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# Intelligent welding system technologies: State-of-the-art review and perspectives

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ABSTRACT

Welding systems are being transformed by the advent of modern information technologies such as the internet of things, big data, artificial intelligence, cloud computing, and intelligent manufacturing. Intelligent welding systems (IWS), making use of these technologies, are drawing attention from academic and industrial communities. Intelligent welding is the use of computers to mimic, strengthen, and/or replace human operators in sensing, learning, decision-making, monitoring and control, etc. This is accomplished by integrating the advantages of humans and physical systems into intelligent cyber systems. While intelligent welding has found pilot applications in industry, a systematic analysis of its components, applications, and future directions will help provide a unified definition of intelligent welding systems. This paper examines fundamental components and techniques necessary to make welding systems intelligent, including sensing and signal processing, feature extraction and selection, modeling, decision-making, and learning. Emerging technologies and their application potential to IWS will also be surveyed, including Industry 4.0, cyber-physical system (CPS), digital twins, etc. Typical applications in IWS will be surveyed, including weld design, task sequencing, robot path planning, robot programming, process monitoring and diagnosis, prediction, process control, quality inspection and assessment, human-robot collaboration, and virtual welding. Finally, conclusions and suggestions for future development will be proposed. This review is intended to provide a reference of the state-of-the-art for those seeking to introduce intelligent welding capabilities as they modernize their traditional welding stations, systems, and factories.

## 1. Introduction

Welding processes and systems play an important role in modern industrial production lines. After decades of evolution, many welding operations using handheld-tools have been replaced by automated welding systems using industrial robots [1–3]. While welding robots have been in use for decades, they are preprogrammed machines with limited, if any, intelligence. Today's welding processes are complicated, with many parameters and a limited understanding of the process mechanism. Meanwhile, users and customers have specific weldment requirements and dynamic work environments. Therefore, welding is moving towards more customized production utilizing next-generation welding systems that can intelligently adjust to changing welding tasks while maintaining high quality. In the age of big data, it is also important to have smart strategies for collecting and sharing welding information, both to improve operations internally and as part of comprehensive life-cycle evaluations in industrial supply chains. For example, tracking in-process welding parameters and post-process weld quality can facilitate the improvement of welding processes, component performance, and subsequent service quality.

While there are many welding methods, the transformation of traditional welding handicraft is being enabled by developments in information science and technology (ICT). Advancements in the fields of computer science, control theory, robotics, and artificial intelligence are enabling the replacement of manual work with automation that is intelligent. These concepts and their associated technologies have been explored in manufacturing research initiatives such as Industry 4.0, smart manufacturing, the internet-of-things (IoT), the industrial internet, big data, artificial intelligence 2.0 (AI 2.0), new-generation intelligent manufacturing (NGIM), and human-cyber-physical systems (HCPS) that are establishing a pattern for future industry [4–10]. These initiatives are providing the necessary drivers, enablers, and platforms for upgrading welding systems into higher levels of intelligence.

Previous reviews have introduced and described several domains of

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**Table 1**
Review papers related to intelligent/smart welding techniques/systems.

| References | Application/scope | Objective (comments) |
|---|---|---|
| Cai et al. [11] | Solid-state metal joining | Providing a review of solid-state (SS) welding including modeling, simulation, and monitoring/diagnostics |
| Chen and Lv [12] | Arc welding process | Ideas of intelligentized welding manufacturing technology (IWMT) |
| Mishra et al. [13] | Friction stir welding process | Sensor based monitoring and control |
| Nizam et al. [14] | Vision based identification and classification of weld defects | Defects in welding environments |
| Reisgen et al. [15] | GMA-welding | Networked, autonomy-capable and cyber-physical system (CPS) supported welding production systems |
| Chen [16] | Arc welding | Intelligentized welding manufacturing technology |
| Liang et al. [17] | Enabling technologies of intelligent manufacturing systems | Intelligent scheduling, process optimization, control, and maintenance |

intelligent welding systems (IWS), as summarized in Table 1. However, to the best of our knowledge, a comprehensive exploration of the literature defining intelligence, addressing the relationships within IWS, proposing a linkage framework, outlining the enabling technologies, and examining future trends in IWS has not been undertaken. To address this gap and better promote the development of IWS, this paper will review and analyze the literature on the evolution and application of intelligent techniques in welding systems. Special attention is paid to the integration within an IWS, including a system framework and key technologies.

The structure of this paper is summarized in Fig. 1. Section 2 introduces the retrieval strategy for literature. Section 3 summarizes the definition and evolution of intelligent welding. Section 4 focuses on enabling technologies for intelligent welding systems. Section 5 examines system integration in the context of emerging concepts and technologies such as Industry 4.0, cyber-physical systems, etc. Section 6 reviews application domains, including control, monitoring, human-robot cooperation, etc. Section 7 discuss the industrial suppliers and integrators in the field of intelligent welding. Section 8 concludes with a summary of possible future R&D directions.

## 2. Literature review methodology

An extensive search of the intelligent welding research literature was undertaken. For expedience, the search was limited to welding technologies, although publications in intelligent manufacturing may also have yielded results in intelligent welding. The preliminary retrieval strategy used key words "intelligent* AND weld*" on the TITLE field in SCOPUS and WOS databases. Its analysis focused on two questions: ***(1)** Who works in this field?* and ***(2)** What has been focused on?* as listed in the publication keywords.

The bibliometric analysis indicates 5 authors and 4 institutions dominate the IWS related literature: S.B. Chen from Shanghai Jiao Tong University, China; Y.M. Zhang and Y.K. Liu from University of Kentucky, USA; L. Wu from Harbin Institute of Technology, China, and I.S. Kim from Mokpo National University, South Korea. The main IWS research topics of these authors are in the areas of sensing, modeling, control, monitoring, optimization, and artificial intelligence as applied to arc welding, laser welding, and friction stir welding. Based on this preliminary review, we modified our complete retrieval strategy by expanding our search terms as shown on Table 2.

## 3. Overview of intelligent welding

It is not easy to directly extract a complete definition of "intelligent welding" from the literature, as it is expressed in various ways in the papers found in the preliminary search. Accordingly, in this section we will briefly review the evolution of welding systems, and examine the foundations of intelligence as an element of manufacturing. Fundamental technologies of the past decades that enable the adoption of intelligence into welding systems are outlined, leading to a general definition of intelligent welding.

### 3.1. Evolution of welding systems

The first arc welding machines developed in the 19th century [12] required a human as a controller to create a weld. The human in this traditional welding system performed all information tasks, including sensing, analysis, decision-making, operation, control, cognition, and learning. This process is highly labor intensive and puts high demand on the human to control process efficiency, consistency, and quality, where human capability to perform complex work tasks can be limited.

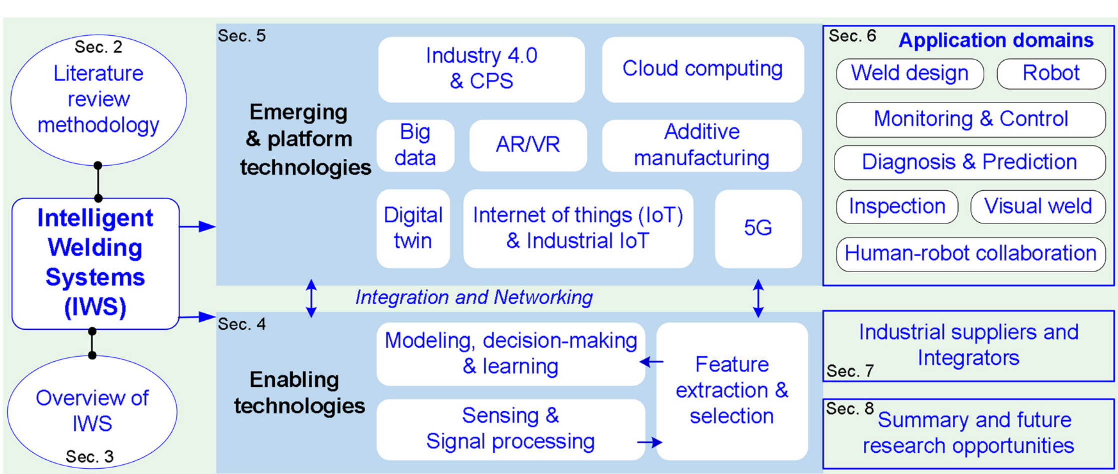


**Fig. 1.** The scope and structure of the review.

**Table 2**
Retrieval strategy for literature on different intelligent welding sub-topics.

| Sections | Keywords | Retrieval strategy |
|---|---|---|
| Sec. 4: Enabling technologies | Sensor, sensing, signal, arc, acoustic, vision… | "weld*" AND ("sens*" OR signal OR acoustic OR vision OR sound OR spectral OR ultrasonic OR image OR "multi sensor" OR "intelligent sens*" OR "signal processing" OR "collection" OR "acquisition") |
| | Feature extraction, feature selection… | "weld*" AND ("feature extraction" OR "feature selection" OR "signal selection" OR "feature construction" OR "feature selection" OR "categorization" OR "signal relationship") |
| | Modeling, expert system, artificial intelligence, machine learning… | "weld*" AND ("model*" OR "intelligen*" OR "artificial intelligen*" OR "AI" OR "expert system" OR "machine learning" OR "neural network" OR "decision making" OR "decision tree" OR "fuzzy logic" OR "algorithms" OR "neural network" OR "unsupervised learning" OR "reinforcement learning" OR "regression learning" OR "transfer learning") |
| Sec. 5: Emerging technologies | Industry 4.0, CPS, Big data, cloud computing, IoT… | "weld*" AND ("Industry 4.0" OR "CPS" OR "cyber-physical system*" OR "big data" OR "cloud*" OR "IoT" OR "Internet of Thing*" OR "industrial internet" OR "digital twin*") |
| Sec. 6: Applications | Robot, programming, control, monitoring, detection, prediction, design, maintenance… | "weld*" AND ("program*" OR "robot*" OR "task*"OR "path*" OR "monitor*" OR "diagnos*" OR "control" OR "fuzzy logic" OR "prediction" OR "identification" OR "maintenance" OR "detection" OR "inspection") |

In the recent past, semi- and fully-automated robotic welding has been widely applied to manufacturing to supplant human shortcomings.

