№ 2(55) 2025
МЕТОДИ ТА ПРИЛАДИ КОНТРОЛЮ ЯКОСТІ
ISSN 1993-9981 print
ISSN 2415-3575 online
https://mpky.nung.edu.ua

Прийнято 18.08.2025. Прорецензовано 19.12.2025. Опубліковано 29.12.2025.

UDK 621.791.05:007.52 DOI: 10.31471/1993-9981-2025-2(55)-108-120

AI-DRIVEN INTELLIGENT CONTROL SYSTEMS FOR ROBOTIC WELDING: STATE OF THE ART AND FUTURE OUTLOOK

Iegorov O. P.
Postgraduate student
Admiral Makarov National University of Shipbuilding
54025, Heroiv Ukrainy pr., 9, Mykolaiv, Ukraine
https://orcid.org/0009-0009-6206-2956
e-mail: alex.yegorov@gmail.com

Abstract. To enhance the level of automation, process stability, and the quality of welded joints in modern industry, the concept of intelligent welding control is being actively implemented. The article analyzes the current state of welding automation technologies and outlines the main directions of their evolution over the next five years. Special attention is given to the application of artificial intelligence methods such as expert systems, fuzzy logic, machine learning, deep learning, and computer vision. These approaches are used to optimize process parameters, monitor the state of the weld pool, detect defects in real time, and improve the accuracy of weld formation. However, most existing solutions remain highly specialized and do not provide full integration between the stages of preparation, execution, and quality control of welding. A significant challenge is the limited ability of such systems to operate online and adapt to changing process conditions, such as temperature fluctuations, variations in part position, or arc instability. The article emphasizes the importance of developing online adaptive control based on multisensor data and artificial intelligence. In particular, it explores the prospects of using deep learning for the analysis of video streams and thermographic images of the weld pool, enabling automatic adjustment of parameters in real time. The application of reinforcement learning opens up new opportunities for optimizing the trajectories of welding robots and selecting welding strategies under uncertainty. Furthermore, the implementation of Internet of Things (IoT) technologies allows the creation of integrated networks of sensors and devices that exchange data for building digital twins of welding processes. Welding automation can be significantly improved in terms of efficiency, flexibility, and quality through the adoption of these AI-based technologies. This advancement is associated with the possibility of safe human–robot collaboration, automatic adaptation to environmental changes, as well as the prediction and prevention of welding defects.

Keywords: intelligent welding control, robotic welding, artificial intelligence (AI), machine learning, deep learning, welding automation.

Запропоноване посилання: Iegorov, O. P. (2025). Ai-driven intelligent control systems for robotic welding: state of the art and future outlook. Методи та прилади контролю якості, 2(55), 108-120. doi: 10.31471/1993-9981-2025-2(55)-108-120

* Відповідальний автор

Introduction

Welding is an essential manufacturing process used across a wide range of industries, from automotive and aerospace to construction. Robotic welding systems have been employed to automate this process, improving productivity and repeatability, since the 1980s. Traditional welding robots were relatively limited in their capabilities, with basic feedback control and limited use of sensors [1]. Advances in control, modeling, and vision have led to much higher precision and repeatability in positioning the welding torch, following complex paths, and generating welds with higher quality, at greater speed. This is illustrated by a demonstration of welding on a deep underwater pipeline. The “brains” of a welding robot, its control systems, must precisely control the robot’s motion, regulate welding parameters, and respond appropriately to various disturbances.

The application of artificial intelligence (AI) to the control of welding robots and processes has seen very rapid development in recent two decades [2]. Core problems such as choosing the right welding parameters, following the joint geometry, or monitoring and ensuring defect-free welds are hard to address fully with conventional controllers. AI provides a data-driven or rule-based form of intelligence which can be used alongside traditional controllers. There has been significant research applying a range of AI techniques – fuzzy logic, expert systems, artificial neural networks (ANN), genetic algorithms (GA), and adaptive neuro-fuzzy inference systems (ANFIS) – to weld process modeling and control. The underlying methods can be used to learn from data, or encode human knowledge, to provide intelligence to control systems. In welding, these need to be able to handle complex nonlinearities and process uncertainty.

