Sustainability of Fusion and Solid-State Welding Process in the Era of Industry 4.0

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Abstract

Manufacturing is considered as the heart of any industrialized developed nation. Welding and joining, being a part of manufacturing activity, contributes a large for the country's long-term growth. In order to sustain in the global competitive environments, welding industries nowadays continue to strive hard for finding new ways do the same function either by mimics from existing product or adopting the concept from nature. This includes not only the cost and energy saving, waste minimization, optimal parameters, and eco-friendly but also with the advent newer computer technologies like smart factories or factories of the

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C. M. Hussain, P. Di Sia (eds.), *Handbook of Smart Materials, Technologies, and Devices*, https://doi.org/10.1007/978-3-030-58675-1_113-1

future, industrial internet of things (IIoT), cyber-physical systems, cloud systems, big data, digital manufacturing, and lastly the Industry 4.0. The present work elucidates the different approaches employed for assessing and improvement in the weld quality using meta-heuristic algorithms, in process weld quality inspection; defects detection and its control in fusion and solid-state welding processes.

Keywords

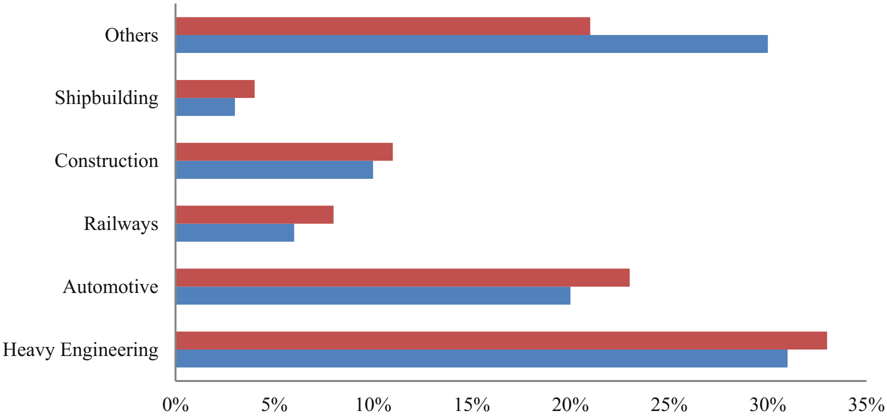
Sustainability · Fusion welding · Solid-state welding · Industry 4.0 · Industrial internet of things · Cyber-physical systems · Cloud systems · Big data · Digital manufacturing

1 Introduction

Manufacturing is considered as the heart of engine development of any developed nation which is directly related to its financial well-being. It consists of use of mechanical, physical, and chemical processes to alter the properties and geometry of raw material into the end products (Rao 2007). Mainly, manufacturing process involves casting, forming, machining, and joining processes. Out of these manufacturing processes welding and joining play an important role in major industries like automobile, aviation, construction, defense, oil and gas, naval, space, etc. which contribute a large for the country's long-term growth. The current scenario of welding process in different sectors in Indian context is explained in Fig. 1 where few newer technologies have been introduced like dynamic oxide control system for aluminum welding, intelligent gas control for large-scale savings in gas consumption, and intelligent arc control for automatic arc adjustment. Similarly, robotics and automation is being deployed by the industries for achieving the high weld quality and productivity improvement. Similarly, welding process related expenses contributed significantly toward the US economy which shows one-third of the total US Gross Domestic Product (Miller et al. 2002).

1.1 Industrial Revolution

From the industrial perspective, a revolution is nothing but a significant change and growth in technology and thereby standard of living of the people. This change in the technology takes place in following ways. The first one called innovation which means modification of the existing product by either conventional trial-and-error approach or process parameter optimization or Jugaad (Frugal Engineering) (Singh et al. 2012; Prabhu et al. 2012) or TRIZ approach (Kohnen 2004). The second one adopting concepts from nature (Wahl 2004). The details of different industrial revolutions are depicted in Fig. 2. The first phase of industrial revolution caused by invention of steam engines led to an increase in production called as "Industry



	Heavy Engineering	Automotive	Railways	Construction	Shipbuilding	Others
FY 2020	33%	23%	8%	11%	4%	21%
FY 2016	31%	20%	6%	10%	3%	30%

Fig. 1 Current scenario of welding process in different sectors in Indian context

1.0." In the second revolution, significant changes were made caused by inventions of electricity and steel making processes and is called as "Industry 2.0." In the third revolution, a rapid transformation happened caused by the application of electronics in manufacturing processes and is called as "Industry 3.0." In the current fourth revolution, transformation from machine led manufacturing to digital manufacturing is called as "Industry 4.0"(Gunal 2019) and is based on nine technologies as shown in Fig. 3. The future industrial revolution is known as "Industry 5.0"wherein with the significant development in the robotics field humans will be able to accomplish considerably better than the Industry 4.0 (Węglowski 2018).

