser welding, Procedia CIRP 74 (2018) 623–627.
[43] J. Reis, G. Gonçalves, Process Modeling and Parameter Optimization for Machine Calibration in Smart Manufacturing for Laser Seam Welding, The Seventh International Conference on Intelligent Systems and Applications (INTELLI), IARIA, 2018.
[44] N. Nayak, A. Ray, An integrated system for intelligent seam tracking in robotic welding. Conceptual and analytical development, in: Proceedings., IEEE International Conference on Robotics and Automation, IEEE, 1990, May, pp. 1892–1897.
[45] W. Jiao, End-to-end prediction of weld penetration in real time based on deep learning, 2020.
[46] J. Muhammad, H. Altun, E. Abo-Serie, A robust butt welding seam finding technique for intelligent robotic welding system using active laser vision, Int. J. Adv. Manuf. Technol. 94 (1-4) (2018) 13–29. http://link.springer.com/10.1007/s00170-016-9481-8.
[47] J. Molleda, J.L. Carús, R. Usamentiaga, D.F. García, J.C. Granda, J.L. Rendueles, A fast and robust decision support system for in-line quality assessment of resistance seam welds in the steelmaking industry, Comput. Ind. 63 (3) (2012) 222–230. https://linkinghub.elsevier.com/retrieve/pii/S0166361512000048.
[48] J. Shah, G. Patel, J. Makwana, P. Chauhan, Optimization and Prediction of MIG Welding Process Parameters using ANN, Gas 150 (170) (2018) 190.
[49] H. Dong, M. Cong, Y. Zhang, Y. Liu, H. Chen, Modeling and real-time prediction for complex welding process based on weld pool, Int. J. Adv. Manuf. Technol. 96 (5-8) (2018) 2495–2508. http://link.springer.com/10.1007/s00170-018-1685-7.
[50] G. Meijuan T. Jingwen L. Erhong, Intelligent Control System of Welding Torch's Attitude for Pipeline Welding Robot, in: 2007 8th International Conference on Electronic Measurement and Instruments, IEEE, 2007, August, pp. 3–665.
[51] T. Wuest, D. Weimer, C. Irgens, K.-D. Thoben, Machine learning in manufacturing: advantages, challenges, and applications, Prod. Manuf. Res. 4 (1) (2016) 23–45.
[52] M.A. Kesse, E. Buah, H. Handroos, G.K. Ayetor, Development of an Artificial Intelligence Powered TIG Welding Algorithm for the Prediction of Bead Geometry for TIG Welding Processes using Hybrid Deep Learning, Metals 10 (4) (2020) 451.
[53] T. Lin, H.B. Chen, W.H. Li, S.B. Chen, Intelligent methodology for sensing, modelling, and control of weld penetration in robotic welding system, Ind. Robot Int. J. (2009).
[54] C. Li, Weld Penetration Identification Based on Convolutional Neural Network, 2019.
[55] Y. Liu, W. Zhang, Y. Zhang, Dynamic neuro-fuzzy-based human intelligence modelling and control in GTAW, IEEE Trans. Autom. Sci. Eng. 12 (1) (2013) 324–335.
[56] G.J. Zhang, S.B. Chen, L. Wu, Intelligent control of pulsed GTAW with filler metal, Welding J. 84 (1) (2005) 9s–16s.
[57] S.A. David, J. Chen, B.T. Gibson, Z. Feng, Intelligent weld manufacturing: Role of integrated computational welding engineering, in: Transactions on Intelligent Welding Manufacturing, Springer, Singapore, 2018, pp. 3–30.
[58] Z. Chen, Visual Sensing and Defect Detection of Gas Tungsten Arc Welding, 2019.
[59] S.B. Chen, Y.J. Lou, L. Wu, D.B. Zhao, Intelligent methodology for sensing, modelling and control of pulsed GTAW: Part 1—Bead-on-plate welding, Weld. J. (USA) 79 (6) (2000) 151.
[60] S. Sudhagar, M. Sakthivel, P. Ganeshkumar, Monitoring of friction stir welding based on vision system coupled with Machine learning algorithm, Measurement 144 (2019) 135–143. https://linkinghub.elsevier.com/retrieve/pii/S0263224119304348.
[61] N. Tauqir, A. Mohammed, Z. Qassim, S. Davut, Applications of Machine Learning to Friction stir Welding Process Optimization, Jurnal Kejuruteraan 32 (1) (2020) 171–186.
[62] S.S. Gill, J. Singh, Artificial intelligent odelling to predict tensile strength of inertia friction-welded pipe joints, Int. J. Adv. Manuf. Technol. 69 (9–12) (2013) 2001–2009.
[63] Y. Zhang, D. You, X. Gao, N. Zhang, P.P. Gao, Welding defects detection based on deep learning with multiple optical sensors during disk laser welding of thick plates, J. Manuf. Syst. 51 (2019) 87–94. https://linkinghub.elsevier.com/retrieve/pii/S0278612518301894.