Intelligent control systems for welding robots use AI or other advanced computational algorithms to provide a form of control that can be adaptive, optimized, or “smart” in certain ways. This is in contrast to simpler, logic-based controllers which have fixed rules and responses. Intelligent systems can learn from sensor data or inputs, predict important outcomes such as weld quality, and adapt their parameters or path as needed. There have been many successful examples, such as using neural networks to predict weld bead geometry and then adjust the travel speed, and fuzzy logic controllers which codify an expert welder’s knowledge into linguistic rules [2].

However, there is also a significant gap between these successes and a fully modernized welding robot for industry, where advanced AI is put to use. Many of the AI welding applications developed so far have been aimed at off-line optimization or monitoring, but not real-time control. Most welding robots to this day use only relatively simple sensor feedback systems, which are unable to cope with more complex situations and cause the robot to go off its desired course. True closed-loop intelligent control systems, which sense the state of the weld and intelligently adapt the process in real time, are only just starting to be developed. In addition, the practical integration of advanced AI into industrial welding systems has many challenges to be solved, such as reliability, data availability, and real-time constraints.

In this paper, we survey the current state of the art in intelligent control systems for welding robots and develop a path forward. We review the major intelligent control approaches that have been applied, and highlight their uses and limitations. Based on recent research and emerging trends, we suggest improvements and new capabilities that are likely to be needed and valuable for 2025–2030. This includes a focus on the increasing roles of deep learning and computer vision, without neglecting other promising AI methods such as reinforcement learning and multi-agent systems.

The goal is to bring some clarity to where research and development can have the most impact and support the design of “smarter” welding robots that can outperform today’s systems in autonomy, quality assurance, and adaptability.

Presentation of the main material

Analysis of modern foreign and domestic research and publications.

To answer our research question "What intelligent control methods have been applied to welding robots and how might they be improved by artificial intelligence in the next five years?", we first performed a focused literature search and qualitative analysis of the results.

Literature Search – articles and proceedings from 2018–2024 were searched for AI-based welding control contributions, using IEEE Xplore, ScienceDirect, Springer, and Google Scholar. Keywords included "intelligent welding system", "robotic welding AI", and "weld defect detection deep learning". Preference was given to peer-reviewed articles and prominent review publications [1, 2] while winnowing down to ~40 key references. These cover a breadth of welding processes (arc, laser, friction stir) and targets for control from low-level regulation to high-level planning.

Categorization – these publications were then sorted into 4 broad categories:

– Welding Process Control – Papers with a focus on regulating penetration, bead shape, etc.

– Robot Motion Control – Works discussing path planning, torch angle, multi-robot choreography.

– Sensing and Monitoring – Sensor integration to improve seam tracking, weld pool monitoring, defect detection.

– System-Level Integration – Broader level descriptions of manufacturing systems with IoT or multi-agent architecture.

These publications were then further classified for the AI technique employed (fuzzy logic, machine learning, evolutionary optimization, etc.), as well as for the type of control being supported (off-line, real-time, or predictive control).

Data Synthesis – Key attributes from each publication are distilled here and are summarized in the tables and figures below. This includes information on the AI method, welding task, and result(s) (accuracy increase, programming speed, etc.) as well as listed open challenges. These data cover easily comparable quantities (track weld defect prediction accuracy [3], latency of feedback systems [4], benefits such as reduction in manual input), as well as qualitative, repeating themes (calls for improved real-time control algorithms [1], standardized datasets).

Terminology – "Intelligent control systems" in this work refer to AI-augmented control methods in addition to more classical PID or hard-coded logic. The AI umbrella term is used broadly here to include machine learning, expert systems, and evolutionary optimization. As applicable, more specialized terms like deep learning, reinforcement learning, and digital twin are defined in context in the sections below, with particular focus on their contributions to welding control. Mathematical definitions are given in a high-level summary.

Limitations – this survey is qualitative and does not involve any new experiments. It is drawn from prior literature which may constrain aspects of our findings and does not exhaust the topic. Our search and organization methodology is reusable and will be continued for future updates for work past 2024. Inclusion criteria and classification framework are listed for reproducibility.

The results we have found provide a baseline to which new and future work can be contrasted in order to identify both progress and remaining needs. We present this data below in a series of tables and figures contrasting past and present intelligent welding systems.