The development of welding has gone through four phases. In phase I, welding was manual with limited efficiency and consistency. Phase II saw the application of automation including robotics, but the process was difficult to model and control. In phase III, welding automation was made easier with "teach and playback" robots, but it was done off-line and had limited ability to respond to disturbances and fluctuations. In Phase IV, intelligence is applied to welding systems to more actively monitor and control welding dynamics and quality. The evolution of welding systems from manual to intelligent is an evolution from human-physical systems (HPS) to the human-cyber-physical systems (HCPS) [4], Fig. 2.

### 3.2. Foundations of intelligent welding

The essence of intelligent welding is in using intelligent techniques and/or machine intelligence to mimic, strengthen, and/or replace human intelligence. By integrating the advantages of humans and physical systems into intelligent cyber systems, welding systems can be greatly enhanced, especially in computational analysis, precision control, and sensing capabilities, as well as in improving the efficiency of human knowledge management, transfer, and application. Then, work efficiency, quality, and stability of the welding system can be improved by transferring relevant human experience and knowledge to the cyber-physical system (e.g., through software and the knowledge base) [4,5].

#### 3.2.1. Fundamental intelligence traits

Modern computational power has enabled the application of many machine intelligence techniques developed in the second half of the 20th century. These machine intelligence techniques have embraced advanced search, combinatorial optimization, and geometric reasoning methods, as well as advanced artificial intelligence that simulates cognitive functions such as learning. However, generalized machine intelligence (e.g., performing the full range of human cognitive abilities) is still a long way off, and thus machine intelligence can only replace human intelligence at reasonable points in an intelligent welding system. The following are human intelligence attributes whose duplication or transfer to machines is useful to IWS [4]:

*3.2.1.1. Context dependent dynamic perception.* The state of manufacturing resources (equipment, computers, and intellectual resources) change continuously throughout the production cycle and life cycle of a product [18]. Distinguishing what is important and requires attention within automated systems (intelligent sensing devices) is context dependent and can provide strong support to the manufacturing service platform in managing manufacturing resources and processes. Sensing devices include two-dimensional barcode, RFID readers, sensors, video capture, GPS, etc. Device signals or knowledge representations within these systems may be incompatible and may require physical or software interface adapters to convert attributes for communication, data storage, or interpretation.

*3.2.1.2. Identification.* Intelligently distinguishing between different states, conditions, components, sub-assemblies, etc. is an important part of automating manufacturing processes [19]. While the meaning in common speech applied to identify is simple – "to make, regard, treat, or associate as the same or identical", it can become a complex problem group or classify different states or conditions in the production environment. However, this area of machine intelligence has

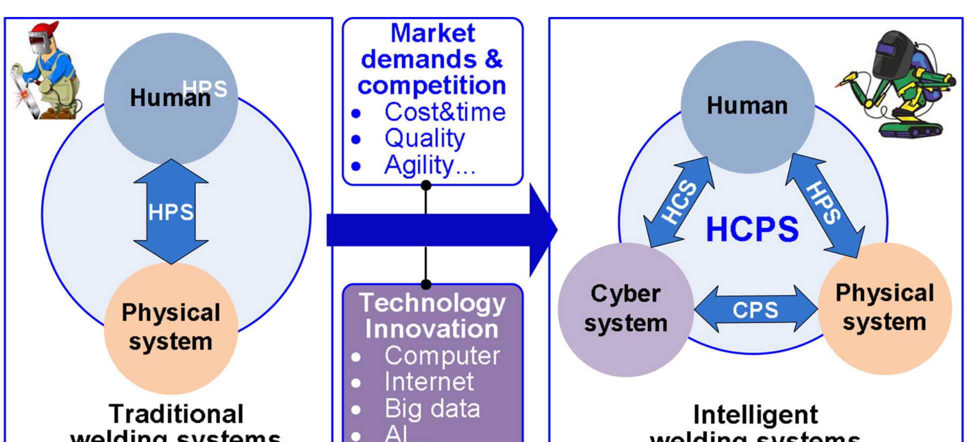


**Fig. 2.** Welding systems: the evolution from HPS to HCPS.

advanced considerably in the past decade.

*3.2.1.3. Categorization*. Once an object or condition has been perceived, frequently it needs to be categorized based on its features to distinguish it from category members and nonmembers before action is taken. Intelligent categorization is useful when systems are presented with new and changing inputs. Categorization is important in learning, prediction, inference, decision-making, language, and many forms of interactions within the production environment.

*3.2.1.4. Goal setting & prioritization*. When tasks are automated, organizational or production goals may not be situationally clear or may be in conflict, and thus intelligence is important to provide direction to routine decisions in automated systems [20]. In this capacity, activities or tasks may require prioritization to determine their order of importance relative to each other for efficient alignment of the activities to the goal(s).

*3.2.1.5. Decision-making*. When an automated system is faced with a multitude of feasible choices, e.g., when categorizing or selecting actions to meet goals, a decision must be made. The best decision(s) should be aligned with organizational goals, and may require balancing positive and negative outcomes to achieve a best global state. The psychoanalytic literature defines this as a cognitive process that is not just about rational analysis, but also includes experience, beliefs, and values when assessing incomplete information. Automating a system when faced with this uncertainty requires a decision-making process that can produce a final choice, which may or may not prompt an action. Machine intelligence mimics the process of choosing an alternative that best captures the values, preferences, and beliefs of the organization.

*3.2.1.6. Prediction & planning*. Choosing the next best action may require an automated system to predict or forecast future states based on possible external influences and probable outcomes from its set of feasible choices. In the psychoanalytic literature, prediction is often, but not always, based upon experience or knowledge. Prediction can help set priorities for activities or tasks, but its application in general artificial intelligence provides guidance for general planning.

*3.2.1.7. Negotiation*. Multiple entities with their own goals and sets of actions may concurrently exist in intelligent automated systems. Thus, it is necessary for these entities to combine through negotiation of their divergent positions into a joint agreement so their individual actions can steer the system to its best global system state.

*3.2.1.8. Learning*. In the psychoanalytic literature, learning is the process of acquiring new, or modifying existing knowledge, behaviors, skills, values, or preferences. In a dynamic manufacturing environment, it is beneficial when intelligent automated systems can learn and make their processes more robust over time, as well as easily incorporate new learning from humans or other sources [21].

These intelligence traits can be combined in the manufacturing environment into higher order cognitive activities such as knowledge representation and modeling, diagnosis, cooperation, and scheduling. For example, scheduling combines the categorization of manufacturing resources with the negotiation of agents representing different production demands and resources, where decisions are made to select the best actions to meet on-time delivery and profitability goals.

#### *3.2.2. Station-level intelligent welding – the welding robot*

Intelligent welding at the station-level is essentially embodied in modern robotic welding technology. Robotic welding is a fundamental technology that enables intelligent welding systems by replicating the physical motions of a human welder. A robotic welder is a reprogrammable multifunctional manipulator designed to maneuver materials, parts, tools or specialized devices in generally repetitive motions to create a welded joint. The first industrial robotic welder, unveiled in 1962 and first used by General Motors, was invented by Devol and Engelberger [22]. It improved efficiency at levels of precision and consistency that were impossible with manual methods while removing workers from hazardous environments. Robotic automation was recognized for its ability to improve greatly the control of the arc weld pool to obtain more uniform weld penetration regardless of the disturbances to the system.

The intelligence of the modern welding robot is captured in its control software, enabled by specialized sensors like laser sensors or cameras. The control system can set welding parameters, control welding procedures, self-diagnosis system faults from predetermined monitoring algorithms, and realize communication with the greater manufacturing environment. In multi-task environments, a welding robot with vision sensors can perform grasping, handling, mounting, welding, and unloading of arbitrarily oriented parts, with tools replaced automatically on the robot wrist according to the nature of the task.

#### *3.2.3. Station-level monitoring and control*

Monitoring and control algorithms form a foundation for intelligent evaluation of weld processes. These algorithms frequently draw upon statistical and signal conditioning procedures to monitor welding for quality and process control. Chu et al. [23] demonstrated effective use of power spectral density and time frequency analysis to analyze GMAW process signatures for welding stability and quality. Ersoy et al. [24] used process signatures to monitor the unstable arcing period to estimate spatter quantity. Hu et al. [25]. use peak-to-peak timing of weld voltage signals to determine weld droplet detachment, controlling the process to avoid sporadic detachments and ensure detachment at normal intervals. Shao et al. [26] used k-fold cross-validation for feature selection and parameter tuning to monitor quality in ultrasonic metal welding processes. Guo et al. [27] integrated univariate statistical control charts with the Mahalanobis distance to monitor non-normal multivariate weld quality observations with flexible control limits to achieve a near-zero misdetection rate while keeping a low false alarm rate. Work in developing statistical monitoring and control for welding [28,29] provides ample process and quality criteria for intelligent welding systems.

### *3.3. Towards a definition of intelligent welding systems*

Researchers have applied different intelligent techniques to improve the efficiency, stability, quality, and welder operational environments in developing welding systems. As shown in Table 3, several sources have proposed definitions for concepts related to intelligent welding systems. In order to refine a general definition of intelligent welding, it is important to clarify what intelligent welding is and what it is not.

While factories can be highly automated, intelligent welding is not only about the degree of automation of the welding floor. It is more about autonomy, optimization, and the ability to adapt to changing circumstances of welding needs in the manufacturing enterprise. Robotic welding is also not intelligent welding, although welding robots are an important enabler for IWS. An intelligent welding system is not just about the introduction of machine intelligence to the production floor, but is an entire ecosystem that includes the humans, experienced welders, smart designers, and skilled operators.

