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REVIEW PAPERS

The state-of-the-art methodologies for quality analysis of arc welding process using weld data acquisition and analysis techniques

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Abstract Arc welding, due to its simplicity, ease of use and low maintenance cost is one of the most widely used welding process in almost all types of modern industries. In this process, voltage, current and welding speeds are the major variable which influences the final weld product. Among these, monitoring welding speed is relatively easy, while monitoring voltage and current is not. This is because welding is a stochastic process in which wide variations in voltage and current occurs and durations of these variations are so short that the ordinary ammeters and voltmeters cannot measure these variations. However, using suitable sensors coupled with a high-speed data acquisition system, real time variations taking place in an actual welding process can be recorded and subsequently analyzed. A careful analysis of these variations using various signal processing, statistical and data mining techniques can provide a very useful information in estimating the quality of final weld product. In this research, a first of its kind, detailed review on various aspects of weld monitoring systems used for weld data acquisition and its subsequent analysis are presented. This will include an in-depth analysis of various electronic sensing and data sampling modules which can be used in the design and development of a Weld Monitoring System. Additionally, this review also includes a brief study on various soft computing, data mining and machine learning techniques on weld data in predicting the quality of different welding parameters. Finally, summary of the review is followed by the scope of future research to pave out some of the new dimensions in exploring the multi-disciplinary area of evaluating the arc welding quality using data acquisition and analysis techniques.

Keywords Arc welding process · Sensors · Data acquisition system · Signal processing · Statistical analysis · Artificial neural networks · Quality analysis

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1 Introduction

Arc welding is one of the most commonly and widely used welding process due to its inherent merits like ease of use, versatility, flexibility, and low maintenance cost. Additionally, the welding quality of this process allows it to be used in almost all type of industries for the construction and fabrication of various structural components. Even though, specifically designed power sources are used in an arc welding process, random arc behaviour and complex modes of metal transfer makes them stochastic in nature. Therefore, dynamic variations in voltage and current makes this process difficult to monitor. But, if these variations are acquired properly, at the same rate as they occur then a careful analysis of the same can be used to understand the arc welding process in a much better way than it is done at present. For a given material, joint design, welding position and welding process, three important factors which governs the quality of the weld are welding power sources, welding consumables and skill of the welders. Till date, the practiced methodology to evaluate the effects of these factors is to examine the quality of the weld produced and not to monitor the real time changes of these parameters during the welding process itself. For example, at the time of welding we are not able to record arc gap variations happening during the actual welding process phenomena. The fact just presented can be further delved by analysing the present practice towards qualifying a welding consumable, procedure or a welder. At present this is done by testing the weld produced using these consumables, procedure and welders, but not by monitoring the real time or actual welding process. This is an indirect method and is just based on the requirement for welds of acceptable quality. However, this practice is expensive, time consuming and the assessment can only be carried out after the weld is completed and it is inspected or tested. On the contrary, if we can record the variations occurring during actual process itself, at the same rate as they occur, then a carefully analysis of these variations (real time monitoring) can give a better insight about actual welding process. Hence, it is clear that the real time monitoring of a welding process using weld data acquisition and analysis techniques can be used to study various aspects of an arc welding process. In this paper, a brief review on different types of electronic sensors, data acquisition modules and data analysis techniques used for monitoring an arc welding process has been delineated.

The article is organized as follows. Section 2 briefly discusses arc welding process. Various sensing and Data Acquisition (DAQ) modules used to develop a Weld Monitoring System (WMS) are discussed appropriately in Sect. 3. Section 4, then presents a detailed discussion on various signal processing, statistical and machine learning methods for post processing of welding data. Important observations along with the future scope are discussed in Sect. 5. Finally, Sect. 6 concluded the work.

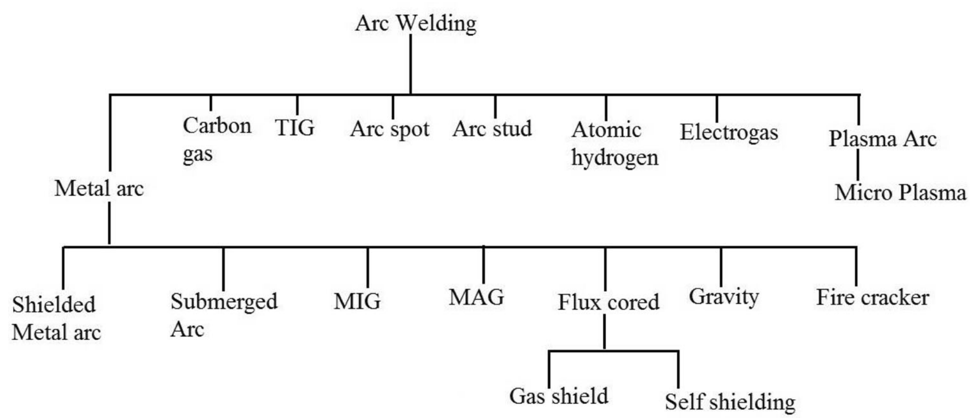
2 Arc welding

Arc welding is one of the several fusion processes for joining metals. In this process the heat required for fusion is generated by an electric arc formed between a metallic electrode and the base metal (cathode and anode). The arc thus formed consists of thermally emitted electrons and positive ions from electrode, work piece and those formed from the ionization of the gases in the arc atmosphere. These electrons and positively charged ions are accelerated in the potential field (arc voltage) between the electrode and the work piece, which are connected to the terminals of the welding power source and produce heat when they convert their kinetic energy by collision at the electrode or work piece. Consequently, due to intense heat produced by the arc, both work piece and the electrode melts in the arc (except in Gas Tungsten and Plasma Arc Welding processes in which electrode is not a consumable and hence not allowed to melt) and form the weld metal for the joint. Arc welding has many variants (Modern Arc Welding Technology 1988); which are shown in Fig. 1. The primary differences between the various arc welding processes are the methods by which molten metal is protected from atmosphere.

In an Arc welding process, there are different type of consumables, shielding gases and power sources used for welding. In addition to this, in the case of welding processes carried out manually like Shielded Metal Arc Welding (SMAW) and Tungsten Inert Gas (TIG) welding, skill of the welder would be an additional variable. In order to ensure a good quality weld, performance of the welding consumables, response of the power source to various physical processes like metal transfer that take place during the weld and ability of the welder to maintain constant arc gap, melting rate, speed etc. while welding is in progress are important. However, under normal circumstances that exist in a welding work shop monitoring the welding voltage and current displayed on the welding machine and monitoring the speed of welding are the two actions that can be carried out without any difficulty. However, processes like metal transfer, fluctuations in the arc gap and response of the welding machines to these variations are too rapid to be displayed by an ordinary voltmeter and ammeter. Hence, it is not possible to evaluate performance of welding power source or consumable or skill level of a welder without an appropriate weld monitoring system. In the absence of such a system, performance of consumable or skill level of welder is evaluated by assessing the quality of the welds produced using the consumable and the welder (American Society of Mechanical Engineers 2015). In this case the assumption is that if the weld is good, then the consumable and the welders are qualified. Performance of the consumable or welder during welding is not monitored. Power sources are tested by applying a resistive load and measuring the voltage and current using calibrated equipment and comparing with those displayed on the machine. In none of these evaluations, signals acquired from welding arc are used.

Hence there is a lot of interest in on-line acquisition of the weld data while welding is in progress as that would reveal dynamic variation in current and voltage that occur during welding. Once a reliable data acquisition is carried out, the data can be suitably analyzed to understand an arc welding process.

Fig. 1 Arc welding process chart



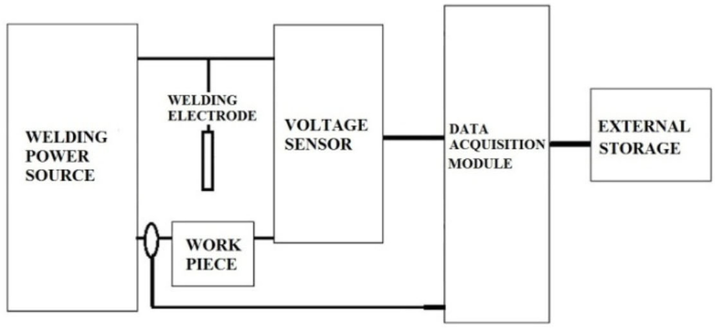
3 Weld monitoring system (WMS) for weld data acquisition

Hardware employed for real time dynamic measurements of welding variables are commonly referred to as Weld Monitoring System (WMS) which consists of data acquisition unit, display and processing unit and other relevant associated sensors. A WMS can be used to acquire various welding process parameters like voltage, current, weld pool image etc. Schematic representations of a WMS to acquire these parameters are shown in Fig. 2.

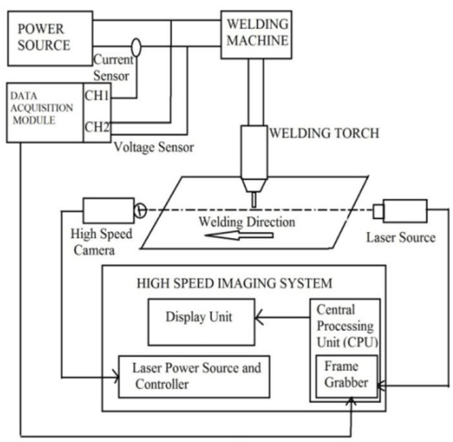
In the recent past many research groups have developed their own WMS and used it to study different welding processes, detection of welding defect, recording the weld data etc. However, the processing units employed in these WMS varies widely from Field Programmable Gate Array (FPGA), microcontrollers, microprocessors, Analog to Digital (A/D) card etc. Massimo et al. (2010) developed their own WMS in which they have used an advanced FPGA system for the measurement and processing of electrical signals from sensors placed on the welding transformer and electrodes has been proposed for detecting faults in real time and with high sensitivity. In Luksa et al. (2006), the authors have designed and developed a microprocessor-based control system for real-time acquisition of weld data, processed it and used the results thus obtained to detect welding imperfections in Gas Metal Arc Welding (GMAW) process. Similarly, Andrej et al. (2012), have developed microcontroller-based WMS for recoding and monitoring all the relevant welding data. The WMS thus developed was capable of data acquisition, aggregation, and wireless transfer to a data server and presentation of this data in the form of a welding diary. Therefore, the proposed technique has substituted the tedious manual filling of the welding data sheet.