Review of Current Intelligent Control Systems in Welding Robotics (up to 2025)

Numerous intelligent control approaches have been implemented in welding robotics, each addressing different aspects of the welding operation. Table 1 provides an overview of key AI techniques used so far, summarizing their typical applications, strengths, and limitations in welding control.

Artificial neural networks (ANN) were widely used to model the welding process in order to establish the relation between welding parameters and welding results, such as bead height or penetration in terms of the travel

Table 1 – Common AI techniques applied in welding robot control (current state up to 2025), with their typical uses

AI Technique	Typical Applications in Welding
Artificial Neural Networks (ANN) [13][14]	Predicting weld outcomes (bead geometry, penetration); mapping sensor inputs (e.g. weld pool image features) to quality metrics; parameter optimization via learned models.
Fuzzy Logic Systems [15][30]	Feedback control based on expert if-then rules (e.g. adjusting voltage or travel speed based on gap measurement); human-readable seam tracking strategies.
Neuro-Fuzzy (ANFIS) [32][33]	Adaptive tuning of welding control rules; combining sensor data of different types (visual, acoustic, etc.) in a unified inference system.
Genetic Algorithms (GA) and Optimization [16][17]	Off-line optimization of weld sequences and robot paths (e.g. minimizing robot travel time or avoiding collisions in multi-robot cells); tuning multiple welding parameters to meet quality objectives.
Adaptive/Model-Based Control (e.g. MPC, expert systems) [35][12]	Real-time control using a process model: maintaining temperature or penetration through MPC; rule-based expert systems for adjusting parameters on the fly.

speed, current, and voltage. ANNs can be employed to train the complex nonlinear relationship of the system, thus achieving better performance than the traditional welding empirical formula. Neural networks have also been applied for processing sensor data and predicting the corrective action to provide to the closed-loop controller as part of a partial closed-loop control [2]. However, as a black-box model, ANNs require large amounts of data to train the model, and the resulting relationship is difficult to interpret.

Fuzzy logic systems were also commonly used to codify the expert knowledge and the rule-based knowledge into the machine-readable format, using fuzzy sets and linguistic variables to represent the rules, such as “IF gap is large, THEN increase wire feed rate”. Fuzzy systems are very interpretable and easy to design, and also robust to noise and uncertainties in the input data, but the lack of learning capability of the knowledge base may be a shortcoming, unless integrated with other data-driven models to update/refine the rules or memberships [2]. Hybrid neuro-fuzzy systems, such as adaptive *neuro-fuzzy inference systems* (ANFIS), were also developed to provide both the learning capability and interpretability. These systems can automatically learn both the rule structure and the membership functions from data, but the design is still complicated and not easily scaled to multiple-output cases.

Optimization algorithms were also leveraged to search for the optimal parameter values or robot paths. For instance, *genetic algorithm* (GA) was used to search for the torch trajectory that produces minimum distortion or collision in a multi-robot cell [2]. However, this approach is normally used offline due to the heavy computational load. Model-based *adaptive control schemes* were proposed to achieve both the thermal consistency and the joint variation compensation [1], using model-predictive control (MPC) or self-tuning regulators, but they also require accurate physical models of the process and could be affected by the process disturbances or model mismatches.

Robots, based on techniques we have described above, are actively used by large enterprises in various industries [6-11]. As Figue 1 shows leading technology is based on fuzzy logic systems.

Benefits from using AI backed robotics range from increased automation rate to pretty accurate prediction error rates as shown in Table 2.

Table 2 – Performance benefits elicited from AI backed robots in enterprise installations

AI Technique	Performance Metrics	Implementation Examples
Fuzzy Logic Systems	68% production automation rate	Samsung Heavy Industries automation
Expert Systems & Adaptive Control	1-2 year payback period	Lincoln Electric WELDES system
Artificial Neural Networks (ANN)	99% first-pass yield (Path Robotics)	TRUMPF AI laser welding, T Systems automotive
Genetic Algorithms & Optimization	11% error reduction in 7 periods	Multi-robot coordination, hydroelectric turbine repair
Neuro-Fuzzy (ANFIS)	<3% prediction error rates	Friction stir welding applications