1.2 Industrial Revolution: A Welding Perspective

In parallel with different industrial revolutions, significant technology also had developed in the welding and Joining. Though the joining of pieces together can be traced back to more than 2000 years, welding emerged as a feasible manufacturing process only in the late 1800s. It is at the heart of many great engineering achievements. It is important for agriculture mechanization, energy generation, clean water supply, and medical devices production (Debroy 2015). The development of fusion and pressure welding processes was caused by eruption of World Wars I and II as shown in Table 1 (Węglowski 2018).

When we say the technology or industrial revolution gets advanced or upgraded, it means that the things are easy-to-use. This also results in resolving the problems or issues that were found in the past technology. This advancement in the technology

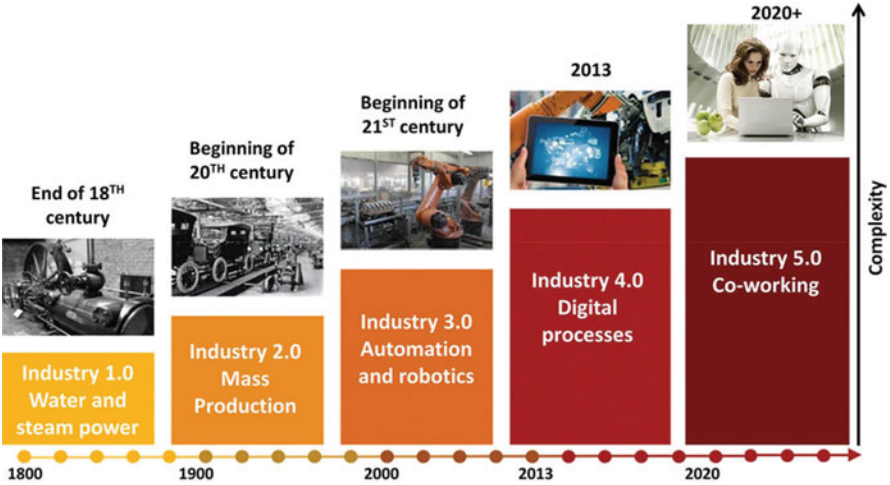


Fig. 2 Industrial revolutions (Petrillo et al. 2018)

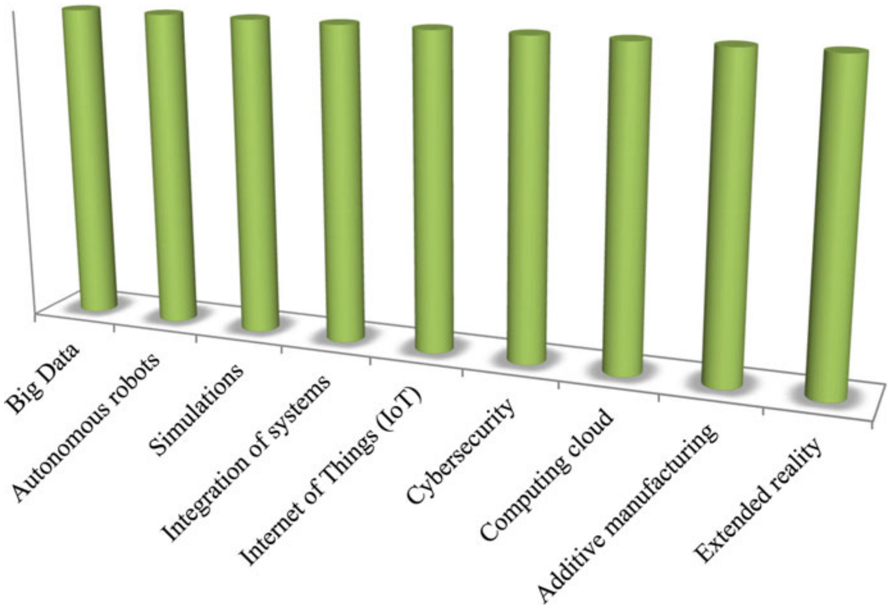


Fig. 3 Nine pillars of fourth industrial revolution

is possible when the manufacturing firms involve the customers or the end users or receive feedback from the customers on the concept design phase of design cycle. In the fourth industrial revolution, most of the welding industries are striving hard to achieve the production efficiency as well as quality effectiveness across the globe.