Generally, an intelligent welding system is an advanced system whose goals are high levels of productivity, quality, flexibility, functional and operational precision, and cost-effectiveness. The system is designed around welding automation (unmanned welding), robots, flexibility, and virtualization. Intelligent welding integrates digital, networked, and artificial intelligence (AI) technologies to replace and/or strengthen human sensory capabilities (e.g., visual, auditory, tactile). It integrates experiential knowledge (e.g., melt-pool behavior, arc sound, weld appearance), judgment (welding experience knowledge

**Table 3**
Definitions of concepts associated with intelligent welding systems.

| Concept | Definition | Refs. |
|---|---|---|
| Robot welding | Robot welding is the use of mechanized programmable tools (robots), which completely automate a welding process by both performing the weld and handling the part. | [30] |
| Intelligentized Welding Manufacturing | Intelligentized Welding Manufacturing (IWM) is preliminarily defined as simulating intelligent behaviors and functions of welder's sense, brain and body activity in welding process by the artificial Intelligence technology. | [12,16] |
| Virtual welding | This system uses a welding robot to carry the torch and sensors to perform the welding and measure the weld pool surface. The human welder holds a virtual torch whose operation is similar as a real torch such that his operation and adjustment are still natural and free in 3D space. | [31,32] |
| Welding 4.0 | Welding 4.0 – ewm Xnet is as welding management system, which they called a step towards more efficient and resource-saving welding technology. | From ewm Xnet |
| WELD4.0 | WELD4.0 is a European project on the education and training of qualified personnel. WELD4.0's main innovation is the inclusion of novel ICT technologies and VET training methods to an existing professional profile in the manufacturing industry, the European Welder, working in the context of Industry 4.0, that will address an actual market need in terms of qualified personnel. | www.weld4.eu |

learning, reasoning and decision-making, etc.), and weld process optimization knowledge. Machines may completely replace welders, but humans and machines may also cooperate to weld components in this system. Today's intelligent welding/manufacturing differs from the 1980′s concept of intelligent manufacturing by being based on "big-data" collected from production processes and operating conditions. This data comes from a variety of sensors placed on devices that can be utilized for multiple applications. Effective extraction and use of information embedded in this data can drive innovation, competitiveness, and growth in manufacturing.

An intelligent welding system will monitor and control operations at the station, system, and system-of-systems (SoS) levels to achieve its various system goals. As noted earlier, station-level intelligent welding systems are primarily robotic welding systems, but more-and-more intelligence will be devolved to the station level, as shown in Fig. 3(a). An example system configuration for a station-level IWS is shown in Fig. 3(b), whose main components are listed in Table 4. Typical tasks conducted in an IWS such as pre-weld procedures, robot planning and control, welding process monitoring and control are listed in Table 5. Integration of several station-level IWS through an industrial network enables the free flow of data across a wider range of areas, improving breadth, accuracy, and depth of resource allocation. System-level IWS may take the form of welding production lines, workshops, enterprises, etc. At the SoS-level, multiple system-level IWS are integrated, through the industrial internet and intelligent cloud platforms. The SoS-level IWS enables horizontal, vertical and end-to-end integration through platforms, building an industry ecosystem with the potential for openness, synergy, and sharing.

In the next section, the enabling technologies for improving the performance of IWS tasks are reviewed. Then, emerging platform technologies and manufacturing research initiatives influencing the direction of intelligent welding will be examined.

## 4. Enabling technologies for IWS

While there are many technologies supporting IWS, the focus of this section will be on more common enabling technologies including sensors and sensing, signal processing and feature extraction, modelling and simulation, decision making and reasoning, and AI and machine learning (ML).

### *4.1. Sensors and sensing techniques*

Analog, digital, and image signal sensors are integrated into welding systems to characterize quantitatively welding parameter information. Example parameters of an arc welding process are current, voltage, travel speed, electrode extension, and electrode diameter. Sensing technology is important for modeling and controlling the welding process, and can include sensors for capturing acoustic, force, visual, voltage, and current signals. The research literature has addressed the strengths and weaknesses of sensing technologies as outlined in Table 6. In recent years, experimental systems with multi-sensor fusion have been developed [29,34] to acquire more accurate process information, thus describing the process more completely, precisely, efficiently, and robustly than can be obtained from a single sensor.

### *4.2. Signal processing and feature extraction*

In laboratory or industrial applications, there is always background noise in welding processes that influences sensor readings. Noise increases data error and can seriously affect secondary processing results. Therefore, signal processing should be used to filter out the noise in a signal. Methods such as amplification, filtering, and statistical methods remove interference components from the signal data so that the signal is as close as possible to the real welding parameters. Signal processing methods have been classified by data type and processing method in the research literature. For example, You et al. [35] and Sun et al. [36] classified data by its source, e.g., single parameter digital signal or image signal data, while Smith [37] classified signal processing methods by frequency or time domain.

#### *4.2.1. Parameter-signal processing*

Parameter signals of force, distance, energy or other physical phenomenon acquired during the welding process are digitally processed by statistical or/and filtration methods. Statistical processing methods include mean squared error (MSE), root mean square error (RMSE), signal-to-noise ratio (SNR), and peak signal-to-noise ratio (PSNR) calculations to highlight signal features [38–40]. Statistical process control (SPC) charts have been used to monitor power, energy, displacement, and sound signals and minimize misdetection error on ultrasonic metal welding systems [26,27]. In general, statistical methods are simple to apply to digital signals, but tend to be less robustness and may drift during repetitive weld testing or processes. Filters, the most common and reliable method for parameter signal processing, operate in three main domains, time, frequency, and time-frequency.

#### *4.2.2. Vision-signal processing*

Welding vision signals captured by CCD or X-ray cameras can give position and shape images, and contain color or grey scale intensity data [41]. Statistical measures such as variance, mean square error, etc., are traditionally used to process image signal data to remove noise [42,43]. However, use of statistical methods is not common for visual signals as they are less flexible. Therefore, various filters have been adopted to remove noise from welding system image signals, including wavelet transformation [12], FFT and the Welch algorithm [44], smoothing algorithm [45], Kalman filters [46], and Gabor filter [47]. For both parameter digital signal and image signal data, hybrid method may be utilized which combine statistical and filtering techniques.

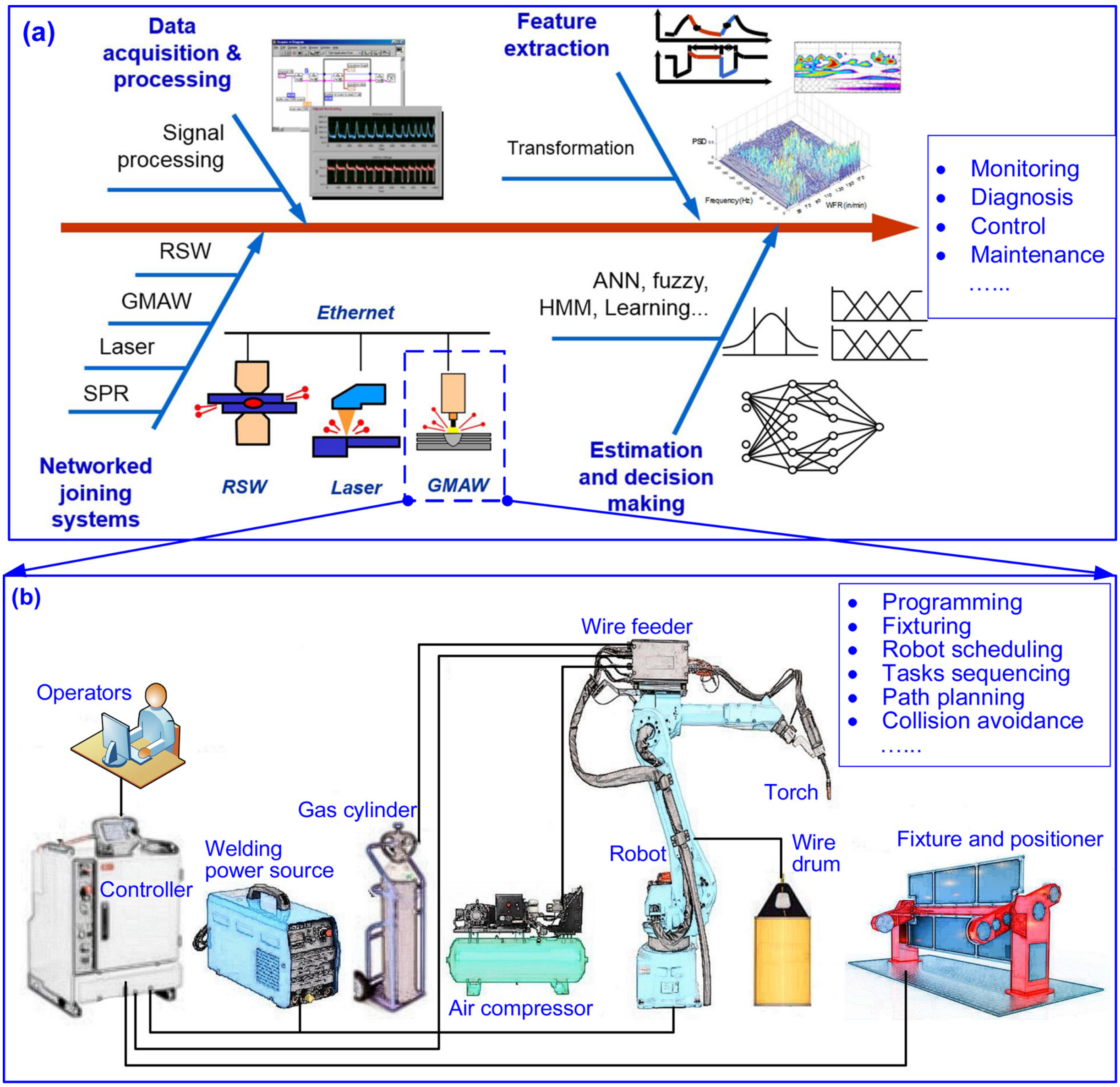


**Fig. 3.** Framework of station-level intelligent welding(a) Flowchart of process monitoring and control, (b) Typical system configuration [33].

These hybrid methods may include image enhancement, regularization, subtraction, simplification, and segmentation [48–50].