In order to acquire the variations in arc voltage and welding current usage of appropriate sensor is extremely important; similarly, for a reliable data acquisition the arc variations must also be acquired at a sufficient sampling rate. For monitoring the spatter in the welded joint area in a GMAW process Siewert and SamardžićI (2002) have used a Hall Effect current sensor and a commonly available Analog to Digital (A/D) converter card to capture various welding parameters. These parameters were sampled at the rate of 1500 measurements/sec and were stored in an external computer. Subsequently, the results thus obtained by analysing the captured process variations revealed that irrespective of the gas mixtures, the spatter can still appear in the welded joint area in a GMAW process. In order to study process disturbances in a GMAW process and to correlate those with electrical signals Wu et al. (2007) have used an A/D card and a robot carrying a welding torch. The welding voltage and current signals were continuously sampled using a Hall Effect sensor at a sampling frequency of 10 kHz and subsequently stored it in an industrial PC. Careful analyses of resultant signals have revealed that the GMAW process disturbances can be correlated to various statistical parameters derived from the acquired welding data. In another study (Kang et al. 2000), arc stability in a GMAW process were predicted by developing a WMS which consists of a A/D converter card with a maximum sampling rate of 200 kHz and a Hall Effect sensor arrangement for measuring the welding voltage and current. The data were sampled at a rate of 5000 samples/s and processed using a digital Low Pass Filter (LPF) having a cut-off frequency of 200 Hz. Filtered data thus obtained was used to develop a multiple regression model to predict the arc stability with a reasonable accuracy.

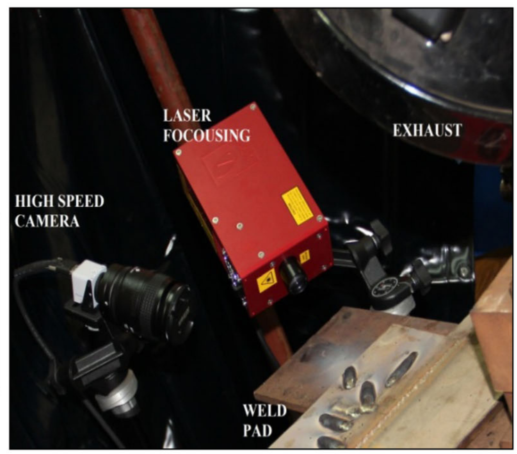
In order to monitor the real time variations and to record welding signals (voltage and current) various researchers have also used a general-purpose Digital Storage Oscilloscopes (DSO). In Savyasachi et al. (2015), the authors have used a DSO and a high-speed camera setup to correlate the variations in the welding signals with varying arc welding parameters. Recently in Vikas et al. (2015), a DSO setup was used to acquire random arc voltage and current using a



(a) Schematic of welding voltage and current acquisition setup



(b) Schematic of weld pool image and data acquisition system



(c) Photograph of a typical image acquistion system

Fig. 2 WMS setup to acquire different welding parameters

Hall Effect sensor and a high voltage differential probe. Data from the sensing unit were transferred to an external computer by maintaining a throughput of 100,000 samples/s. This data was then filtered using a Fast Fourier Transform—Low Pass Filter and the signal patterns were correlated with SMAW process parameters. Similarly, in Vikas et al. (2018a), electrical signals were acquired using similar DSO setup to study the role of shielding gases and the effect of varying current in a GMAW process. Vikas et al. (2017) have established their own weld monitoring system using a DSO and relevant sensors to record the random arc variations while welding is in progress. The data thus acquired were used to implement a SOM model in order to monitor the progress of learning of various trainee welders in a SMAW process. In a separate study, in order to monitor the burn through defect in a GMAW process Adolfsson et al. (1996a) have established a real-time online monitoring system using LEM Module LT 500-S based current sensor and an instrumentation amplifier for voltage measurement. Hewlett Packard 2454S based dedicated DAQ system was used to acquire the resultant signals at the rate of 32.768 kHz and transferred it to an external computer for post processing. The data thus obtained were subsequently analysed and a novel technique or the automatic detection of burn through defects in a GMAW process were proposed. Adolfsson et al. (1996b) have used the WMS proposed in Adolfsson et al. (1996a) to study the weld quality produced by robotized short-arc welding (in GMAW process) and developed a simple Sequential Probability Ratio Test (SPRT) change detection algorithm and shown that it is indeed possible to detect the welding quality automatically on a real time basis. Aviles-Viñas et al. (2016) have developed a WMS for training an industrial robot in order to produce good quality bead geometry. For this purpose, the authors have used a 6-DOF KUKA KR16 industrial robot with KRC2 robot controller to power the robot arm. A KCP control panel was interfaced with an external computer to display different welding parameters. For sensing welding current, CSNS300M Hall effect current sensor of 600A range was deployed. In order to measure the melting temperature on the test plate a CTL2MH Infrared sensor (temperature range between 385 and 1600 °C) was used. In turn, the data from these sensors were obtained with the help of a microcontroller-based data acquisition system by maintaining a sampling rate of 1 kHz. Subsequently, a real-time computer vision algorithm was developed to predict various welding parameters with an accuracy of 95%.

For detecting the defects as they occur in a GTAW process Zhang et al. (2014) have established a WMS using a welding test-bed of multiple freedom of motion with OTC INVERTER ELESON 500P-type TIG welding power, VSM030D/5 V hall voltage sensor, signal shaping circuit and a data acquisition system. The weld data were acquired at a sampling rate of 28 kHz and visualized using a VC + + interface. A prediction algorithm was then developed using the sampled data to predict a few detects like lack of penetration, surface depression and burn through.

In addition to voltage and current variations, many research groups have also acquired weld pool image and arc sound data for evaluating the welding parameters. Li et al. (2014) have acquired weld pool image in Metal Active Gas (MAG) welding process using a CCD camera module. For acquiring arc voltage and current, a Hall Effect based sensor was employed. Similarly, arc position was monitored with the help of groove photoelectric switch and a disk arrangement. The outputs from all these sensors were fed to a Data Acquisition Card for post processing. In a separate study, Xue et al. (2007), have established their own WMS consisting of CCD sensor system to capture the foreside of the molten pool and the original weld joint image. These images in turn, were digitized and processed using wavelet transform based algorithm to predict the edge of the molten pool. They have also implemented a PID controller (Ang et al. 2005) arrangement to manipulate the welding gun by applying a control signal to a servo system for producing an accurate weld joint closest to the desired track. Wu et al. (2016), has used a CCD camera to acquire the weld pool image by establishing a WMS with the help of a six-axis motorman robot and a dual-sensor data acquisition system consisting with an omni-directional MP201capacitance microphone. The data were acquired and processed to establish a correlation between the keyhole geometry and acoustic signatures for monitoring the penetration state in a Variable Polarity Keyhole Plasma Arc Welding (VPKPAW). The results have clearly shown that that the keyhole geometry and acoustic features are indeed related to the dynamic behavior of keyhole. In Bo et al. (2010), the authors have proposed a unique way for predicting the penetration status in a pulsed GTAW process by designing a monitoring system which works on multi-sensor fusion technology. For sensing welding current, a Hall Effect sensor was used, similarly, in order to sense arc sound signals a microphone was employed. The topside and backside image of the weld pool were captured using a CCD camera and DAQ module. The weld data thus obtained were carefully analyzed by Dempster–Shafer (D-S) evidence theory and subsequently, it was concluded that the multi-sensor fusion technology performs much better than single sensor technology in predicting the penetration status in a pulse GTAW process. For better readability a brief summary of all the relevant WMSs is also tabulated in Table 1.

3.1 Design and development of DAS for establishing an effective WMS

A careful analysis of the literatures presented above and tabulated in Table 1 on various WMSs infers that a Data Acquisition System (DAS) coupled with a suitable sensing module is the heart of a WMS. A typical schematic of a DAS is shown in Fig. 3. From this figure, it can be inferred that a data acquisition system mainly consists of a sensing module (to sense voltage, current, sound, weld pool image etc.), an isolation circuit, amplifier circuits, filtering module and analog to digital converters. The isolation circuits in these systems are generally used to prevent signal conditioning module and ADC circuits from short circuits and high voltage spikes (Andrej et al. 2012). The signal conditioning module which comes next basically consists of an amplifier and a filtering circuit. In general, welding process mainly deals with high magnitude of voltage and current and therefore it is advised to use an isolation and instrumentation amplifier to establish an effective WMS such that it only transmits the desired welding signals by eliminating high common mode voltage signals. Additionally, the combination of both isolation and instrumentation amplifiers can also be used to maintain ground separation among various sensing modules to prevent ground loops (Franco 2002). Here it should be noted that high common mode signals (Pallas-Areny and Webster 1991) can further be minimized by incorporating a differential probe for voltage measurement.

Although, amplifier module discussed above can be used to minimize common mode and ground loop noise, there can be various other noise sources that may exists in a welding environment. Therefore, before designing the filtering module to minimize such noises, it is pertinent to understand their existence during actual welding process. Hence, a brief discussion of the same is given below in Sect. 3.1.1, which will be followed by various filtering mechanisms for effective measurement.