[64] W. Cai, J. Wang, L. Cao, G. Mi, L. Shu, Q. Zhou, P. Jiang, Predicting the weld width from high-speed successive images of the weld zone using different machine learning algorithms during laser welding, Math. Biosci. Eng. MBE 16 (5) (2019) 5595–5612.
[65] J. Günther, P.M. Pilarski, G. Helfrich, H. Shen, K. Diepold, Intelligent laser welding through representation, prediction, and control learning: An architecture with deep neural networks and reinforcement learning, Mechatronics 34 (2016) 1–11. https://linkinghub.elsevier.com/retrieve/pii/S0957415815001555.
[66] C. Stadter, M. Schmoeller, L. von Rhein, M.F. Zaeh, Real-time prediction of quality characteristics in laser beam welding using optical coherence tomography and machine learning, J. Laser Appl. 32 (2) (2020) 022046. http://lia.scitation.org/doi/10.2351/7.0000077, https://doi.org/10.2351/7.0000077.
[67] M. El-Banna, D. Filev, R.B. Chinnam, Intelligent constant current control for resistance spot welding, in: 2006 IEEE International Conference on Fuzzy Systems, IEEE, 2006, July, pp. 1570–1577.
[68] D. Zhao, Y. Wang, Z. Lin, S. Sheng, Quality Monitoring Research of Small Scale Resistance Spot Welding Based on Voltage Signal, ISIJ Int. 53 (2) (2013) 240–244. http://jlc.jst.go.jp/DN/JST.JSTAGE/isijinternational/53.240?lang=en&from=CrossRef&type=abstract.
[69] D.i. Wu, H. Chen, Y. He, S. Song, T. Lin, S. Chen, A prediction model for keyhole geometry and acoustic signatures during variable polarity plasma arc welding based on extreme learning machine, SR 36 (3) (2016) 257–266.
[70] S.C. Chi L.C. Hsu, A fuzzy radial basis function neural network for predicting multiple quality characteristics of plasma arc welding, in: Proceedings Joint 9th IFSA World Congress and 20th NAFIPS International Conference (Cat. No. 01TH8569), IEEE, 2001, July, pp. 2807–2812.
[71] S.B. Chen, T. Qiu, T. Lin, L. Wu, J.S. Tian, W.X. Lv, Y. Zhang, Intelligent technologies for robotic welding, in: Robotic Welding, Intelligence and Automation, Springer, Berlin, Heidelberg, 2004, pp. 123–143.
[72] YuKang Liu, Toward intelligent welding robots: virtualized welding based learning of human welder behaviors, Weld World 60 (4) (2016) 719–729. http://link.springer.com/10.1007/s40194-016-0340-x.
[73] I.S. Kim, Y.J. Jeong, C.W. Lee, P.K.D.V. Yarlagadda, Prediction of welding parameters for pipeline welding using an intelligent system, Int. J. Adv. Manuf. Technol. 22 (9-10) (2003) 713–719. http://link.springer.com/10.1007/s00170-003-1589-y.
[74] D.A. Sanders, G. Lambert, J. Graham-Jones, G.E. Tewkesbury, S. Onuh, D. Ndzi, C. Ross, A robotic welding system using image processing techniques and a CAD model to provide information to a multi-intelligent decision module, Assem. Automat. 30 (4) (2010) 323–332.
[75] A. Khdoudi, T. Masrour, Prediction of Industrial Process Parameters using Artificial Intelligence Algorithms, arXiv preprint arXiv:1812.10537, 2018.
[76] M.M. Kumar, M.S. Tripathi, Artificial Intelligence based optimization of weld bead geometry in laser welding of Al-Mg alloy sheet.
[77] J. Günther, P.M. Pilarski, G. Helfrich, H. Shen, K. Diepold, First Steps Towards an Intelligent Laser Welding Architecture Using Deep Neural Networks and Reinforcement Learning, Procedia Technol. 15 (2014) 474–483. https://linkinghub.elsevier.com/retrieve/pii/S2212017314001224.
[78] A. Sumesh, K. Rameshkumar, K. Mohandas, R.S. Babu, Use of Machine Learning Algorithms for Weld Quality Monitoring using Acoustic Signature, Procedia Comput. Sci. 50 (2015) 316–322. https://linkinghub.elsevier.com/retrieve/pii/S1877050915005438.
[79] R. Kshirsagar, S. Jones, J. Lawrence, J. Tabor, Prediction of Bead Geometry Using a Two-Stage SVM–ANN Algorithm for Automated Tungsten Inert Gas (TIG) Welds, J. Manuf. Mater. Process. 3(2) (2019) 39.
[80] D. Marić, M. Duspara, T. Šolić, I. Samardžić, Application of SVM Models for Classification of Welded Joints, Tehnički vjesnik 26 (2) (2019) 533–538.