### 4.2.3. Feature extraction and selection

Feature extraction and selection in welding is very important to reduce the feature sample dimension and select the best feature subset or subset combination for analysis or prediction. An effective feature

**Table 4**
Typical system configuration of IWS.

| Classification | Element | Functional Requirements |
|---|---|---|
| Handing system | Fixture | A device that holds the workpiece steadily in place during the welding operation, usually fixed on a positioner. |
| | Clamping and locating devices | The fixtures come with many types of clamping and locating options for different operation needs. |
| | Work piece positioners | Moves or orientates the workpiece, in the form of a turntable, a turn-tilt positioner, and even a six-DoF robot manipulator. |
| Welding Robot | Robot arm | A robot arm with the proper specifications such as work envelope, degree of freedom, repeatability, payload, weight and mounting limitation will be able to meet the application requirements |
| | Robot controller | Besides playing the key role in achieving the motion specifications, should be able to cater the needs of the welding requirements, even to control additional tasks such as workpiece positioning, production sequencing, and worker safety |
| Welding equipment | Power sources | The power sources supply the necessary power for the welding processes. |
| | Welding torch | To direct welding electrode into the arc, conduct current to the electrode, and provide shielding gas to the weld pools in arc welding. |
| | Wire feeders | Add filler metal during welding. |
| | Weld controller | Monitoring and control of the welding process |

**Table 5**
Typical tasks for IWS.

| Classification | Task | Objective |
|---|---|---|
| Pre-weld | Design and system integration | Design of welding system, system configuration and process parameters |
| | Modeling and simulation | Modeling and simulation of the component, welding robot and welding process, etc. |
| | Programming | Programming of robot path and motion. |
| | Fixturing and calibration | Prepared the parts for weld |
| Robot optimization and control | Tasks sequencing | Determine the sequence of the welding tasks |
| | Path and motion planning | Plan the welding path from one to the next |
| | Collision avoidance | Avoid the collision between robot and welding parts |
| Welding process | Process modeling | Modeling and simulate the welding process for parameter optimization |
| | Process monitoring and control | Monitoring the welding parameters and make adjustments accordingly |
| | Inspection | Inspect the welding quality and performance |

**Table 6**
Different sensing technique for welding.

| Type | Method | Advantages and disadvantages |
|---|---|---|
| Arc sensing | Arc voltage signal, current signal | No additional device, using electric arc as monitoring section, no additional error and good real-time tracking; fluctuations in the electrical welding arc signals, |
| Computer vision sensing | Active vision and passive vision | Huge information content and non-contact; difficult in 3-D seam-tracking, geometrical constraints of the light source and vision system |
| Arc sound sensing | Sound intensity | No tactile, as the important information for monitoring of welding dynamic and quality characteristic; |
| Welding arc spectral | Arc spectra collected | Arc emission spectra containing abundant information of arc physical conditions and chemical compositions; high redundancy, difficult to establish a precise mathematical relationship between the defects and the corresponding spectral signals |
| Ultrasonic sensors | Transmitter /receiver | Robust in the harsh environments, devices lighter and more compact, feasibility in real-time seam tracking |
| Electro-magnetic sensors | Electromagnetics principle | Hardly affected by the intense arc light and fumes, deviations of sensor position from the weld line were detected without using a scanning motion |
| Infrared sensors | Thermal imaging system | Simultaneous penetration depth, bead width and torch position control is possible. |
| Multi-sensor | 2 or more type of sensors | A single sensor cannot acquire adequate information to describe welding status; get better result than single sensor |

extraction method is needed to remove redundant information, thereby providing a streamlined feature sample. Isabelle and Andre [51] decomposed feature extraction to feature construction, preprocess transformations such as standardization, normalization, signal enhancement, extraction of local features, linear and non-linear space embedding methods, non-linear expansions, and feature discretization, followed by feature selection, which determines the features that are relevant and informative. The three steps of feature selection are to first generate candidate feature subsets through a search strategy. Search strategies can be divided into exhaustive, random, and heuristic search methods. Second, the subset pros and cons are evaluated with pre-determined criteria. Evaluation criteria can be roughly divided into filtering and wrapper methods. The filtering method can be further divided into distance, information measures, dependence, and consistency measures [51]. Finally, the features are validated for their information content.

Each welding process has basic features that can be analyzed for unique characteristics. For example, voltage, current and sound signals in arc welding can indicate when an arc is interrupted, while vision signals can characterize weld pool size and shape. Table 7 summarizes distinctive features of several welding processes. Features extracted from signals should be evaluated for their value to models, evaluation schema, decision-making, or learning algorithms, with clear mapping to process objectives such as weld quality, stability, etc. Example feature extraction and selection methods are shown in Table 8.

### 4.3. Modeling and simulation

Robot, process, and system models for intelligent welding systems are generally developed from theoretical and analytical studies, empirical models, or numerical models [57]. These models have been classified into weld geometry descriptions, characteristic parameters, and welding process dynamic models [58].

Intelligent welding systems require models that can predict welding states and conditions. Important issues for welding models are heat input and material behavior, which directly relates to weld quality [58,59]. Empirical models, also called black box models, mathematically describe welding conditions based on physical observations and can better describe the relationships in a system, but can have large errors when extrapolating beyond the observation range. Analytical models, also called white box models, analyze physical or chemical dynamics of the welding systems through theoretic equations developed from thermodynamic and motion laws. Due to assumptions made for tractability, the accuracy of analytical models is usually low. Finite element models (FEM) can be more precise, including for the modeling of components and work cells, as they can account for many practical considerations. FEM are only applicable to off-line modeling due to

**Table 7**
Typical features of welding processes.

| Weld process | Typical features |
|---|---|
| Arc welding | Base current, peak current, average current, base voltage, peak voltage, average voltage, voltage positive-half-wave, voltage negative-half-wave, pulse peak, weld pulse base period, different frequency band and, precise edge localization, light intensity |
| Spot welding | Horn height before the main vibration, horn height after the main vibration, maximum power value in the power signal, weld time during the main vibration |
| Laser welding | Greyscale variation, plume features, spatter features, visible light emission, plume growing direction, plume size, molten pool size, molten pool height, illumination light reflection, molten pool weight, molten pool length, keyhole position, keyhole size, length and inclination angle of the beam |

**Table 8**
Example of feature extraction and selection in welding systems.

| Method & algorithm | Welding data source | Applications | Ref. |
|---|---|---|---|
| Stepwise forward feature selection; k-fold cross-validation; Fisher's discriminant ratio | Power and sound signal | Ultrasonic welding | [26] |
| Fitness function; genetic algorithm | Arc sound signals | GTAW | [52] |
| Hybrid Fisher-based filter and wrapper; support vector machine (SVM) | Spectrum, sound and voltage signals | Pulsed GTAW | [34] |
| Wavelet packet transform; improved Welch algorithm | Arc voltage | GTAW | [53] |
| Evaluation function with Euclidean distance and inside distance | Arc signal | Pulsed MAG welding | [54] |
| Random forest classifier; and machine learning techniques | Images by high-speed mid-infrared-camera and near-infrared camera | Laser welding | [55] |
| Discrete wavelet decomposition, segmentation, the artificial bee colony (ABC) | A combination of plunge force, feed rate, and spindle rotation speed | Friction stir welding | [56] |

their large computation requirements.

Establishing practical theoretical models can be difficult in time-sensitive, complex systems with variation and uncertainty. Therefore, the artificial intelligence tools developed in recent years have been applied to welding processes. Knowledge-based intelligent models combine analytical models with expert systems, artificial neural networks, fuzzy models, and machine learning. With the aid of large-scale input and output signals from complex and uncertain objects and environments, intelligent models can use a rule-based system of inductive and inferential mechanisms to predict welding states and conditions. Recently, big-data driven intelligent models provide alternative methods to maintain/improve model accuracy and stability [60].

### *4.4. Decision-Making*

Decision-making strategies are of major interest in the development of automated process and condition monitoring. Only a few specialized papers have been found in the area of decision-making within intelligent welding [61,62]. The simplest strategy is to use of parameter threshold(s) to recognize a system change, but this strategy is limited as it is inflexible in time or case. Finite duration/position thresholds placed at different segments of a cycle improves upon this limitation. Statistical Process Control (SPC) uses statistical thresholds to identify changes outside of natural variation. Part signatures, produced from cycle averaging repeated observations of parameters, can provide a step function or flexible parametric or nonparametric curves to trigger decision action on non-conforming parts. Similar to part signatures, waveform recognition was developed to be insensitive to variation. The most sophisticated decision-making strategy is pattern recognition. With the features extracted by signal processing, one can take advantage of a number of pattern classification methods such as linear discriminant function, fuzzy logic, neural net, fuzzy neural net, decision tree, support vector machine, etc. Other related methods include search algorithms, combinational optimization, and spatial geometric reasoning methods [63,64]. Due to the proliferation of feature extraction and classification tools, this is an area where much research has been done.

### *4.5. Artificial intelligence and machine learning*

Artificial intelligence (AI) is a computer system that mimics human cognitive processes by training the system to perceive its environment, make decisions, and take action. AI systems rely on learning algorithms, such as machine learning and deep learning, along with large sets of sensor data with well-defined representations of phenomena [65]. Machine learning (ML) is typically shorthand for “traditional machine learning”, which usually excludes deep learning, where humans use expertise to manually select features and train models [66]. Common ML techniques include decision trees, support vector machines (SVM), and ensemble methods. Deep learning is a subset of ML modeled loosely on the neural pathways of the human brain, where deep refers to the multiple neural layers between the input and output [67]. In deep learning the objective is to train algorithms that generalizes from features to predict outcomes, but these algorithms are not explanatory models. Common deep learning techniques include convolutional neural networks (CNNs), recurrent neural networks (e.g. long short-term memory networks), and deep Q networks.