Table 1 Development of welding technologies (Węglowski 2018)

Year	Country	Inventor	Process
1802	USA	Robert Hare	Oxy-Hydrogen Welding
1885	Russia Kingdom of Poland	Nikolaj Benardos Stanislaw Olszewski	Carbon Arc Welding
1895	Germany	Hans Goldschmidt	Thermit Welding
1901	France	Charles Picard Edmond Fouche	Oxyacetylene Welding
1902			
1904	Sweden	Oscar Kjellberg	Manual Metal Arc Welding (MMAW)
1926	USA	H. M. Hobart P. K. Devers	Gas Tungsten Arc Welding (GTAW)
1929	USSR	D. A. Dulczewskij	Submerged Arc Welding (SAW)
1948	USA	P. K. Devers	Gas Metal Arc Welding (GMAW)
1949	USSR	B. E. Paton G. Z. Woloszkiewicz	Electroslag Welding
1949	Germany	K. H. Steigerwald	Electron Beam Welding (EBW)
1953	USA	Robert M. Gage	Plasma Welding
1953	USSR	K. V. Lyubavskii N. M. Novoshilov	CO_2 shielded MAG Welding
1953	USA	A. A. Bernard	Self-shielded Flux Cored Arc Welding (FCAW)
1962	USA	M. S. Holander	Friction Welding (FW)
1965	USA	Robert Soloff and Symour Linsley	Ultrasonic welding
1970	Great Britain	Martin Adams	Laser Beam Welding (LBW)
1977	Germany	W. M. Steen	Hybrid Laser Welding
1981	Canada	John G. Church	T.I.M.E. Welding
1991	UK	Wayne Thomas	Friction Stir Welding (FSW)
2004	Austria	Manfred Schorghuber	CMT Welding

On the contrary, few of the small-scale industries (SSI) are in dilemma whether to go or not with such industrial revolution due to high initial investments in such a welding metamorphism world. It is well agreed that at the start of any of the industrial revolution, initially the cost of the product is comparatively higher than the previous one. This cost is acceptable over a period of time, which in turn, the living standard of people and hence significant development of that country.

Węglowski (2018) suggested few approaches related with welding engineering of the fourth industrial revolution as: (1) welding technologies should move from traditional push forward approach to acquisition approach, (2) intelligent robots and software programs flexibility, (3) welding programs integration into "smart" production processes, and (4) flexibility of welding software provider. Digitization, control systems, and transfer of data are the important measures of the fourth industrial revolution.

Selection of weld process parameters are generally based on parent material, thickness, and other related parameters that can be successfully implemented when welding knowledge is digitized accordingly. As explained earlier most of the welding manufactures are already taking inventive steps to store welding data intelligently which will be ready for documentation and data analysis. Still, at which level of detail the data must be available has not yet been precisely evaluated for the creation of appropriate algorithms (Posch et al. 2018). On the contrary, lot of development also has been done in the virtual simulation module, for example, augmented reality and virtual reality (AR/VR) for training purpose. It consists of doing virtual welding where a welding torch is controlled by simulating it in tutorial and training mode, its evaluation, etc. (Torres-Guerrero et al. 2019).

2 Sustainability

More than one million workers across the globe are presently engaged as full-time welders. A number of epidemiologic studies have reported that a higher incidence of respiratory illness in welders takes place (Antonini et al. 1996), and there is an ardent need of innovative welding technologies that not only create elegant products but indeed eliminate these health- and environment-related issues. Hence, sustainability or sustainability development is vital for welding industries in any of the industrial revolutions. As it has a variety of dimensions, important aspects, performance measures and it is dynamic one. Although in manufacturing studies economic, societal, and environmental sustainability have given a prime importance (Bi 2011), still sustainability is considered a complex, unstructured issue and is a vital issue for the current and future perspectives (Garetti and Taisch 2012).