3.1.1 Electrical noise and its filtering in welding environment

Electrical noises in a welding environment are generally defined to be as the undesirable electrical signal which tries to interfere with the desired or original signals. These noises can be constant or transient in nature. Transient noise basically occurs in the form of a pulse with decaying

Table 1 Comparative analysis of various WMS on the basis of sensing and Data acquisition and processing/controlling Module

Authors	Year	Title	Sensors Used	Data acquisition and processing/controlling Module
Massimo et al. (2010)	2010	Welding Monitoring System Based on Real-Time Electrical Signal Analysis	Voltage and Current sensors	DSP using Field Programmable Gate Arrays (FPGA) NI 7830 PCI acquisition board
Luksa et al. (2006)	2006	Collection of arc welding process data	Voltage and Current sensors to measure AC (true RMS) and DC voltage (0—60 V) and AC or DC current (0—1000 A)	A microprocessor-based system PLCC and DIP devices Low Pass Filter implementation
Andrej et al. (2012)	2012	Online monitoring, analysis, and remote recording of welding parameters to the welding diary	LEM LF 1005-S and LEM HTFS 400 Hall effect based current sensor, current range up to ± 1000A and ± 600 A resp.	ATmega328 microcontroller with 16 MHz clock speed, six analog inputs and 1 KB EEPROM Sampling rate: 2 kilo Samples/s NI 6221 DAQ Device Sampling rate: 10kHZ
Siewert et al. (2002)	2002	Application of an on-line weld monitoring system	Hall effect-based sensors	Analog to Digital Converters (A/D) cards Sampling rate: 15,000 samples/sec/channel
Wu et al. (2007)	2007	Real-time sensing and monitoring in robotic gas metal arc welding	Hall effect-based sensors	Analog to Digital Converters (A/D) cards Sampling rate: 10 kHz Low Pass Filter implementation
Kang et al. (2000)	2000	A Study on the Development of the Arc Stability Index using Multiple Regression Analysis in Short-Circuit Transfer Region of Gas Metal Arc Welding	Hall effect-based sensors	Analog to Digital Converters (A/D) cards having a maximum sampling rate of 200 kHz Sampling rate: 5000 samples/s Digital Low Pass Filter implementation
Vikas et al. (2015)	2015	Analysis of shielded metal arc welding using Digital Storage Oscilloscope	Hall effect current sensor (selectable between 1 mA/A or 10 mA/A) 500 MHz band width high voltage, differential probes for voltage measurement	DSO as a data acquisition system (Agilent Technologies, DSO7054B) of 500 MHz Low Pass Filtering Sampling Rate: 100,000 samples/s
Adolfsson et al. (1996a)	1996	Automatic detection of burn-through in GMA welding using a parametric model	LEM Module LT 500-S current sensor instrumentation amplifier for voltage measurement	Hewlett Packard 2454S based dedicated DAQ module Sampling rate: 32.768 kHz Low Pass Filter implementation
Adolfsson et al. (1996b)	1996	Quality monitoring in robotized welding using sequential probability ratio test	LEM Module LT 500-S current sensor instrumentation amplifier for voltage measurement	A dedicated DAQ module Sampling rate: 8.192 kHz Low Pass Filter implementation
Aviles-Viñas et al. (2016)	2016	On-line learning of welding bead geometry in industrial robots	CSNS300M Hall effect sensor CTL2MH Infrared sensor for temperature measurement	Microcontroller together with a developed ad-hoc circuit board Sampling rate: 1 kHz KRC2 controller
Zhang et al. (2014)	2014	Online welding quality monitoring based on feature extraction of arc voltage signal	VSM030D/5 V hall sensor	Analog to Digital Converters (A/D) cards Sampling rate: 28 kHz Discrete Wavelet Transform signal processing

Table 1 continued

Authors	Year	Title	Sensors Used	Data acquisition and processing/controlling Module
Li et al. in (2014)	2014	SVM-based information fusion for weld deviation extraction and weld groove state identification in rotating arc narrow gap MAG welding	Hall Effect current and voltage sensor Photoelectric switch and a disk Arrangement for position sensing CCD camera for sensing the image of the weld pool and rotating arc	DAQ Card Image DAQ Card
Xue et al. (2007)	2007	A Wavelet Transform-Based Approach for Joint Tracking in Gas Metal Arc Welding	CCD sensor system for image capture	A high-resolution A/D converter card PID Controllers Discrete Wavelet Transform signal processing
Wu et al. (2016)	2016	A prediction model for keyhole geometry and acoustic signatures during variable polarity plasma arc welding based on extreme learning machine	MP201capacitance microphone for sound sensing, frequency range from 20 Hz to 20 kHz CCD camera (XVC-1000)	Image Acquisition System Signal Conditioner (MC104) Discrete Wavelet Transform Processing
Bo et al. (2010)	2010	Prediction of pulsed GTAW penetration status based on BP neural network and D-S evidence theory information fusion	Hall effect based current and voltage sensors Microphones for sound sensing CCD cameras for image capture	Data Acquisition cards Control Circuit for overvoltage protection

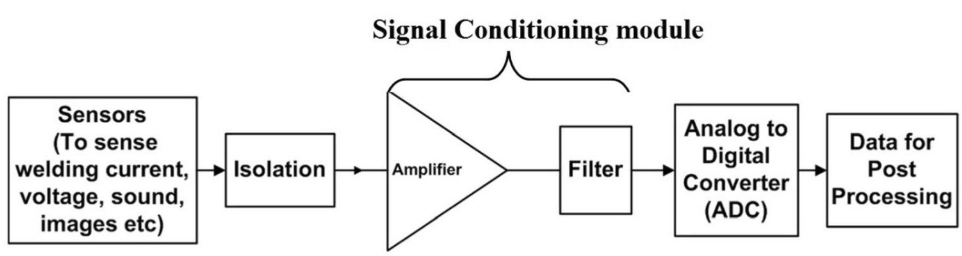


Fig. 3 A typical DAS for establishing an effective WMS

oscillations (for example, a lighting event may generate a transient noise). Whereas, constant noise generally occurs due to the predictable 50 or 60 Hz hum from the power electronic circuits (Web 2015) placed in a welding workshop. Hence, some of the electrical noises that may affect the sensing and data acquisition module in a WMS are, thermal noise originating due to the movement of electrons in an electrical network, imperfections in the designing of the electrical circuits, electrostatic interference, electromagnetic interference, radio frequency interference from radio systems radiating signals and cross talks. In welding equipment, which produce quick changes, these noises are unavoidable and due to switching surges a WMS is prone to such noises. Hence, these noises will contaminate weld data. Additionally, welding equipment which comprises of silicon-controlled rectifiers (Modern Arc Welding Technology 1988), noise due to 'notching' also occurs. The switching of these devices causes sharp inverted spikes during commutation. Additionally, arcing generated in power-switching devices sparks and high-frequency harmonic current components may also produce electromagnetic interference. Hence, proper isolation is essentially required to avoid these kinds of disturbances. Consequently, due to the presence of various noise sources, the raw data obtained with a WMS may have unwanted noise, many a time the noise magnitude is so high that the actual signal gets buried into the noise, this makes the detection even more difficult (Gu et al. 2002; Padovese 2004; Shi et al. 2004). Hence, the proper design and development of filters (Fig. 4) play an important role in maintaining the integrity of the welding signal. Various filters such as low pass, high pass, band pass and band reject filters can be implemented either in hardware (analog type) or in software (digital type). Both have their own merits and demerits, a comparison between these two are tabulated in Table 2. Further, both analog and digital filters can be implemented using various techniques such as Butterworth, Chebyshev, Bessel and Elliptic (Winder 2002). For weld data filtering, ripples in the passband have to be less (preferably less than 0.1 dB) and must have a very high attenuation in stop band (at least 80 dB). In other words, the filters implemented in a WMS must have a flat amplitude response and linear phase response (Adolfsson 1995). Also, it should be noted that before sampling the welding data using an ADC, the resultant signals need to be passed through an anti-aliasing filter to satisfy the Nyquist criteria (Winder 2002) for faithful reproduction of weld data. Subsequently, the weld data has to be sampled using ADC, a brief description of the same is delineated in Sect. 3.1.2.

3.1.2 ADCs for establishing an effective WMS

Referring to Fig. 3, one can infer that the next important block to implement an effective WMS is an ADC circuit module. Therefore, for reliable weld data acquisition, understanding of suitable ADCs is of prime importance and it has been noticed that none of the existing literatures emphasizes on the guidelines to select an appropriate ADCs in establishing an effective WMS. A brief description of various ADCs along with their important specifications is tabulated in Table 3. From this table it can be inferred that for the application requiring moderate accuracy, moderate sampling rate and relatively low power consumption, Successive Approximation Resistors (SAR) type of ADC seems to be best. Therefore, in arc welding processes such as SMAW, GMAW etc. where arc variations occur for very short duration of time and which does not require high frequency voltage circuits, SAR type of ADCs can be deployed for designing a reliable DAS (Web 2016; Vikas et al. 2020). In contrary, the arc welding process such as TIG welding, where arc initiation leads to generation of extremely high frequency voltage (in KV) signals, ultra-high-speed ADCs such as FLASH type can be deployed.

4 Post processing of weld data acquired using WMS

Weld data sampled from the WMS established above, must be subjected to detailed analysis in order to correlate the actual welding parameters with the acquired signal properties for accessing the quality of final weld product. Many researchers have used signal processing, statistical and soft computing techniques like data mining, computer vision, machine learning, and deep learning techniques for this purpose; in the upcoming sections weld data treatment using these techniques will be discussed.

4.1 Signal processing

By incorporating suitable signal processing techniques, the reliability of the welding signals obtained from a WMS can be enhanced. This in turn, will help in establishing a proper correlation with welding parameters and subsequently, real time quality control (or monitoring) of a welding process can be done to achieve a high-quality weld product with lesser cost. Therefore, in order to enhance the reliability of the welding data, noise emanating from harsh welding environment needs to be minimized using both analog and digital filters. Once the weld data is sampled using ADC (discussed in Sect. 3.1.2) and stored in an external storage device the immediate task that needs to be carried out is to

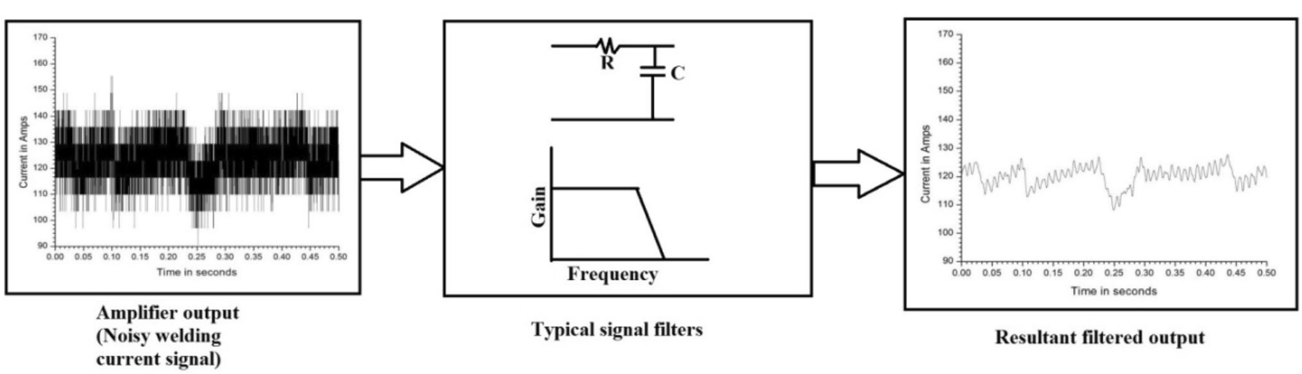


Fig. 4 A typical filtering operation with noisy welding current at input and its filtered output