Welding systems have uncertain, nonlinear processes affected by multiple factors and in which complex physical and chemical reactions occur, making it difficult to rely on experience or simple mathematical formulas to establish accurate models [68]. In recent years, ML has been applied to tackle this challenge [55,69,70], and many methods, tools, and techniques have been developed and implemented in a variety of applications as ML has grown an independent domain,

**Table 9**
Different artificial intelligence methods/models.

| Algorithm | Advantages | Application areas |
|---|---|---|
| Rough set theory | Not need any preliminary or additional information about data | Deal with new uncertain information systems |
| Decision tree | Create a comprehensive analysis of the consequences along each branch | Classifying the features of the signals |
| Artificial Neural Network (ANN) | Complex nonlinear mapping, self-learning, and generalization capabilities | Solve complex problems with internal mechanisms |
| Support Vector Machine (SVM) | Less sample, global optimal | Classification and regression analysis |
| Genetic Algorithm (GA) | Good global search ability | solving optimization problems: combinatorial problems, planning |
| Convolutional neural network (CNN) | Reduced parameter number, invariance of shift, scale and distortion | Surface integration inspection and machinery fault diagnosis |
| Restricted Boltzmann Machine (RBM) | Robust to ambiguous input and training label is not required in pre-training stage | Dimensionality reduction, classification, regression, and feature learning |
| Deep Belief Network (DBN) | Can be trained layer-wisely to be more efficiently | Predictive analytics & defect prognosis |
| Auto Encoder (AE) | Irrelevance in the input is eliminated, and meaningful information is preserved | Machinery fault diagnosis |
| Recurrent Neural Network (RNN) | Short-term information is retained and temporal correlations are captured in sequence data. | Predictive analytics & defect prognosis, feature learning from sequence data |
| Reinforcement learning | Maximizes performance | Representation, prediction, and control learning |

Table 9. The unique advantage of ML include its ability to handle high dimensionality problems and data, discover formerly unknown (implicit) knowledge and identify implicit relationships within data sets, and an increased usability of algorithms in new applications. ML applications include model prediction and parameter optimization, path planning and welding sequence, process control and quality monitoring, defect recognition, and classification. The algorithms can be widely used, independently (standard or customized algorithms) or combined to make use of their strengths while mitigating their weaknesses. Related application framework and scenarios will be reviewed in detail in Section 6.

## 5. Emerging platform technologies

Platform technologies provide organizing frameworks, connectivity, analytics, and intelligence to the basic enabling technologies of sensing, signal processing, feature extraction, and modeling. In this section, the progress and potential influence of emerging platform technologies are reviewed, including Industry 4.0, cyber-physical systems (CPS), internet-of-things, big data, cloud computing, virtual and augmented reality (AR/VR), and blockchain. Their application in welding systems can occur at the station level, the system level, and the system of systems level.

### 5.1. Industry 4.0 and CPS

Industry 4.0 is a German initiative that emphasizes that traditional manufacturing systems should be fully integrated with new IT systems [6,71]. Industry 4.0 highlights horizontal integration through value networks, vertical integration and networked manufacturing, and end-to-end digital integration of engineering systems across the entire value chain. Industry 4.0 is closely related with smart manufacturing, CPS, information and communications technology (ICT), and Enterprise Architecture (EA) [72].

For welding technology, Industry 4.0 can be characterized by the interaction of intelligent work pieces and components, and intelligent tools. Reisgen et al. [15] has focused on pragmatic applications of the Industry 4.0 framework and elements to shielded gas metal welding. They described a networked, autonomously-capable and CPS supported welding system with networked product quality.

### 5.2. Digital twin

A digital twin is a virtual representation describing a physical production process at a level of detail that is as comprehensive as is required for its purpose. In a broader sense, a digital twin is an integrated system that can simulate, monitor, calculate, regulate, and control processes and systems status [73–75]. For example, a digital twin for a robotic welding arm could be a mechanism model whose parameters, positions, and movement predictions accurately reflect all important aspects of a physical linkage. Zheng et al. [76] built a digital twin for a real-time monitoring system based on a welding production line in order to provide a reference for enterprises. Their system ensures operational efficiency of equipment in production line, while providing welding quality data of the product. Tabar et al. [77] introduced a geometry assurance digital twin to identify weld point geometry and applied it to three automotive body-in-white assemblies, reducing the size of the optimization problem. A digital twin approach can help save time in obtaining satisfactory geometrical error levels.

### 5.3. Internet of things and big data

The internet-of-things (IoT) refers to the idea of creating a network of computers, machines, and people that are uniquely identified and that can share data. The IoT has the potential to improve welding system by storing the latest procedures and regulations, manage and renew qualifications of welders, provides improved quality control, verify product quality, detect and place orders for consumables and gas, suggests training requirements, and provides welding project management assistance. Big data refers to the new data-processing applications that are required to analyze data sets that are too large and complex for traditional methods. For example, high volume data from robot cells can be remotely accessed and easily supervised from local networks. Welding process archiving systems, applied as part of quality management, are capable of storing huge amount of data that can be efficiently processed by big data systems [78,79]. These programs are more efficient when run remotely so that welding robots do not have to be withdrawn from production.

### 5.4. Cloud computing and cloud manufacturing

Cloud computing is the provision of scalable, on-demand computer resources, including data storage and computing power, that is accessed remotely by the user usually through an internet. Cloud computing has enabled a new computing- and service-oriented manufacturing model, called cloud manufacturing (CMfg), proposed to enhance resource utilization and reduce resource and energy consumption. The need for data sharing and storage within an organization permits information to be downloaded and updated from any geographical location. Welding station computations and analysis related to welding parameters and weld output can be enhanced with other advanced computing methods like machine learning and big data conducted in the cloud [80].

Chen et al. [81] proposed a cloud based expert system for fusion welding systems, where the welding requirements are uploaded and the cloud-based expert system gives feedback in real-time as a welding procedure document (WPS). Wang et al. [82] proposed a cloud integrated submerged arc welding process, where cloud services store mathematical models related to weld torch trajectory and weld specimen geometry and feeds computations back to the automated welding machine. Oto et al. [83] tested a cloud-based algorithm to evaluate weld quality based on the weld seam edge detection. This prototype system segmented low contrast welding images, compared them to weld defect reference images with the help of artificial neural networks, and sent the results back to the weld cell. Cloud computing has been used with welding and painting robots in several factories to reduce production line downtime by tracking the robot performance characteristics [80].

### 5.5. Other emerging technologies

Other technologies that have the potential to enhance intelligence in welding systems include virtual and augmented reality, 5 G, and blockchain [84–88]. For example, blockchain has the potential to enhance data security in cloud-based IoT and will enhance the trust and protection of data exchanged in the distributed infrastructure of a system-of-system intelligent welding [89]. Select emerging technologies particularly significant to IWS are summarized in Table 10.

## 6. Application framework for IWS

Intelligent welding is an evolving concept. No matter which process is addressed, e.g., arc, laser, friction stir welding, or spot welding, at least four aspects of the welding process require intelligence:

- ***Monitoring–***What is happening or has happened?
- ***Diagnosis and Understanding–*** Why is it happening and its mechanisms? E.g. the knowledge base for cogitative understanding.
- ***Evaluation and Prediction–*** Where is the system now and where is it headed?
- ***Control–*** Should the system state change and how should that change be executed?

**Table 10**
Related research about emerging technologies within IWS.

| Concept | Objective (comments) | Refs. |
|---|---|---|
| Industry 4.0 and CPS | Networked, autonomy-capable and CPS supported welding production systems within a concept of networked product quality | [15] |
| Cloud and IoT | Data-driven welding expert system based on IOT | [81] |
| Digital twin | A digital twin case of a welding production line is built and studied. | [76] |
| Industry 4.0 | The technological elements of Industry 4.0 in the robotization of welding | [78] |
| Cloud and future factory | Use cloud computing to share the welding parameters and maintain a virtual library for ready reference irrespective of the user location | [80] |
| Augmented reality | To improve the precision and accuracy of manual spot-weld placements | [84] |
| Industry 4.0 and CPS | Intelligent welding technologies based on a 5C architecture of CPSs | [90] |
| IoT and Industry 4.0 | Data communication, welding parameter detection, data storage | [91] |

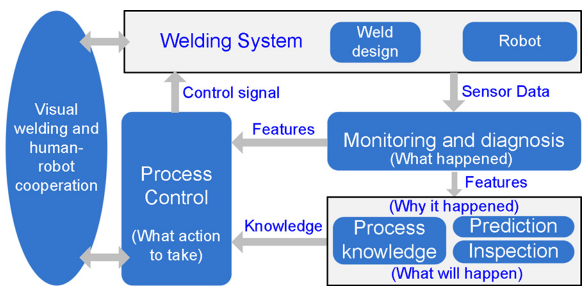


**Fig. 4.** Application architecture of IWS.

These four aspects come together in the framework illustrated in Fig. 4, where specific application components include weld design, task sequencing and path planning, robot programming, process monitoring and control, quality inspection, and visual welding and human-robot cooperation.

### 6.1. Pre-weld design

Welding is a complex, non-linear process involving a large number of parameters. It is difficult to use direct mathematical formulas to map its inputs and outputs before welding. Machine intelligence, especially optimization algorithms, can be applied to design welds and their process parameters based on quality goals and other factors. Enablers required for design and process optimization include:

- Data base of design parameters including joint type, materials type, position, thickness of plate or sheet, and process parameters.
- Standardized product designs.
- Quality documentation (standards) correlated to the design.

It may be possible to data-mine design parameters and standards, and quality specification information from existing documentation using machine intelligence. For example, Qiu et al. [92] established an expert system for welding process design, based on welding process related knowledge, standards, and expert experience. Miller et al. [93] describe a methodology and created a reference implementation to aid design engineers during conceptual design. This decision support tool is used to understand design decisions and their relation to the weldability of a design. The trend in welding parameter design is toward hybrid intelligent methods combined with expert systems as AI techniques, IoT, mobile internet, cloud computing, and big data analytics evolve [10,81,94,95].

#### 6.1.1. Welding fixtures

A fixture holds a workpiece in place during the welding operation and can be integrated with a positioner that orientates the workpiece. The fixture is designed for the size, configuration, and joint locations of the workpiece, the welding process type, and ease of workpiece loading and unloading. Sensors can be included in the fixture to monitor for workpiece presence or detect the accuracy of the workpiece position. To reduce manufacturing costs, flexible fixture systems are designed to fixture multiple workpieces. Computer-aided fixture design (CAFD) has focused over the past decades on incorporating expert systems, GA, ant colony algorithms (ACA), and artificial neural network (ANN) to embed design knowledge into semiautomatic or automatic CAFD systems. However, little effort has been directed at welding, with almost all literature focused on machining fixtures [96,97]. To further improve the intelligence of welding fixture, there is a need for integrating intelligent modeling and control techniques with the optimization and verification of welding fixture performance.