As of now, there is no specific definition for sustainability or sustainability development. According to the past studies (Garetti and Taisch 2012; Agustiady and Badiru 2013) sustainability is a way for improving living standards and comfort for the current and future perspectives. In the global competitive environment, in order to be sustainable , manufacturing industries need more efforts in terms of time and cost for their products (Garetti and Taisch 2012; Garbie 2013). Kamble et al. (2018) suggested a framework for sustainable industry 4.0 which consists of Industry 4.0 technologies, process integration, and sustainable outcomes as depicted in Fig. 4. Their proposed framework considers that Industry 4.0 provides the business units integration through the cyber-physical systems which make the manufacturing system more flexible, efficient, and eco-friendly.

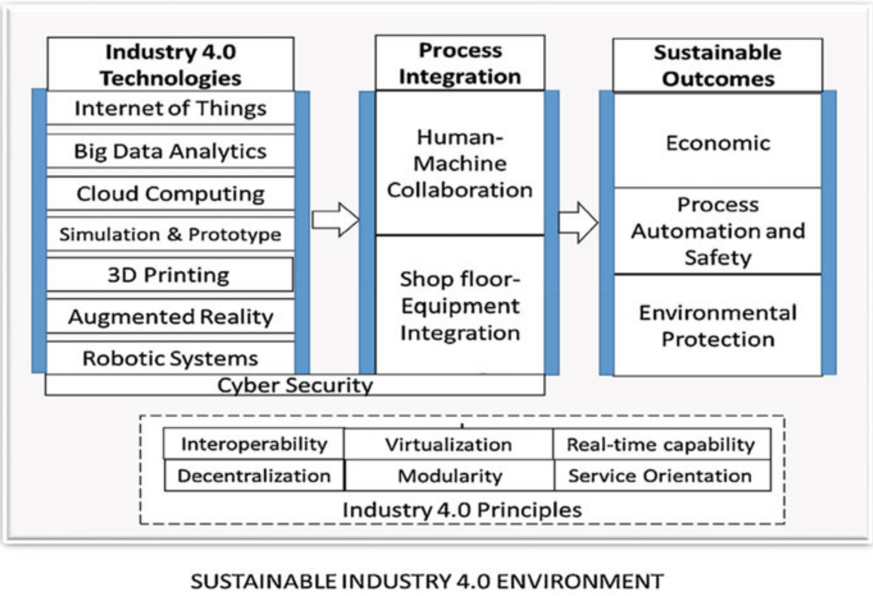


Fig. 4 Framework for sustainable Industry 4.0 (Kamble et al. 2018)

2.1 Industry 4.0 in Fusion and Solid-State Welding

Globally, in the arena of fourth industrial revolution welding equipment manufacturers are already supplying their consumers with the state-of-the-art welding solutions. In 2013 Fronius launched Trans Process Solution Intelligent (TPS/i) system where the system interfaces are incorporated into system bus architecture and is able to provide data in a real time. This data can be used to monitor, analyze, and document the process (WeldCube). In addition to this, the company also has developed a system of facilitating welder training (Virtual Welducation) and a WeldConnect software program. Byrd et al. (2015) have employed virtual reality simulations VRTEX® 360 as an assessment tool for experienced and trained novice welders. Sirius Electric offers ultrasonic welding machine that has remote software administration and control facility. Similarly, ABICOR BINZEL offers a system that manages the welding gases (Węglowski 2018). In recent years, SMW Group, Queensland, have automated their welding repair processes with advanced laser seam tracking, adaptive welding software, a new generation welding system, and a modular configuration robot. They are able to reduce welding time by 70–90%, reduction in overall production costs, improvement in safety, quality, and reporting.

The first novel method proposed by Backer et al. (De Backer et al. 2014; De Backer and Bolmsjo 2013; De Backer 2014) for friction stir welding (FSW), process to monitor, and control system architecture where the temperature controller modifies the robotics FSW spindle speed for maintaining a constant weld temperature.