Table 2 Comparison between Analog and Digital Filters (Winder 2002)

Filter Types	Filter parameters						
	Design Complexity	Additive Noise	Delay	ADC Input Protection	Cost	Programmable	Aging
Hardware (Analog) filters	High design complexity	Addition of noise due to components (i.e., Thermal, Johnson noise etc.)	Low	Required	Comparatively higher	No	Performance of the component degrade with time
Software (Digital) Filter	Easily implementable	Only quantization noise	High	Not required	Less expensive	Yes	Does not age

Table 3 Comparative analysis of various ADCs used in DAS in establishing an effective WMS (Web 2016)

Type of ADC	ADC Characteristics					
	Conversion Time	Resolution	Conversion Method	Size	Disadvantages	Where to use?
Flash (Parallel)	Fastest among all ADCs. Conversion time is independent of resolution	Very Low resolution. Limited resolution, up to 8 bits only	Increased complexity due to higher requirements of comparators and resistors	Exponential increase in power consumption and die size with resolution	Metastability, High Power consumption, requires large area and is expensive	Extremely fast conversion rate but high-power requirements
SAR	Directly proportional to number of bits and in turn to resolution	Medium to high	Internal circuitry runs at higher speed, Binary search algorithm	Directly proportional to the resolution	Limited data throughput ($\sim$ 5Msps)	Application needing low power, small size, moderate resolution and moderate noise immunity
Dual Slope	Doubles with the numbers of bits	Medium to high	Integrating the unknown input signal and subsequently compared with a threshold value	Independent with the resolution	Slowest among all and accuracy depends on precision external components	Application needing low power consumption and requires higher SNR
Pipeline	Directly proportional to resolution	Medium to high	Parallel structure and the working of each stage depend on a few bits	Directly proportional to the resolution	Increased power consumption and higher latency	Application needing conversion rate up to 100 + Msps, lower power consumption requirements than flash
Sigma Delta	Depends on data output rate and resolution	High resolution	Oversampling method and uses a band passes rejection mechanism	Independent with the resolution	Digital to Analog converters are required, increased power consumption	Application needing higher accuracy moderate throughput

process these signals using suitable digital filtering techniques. The two of the most common digital filtering techniques that are used in the welding domain is Fast Fourier Transform (FFT) technique and Multi-Resolutional Analysis using Discrete Wavelet Transforms (DWT) (Savyasachi et al. 2015; Bo et al. 2005). Both signal processing techniques are widely used in weld signal processing (Savyasachi et al. 2015) and both have their own advantages and disadvantages.

For signal processing applications, depending on frequency response, a FFT filter can be either low pass, high pass; band pass or a band reject type. Further, these FFT filters can also be designed using either Finite Impulse Response (FIR) or Infinite Impulse Response (IIR) techniques. In general, a FIR type of filters has sharper transition, low filter order, constant phase delay and higher stability. These are the some of the basic requirements for designing a suitable digital filter for welding applications.

Therefore, various research groups across the globe have implemented such filtering techniques for their applications (Andrej et al. 2012; Wu et al. 2007; Savyasachi et al. 2015; Adolfsson et al. 1996a).

From the discussion presented above, the popularity of FFT based filtering mechanisms for welding applications can be clearly understood. Here it should be noted that FFT based filters are only suitable for stationary signals, where all the frequency components exist for the entire duration of the signal (Gu et al. 2002). But welding signals are non-stationary in nature, in which different frequency components exists at different intervals of time (Gu et al. 2002) and therefore FFT based filtering techniques may not be very suitable for filtering welding signals. Contrary to FFT the other filtering techniques which can treat non-stationary signals appropriately to provide both time and frequency information can be explored. Among various such techniques, one of the most popular filtering mechanisms is Multi-Resolution analysis (MRA) based wavelet transforms. Many researchers have used such techniques to obtain the time–frequency representation of the Welding signal (Wang and Zhou 2003; Xiaoniu et al. 2002; Yuezhou et al. 2001; Jiaxiang et al. 2004; Heng et al. 2003; Matz et al. 2004; PaulS 2004; Rajesh et al. 2004). MRA is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. Depending on the wavelet basis, extent of noise suppression and in turn the extraction of the desired signal will vary. In order to extract the original signal, the wavelet coefficients are estimated by keeping the frequency component below a certain threshold. In Kuanfang et al. (2011), Zhou and QingLi (2001), Zhou and Guan (2007), Wang (2005), the authors have used Discrete Wavelet Transform (DWT) to process the noise by keeping a soft threshold to de-noise the arc welding signals and to extract various signal characteristics (Kuanfang et al. 2016; Ujjwal et al. 2015; Caglar 2012). But, it should be noted that the performance of DWT filtering heavily depends on the arc signal levels, therefore, selection of appropriate wavelet becomes crucial to achieve efficient filtering of the welding data (Kuanfang et al. 2011). Consequently, several methods over the years have been evolved for selecting appropriate wavelet, namely the autocorrelation test; the usage of cross-correlation function and the minimization of the Shannon entropy test (Krzysztof et al. 2015; Misiti et al. 2007). In general, comparison of all the three wavelets to examine the surface texture of machine parts reveals that the Shannon entropy test is the most suitable approach for wavelet selection. But, for welding signals, Li et al. (2012) have proposed that the Energy-to-Shannon Entropy ratio test gives better performance in correlating the arc stability with wavelet energy. Hence, it is suggested that the users carefully examine all these tests before making any decision on the suitability of the mother wavelets for their particular application.

4.2 Statistical data processing

Welding data from past many years have also been modelled and optimized for various aspects of welding parameters using different statistical methods like mean, median, mode, variance etc. (Rosentha 1946; Nishiguchi 1975; Szekely 1986; Shinoda and Doherty 1978). Other statistical tools like, independent component analysis, Statistical Process Control, Taguchi'sMethod (Taguchi's welding experiment 2004) and regression analysis (Li and Gao 2014) were also explored over the time. In Li and Simpson (2009), using various statistical techniques the authors have derived the range of parameters from the welding data. The parameters thus obtained were used for fault discrimination by using independent component analysis for separating the sampled data from the arcing and short-circuiting mode of metal transfer. Such statistical tools have also been used to study the alloy enrichment in the weld metal deposited using cellulosic electrode as function of welding parameters (Ramirez and Johnson 2010). In Cook et al. (1997), Statistical Process Control (SPC) technique was used to extract the range of various statistical parameters like mean and standard deviation. Changes in these statistical parameters are displayed using control charts and are correlated with weld quality using trending analysis, tolerance analysis, and sequential analysis techniques.

Similarly, other statistical non parametric modeling tools like Gaussian Process Regression (GPR) are used in Dong et al. (2016a); Sterling et al. (2015) to model the welding characteristics for improving the welding parameters in a GTAW process. The predicted welding characteristics were validated by performing various experiments and it was concluded that the proposed modeling tool can be used for accurate real time weld quality analysis and monitoring purpose. In Kim et al. (1996), a statistical mathematical model has been proposed to correlate the welding process parameters with the weld bead geometry. For this purpose, partial-penetration, single-pass and bead-on-plate welds were made by the authors on 12 mm mild steel AS 1204 flats by varying different welding process parameters. Subsequently, the relationships between weld bead geometry and welding process parameters were obtained using a set of formulae relating input variables to that of output parameters. Finally, results obtained were experimentally verified and a mathematical model was developed between GMAW process parameters and its bead geometry. Although, good correlations were obtained, this particular research was mostly centered towards an offline learning and hence, adaptability to change for this particular method is limited.

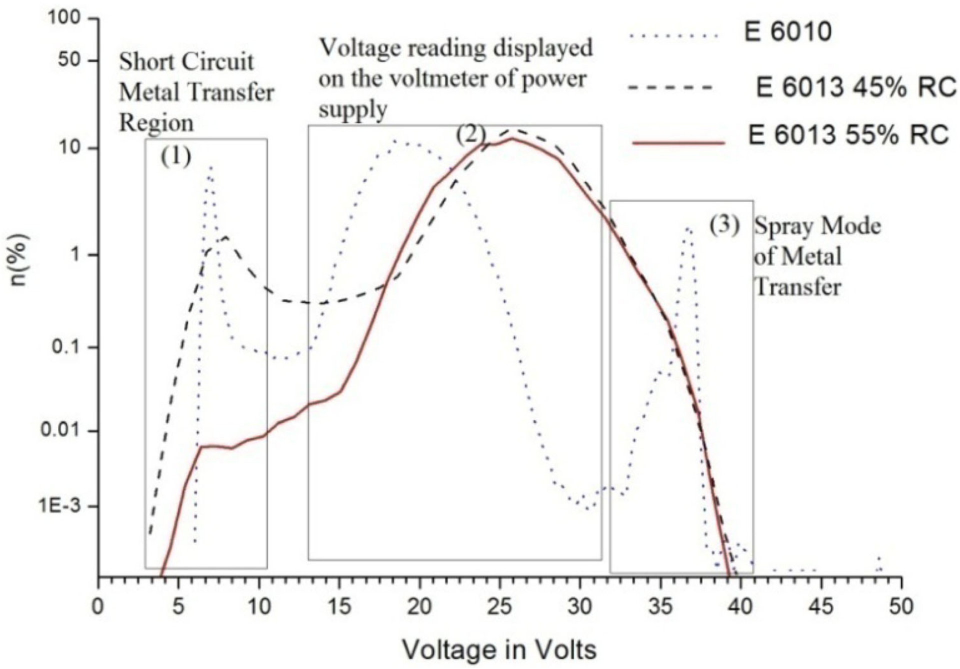
Ganjigatti et al. (2008) have used the regression analysis to determine the input and output relationships of the MIG welding process. With the help of various statistical tools like linear and nonlinear regression analysis these input output relations were established. These regression analysis were than compared and on the basis of average RMS deviation it was concluded that the linear regression performs better than nonlinear regression. Horvat et al. (2011) and Cudina et al. (2008) have acquired the sound signals generated during a GMAW process and subsequently processed the same using a novel statistical algorithm for monitoring and predicting the process quality and stability. For this purpose, the welding current were carefully monitored and processed to predict the emitted sound during actual welding process. For different materials, welding conditions and specimen the proposed algorithm were tested and good correlations between all of them were reported. Kolahan and Heidari (2010) have used a set of experimental data and regression analysis to optimize and model a GMAW process. For this purpose, essential data sets were generated by performing actual tests using Taguchi's method. And finally, to obtain the desired bead geometry (width, height and penetration) the relationships between input and output process parameters were established with the help of different process variables such as wire feed rate, voltage, torch angle, nozzle-to-plate distance and welding speed.