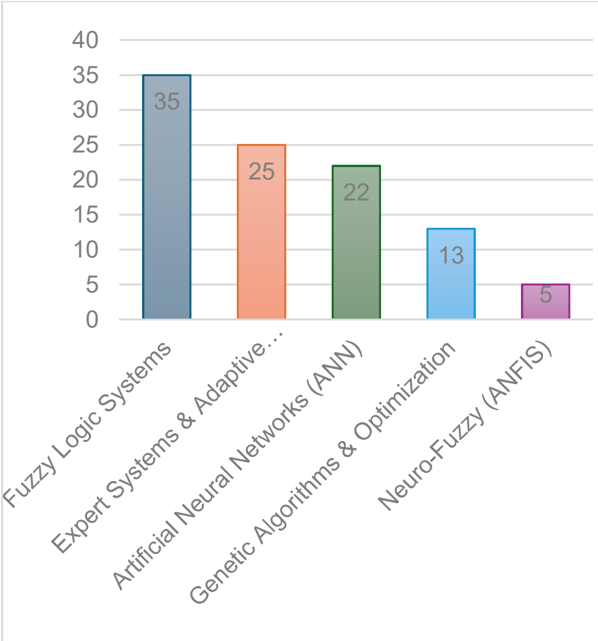

Figure 1 – Welding robots AI technology distribution on the market

Most of the reported AI-based systems have been validated only in laboratory conditions and on specific welding setups [2]. ANN trained for bead dimension prediction or control on one material and joint configuration may not transfer to other materials and joint designs. Fuzzy systems tuned for one welding process and a certain range of input parameters may not be applicable for another welding process and require reconfiguration. This is a fundamental limitation, namely the lack of generalization to new conditions. The vast majority of existing systems can do very well when the conditions are known and part of the training data. In all other cases, they must be retrained.

Another problem area which remains understudied is the online adaptive control of welding processes in real time. The vast majority of AI use cases for welding robots are still offline in nature. For example, optimizing welding parameters or analyzing a finished weld for its quality and defects. This is in part due to the inherent nature of welding as a complex and dynamic process which involves many fast-varying and interrelated variables such as current, voltage, travel speed, wire feed rate, arc force, or thermal radiation [1]. Real-time control would require AI models to make fast predictions with low-latency on embedded hardware. Penttilä et al. (2023) recently demonstrated a fully closed-loop ANN-based control system that could adapt welding parameters online during welding based on the data from a laser sensor to successfully maintain a consistent weld bead [4].

Quality monitoring and feedback for real-time control is another area which is just starting to see development. The vast majority of the post-weld quality inspections such as X-ray is done only after the weld is completed, which is a rather late time to detect and fix a defect. Newer approaches are being developed to use in-process data from welding sensors and vision systems to monitor and detect weld quality issues such as porosity, burn-through, or spatter in real-time during welding [3]. CNNs have been used to classify weld images in terms of defects with over 95% accuracy, but they lack interpretability and suffer from performance loss when the conditions during welding change from those of the training data

[3]. This challenge will have to be addressed by explainable AI and better training data.

Intelligent welding systems are also currently used mostly in a standalone way and to scale will need to be integrated into larger manufacturing systems. IoT and digital twin technologies are emerging as a means to connect and integrate welding robots into a networked, adaptive production line [5], where each agent has specialized capabilities.

Emerging Trends and Future Demands (2025–2030)

The subsequent technical trends and possible subfields, according to our estimation of the current technical potential, may apply in the development of intelligent welding control systems in the upcoming five years. See Figure 2 for perceived deployment times [12-16].

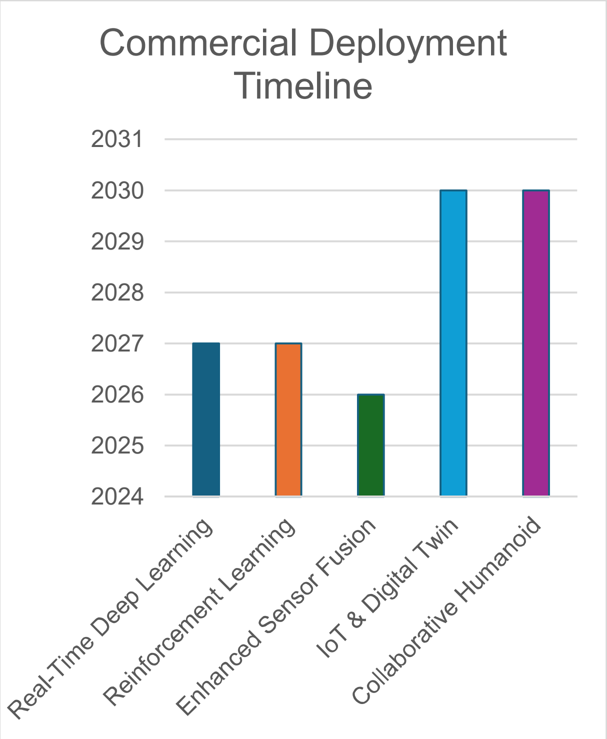

Figure 1 – Commercial deployment timeline for emerging AI technologies in welding