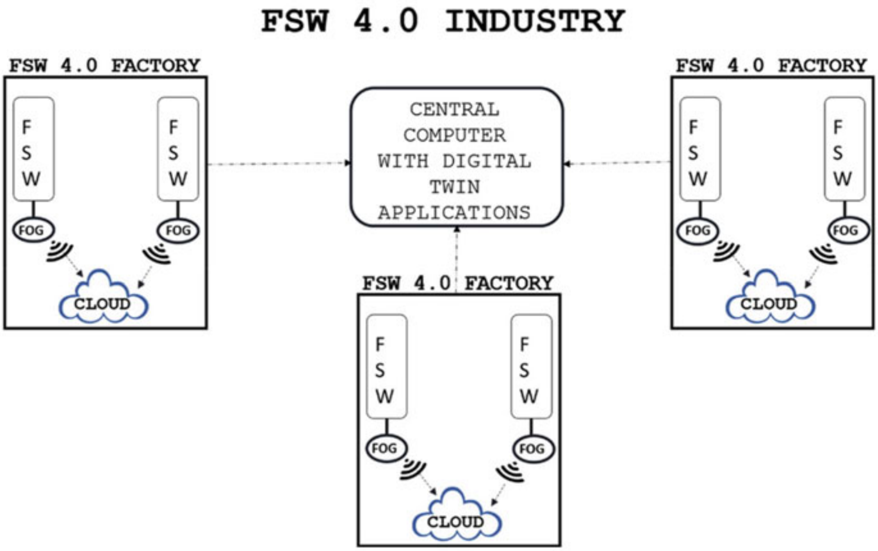


Fig. 5 FSW smart industry (Mishra et al. 2018)

Later Mishra et al. (2018) reviewed different techniques and methods for sensor-based quality and control monitoring of defects in FSW. They proposed a roadmap to achieve the goal of Industry 4.0 in FSW as can be seen in Fig. 5. They also proposed an FSW monitoring and control architecture similar to Backer et al. (De Backer et al. 2014; De Backer and Bolmsjo 2013; De Backer 2014) with addition of different sensor modules which integrates the existing experimental data that acts as a knowledge base and the different sensory systems which captures, extracts, processes, and monitors the data, and finally using correlation the final decision is made. On the similar platform, different welding equipment manufacturers provide the equipment that meet the expectations of Industry 4.0 either by adopting existing technologies or retrofitting.

Another vital component of Industry 4.0 is digital twins. It is a kind of virtual simulator which mimics the physical object/system/process and it can be employed for analysis and to simulate the process in a real-world environment so as to accommodate the changes, optimize the process parameters, and improve the weld quality, reduce time, and costs. SORPAS® created first resistance spot welding process digital twins for its complete lifecycle from designing, optimizing, planning, producing, and evaluating the welds. With the exploitation of machine learning and artificial intelligence (AI) approaches, the weld digital twins work with physical welding process in dynamic environment (Fig. 6).

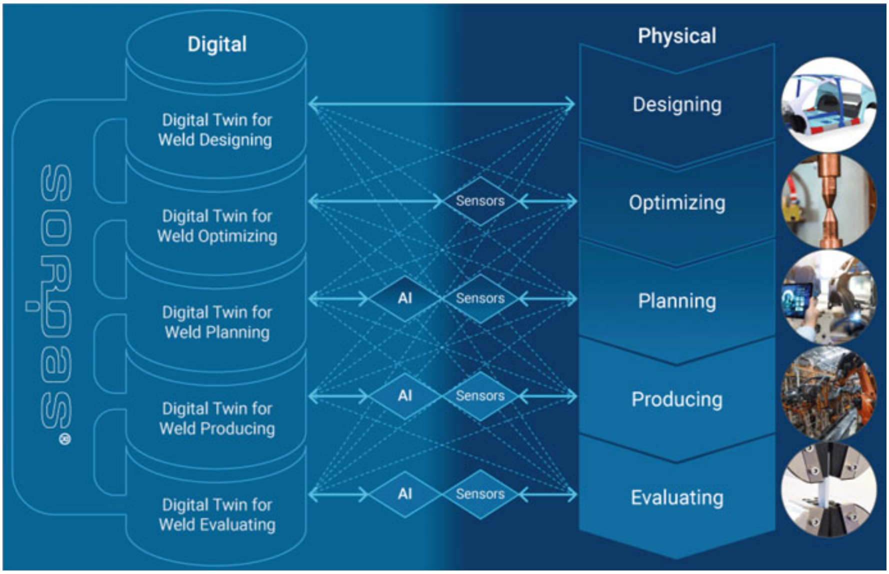


Fig. 6 Digital twins for resistance spot welding (Ref. www.swantec.com)

2.2 Industry 4.0 in Fusion Welding Process

The concepts like Industry 4.0, the smart factory, and digital transformation provide several greater prospects for welders. Due to digitization of welding equipment, there is enhancement in productivity and efficiency of the welding process. Similarly, superior weld quality, repeatability, better conditions for welders, and sustainable competitiveness are obtained. The computers alone provide right decisions similar to experienced welders. To achieve this, the high-performance information and communication technology along with sensors, powerful network infrastructure for data transfer, communication security, and storage are needed.