### 6.2. Task sequencing and path planning

An industrial robot's workflow consists of a set of tasks repeated multiple times, for example, to weld a seam or cut a hole. The sequence of tasks affects the quality and efficiency of the welding process, where the welding sequence has a significant effect on deformation and to a lesser degree on residual stress. Effective robot path planning is crucial for efficient welding of large and complex structures. For example, the high initial investment of remote laser welding (RLW) requires the robot perform its welding tasks with minimal idle movement to guaranteed long-term profitability. Therefore, efficient task sequencing, process planning, and effective robot programming techniques are required [98].

Traditionally, a welding sequence and robot path are determined by experience. Sometimes a design of experiment is required, however, this can be infeasible if there is a large number of welding beads. The integration of motion planning and task planning has received significant attention in the robotics community [98]. Computing a robot's path can be naturally modeled as a traveling salesman problem or one of its extensions. Path planning and task sequencing are combinatorial optimization problem with constraints such as cycle time, energy consumption, and collision avoidance. Table 11 shows typical intelligent applications in task sequencing and path planning. Virtual tools like finite element analysis and robotic simulators support this optimization. Innovative AI/ML techniques for welding sequence optimization and robot planning [95] like bionic algorithms, genetic algorithms, graph search, artificial neural networks, and particle swarm optimization can improve product quality and process efficiency. Some challenges in the implementation of multi-objective functions are consideration of deformation, residual stress, and robot travel time. Reinforcement learning and hybrid techniques have been successfully implemented in similar problems and are promising for intelligent welding.

### 6.3. Robot programming

Welding robots can be programmed through on-line, off-line, or automated methods. On-line programming requires an operator to move the welding gun along the weld path before welding, with the trajectory of the welding gun captured for the robot. The robot duplicates the welding gun trajectory for production. Off-line programming (OLP), illustrated in Fig. 5, utilizes 3D CAD data to simulate the weld path and generate the robot's program. OLP's can have advantages over

**Table 11**
Typical intelligent applications in task sequencing and path planning.

| Problem | Methods/Algorithms | Goals | Welding type | *Refs.* |
|---|---|---|---|---|
| Task sequencing | Reinforcement learning | Reduce deformation | GMAW | [99] |
| | Evaluating evolutionary algorithms | Reduce geometrical variation | Spot welding | [100] |
| | Elitism based genetic algorithm | Reduce deformation | GMAW | [101] |
| Path planning | Clustering guidance multi-objective particle swarm algorithm | Shortest path length and minimum energy consumption | Spot welding | [102] |
| | Double global optimum genetic algorithm–particle swarm optimization | Optimize the welding path | Spot welding | [63] |
| | Adaptive pass planning approach | Ensure minimum joint movement subject to constraints | Arc welding | [103] |
| Both | Meta-heuristic based on greedy randomized adaptive search procedure | Integrated solution to task and path problems | Remote laser welding | [98] |

on-line programming in cost-time, flexibility, productivity, and safety. Work to make OLP more intuitive includes an OLP toolbox for RLW that generates close-to-optimal robot programs [98]. However, both on-line and off-line programming require robotics knowledge and programming skills. Flexible operations where welds are continuously changing find these methods are insufficient. Therefore, efforts have been made to generate welding programs more automatically and intelligently in off-line environments for fast deployment [104].

An industrial example for automating robot programming is *RiansWeld*™ from *Kranedonk Productions Systems* [105]. Key modules include a kinematic model to calculate joint angles for robot position and orientation, and a work cell component collision model. Weld seams are identified by finding plate edges that align with other plate surfaces. This software links weld geometry with weld parameter specifications through a database of weld parameter settings and path details for many different welds and materials. In summary, weld location, robot accessibility, and appropriate weld parameters are determined automatically. Another example is *Desk Top Programming & Simulation System* (DTPS) for Panasonic robots for automatic path generation (APG). APG uses CAD system data, enterprise resource planning (ERP), and Excel spreadsheets to automatically generate complete programs for the welding robot. The generated path is checked for simulation, reach, and collision by the DTPS software. DTPS permits the development of custom robot software to program different products automatically within a product family.

Changing conditions during welding due to manufacturing tolerances and thermal deformations has led to the development of adaptive welding robot programming. For example, a system for programming RLW robots was developed by Kos et al. [106] that integrates an adaptive 3D seam tracker into a robot controller to achieve better beam position on-the-fly compared to manual teaching methods. The process positions the beam relative to the seam in real-time using vision data and an illumination laser. Positioning accuracy of under 0.05 mm was achieved for a range of welding speeds. Only approximate teaching of the first welding point is needed, thus enabling faster teaching times. Another example is the use of augmented reality (AR) for robot programming in unstructured welding environments. Ni et al. [85] developed an interface using AR with haptic feedback for remotely programming welding robots. Compared with the traditional OLP that relies on CAD models or contact between the robot and the workpiece, motion path programs are determined quickly and intuitively without prior knowledge of the workpiece. In the future, more integrated intelligent programming methods are expected as more accurate sensor/vision technologies, 3D CAD/PLM software, and intelligent algorithms are developed, blurring the boundary between online and offline programming.

### 6.4. Process monitoring and diagnosis

The state of a process is estimated by extracting relevant information from sensor data. Machine intelligence can be applied to process monitoring by determining if processes are going out-of-bounds or what is going wrong (perception and identification), how is it going wrong (categorization), what the process parameters should be (goal setting), what corrective action should be taken (decision making), and how the process can be made more robust over time (learning).

#### 6.4.1. Monitoring weld phenomenon

Weld phenomenon or attributes monitored generally include gap defects, surface defect identification, thermal and process conditions, and weld seam tracking, etc., where weld quality assessment is highly related to the observed phenomenon. For example, laser weld quality can be characterized by the bead geometry and distortion of the weld, and mechanical properties inferred from observed phenomenon. Weld defect detection and classification ensures that high-quality welds are free of incomplete penetration, incomplete fusion, undercutting, slag inclusions, flux inclusions, porosity, cracks, warpage, spatter, etc.

In arc welding, some attributes that are monitored are welding current, voltage, arc sound, or temperature. In laser welding, monitoring is performed in three steps: during the pre-process the weld seam is tracked, in-process the melt pool, weld defects, spatter etc. are monitored, and post-process the weld is examined for its geometry and visible defects [107]. Characteristics commonly monitored in friction stir welding are defects, position of the tool over the seam, and weld

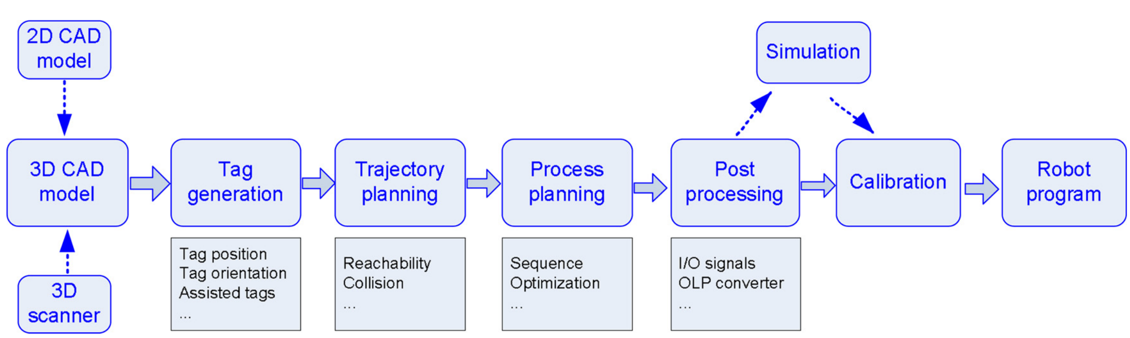


**Fig. 5.** Key steps of off-line robot programming.

**Table 12**
Example applications for weld quality monitoring.

| Monitoring Goal | | Data Used | Analysis Techniques | Weld Type | Ref. |
|---|---|---|---|---|---|
| Identification and classification of weld defects | weld beads | Radiographic images | Feed-forward multilayer perceptron (MLP) with back propagation learning algorithm | n/a | [108] |
| | normal/ abnormal welds | Acoustic signal, signal-processing methods | ANN, a back propagation (BP) network with three layers | Laser welding | [109] |
| Defect detection | including monitoring | Multi-sensor fusion of image data | SVM | High-power disk laser welding | [110] |
| | weld defect | Images | Modified background subtraction method based on Gaussian mixture models | Thin wall metal canister welding | [111] |
| | including weld strength model | Plunge force signals | Support vector machine learning based support vector regression model | Friction stir welding | [112] |
| General quality monitoring | real-time weld status | Multi-sensor data | Deep learning based on stacked sparse autoencoder | Laser welding | [113] |
| | find defects region | Patches cropped from x-ray images | Deep neural network, sliding-window approach; sparse auto-encoder | n/a | [114] |
| Weld geometry | good weld or not | Acoustic Signature | Machine Learning Algorithms using decision tree | Shielded metal arc welding | [115] |
| | backside width | Computer vision, static images | Linear regression and bagging trees | GTAW/butt joint welding | [116] |
| | penetration | Acoustic signatures | Extreme learning machine | Variable polarity plasma arc welding | [117] |

zone temperature.

#### 6.4.2. Application of welding monitoring

Both direct and indirect monitoring methods are available [13]. Direct monitoring methods use optical, laser, X-ray, camera vision, etc., to monitor weld quality, track weld seams, and identify weld defects and geometry. Appropriate analytical and empirical models allow highly accurate estimates of process parameters from these inputs. However, these measurement technologies are relatively expensive and can be susceptible to error due to unstable environmental conditions or equipment interference. Therefore, many direct methods are limited to laboratory use. Indirect monitoring methods using easier to measure physical parameters such as current, power, force, torque, vibration, etc. were developed to overcome the problems of direct monitoring. Despite needing more computational effort and having less accuracy, they are economical and more suitable for industrial use.

Characteristics or features extracted from the signals obtained from monitoring should be correlated to intelligent welding goals. As mentioned in Sec. 4, extraction and selection of appropriate features is vital to monitoring signals and images for accurate recognition of process signatures. Table 12 presents a list of intelligent welding quality analysis techniques typical of the literature, grouped by the monitoring goal.