Real-Time Deep Learning - deep learning models for real-time analysis of weld pool conditions, which are already used offline in some research contexts today, will be more widely used in an online fashion by welding robots in the future (by 2030). Vision-based welding control systems based on CNNs are in fact already used for online monitoring of the weld pool today with high defect detection accuracy under varying conditions [3]. Challenges include transferring models to embedded edge-computing hardware with enough speed and robustness to all relevant variations [1]. Efficient neural network architectures and specialized AI hardware will allow the welding system to see and understand the weld condition in real time and to automatically make alignment, parameter, etc. adjustments as a human expert would in the future.

Reinforcement Learning (RL) – RL techniques allow for the learning of optimal welding strategies in simulated trial-and-error and their immediate application in the production environment. The ability of RL to derive improved welding sequences to reduce residual stress is already demonstrated in preliminary work [1]. With improvements in simulators and computing power expected by 2025, RL-driven adaptive controllers will be more realistic to use to guide complex operations such as multi-pass welding or online parameter adaptation. Recent review papers on RL and welding emphasize the potential of RL for advanced control capabilities that can outperform manual tuning for welding problems that are too complex or uncertain for human experts [1].

Sensor Fusion and Advanced Analytics – advanced sensor fusion techniques will allow the use of multiple types of sensors (visible and infrared cameras, laser scanners, force sensors, acoustic sensors, etc.) to obtain a better real-time understanding of the welding process in the future [1]. For example, AI-driven analytics on data from thermal cameras and optical cameras might be fused to improve defect detection performance. Improved hardware and software will allow for more extensive data collection via sensors with higher resolution, sampling rate, and response time [1]. New big data analytics methods will also make use of large amounts of aggregated weld data collected in IoT-connected factories to identify performance patterns and to continuously optimize controls. This would be in line with the general goals of the Industry 4.0 movement [5].

Table 3 – Emerging AI technologies KPI as leading companies

Emerging Technology	Key Performance Indicators	Leading Companies
Real-Time Deep Learning	99% first-pass yields, 50ms detection time	Path Robotics, PHOENIX framework
Reinforcement Learning	<11% error in 7 periods, autonomous learning	FANUC, Inbolt, General Motors
Enhanced Sensor Fusion	98.9% segmentation accuracy, 0.0255s processing	IBM, YOLOv5 integration
IoT & Digital Twin	97.35% detection accuracy, 0.08mm tracking error, 96.65% tracking precision	Schneider Electric, Yaskawa
Collaborative Humanoid	94.44% behavior classification accuracy, 15% throughput increase, 85% idle time reduction	HD Hyundai, Persona AI

IoT and Digital Twins – the current perception of welding operations as isolated, stand-alone processes is expected to shift to fully networked systems by 2030. Digital twins, i.e. virtual models which replicate the real-world welding setup and its processes, will be used to simulate welding operations to a larger extent and to optimize control strategies before their implementation in the real system. Validation of virtual sensors is a welding task which has already been discussed for the seam tracking task in the literature [2]. Through IoT connectivity, welding robots will share real-time status and quality data enterprise-wide for live monitoring, predictive maintenance scheduling, and optimized process adjustments [1]. This should improve flexibility and operational efficiency.

Collaborative and Human-Centric Approaches – intelligent welding systems will be used in a more collaborative manner with human welders rather than solely as replacements in isolated robot cells in the future. Cobots and AI will be combined to perform more of the highly repetitive or physically strenuous or unpleasant tasks while humans perform the complex decision-making and teaching. Advanced operator interfaces such as augmented reality (AR) are already being used to aid operators in robot programming and path planning [1]. It is possible that by 2025–2030 a skilled welder could supervise the operation of multiple cobots in parallel and teach or correct them as needed. AI systems will have to be more adaptive, transparent, and safety-aware in their algorithms to account for humans in their operational environment. This will improve productivity and broaden the acceptance of welding systems.