[81] J. Zeng, B. Cao, R. Tian, Quality Monitoring for Micro Resistance Spot Welding with Class-Imbalanced Data Based on Anomaly Detection, Appl. Sci. 10 (12) (2020) 4204.
[82] D. Lee, N. Ku, T.-W. Kim, J. Kim, K.-Y. Lee, Y.-S. Son, Development and application of an intelligent welding robot system for shipbuilding, Rob. Comput. Integr. Manuf. 27 (2) (2011) 377–388. https://linkinghub.elsevier.com/retrieve/pii/S0736584510001055.
[83] A. Narayana, T. Srihari, Optimization of weld bead geometry in MIG welding process using response surface methodology, Int. J. Sci. Technol. 2 (4) (2012).
[84] I.S. Kim, Y.K.D.V. Prasad, L.A. Stoynov, A study on an intelligent system to predict the tensile stress in welding using solar energy concentration, J. Mater. Process. Technol. 153-154 (2004) 649–653. https://linkinghub.elsevier.com/retrieve/pii/S0924013604003504.
[85] P. Kah, M. Shrestha, E. Hiltunen, J. Martikainen, Robotic arc welding sensors and programming in industrial applications, Int. J. Mech. Mater. Eng. 10 (1) (2015). http://link.springer.com/10.1186/s40712-015-0042-y, https://doi.org/10.1186/s40712-015-0042-y.
[86] H. Guo, J. Pandher, M. van Tooren, S. Wang, Process modelling of induction welding for thermoplastic composite materials by neural networks, 2019.
[87] Y. Gong, Z. Lin, J. Wang, N.a. Gong, Bringing Machine Intelligence to Welding Visual Inspection: Development of Low-Cost Portable Embedded Device for Welding Quality Control, Electron. Imag. 2018 (9) (2018) 279-1–279-4. http://www.ingentaconnect.com/content/10.2352/ISSN.2470-1173.2018.09.IRIACV-279.
[88] A. Hedkvist, Predictive maintenance with machine learning on weld joint analysed by ultrasound, 2019.
[89] M. Weigelt, A. Mayr, J. Seefried, P. Heisler, J. Franke, Conceptual design of an intelligent ultrasonic crimping process using machine learning algorithms,

Procedia Manuf. 17 (2018) 78–85. https://linkinghub.elsevier.com/retrieve/pii/S2351978918311314.
[90] G. Vetrichelvan, S. Sundaram, S.S. Kumaran, P. Velmurugan, An investigation of tool wear using acoustic emission and genetic algorithm, J. Vib. Control 21 (15) (2015) 3061–3066.
[91] S. Senthil Kumaran, A. Daniel Das, An Examination of Seamless Ferritic tube and Austenitic alloy tube plate joining by Friction Welding process, Mater. Today: Proc. 5 (2) (2018) 8539–8546. https://linkinghub.elsevier.com/retrieve/pii/S2214785317328249.
[92] S.K. Selvaraj, M.K. Nagarajan, L.A. Kumaraswamidhas, An investigation of abrasive and erosion behaviour of AA 2618 reinforced with Si3N4, AlN and ZrB2 in situ composites by using optimization techniques, Arch. Civil Mech. Eng. 17 (1) (2017) 43–54.
[93] S. Senthil Kumaran, S. Muthukumaran, C. Chandrasekhar Reddy, Suitability of friction welding of tube to tube plate using an external tool process for different tube diameters - A study, Exp. Tech. 37 (2013) 8–14, https://doi.org/10.1111/j.1747-1567.2011.00765.x.
[94] S. Muthukumaran, S. Senthil Kumaran, S. Kumar, Friction welding of Cu-tube to Al-tube plate using an external tool, Trans Indian Inst Met 64 (3) (2011) 255–260. http://link.springer.com/10.1007/s12666-011-0052-2.

Further Reading

[1] Y.K. Liu, Y.M. Zhang, L. Kvidahl, Skilled human welder intelligence odelling and control: part I-modeling, Weld. J. 93 (5) (2014).
[2] Z. Bingul, G.E. Cook, A.M. Strauss, Application of fuzzy logic to spatial thermal control in fusion welding, IEEE Trans. Ind. Appl. 36 (6) (2000) 1523–1530.
[3] B.N. Panda, M.R. Babhubalendruni, B.B. Biswal, D.S. Rajput, Application of artificial intelligence methods to spot welding of commercial aluminum sheets (BS 1050), in: Proceedings of Fourth International Conference on Soft Computing for Problem Solving. Springer, New Delhi, 2015, pp. 21–32.
[4] S.S. Shekhar, Artificial Intelligence in Automation, Artif. Intell. 3085 (06) (2019) 14–17.
[5] V.S. Gujre, R. Anand, Machine learning algorithms for failure prediction and yield improvement during electric resistance welded tube manufacturing, J. Exp. Theor. Artif. Intell. 32 (4) (2020) 601–622.