Many authors (Simpson 2007a,b, 2008a, b, c) have also used signature image and statistical technique to study different aspects of arc welding process and to demonstrate that the fault recognition in a GMAW process is indeed possible on real time basis. The signature image technique is also useful in identifying an unknown fault occurring in a welding environment (Simpson 2007a, 2008a). In Simpson (2007b), same authors have further utilized the signature images for real time computation for quality monitoring and fault detection in automated welding in an industrial production environment. This method employs a basic set of orthonormal signatures to describe good quality reference welding according to process specifications, followed by a statistical estimation. The estimates allow a determination of whether the production signatures belong to the reference set for good welding or not. In Simpson (2008b), they further propose a method for determining a stability index during welding. In this work, signature images were obtained using welding voltage and current data. It is then shown that, with a reasonable choice for the signature image window scaling, the stability index agrees with welding experience in the GMAW transfer modes of short circuiting and spray transfer. The effect of changing welding consumables, wire and shielding gases are also illustrated and the connection between the stability index and metal transfer phenomena was investigated.

Another statistical technique for detecting flaws in GMAW process was proposed in Song Li (2000), where various signal parameters were identified which were sensitive to the irregularities in the weld and further techniques were suggested to identify these defects. Subsequently, a Self-organizing Maps (SOM) based modelling technique was proposed to evaluate the welding quality from any sensing system and its usage in automatic welding of mass production parts were discussed in detail. Similarly, the other advanced statistical tools like Probability Density Distributions (PDD) (Rehfeldt and Polite 1998; Chen et al. 2009; Santhakumari et al. 2014; Xiao and Welding 2011; Rehfeldt and Rehfeldt 2003; Vikas et al. 2016, 2018b, 2019), several research groups across the globe have correlated various welding process parameters to that of the acquired weld signal parameters for evaluating the performance of arc welding process. PDD is a plot of the percentage of the total data acquired for each of the discrete values (Vikas et al. 2016). Figure 5 represents a typical PDD plot using E 6013 and E 6010 electrode. In this figure, it can be seen that the voltage PDD for the weld made by E6013 electrode has two distinct peaks, one at the low voltage and the other at the high voltage. The first peak in this PDD corresponds to short circuit mode of metal transfer happening in E 6013 types of electrodes whereas the second peak in the voltage PDD corresponds to the steady-state voltage value. Similarly, for E 6010 electrodes, in addition to two peaks there is an additional peak towards higher voltage values. This peak indicates the spray mode of metal transfer taking place in E 6010 types of electrodes (Vikas et al. 2016).

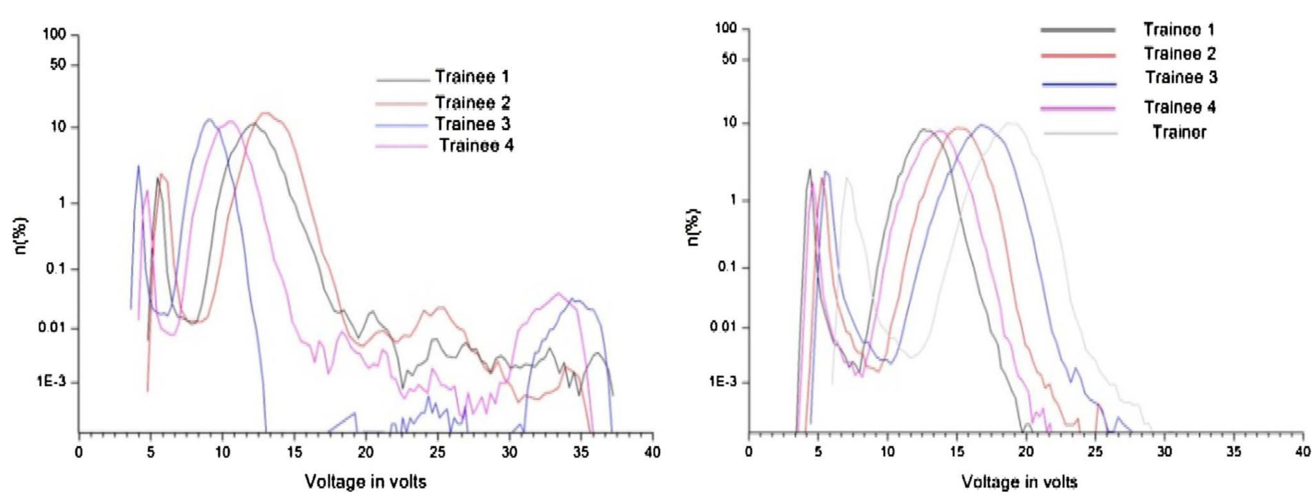
Many researchers have reported that the signature pattern of this PDD changes as the variations in the actual welding parameters takes place (Rehfeldt and Polite 1998; Chen et al. 2009; Santhakumari et al. 2014; Xiao and Welding 2011; Rehfeldt and Rehfeldt 2003). For example, a variation in the Rutile Content (RC) in welding consumables can be easily identified by noting down the PDD plot of that particular electrode (please see Fig. 5) (Vikas et al. 2017). This figure also depicts the region corresponding to different modes of metal transfer in a welding electrode. Hence, one can easily use such statistical tool to evaluate welding process. Extending this discussion on weld quality analysis using PDD technique, in Vikas et al. (2016, 2017), it was noticed that with training the voltage PDD plot of a trainee welders was changing its signature and just by examining this PDD curves one can also monitor the rate at which the welders learn the welding skill (see Fig. 6). Chan et al. (2009) have correlated the welding arc parameters with PDD curve and shown that the arc stability can be improved with the use of nano powders

Fig. 5 Signatures patterns of E 6013 and E 6010 electrodes in a PDD plot, it can be seen that: (**a**) the PDD plots of different electrodes are different (**b**) lower voltage regions corresponds to short circuit metal transfer (**b**) mid region of the plot depicts the voltage reading of the voltmeter of power supply (**c**) E 6010 electrodes had an extra peak at higher voltages due to spray modes of metal transfer in these electrodes (Vikas et al. 2016, 2017)



of $CaCO_3$ in the flux coating. Recently, acquisition of CO_2 welding (GMAW) signals using a data acquisition system and their subsequent analysis using VC + + and MATLAB mixed programming to obtain PDD and power spectral density (PSD) has also been reported (Xiao and Welding 2011). Very recently, evaluation of welding power source and filler wires through signature analysis has been reported (Santhakumari et al. 2014), in this research the authors have evaluated the dynamic characteristic of the arc welding power source and used welding current PDDs to study the instantaneous fluctuations that appears in flux cored wire arc welding process.

Hence, it is clear that in addition to the traditional statistical tools, the advanced statistical tools like PDD can indeed be used to analyze various aspects of a welding process. Making use of the PDD results presented in Vikas et al. (2016, 2017), an intelligent system with a feedback control can be design and developed to incorporate the resultant PDD variations in the welding power source itself for welder training. If this can be done then at the time of actual welding process itself welders can get a real-time feedback to adjust or to maintain a proper arc gap. This in-turn will also help in self learning of welding in a shorter span of time.



(a) Initial days of training **(b) Towards the end of trainees training.**

Fig. 6 Voltage PDD of trainee welders at different stages of training (Vikas et al. 2017)

4.3 Machine learning approach for weld data analysis

Welding data acquired and filtered has also been processed using Fuzzy Logics, Artificial Neural Networks (ANN), and Deep Neural Networks (DNN) models for predicting various welding parameters like bead geometry, welding defects etc. Complete process flow for applying a machine learning approach to welding data are shown in Fig. 7, using this process various researchers have utilized the advantages of soft computing tools like ANN (Aviles-Viñas et al. 2016; Wu et al. 2000, 2001, 2004, 2016; Lv et al. 2013; Chan et al. 1999; Sreeraj and Kannan 2012; Akkas et al. 2013; Seyyedian et al. 2012; Chen and Feng 2014; Iqbal et al. 2011; Kim et al. 2004; Ismail et al. 2013; Dong et al. 2016b; Wan et al. 2017; Rong et al. 2016; Gao et al. 2011, 2007; Hailin et al. 2012; Chen and Chen 2010; Muniategui et al. 2016) for quality analysis of arc welding process parameters. An ANN basically works by finding an optimum weight of each node in a perceptron structure as shown in Fig. 8. Bo et al. (2010) have utilized ANN on the experimentally obtained data for predicting the penetration status in a pulsed GTAW process. The predicted results in turn were validated by fusing Dempster–Shafer(D-S) theory. Similarly, Lv et al. (2013) have used the ANN technique on the arc sound signals for predicting the penetration state and welding quality of a GTAW process by extractinga total of 23 features in time and frequency domain at different penetration states.