The literatures on fusion welding process in Industry 4.0 are limited. In most of the reported work, machine learning approach has been used which is often termed as “intelligent welding.” Computational modeling and simulation is the heart of intelligent weld manufacturing. Chen et al. (2000) have described the framework for intelligent weld manufacturing. It requires a multidisciplinary integrated computational welding engineering approach (process, automation, control, microstructure, and property) for intelligent weld manufacturing (David et al. 2018). In gas tungsten arc welding (GTAW), gas metal arc welding (GMAW), laser welding, and resistance welding machine learning approach were employed to optimize weld process parameters, enhance weld quality, defect detection, etc. (David et al. 2018). Similarly, with development of bioinformatics model of machine learning, risk and danger associated with welding processes can be minimized (Mahadevan et al. 2021). The example shows that how fusion welding process works well in the arena of Industry 4.0. Cold metal transfer (CMT) welding is advanced joining process; a variant of GMAW which includes filler wire feed drive in a close loop control gives extremely stable arc, low heat input, and spatter free process to join different material combinations.

Vendan et al. (2020) have adopted data from Kumar et al. (2016) to optimize the CMT welding process parameters of Aluminum 6061 using supervised machine learning. The initial process parameters were considered as welding current (50 A, 60 A, 70 A) and weld speed (400, 500, and 600 mm/min), respectively, whereas the performance measures were penetration depth, width of weld pool, and height of reinforcement. After their initial study, they used machine learning techniques for data analysis and predicting the optimal process parameters. They employed NumPy and Pandas for data analysis and Seaborn and Matplotlib for data visualization. They employed seaborn library for making the co-relation of independent variables. After co-relation matrix the next essential step is data preprocessing which is used for nonlinearity. Generally, it is applied using linear regression technique for training the higher degree model. After data preprocessing the next step is prediction analysis using Scikit-Learn. They employed a typical method of dividing the data into 80% of trained data and 20% of test data from the dataset for predicting the dependent parameters. After training the model, it is again used for data prediction. Recently, ADLINK Technology Inc. provided built in Intel® distribution of OpenVINO™ toolkit for automated arc-welding porosity defects in real time. By means of neural network (NN), the two things are performed by the system, that is, first it identifies the defects in real time, and second is auto-stopping the welding process using robot actuation prior to the defect is extended and the part is damaged beyond repair. Further, the NN model can also retrained for detecting other type of defects in the welding process. EWM AG Xnet 2.0 provides welding management system like a smart factory with digital transformation. The Xnet 2.0 is a kind of intelligent monitoring system which keeps transparency in the welding processes right from process planning, actual production, and final cost estimation of weld seams. Recently, Novarc Technologies launched the NovEye™, a vision-based software that employs machine learning for keeping high accuracy track at the root pass, also measures the root gap and automatically detects the tracks.

Recently, Kemppi India Pvt. Ltd. launched the X8 MIG Welder, an intelligent welding system which provides connectivity to the WeldEye welding management software and innovative performance software. The WeldEye welding management software provides simplicity, traceability, and WPS management in welding production.

2.3 Industry 4.0 in Solid-State Welding Process

Similar to the fusion welding process, the literatures are scarce on Industry 4.0 in solid-state welding process . The following examples show that how solid-state welding process well in the arena of Industry 4.0. The FSW is advanced welding process, also called "green" technology owing to its versatile benefits (Mehta and

Badheka 2016). In contrast to the traditional weld techniques, it consumes notably less energy. It involves complex material displacement and plastic deformation. Researchers across the globe now understand the merits of using the solid-state welding method as a potential alternative for difficult-to-weld material. Due to its solid-state nature, it is expected to result in components with superior metallurgical and mechanical properties.