Multiple sensor fusion is regarded as a key technique for process monitoring as using a single sensor is only effective for identifying a few kinds of weld defects. Some examples of multiple sensor fusion include integration of photodiode sensing and acoustic, plasma charge, and/or visual sensing, and integration of multiple visual images [29,118–122]. More and more AI algorithms are being applied to monitoring, such as ANN, RBFNN, BPNN, SVM and deep learning [123]. Another promising trend in monitoring are its full integration with other applications domains or procedures, including representation, prediction, learning, and control.

### 6.5. Process prediction

Machine intelligence can be applied to quality prediction by observing the current state and predicting expected future state(s) using identification, categorization, and decision-making. Decisions can be made for immediate corrective action through feedback to process control, or when assessing risk in quality assurance planning when there is a delay in the response.

#### 6.5.1. Prediction parameters

Parameters used as inputs for prediction models mentioned in the literature include welding parameters (e.g., arc current and voltage and welding speed), weld quality and appearance (e.g. defects including deformation, distortion and cracking), mechanical properties, and behavior (e.g. phase transformations and tool wear) [124]. Pre-welding prediction occurs when welding states are predicted before actual welding is initiated, while in-welding prediction is used to predict welding quality issues during the welding process.

#### 6.5.2. Application of welding prediction

Methods applied to predict welding states include empirical and physics-based models, conventional statistical tools, neural network, and expert system. Recent advances include the application of corrective neural network, computer-based intelligent system, methods with signal features, AI with database, and machine learning methods [56,125–127].

Predictive design and optimization of welding parameters allows for pre-process adjustment of parameters to avoid an unsuitable weld design. The expectation is these prediction models will permit the production of good welds without the need for experienced welding personnel. During the welding process, the goal of predictive models is to enhance weld process performance and quality through real-time

**Table 13**
Example applications for weld quality prediction.

| Prediction Goal | | Data Used/Input | Analysis Techniques | Welding Type | Ref. |
|---|---|---|---|---|---|
| Welding process | control learning | Original images | Deep neural networks and reinforcement learning | Laser welding | [125] |
| | quality prediction | Power (W), Laser welding speed (mm/min), Distance of stand-off (mm) | Support vector regression (SVR) | Laser welding | [130] |
| | welding skill learning | An optic camera and a laser-based sensor | Real-time computer vision algorithm (ANN based learning method) | GMAW | [131] |
| Weld geometry | keyhole | Acoustic signatures | Extreme learning machine | Plasma arc welding | [117] |
| | backside width | Computer vision approach, passive vision images | Linear regression and bagging trees | GTAW/ butt joint welding | [116] |
| | weld bead | Wire feed rate, travel speed, dwell time, oscillating amplitude, and welding position | Response surface methodology (RSM) based on central composite design (CCD) | GMAW | [132] |
| Weld penetration & performance | penetration status | Electronic, visual, and sound information | D-S evidence theory, back-propagation (BP) neural network | GTAW | [133] |
| | including tensile strength | Beam power, travel speed and focal position | ANN and GA | Laser welding | [134] |
| | tensile strength | Rotational speed (rpm), and feed rate (mm/min) | Gaussian process (GPR) regression | Friction stir welding | [135] |

parameter tuning. These models can also contribute to the optimization database for welding parameters [116,128,129]. In-process prediction algorithms must be computationally efficient if they are to contribute to real time control of welding process [125]. Table 13 lists example literature in quality prediction for welding, including goals, data used, processing techniques, and welding types.

### 6.6. Process control

Machine intelligence can be applied to process control to select process goals (goal-setting), best adjust the process (decision-making), and gradually improve process robustness over time (learning). It is assumed that process monitoring can provide identification & categorization of the weld process in support of these activities. Higher order machine intelligence could include system-wide prediction & planning.

#### 6.6.1. Control schemes

Various control schemes have been proposed for welding, including position, force, torque, temperature, power, voltage, and current control. For example, in arc welding, control parameters usually include current, voltage, and feed rate [136]. In laser and resistance spot welding (RSW), laser power and current are the most common control parameter [137], respectively. In friction stir welding (FSW), common control parameters include force, torque, and temperature [138]. In ultrasonic welding, common control parameters are current and weld clamping pressure.

#### 6.6.2. Control techniques and methods

Both open-loop and closed-loop control are used in welding. However, open-loop control methods are generally poor due to uncertain, nonlinear, time-varying, and strong coupling between parameters observed in the welding system. Closed-loop control compares sensor information of system states to desired states when commanding adjustments to robot actuators and welding guns [13]. Typical close-loop control techniques in welding are discussed in the following sections.

PID control as an industry standard is by far the most common control algorithm in welding. Other control algorithms used are PSD control, adaptive control, fuzzy logic control, neural network control, sliding mode control, learning control, and intelligent control [139]. Adaptive control, as a real-time control technique, is generally used for online parameter optimization [140]. Adaptive control systems must be provided continuous information about the present state to compare to desired states in order to modify parameters to achieve desired performance. Three major variants of adaptive control are adaptive control with constraints (ACC), adaptive control with optimization (ACO), and geometry adaptive control (GAC) [141]. While adaptive control techniques are more expensive, they can lower the total cost of welding systems by reducing labor, time, and documentation costs in testing, less rework of components, and reducing safety compliance costs.

Various artificial intelligence approaches have been applied to welding control systems, including neural networks, Bayesian probability, fuzzy logic, machine learning, expert system, and genetic algorithms [16]. Machine learning control techniques are drawing attention due to their reliability and accuracy [125,142]. Table 14 summarizes select literature on intelligent control in welding.

### 6.7. Quality inspection and assessment

Machine intelligence can be applied to quality inspection by identifying weld features or defects (perception and identification), the state of the weld (e.g., good/bad/other categorization), what action should be taken (goal setting and decision-making, e.g. for rework, post-process grinding and polishing, or nothing if the defect is not expected to impact performance), or to improve process robustness (learning). In

**Table 14**
Select applications of intelligent control in welding.

| Controller objective | Control parameter(s) | Control method | Welding type | Refs. |
|---|---|---|---|---|
| Weld pool geometry | Power and velocity | Deep neural networks and reinforcement learning | Laser welding | [125] |
| | Current and welding speed | Adaptive PID based on reinforcement learning (RL) | GTAW and GMAW | [142] |
| Weld geometry | Current and welding speed | Predictive control algorithm | GTAW | [143] |
| | Filler metal rate | Self-learning fuzzy neural network controller | GTAW | [144] |
| Arc current | Arc length and energy | Adaptive sliding mode controller | SMAW | [145] |
| | Arc current | Adaptive fuzzy sliding mode controller (AFSMC) | Shielded metal arc welding (SMAW) | [146] |
| Welding energy | Clamping pressure | Real-time controller | Ultrasonic metal welding | [137] |

the literature, weld quality inspection and assessment has been studied from pre-, post- and in-process perspectives.

### 6.7.1. Pre-and post-process inspection

Pre-process assessment generally focuses on weld seam tracking. In order to ensure weld quality, it is important for the welding system to track and follow the weld seam accurately. Common approaches include image processing (camera), machine vision, and ultrasound [1,147,148]. Post-process inspection can require the physical destruction of the completed weld joint. Destructive testing (DT) is used to detect various mechanical and physical characteristics when developing welding parameters or for SPC, and may be the only definitive means of detecting flaws, e.g. destructive tensile bend tests of the weld root [149]. Common post-weld destructive testing methods include tensile, fatigue, and root bend tests, micrographic cross-sections, and the examination of fracture surfaces.

Non-destruction testing (NDT) was developed because many critical joints require validation of the finished weld in irreplaceable components. Commonly used methods include visual, liquid penetrant, magnetic particle, ultrasonic, and radiographic (X-ray). However, advanced NDT methods have been developed due to the difficulty of detecting some types, sizes, and orientations of defects encountered in welding. Typical advanced NDT methods are phased-array ultrasonic testing, laser ultrasonic testing, acoustic emission, multi-element eddy-current sensors, superconducting quantum interference, and shearography [150]. Advanced signal processing and computing have led to multi-sensory data fusion algorithms for synergistic defect discovery [149,151,152]. Data fusion algorithms in NDT include fuzzy logic, neural network, support vector machine, and machine learning [153,154].

### 6.7.2. In-process evaluation

A complementary evaluation technique to strict NDT methods is in-process evaluation of weld conditions. This method is related to monitoring and prediction techniques (Sections 6.4 and 6.5) and has been referred to as monitoring or online NDT, with a promise to reduce costs and improve NDT effectiveness. Online NDT employs dimensional reduction, discrete Fourier transform, neural network, and machine learning techniques to determine the correlation between various process parameters and quality metrics [155–157]. Table 15 lists typical methods for online NDT weld quality inspection and assessment, with its quality assessment stage and its principal quality criteria.

## 6.8. Human-robot collaboration

In many cases it is difficult to fully automate welding systems due to technical and organizational limitations. Economic risks from a high number of part variants and the complexity of reliably managing the welding process may also prevent full automation. Many small enterprises also lack experience in operating automated systems. In this context, flexible and adaptable systems that can be applied to a variety of tasks should be developed. One approach to flexibility is human-robot-collaboration (HRC), where the advantages of humans (adaptive intelligence) and robots (better movement accuracy and less physical limitations) are combined. In HRC, robots dynamically modify their preplanned tasks to collaborate with human operators in a shared workspace. Code pre-generated for traditional robot applications is too rigid to support effective human-robot collaboration. Thus multi-modal symbiotic communication and adaptive control methods have been a research focus [158]. These methods include voice processing, gesture recognition, haptic interaction, and brainwave perception. Topics related to HRC welding include human-robot communication, planning, optimizing and synchronizing motion, human safety are summarized in Table 16.