ANN Back-Propagation (BP)and Support vector Machine (SVM) models were widely used in welding area to predict various aspects of weld bead geometry (Wu et al. 2016; Chan et al. 1999; Sreeraj and Kannan 2012; Akkas et al. 2013; Seyyedian Choobi et al. 2012; Kim et al. 2004; Ismail et al. 2013; Dong et al. 2016b). For example, a BP based algorithm of ANN was used in Chan et al. (1999), datasets of around 96 welds were made and welding voltage, current and wire travel speed were used to predict bead width, bead height, penetration status etc. Similarly, Chen et al. (2014), have predicted the weld bead geometry in an underwater wet welding process by implementing a BP based ANN modeling technique on the weld seam image, voltage and current signals which are obtained by their WMS having visual and arc sensors installed on it. In Kim et al. (2004), an ANN model was developed for predicting the weld bead width using important process parameters in robotic GMAW process. For this purpose, the ANN models were developed using the error BP based ANN algorithm and the Levenberg–Marquardt approximation (LMA) algorithm. A comparison between the

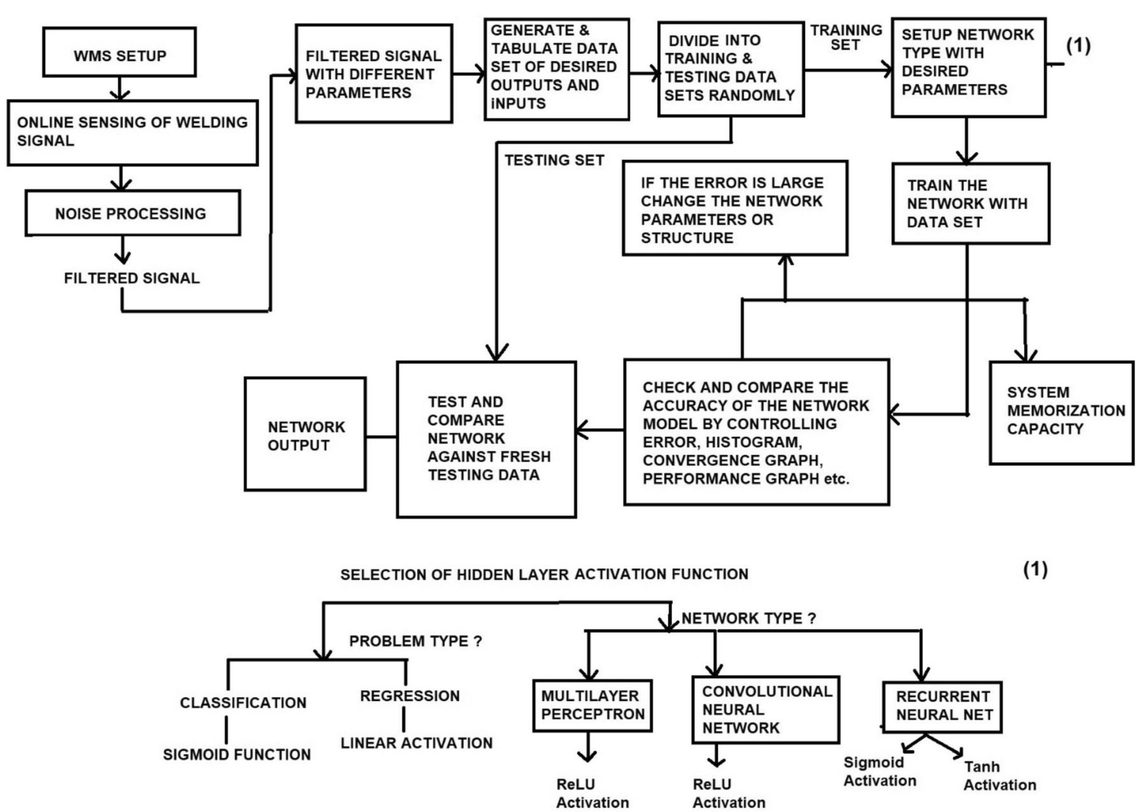


Fig. 7 Process chart of a typical weld data analysis using machine learning approach

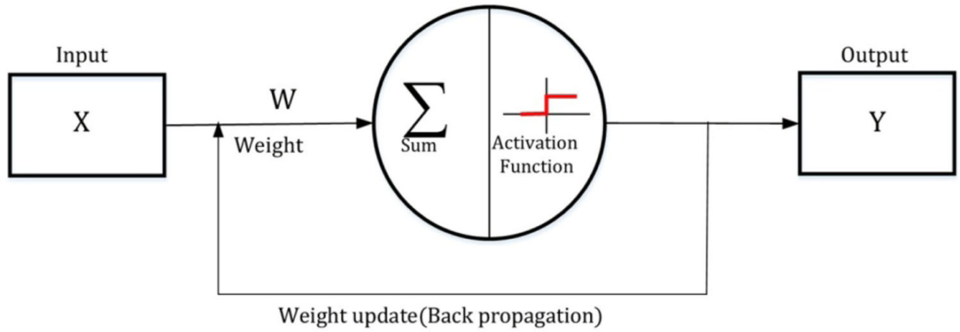


Fig. 8 Perceptron structure of an ANN (Muniategui et al. 2017)

simulated data with that of actual robotic welding experiment's data revealed that the LMA algorithm reduces the root mean squared (RMS) error value significantly. Hence, the LMA method can be better choice in predicting the bead geometry in a robotic GMAW process. Similarly, for predicting the bead geometry in a laser welding using the welding process parameters an intelligent algorithm was developed in Ismail et al. (2013) and it was concluded that the ANN model has the better prediction capability than that of mathematical regression model.

A Back-Propagation (BP) based ANN model can also be used in predicting the angular distortions in an arc welding process. Rong et al. in (2016) has used an Inherent Strain considering the Actual Bead Geometry (ISBG) based techniques and a BP based technique for angular distortion prediction and compared the performance of the two methods. A comparison between the two algorithms reveals that the BP based ANN algorithms are having a maximum forecast error (ERR) and average relative error (ARE) of -7.077% and 4.772% resp., whereas the ISBG method is having an ERR of around -3.318%. Hence, an ISBG method predicts the angular distortion in a much better than a BP based ANN method. In addition to BP based ANN and ISBG techniques a feed-forward ANN (FFNN) algorithm can also be used for accurately predicting the angular distortions; the same has been reported in Seyyedian Choobi et al. (2012), and a multilayered FFNN algorithms were developed using MATLAB in order to predict the behavior of angular distortions in thin butt-welded plates. In a separate study Gao et al. (2011) have shown that a non-linear ANN BP modeling technique can also be used to predict the seam tracking in an arc welding process.

Various researchers have also used the unsupervised machine learning techniques in predicting different arc welding parameters (Song et al. 2000; Vikas et al. 2016; Lv et al. 2013). With the help of Self Organising Map (SOM) based unsupervised based learning technique the welding skill of passing out trainee welders from a weld training institute were graded with good accuracy in Vikas et al. (2016); Lv et al. 2013). Similarly, in Song Li (2000), using a SOM based technique, signal features were extracted and automatic detection of weld defects of short-circuit gas metal arc welding were predicted to get the weld quality information and for finding out the defects in the final product. This is important for on-line monitoring of weld quality especially in Robotic welding and lays the foundation for the further real-time control of welding quality. But, due to improper training parameters the prediction accuracy in this case was found to be less.

One of the other useful techniques of artificial intelligence is a fuzzy logic approach-based model. A fuzzy system basically describes the degree of truth rather than actual true or false and hence a proper implementation of fuzzy algorithms can predict several welding related parameters, a basic fuzzy neural network map is shown in Fig. 9. In Chen and Chen (2010), such a fuzzy network was constructed using welding current, voltage and weld pool's image to predict the penetration status in a GTAW process. In Muniategui et al. (2016), a fuzzy system was used to study the degradation of the welding electrodes by assessing the produced part quality and electrode degradation state for optimizing the electrode usage to achieve zero manufacturing defects.

From the above discussions and a careful examination of each of the techniques, one may conclude that each of the techniques presented above are having certain advantages and disadvantages; consequently, combining different techniques into one is widely used in data mining field, this method leads to better prediction efficiency than a single machine learning technique. In the welding area also, these techniques are widely used. Several research groups have intelligently used fuzzy method with ANN models (Akkas et al. 2013; Hailin et al. 2012; Chen and Chen 2010; Muniategui et al. 2016; Wu et al. 2000, 2001, 2004; Gao et al. 2007). For example, in Hailin et al. (2012) it was seen that a Fuzzy neural network control method based on BP based ANN algorithm can be used to generate a smooth and better control signal to change the arc gap on real time basis. Similarly, a combination of ANN and neuro fuzzy system model was obtained by considering various welding parameters to effectively predict the weld bead geometry

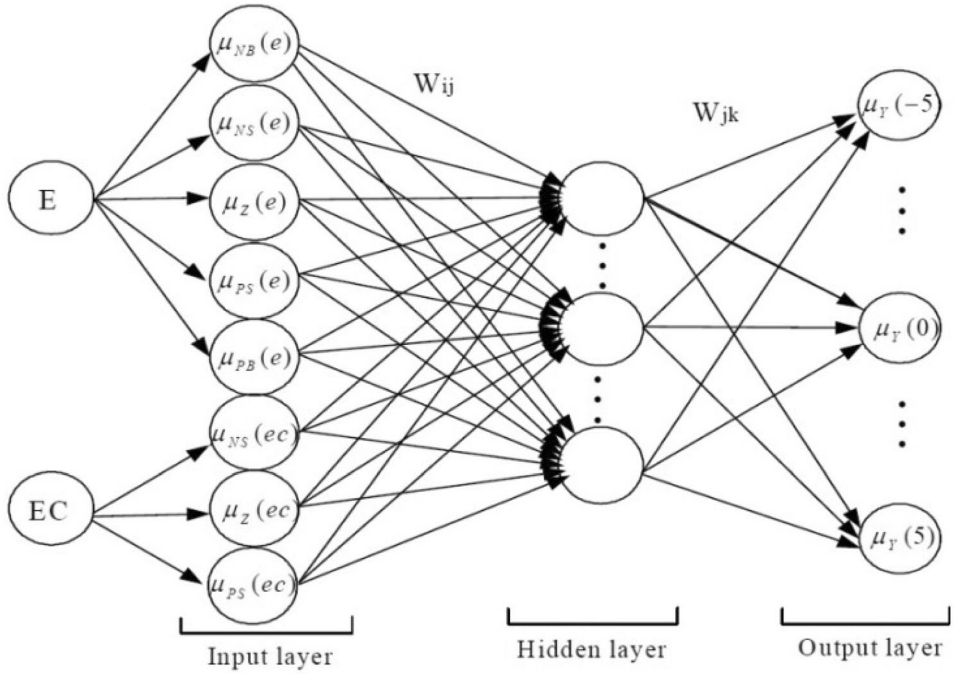


Fig. 9 The structure map of fuzzy neural network (Hailin et al. 2012)

(Akkas et al. 2013). In Hailin et al. (2012), Chen and Chen (2010), Muniategui et al. (2016), Wu et al. (2000, 2001, 2004), Gao et al. (2007) intelligent monitoring and recognition of short circuiting and process disturbance in GMAW process using fuzzy c-means, neural network and Fuzzy Kohonen clustering network (FKCN) were reported. The FKCN model thus developed was accurate enough to predict all the 24 cases used in the study. In a separate study Gao et al. (2007) have implemented FKCN model using welding voltage and current for monitoring the welding defects in the real time basis. Prediction accuracy of more than 90% was reported, which further indicates the efficacy of fuzzy based clustering networks. Kalaichelvi et al. (2013) have used a combination of Fuzzy—Genatic Algorithm (GA) based control technique to optimize a GMAW process. Fuzzy logic deigned in this study was used to control the welding current, arc voltage and to tune the controller parameters. Subsequently, the performance of two controllers was compared in MATLAB and experimentally analysed and it was concluded that the proposed system has good accuracy and control.