Most of the available literature has applied ANN, adaptive neuro-fuzzy inference system (ANFIS), support vector machine (SVM) techniques to optimize FSW and FSSW processes. Fleming et al. (2008) and Gibson et al. (2013) employed dimensional reduction techniques for weld quality, and defect formation and tool wear (Gibson et al. 2018). Hartl et al. (2020) used ANN for predicting weld surface quality. Shojaeefard et al. (2015) used ANN to correlate tool parameters (pin and shoulder diameter) and heat-affected zone, thermal, and strain value in the weld zone. Fleming et al. (2007) employed SVM for fault detection like gap occurrence and find out the gap depth in FSW process. Fratini et al. (2009) integrated ANN to finite element model (FEM) and calculated the average grain size values of butt, lap, and T type FSW joints. Boldsaikhan et al. (2006, 2011) used artificial neural network (ANN) for defect detection. They statistically correlated, controlled, and developed a system for weld quality evaluation using tool X, Y forces, and the tool torque feedback signals. The force signal feature extraction, and generation of feature vectors for each of the force signal was evaluated using Discrete Fourier Transform (DFT). The ANN was applied to these resulting feature vectors which categorize the weld into two. The first category has/not has metallurgical defects and the second category gives the weld strength as per requirement. The obtained results were promising; still some issues were suggested like noise, network robustness, prefiltering of machine dependent component of output signals before categorization. Vendan et al. (2020) have adopted data from Suban et al. (2017) to optimize the FSW process parameters of AA6061/TiB_2/SiC metal matrix composite by varying weight percentages of SiC, B_4C, and TiB_2 using supervised machine learning. The initial process parameters were considered as tool rotational speed (600, 800, and 1000 rpm) and weld speed (50, 60, and 70 mm/min), respectively, whereas the performance measures were mechanical properties. A similar procedure was employed to predict the optimal process parameters as explained in case of fusion welding. Based on these, it is able to get the predicted values for the performance measures along with other characteristics as torque developed, experimental heat generated, and theoretical heat input.

In their another work (Vendan et al. 2020), they have applied supervised machine learning in Magnetically Impelled Arc Butt Welding (MIAB) process. The process was studied by the E. O. Paton Electric Welding Institute and after its development it was commercially applied by Kuka Welding systems. The process is fully automated solid-state welding and able to weld tube diameters approximately 10–220 mm with wall thickness of 0.7–13 mm. Vendan et al. (2020) have optimized the MIAB process parameters of alloy steel tubes (T11) by varying current and time using supervised machine learning. They considered following parameters notch strength ratio, ultimate tensile strength, and mean weld interface hardness as performances.

A similar procedure was employed to predict the optimal process parameters as explained in case of fusion welding and FSW process. Based on these, it is able get the predicted values for the performance measures.

Jayaraman et al. (2011) have employed ANN approach for predicting tensile strength of high strength Aluminum A356 alloy. Tansel et al. (2010) have applied genetically optimized NN system (GONNS) to evaluate the optimal process parameters of FSW process. Satpathy et al. (2018) have developed the regression, ANN, and ANFIS models for simulating and predicting the joint strength of ultrasonic metal welding of dissimilar sheets of Al-Cu. Dewan et al. (2016) developed ANFIS model to predict the tensile strength of FSW joints. Zhu et al. (2002) have applied SVM technique to predict the welding joint quality.

Conventional optimization methods give local optimal solution and are not robust. The meta-heuristics (MH) is a global search technique which deals with all kinds of objective functions and design variables and these are flexible as there is no need of data training (Saka et al. 2016). Significant research is reported in the literature (Rao and Pawar 2010) that the conventional techniques such as Powell's Method, Fletcher-Reeves Method, Dynamic Programming, and the Reduced Gradient Method, etc. have been employed for such kinds of problems. However, these techniques lack to perform well over a wide range of problems. With these issues as an input, efforts are being made to model and optimize the complex problem using MH techniques. Most frequently employed algorithms in the literature are scatter search (SS), simulated annealing (SA), Tabu search (TS), artificial immune system (AIS), Ant Colony Algorithm (ACO), differential evolution (DE), multi-objective GA (MOGA), particle swarm optimization (PSO), imperialist competitive algorithm (ICA), teaching learning-based optimization (TLBO), and artificial bee colony algorithm (ABC). However, there is a need to explore these and other hybrid algorithms in welding applications for optimization of process parameter and predicting the performance measures.

Nadeau et al. (2020) applied different machine learning algorithms for predicting the defective welds over various process variables. Out of these machine learning models, K-nearest neighbor (KNN) technique performs best for predicting defective welds. Automatic identification algorithm was developed by Sikora et al. (2013) for detecting and classifying the weld defects by employing X-ray radiograph images. Chen et al. (2003) studied online monitoring of FSW process and defects using acoustic emission technique. A fractal dimension algorithm (Das et al. 2016), Power spectral density (Das et al. 2018) was employed to extract various acquire signals for weld process monitoring and detect the defects. Thermography was employed for online monitoring to measure the weld joint quality using FSW process by monitoring temperature plots during the welding (Serio et al. 2016; De Filippis et al. 2017). A free vibration technique was employed as NDT to find out weld quality which depends on natural frequencies of the weld samples (Crâştiu et al. 2017).