Planning and negotiation in HRC welding are different from task planning in pure robotic welding systems. As HRC is more complicated and uncertain, the aim of planning and negotiation is frequently to allocate limited resources and dispatch tasks so that the operations are more optimal. Examples of constraints to this problem include the capability and availability of the resources, the time required, energy saving, human safety, controllability, etc. Supporting technologies include human motion prediction, resource monitoring, real-time scheduling, optimization, and deep learning [160]. An example is the application of HRC to welding filter units, where, with the addition of skill-based process planning, different tasks are completed by actively assigning them to an operator or the robot based on individual skill sets [159]. The efficiency of automated systems can also be improved through the use of cooperation methodologies. Here, an operator can safely work with a variety of HRC enabled robots, as the system can be adjusted for different robots and safety mechanisms, enabling the development of flexible and economic welding processes. In addition, human factors in knowledge acquisition and motivation, brainwave-driven robot control, deep learning, and human-centered design are being investigated in HRC intelligent welding [159,161,162]. In summary, the collaboration of robot and human intelligence will be an important paradigm for IWS, especially from the perspective of HCPS.

## 6.9. Virtual welding

Another field for human-robot collaborative welding is virtual welding [163]. A framework for better intelligent welding robots was developed in the past decade based on learning from human welders in a virtual welding environment. This system permits human decision-making to be monitored and recorded in a realistic environment. A human welder holds a virtual torch whose operation is similar to a real torch through which he can observe and control the welding operation. The actual weld is performed by a welding robot equipped with sensors that measure the weld pool surface. The welder observes an image of the weld pool surface projected onto a mock work piece under the virtual torch. His adjustments are monitored and implemented by the welding robot. Experiments have shown that better performance is achieved through human-robot collaboration compared with that from either humans or robots separately. The authors conclude that the intelligence and sensing versatility of human welders combined with the precision and consistency of welding robots leads to precision welding similar to or better than skilled welders.

**Table 15**
Quality criteria and techniques for quality inspection and assessment of welding.

| Quality assessment stage | Principal quality criteria | Techniques | Refs. |
|---|---|---|---|
| Pre-process | Part geometry, gap, seam tracking | Machine vision, ultrasound | [1,147,148] |
| In-process | Weld defect, pool dimensions | Online NDT, dimensional reduction techniques, discrete Fourier transform, neural network, and machine learning | [155] |
| Post-process | DT Mechanical and physical characteristics | Mechanical testing (such as tensile, fatigue and root bend tests), macro-sections, and examination of fracture surface | [149,152] |
| | NDT Weld geometry, defect size, types and orientations | Visual, liquid penetrant, magnetic particle, ultrasonic and radiographic (X-ray); and phased-array ultrasonic testing, laser ultrasonic testing, acoustic emission, multi-element eddy-current sensors | |

**Table 16**
Tasks and approaches to human-robot collaboration [158,159].

| Tasks | Approaches |
|---|---|
| Sensor and communication | • Contact-based sensing<br>• Contact-less sensing<br>• Localization, mapping and tracking<br>• Sensor data fusion and integration |
| Safety and collision avoidance | • Monitoring<br>• Passive collision detection<br>• Active collision avoidance |
| Task planning and negotiation | • Context awareness and resource monitoring<br>• Task planning and scheduling<br>• Robot motion planning<br>• Human-Machine Interface |
| Adaptive control | • Multimodal programming<br>• Intelligent algorithms<br>• Programming-free control<br>• Brainwave-driven control |
| Mobile worker assistance | • Worker tracking and identification<br>• AR-based in-situ decision support<br>• Ergonomic and psychological aspects |

## 7. Industrial suppliers and integrators

Major industrial companies that manufacture robots with IWS features include ABB, Kuka, Fanuc, Yaskawa/Motorman, and Kawasaki. These companies supply complete welding systems that include power sources from suppliers such as Miller, Lincoln, Fronius, SKS, and Panasonic. Example system integrators who provide IWS related software and hardware are listed in Table 17. Most integrators provide welding documentation management, Wi-Fi/Ethernet connectivity, cloud service, data management, real-time control and quality analysis reporting functionality, but published sources do not show their utilization of artificial intelligence or machine learning at scale. Leading edge robot makers are only beginning to incorporate AI and machine learning. It will likely be several years before advanced AI and machine learning techniques are integrated at scale in industry supplied IWS equipment.

## 8. Summary and future research opportunities

In summary, the main contributions of this paper are the presentation and discussion of the concepts, system architectures, and development of intelligent welding systems. A comprehensive review of enabling technologies has been provided, including sensing and signal processing, feature extraction and selection, modeling, decision-making, and learning. Emerging platforms and their potential application to IWS are also reviewed. Applications of machine intelligence to welding processes and systems are reviewed and discussed, including weld design, welding robot programming and planning, welding process monitoring and control, quality inspection and assessment, and HRC.

### 8.1. Future perspectives

The processes and systems in intelligent welding systems are very complex, driven by practical applications, and are still evolving. From the review of the state-of-the-art in transforming welding stations, systems, and factories into intelligent welding systems, several directions for further development have emerged.

- An interesting area of IWS is the development of autonomous welding systems that combine welding robots with welding tools and power sources. Better integration of welding simulation models and machine-readable expert knowledge into the process control systems will improve the ability to react autonomously to changes in process conditions. Autonomous welding systems should not only

**Table 17**
Examples of suppliers for IWS.

| Name | Specializations |
|---|---|
| Insight Welding Intelligence (Miller) | The Insight portfolio ranges from basic dashboards that report operator productivity and weld parameter verification to real-time operator feedback in the weld cell. Improve first-time weld quality by identifying missed welds, detecting weld defects and achieving full traceability. Most importantly, Insight solutions are capable of monitoring your entire fleet, regardless of equipment brand. (www.millerwelds.com/products/insight) |
| WeldEye (Kemppi) | WeldEye is a universal solution to manage welding production. A balanced combination of software, hardware and service, WeldEye creates value through insight into WPS compliant welding quality, personnel qualifications, and much more. (www.weldeye.com) |
| WolfArc™ | WolfArc delivers the next generation of robotic welding technology with proprietary software enabled communication between the Power Wave and the ABB robot controller. WolfArc produces high quality welds quickly, easily and intuitively. (www.wolfrobotics.com) |
| Kranendonk | Supply custom-build robotic solutions for wide range of industries including shipbuilding, offshore, transport, structural steels, and (head office) process and power (www.kranendonk.com) |
| Cloos | Develop and supply personalized turnkey-automated welding solutions (cloosrobot.com) |
| OTC DAIHEN | Manufacture and supply welding equipment (primarily digital inverter welding supplies), cutting equipment, torches, robots, positioning equipment, standard and custom arc welding cells, and accessories (www.daihen-usa.com) |
| Valk Welding | Develop and deliver robotic welding systems, which are intended for flexible production of small to medium-large series (www.valkwelding.com) |

enable online or real-time adaption in dynamic environments, but also be capable of self-optimization based on quality criteria.

- This literature survey found many machine leaning algorithms have found applications in IWS, including design, monitoring, control, prediction, and inspection. However, selecting the best machine learning techniques for each application is still unanswered. More effort should be made to improve the generalization, robustness, and repeatability of machine learning algorithms, including hybrid combinations of different algorithms, to maximize the potential of IWS.
- Welding robots, as a foundational technology, are critical station-level integrators of IWS. Continued development and application of computers, sensors, communication networks, and artificial intelligence technologies as independent technologies will occur. However, greater effort should be made toward their holistic integration, optimizing the combined sensor, welding, and robot parameters with the objective of more adaptive and efficient welding robots.
- The limits of single parameter signals for welding performance monitoring and control has inspired research into sensor fusion, but this work's general application and transferability to new situations, its stability, and the fusion of information content of signals needs further development. However, the trend in sensors and sensing technology research toward three-dimensional vision sensing and information fusion and intelligent modeling is enabling to intelligent sensing systems.
- Effective welding process models are the foundation for optimal decision-making and intelligent control in IWS. Although numerical and analytical models give scientific insight into welding process, they are inadequate to the high uncertainty, complexity, and time criticality necessary for IWS. Big-data driven models have a better potential to solve this limitation. Hybrid models based on in-depth integration of numerical or analytical models with big-data driven models could further improve IWS capability. More work in hybrid intelligent modeling is necessary, along with efficient storage, data management and processing, and sharing of historic data to provide the big-data necessary for hybrid/ AI model development.
- Several papers discuss the advantages and drawbacks of different approaches to IWS control systems used to monitor, extract, and understand the underlying welding physics in real time. More adaptive control techniques, such as reinforcement learning, digital twin, and cloud and distributed (fog or edge) computing platforms will help improve and refine physics-based models.
- A better understanding of human-computer interaction and human-robot collaboration in welding systems will improve the transfer of intelligence to welding. Operators/humans should better understand machine status, and machines should better perceive the real-time status or emotion of humans. In the meantime, welder/technician training and learning for the coming intelligence age is necessary, so that new technologies such as simulators, virtual reality, and augmented reality can be effectively used by the workforce.
- As product design is moving toward mass customization and personalization, so must welding services in the future. Personalized/ smart welding products and services based on platform technologies including CPS, IoT, and cloud manufacturing can help realize green, efficient, and humanized IWS in the context of Industry 4.0. Welding-based additive manufacturing technology will make it possible shorten production cycles and reduce manufacturing costs.

### 8.2. Deployment of intelligent welding

The following outlines factors to consider for the systematic implementation of intelligent welding considering the state-of-art of intelligent welding in academia and industry and the general global evolution of intelligence in manufacturing:

(1) From the design-production-product perspective, the feasibility of communizing and standardizing the product line should be studied to facilitate the welding processes. The full "design-assembly-welding-test-sale-service" life cycle of product families should be studied to realize the potential of 'intelligence' for the entire supply chain.
(2) From perspective of technological maturity, time, and cost, industry should invest in intelligent welding in the following order: automation (including but not limited to robotics), digitalization (sensors and data collection infrastructure), networking (communication and linkage infrastructure), and finally artificial intelligence (machine intelligence algorithms with well-defined goals). Applying general artificial intelligence to welding requires further maturation of the field of industrial AI. This prioritization is implied by the technological maturity of the industry sectors and the general difficulty of implementing machine intelligence into the factory.
(3) From the system perspective, intelligent welding should be deployed first at the station level, then to the shop floor, and finally throughout the factory. Potential gains from integrating systems-of-

systems can be large, but most learning will take place at the station and shop floor level. Welding research should strive to realize welding intelligence gradually, with a clear technology roadmap and piloting projects to ensure technological maturity before full-scale deployment.

## Declaration of Competing Interest

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

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