Wu et al. (2017) used an intelligent combination of Deep Belief Network (DBN), DNN variant, and t-Stochastic Neighbor Embedding (t-SNE) techniques to monitor and identify the penetrations values in a Variable Polarity Plasma Arc Welding (VPPAW) process. With rigorous theoretical and experimental comparative analysis it was shown a DBN performs better with an accuracy of around 97.62%. This indicates the benefit of using these intelligent algorithms. Sarkar et al. in (2016) have used a combination of multiple regression analysis (MRA) and artificial neural network (ANN) models for accurately predicting the weld bead geometry and Heat-affected zone width in submerged arc welding process. Wan et al. (2017), has done a comparative analysis of back propagation neural network (BPNN) and probabilistic neural network (PNN) model for analyzing the quality of small-scale resistance spot welding process. The developed models were used to extract the features from the dynamic resistance and electrode voltage curve. It was found that the weld quality and the variations of the extracted features were more sensitive to welding current rather than the electrode force. Finally, a comparative analysis among the models revealed that the PNN model is more appropriate for quality level classification whereas the BP based ANN model was more appropriate in the analysis of failure load.

Several authors have also proposed the implementation of ANN models with Support Vector Machine (SVM) models for better results (Wu et al. 2016, 2017; Sarkar et al. 2016; You et al. 2015; Escribano-García et al. 2014). In You et al. (2015), a mixed model of ANN and SVM were developed for real time monitoring of a laser welding process and it was concluded that using an ANN and SVM models in tandem, even with smaller training samples, leads to higher prediction accuracy. The point just now made becomes more clearer if we refer to the work proposed by Escribano-García et al. (2014), in this work, to optimize the welding process the authors have implemented Quadratic Regression (QR) model using Response Surface Methodology (RSM) and compared it with isotonic regression (IR), Gaussian processes (GP), artificial neural networks (ANN), support vector machines (SVM) and regression trees (RT)) models of data mining for predicting various welding properties. The results have shown that for lesser data sets, data mining (DM) techniques generally have poor generalization property. To have an improved generalization features, a prediction model based on Extreme Learning Machine (ELM) technique can be used (Wu et al. 2016; Nandhitha 2016).

From the analysis of various literatures, it is certain that the combination of different machine learning techniques certainly improves the prediction ability of the machine learning model. Now a days with the advancement in computational technology it is easier to process an ANN model with multiple layers between its input and output. This increase in ANN layers allows having precise mathematical manipulations to relate input and output of a process. These multiple layered ANN model is also known as Deep Neural Network (DNN) which can be efficiently implemented in a real time process as well (Redmon et al. 2016; Zamanzad Gavidel et al. 2019). In welding field similar models were implemented to analyze various process parameters and to detect welding defects in real time. Shin et al. (2020) have compared the performance of an ANN and DNN model as shown in Fig. 10 to detect the welding porosity defect in real time using welding voltage signal. For this model, six process variables (X_1 (s[V]), X_2 (s[V_s]), X_7(T_a), X_8 (N[T]), X_9 (s[Ts]), and X_{12} (s|V(T_a)|)) were selected as the variables to input layer for both ANN and DNN model. Results obtained using DNN model outperformed its ANN counterpart by more than 15% accuracy level. Similarly, in Keshmiri et al. (2015), Keshmiri et al. have used DNN model to predict different bead parameters in MIG, SMAW and TIG welding process. For this purpose, the authors have implemented three hidden layers using a sigmoid function and one last layer were used to generate the final output using a linear transformation. Input parameters such as current, voltage, and wire speed were used to estimate the bead geometry (Weld bead width and the depth of penetration). Finally, it was concluded that the proposed DNN model can be used to model different welding process with good accuracy and with lesser data points. However, the model can further be improved to reduce errors in the estimation. Similarly, Muniategui et al. (2017) have used a DNN model for monitoring a Spot-Welding process by extracting the information from 150,000 photographs of the welded parts. The results obtained using DNN algorithms have shown a better prediction ability than a fuzzy algorithm-based prediction. Hence, there is no doubt that a DNN model will have a better prediction ability than its any other ANN counterpart. But one should keep in mind that in addition to a good computational facility a DNN models requires a very large data set, greater than the other ANN algorithms for better accuracy.

For better readability, a comparative analysis of various data mining techniques presented in this work is summarized in Table 4.

5 Important observations and future scope in existing weld data acquisition and analysis techniques

From a careful analysis of the literatures presented above it is clear that for the quality analysis of arc welding process using weld data acquisition and analysis techniques, the efficacy of both WMSs and data mining techniques are of prime importance. Hence, before applying any soft computing techniques for weld parameter prediction/optimization, it is extremely important to ensure the reliability/accuracy of the weld data acquired from a WMS. Therefore, some of the important observations that one needs to keep in mind before establishing a WMS (Figs. 2 and 3) are delineated below:

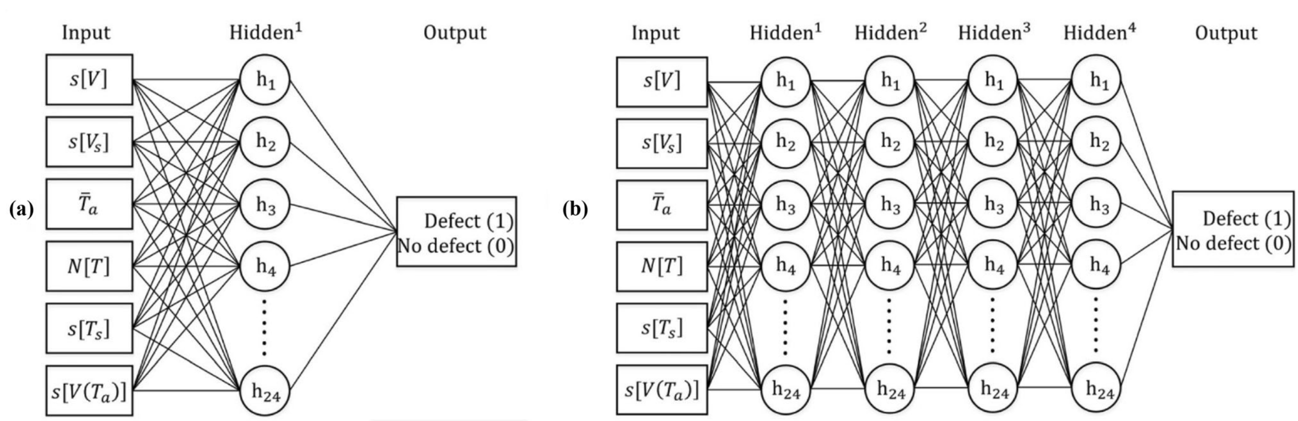


Fig. 10 Artificial intelligence structures. (a) ANN structure and (b) DNN structure (Shin et al. 2020)

Table 4 Comparative analysis of various data processing techniques used for weld quality analysis

Authors	Year	Welding Process	Material	Tools and Technique	Resultant output and the conclusion
Aviles-Viñas et. al. (2016)	2016	GMAW	Mild steel SAE 1018	ANN, Fuzzy	Training an industrial robot for specific welding parameters. 95% prediction accuracy
Ramirez and Johnson (2010)	2014	GTAW	–	Regression	Prediction of precise seam tracking
Dong et al. (2016a)	2016	GTAW	Stainless steel	GPR	Prediction of weld bead geometry
Sterling et al. (2015)	2014	TIG	Mild steel	Regression	Optimization of the welding parameters
Li et al. (2000)	2000	GMAW	Steel	SOM	automaticallyrecognition of GMAW process disturbances
Lv et al. (2013)	2013	GTAW	Aluminum Alloy	ANN	Penetration of penetration state and welding quality Prediction accuracy of prediction accuracy of 83.7%
Chan et al. (1999)	1999	GMAW	Steel	ANN	Prediction of bead geometry
Sreeraj et al. (2012)	2012	GMAW	Stainless steel	ANN	Optimization of welding process parameters to get optimum dilution
Akkas et al. (2013)	2013	SAW Process	Low carbon steel	ANN, Neuro Fuzzy approach	Developed the relationship between bead geometry and process parameters
Seyyedian et al. (2012)	2012	GTAW	304 stainless steel	ANN	Prediction of welding angular distortions
Chen et al. (2014)	2014	UWW	6-mm-thick Q235	ANN – BP neural network	Parameter prediction of weld seam-forming in under water welding
Iqbal et al. (2011)	2011	GTAW	Low alloy steel	ANN	Prediction of weald bead geometry for complex and nonlinear manufacturing processes 15% prediction error
Wu et al. (2016)	2016	VPPAW	6-mm-thick aluminum alloy	ELM, SVM and ANN	Prediction of the keyhole geometry
Ill-Soo et al. (2004)	2004	GMAW	Mild Steel	ANN	Prediction of bead width Slow training system
Ismail et al. (2013)	2013	Laser welding	Steel	ANN	Prediction of bead width with wide range of process parameters
Dong et. al. (2016b)	2017	GTAW	Steel	SVM	Prediction of weld bead geometry
Wan et al. (2017)	2017	Resistance spot welding	Titanium alloy	BPNN and PNN	Quality analysis of RSW process Failure load estimation
Rong et al. (2016)	2016	GTAW	Steel	ANN	Prediction of the angular distortion
Gao et. al. (2011)	2011	GTAW	Low carbon steels Q535	LR-ANN	Estimating the seam position under varying welding currents
Hailin et al. (2012)	2012	GMAW	Steel	Fuzzy Logic and BP Algo	Generation of control signal to adapt weld gap Improving weld quality
Chen et al. (2010)	2010	GTAW	Steel	Fuzzy Logic	Prediction of penetration status
Muniategui et al. (2016)	2016	RSW-P	Aluminum	Fuzzy Logic	Electrode degradation analysis
Gao et al. (2007)	2007	GMAW	Mild steel	A Fuzzy Kohonen clustering network (FKCN)	Real time defect identification 90% accuracy
Kalaichelvi et al. (2013)	2013	GMAW	Mild steel	GA, Fuzzy Logic	Designing of fuzzy logic control to control welding parameter