Even though the parameter optimization and corresponding prediction of the characteristics has been done, still one has to see these welding processes from the sustainability viewpoint. Jamal et al. (2020) have done sustainability assessment for

Table 2 Category scores for fusion and solid-state welding processes (Jamal et al. 2020)

Category	GTAW	GMAW	FSW
Physical performance	0.23	0.21	**0.39**
Environmental impact	0.20	0.72	**0.92**
Economic impact	0.34	**0.58**	0.14
Social impact	0.56	0.56	**0.96**

fusion and solid-state welding process using statistical approach by data collection and segregation into environmental impact, economic impact, social impact, and physical performance. They have considered weld yield strength and toughness under physical performance; carbon footprint, material wastage auxiliary material usage, and weld emissions under environmental impact; cost of consumables, labor, energy, welded part, and equipment under economic impact; and finally incident rate under social impact. After that normalization has been made for above indicators by assigning weights for each category. Finally they determined overall sustainability score and its comparison with each of the welding processes. It was concluded based on the statistical approach that FSW is the most sustainable process due to the highest physical performance, social impact, and environmental impact scores in comparison with GTAW and GMAW processes. Table 2 shows the summary of category scores for fusion and solid-state welding processes. It can be observed from Table 2 that FSW process did not score more due to initial tool plunging time, and FSW tooling cost. While GMAW achieved maximum score due to less cost of fillers, its storage, transport, and use. Chang et al. (2015) employed life cycle assessment approach to evaluate social and environmental impacts of fusion welding processes. Life cycle assessment (LCA) and social life cycle assessment (SLCA) are the modern techniques used for the evaluation of social and environmental impacts which affects the product, or process. “LCA is an ISO standard technique employed to assess environmental impacts of products through its entire life cycle.” On the contrary, “SLCA is a technique employed to assess social and socio-economic impacts related to human beings affected by products/services throughout the life cycle” (Chang et al. 2015). Chang et al. (2015) considered manual metal arc welding (MMAW), manual GMAW, automatic GMAW, and automatic laser-arc hybrid welding (LAHW) processes for LCA and SLCA. It is revealed that the MMAW process gives maximum environmental impacts in terms of nature, and welders’ health issues when compared with other considered welding processes. Nobrega et al. (2019) have reviewed different manufacturing processes including welding from the sustainable point of view. Garbie (2016) has estimated the sustainability based on the three pillars, namely, economic (E), societal (S), and environmental (N). The sustainability/sustainable development (S/SD) is expressed as:

$$S/SD_{\text{Manufacturing Enterprise}} = \left\{ \begin{array}{c} S/SD_E \\ S/SD_S \\ S/SD_N \end{array} \right\} = f\,(S/SD_E, S/SD_S, S/SD_N)$$

$$S/SD_{\text{Manufacturing Enterprise}} = w_E\,(S/SD_E) + w_S\,(S/SD_S) + w_N\,(S/SD_N)$$

Where

$S = SD_E$ is the value of attribute of economic issues (E) with respect to S/SD assessment

$S = SD_S$ is the value of attribute of social issues (S) with respect to S/SD assessment

$S = SD_N$ is the value of attribute of environmental issues (N) with respect to S/SD assessment

w_E, $w_{S,}$ and w_N are the relative weights of the economic, societal, and environmental issues, respectively. These are estimated using the analytic hierarchy process (AHP) and determine the S/SD index of the manufacturing enterprise.

3 Conclusion

The present chapter elucidates the sustainability of fusion and solid-state welding process in the era of Industry 4.0. It covers different approaches employed for assessing and improvement in the weld quality using meta-heuristic algorithms, in process weld quality inspection; defects detection and its control in fusion, and solid-state welding processes. However, sustainability of fusion and solid-state welding process in the era of Industry 4.0 is a missing link that needs to be taken into consideration. Furthermore, welding simulator can be considered as mandatory assessment tool for welder qualification. Past studies have applied statistical approaches and AHP-based assessment for sustainability of manufacturing enterprise. Such similar kind of assessment for sustainability of fusion and solid-state welding process gives remarkable insights into the fourth industrial revolution.

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