Table 4 continued

Authors	Year	Welding Process	Material	Tools and Technique	Resultant output and the conclusion
Wu et al. (2017)	2017	VP-PAW	Aluminum alloys	DBN and t-SNE	Development of penetration identification system
Sarkar et al. (2016)	2016	SAW	AISI 1015 mild steel	ANN and MRA	prediction of weld bead geometry and HAZ width
Escribano-García et al. (2014)	2014	GMAW	Steel	RSM, LR, GP, SVM and ANN (a comparison)	Evaluation of mechanical properties of GMAW Process
Nandhitha et al. (2016)	2016	GTAW	–	RBN, ELM and GRNN	Current deviation prediction with 98.5% accuracy
Keshmiri et al. (2020)	2015	MIG, SMAW and TIG	Steel	DNN of four hidden layer architecture	Estimation of bead parameters
Muniategui et al. (2015)	2017	RSW	Aluminum	DNN and Fuzzy Logic	Prediction of degree of degradation of electrodes

(a) Throughput (Data sampling rate) of the data acquisition system should be reasonably high so that the system can acquire all the possible variations happening in physical process.
(b) It should withstand high voltage, current and frequency fluctuations happening in a welding environment over a long period of time (by implementing appropriate isolation, grounding and shielding circuits).
(c) The Baud rate of the WMS must be sufficiently high for a reliable transfer of the resultant data to an external computer for post processing.
(d) It should be cost effective, extremely portable and can be integrated to the welding machine for in situ analysis of an arc welding process.

Keeping the above listed parameters in mind, referring to Table 1 and analyzing the statistical distributions of various literatures (Fig. 11), it is clear that majority of researchers have preferred DAC or ADC cards while implementing DAS for their WMS. But very few studies have explored a Programmable System on Chip (PSoC) (Web 2016) based system for DAS application and control in a WMS. A PSoC is a technique where all the component of electronic circuitry can be designed in single IC and therefore, whole electronic circuitry can be minimized. Even noise immunity can be improved, which plays an important role during electronic measurement at the time of actual welding process. A PSoC has one microcontroller or microprocessor or a Digital signal Processor core. It also has other blocks like, Read Only Memory (ROM), Random Access Memory (RAM), and Flash Memory etc. It can have Universal Serial Bus (USB), Universal Asynchronous Receiver/Transmitter (UART), a Serial Programming

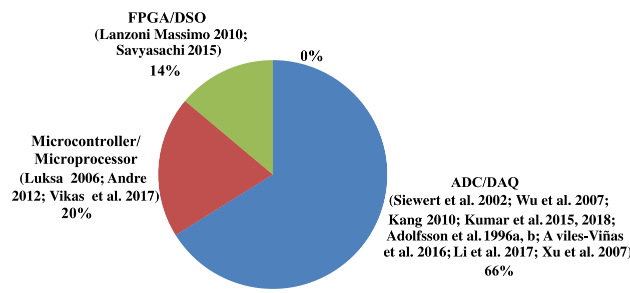


Fig. 11 Modules used for weld data acquisition in design and development of WMS

Interface (SPI), and an Ethernet Port (Web 2016). Hence, PSoC provides a perfect platform to design any welding specific embedded design that needs to be on a single board. Consequently, a PSoC based dedicated WMS is something which needs to be explored more in the welding technology.

The literature presented on WMS in Sect. 3 also shows that till date, there is no single power source available with inbuilt data logger and analyser, which can provide the output to monitor the quality of weld on a real time basis. The development of real time data logger and analyser and incorporation of this system to the power sources would be an innovative concept to evaluate different welding parameters (welder's skill, quality of power sources, quality of electrodes etc.). A separate study can be carried out to amalgamate the DAS into the power source itself for in-situ monitoring of the actual welding process as and when required.

Similarly, from the existing literatures on WMS (Sect. 3) it is also seen that to have an effective and precise correlation between the welding quality and the variations in the electrical signals, the rate of weld data acquisition must be sufficiently high. Data at a speed lower than that of the actual events occurring during welding process would result in modification of the process information. But existing literatures does not provide any guidelines to optimize the sampling rate for one's application. This is important as the rate of data acquisition also impacts the design and development of various components of a DAS, in turn effecting the establishment of a WMS. Further studies can be carried out to optimize the weld data sampling rate for reliable data acquisition and analysis purpose.

As far as the post processing of the weld data are concerned, one has no doubt that for estimating weld parameters with reasonable accuracy the automation technology needs to be improved by implementing adaptive algorithms and intelligent controllers. The same was noticed while analysing various literatures presented in Sect. 4 where, various soft computing and data mining techniques were joined to achieve better accuracy. The dependency of all such techniques in weld data analysis methodologies can also be observed from Fig. 12. An exhaustive analysis on all such literatures reveals that ANN is indeed the most widely used soft computing techniques among the research community (Martinez and Alfaro 2020) (Fig. 13). But, to enhance these ANN models, researchers from various domains need to work together in order to achieve optimized prediction accuracy with least computational cost.

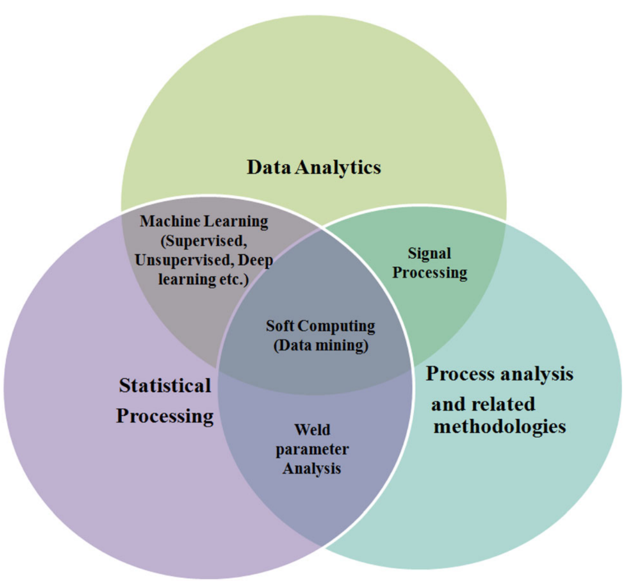


Fig. 12 Venn diagram depicting various post processing methodologies used for weld data analysis

6 Conclusion

In this paper, a brief review on weld data acquisition and analysis techniques for the quality evaluation of arc welding process has been discussed. From the bibliographic analysis, it was noticed that various WMS based on microprocessors, microcontrollers, FPGA's etc. have been designed and developed for weld data and/or image acquisition purposes. Subsequently, various welding parameters such as voltage, current, speed, image etc. were sensed using suitable sensors and filtered for noise, before subjecting them for any meaningful analysis. The data thus obtained were analysed using various statistical and machine learning tools. A careful analysis of these data mining techniques reveals that both supervised and unsupervised based learning models were used for decision making. And it was seen that a combination of different machine learning models into one, improves the weld parameter detection efficiency. Advancements of computational resources have allowed the usage of multi layered ANN models for better results. With a systematic review of the WMS in tandem with these data mining techniques one is having no doubt that an effective WMS have great potential for real time monitoring and defect analysis for an arc welding process. However, most of existing research works have been carried out only in laboratories using data acquisition system specifically designed for this purpose. There is hardly any literature that discusses use of such system in actual welding fabrication. This is because development of WMS and data analysis procedures still remains in R&D phase and yet to reach the welding shop floor. Further, cost of WMS is significantly higher than welding equipment and expertise required for analysis is much different from expertise of a shop floor welding engineer. In recent times, welding equipment manufacturers have come up with weld data acquisition system and analysis techniques, which can be integrated with welding power source and acquire the voltage and current data at reasonable speed which can be used to verify whether welding parameters confirm to those provided in welding procedure specification (Kemppi pro evolution 2016). Improved versions of such systems need to come into real fabrication industries, this is only possible if researchers from different backgrounds come together to work towards for the improvement of WMS hardware and data mining network models for efficient prediction and better control in monitoring a welding process. Hence, it is a high time to establish a collaboration between various research groups, institutes, universities etc. to unite and work together to explore this interdisciplinary area of science and technology.

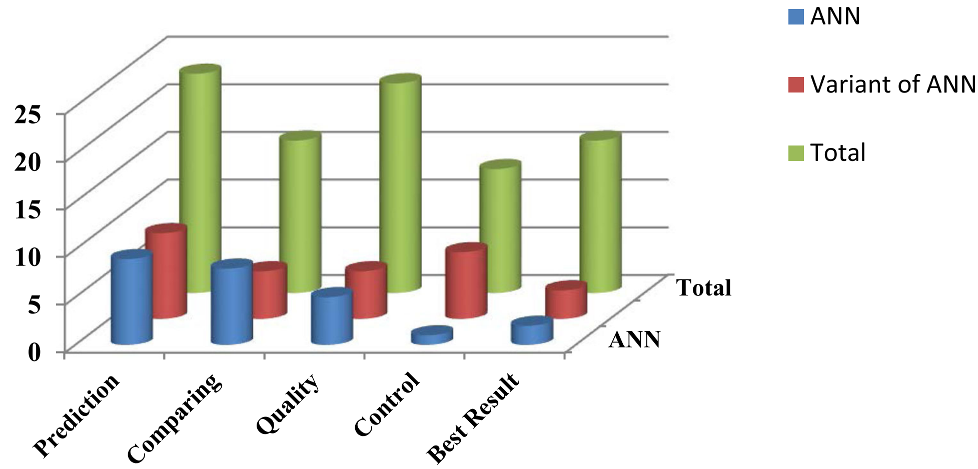


Fig. 13 Comparative analysis of various ANN and ANN variants

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Declarations

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