Leading technology and production companies came up with expected key performance indicators (KPIs) to measure effectiveness (see Table 3).

Sustainability and Resource Efficiency – a greater focus on the economic efficiency and sustainability of welding operations will also guide the development of welding controls in the future. AI can be used to optimize the energy efficiency of welding processes by precisely tailoring parameters to the welding requirements to avoid excessive heat inputs that cause greater distortion and energy waste [1]. AI-based defect prediction or prevention capabilities will minimize rework and material wastage. Predictive maintenance via AI analytics will reduce downtime and accidents by predicting when a tool or equipment is likely to fail or underperform. AI may also allow more use of new sustainable welding materials that are more difficult to work with using traditional controls. The need to preserve the environment and use resources as efficiently as possible will drive continued efforts to improve welding processes using AI while maintaining quality standards. These trends will be summarized in the next section.

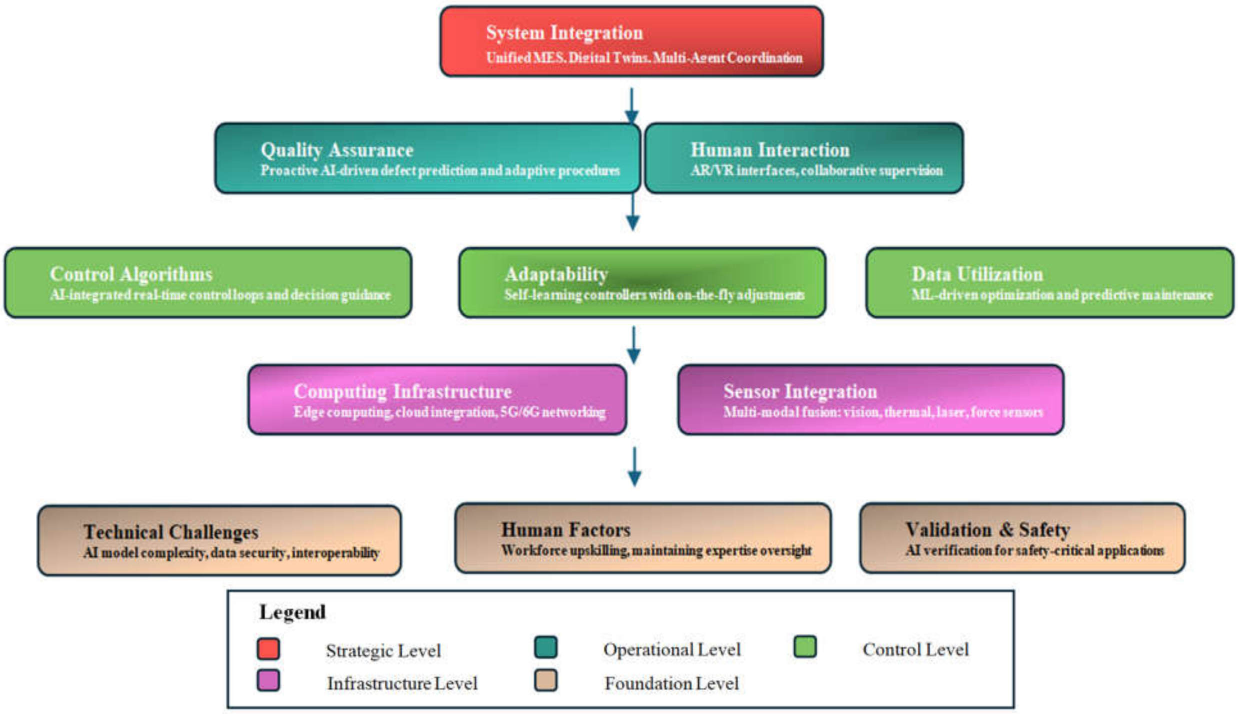

Figure 3 – Intelligent Welding Control Systems: Hierarchical Architecture

Intelligent Welding Control Systems: Hierarchical Architecture

Analysis, we have conducted across available sources, led to identifying pillar aspects intelligent welding control system should adhere to. These pillars are: system integration, quality assurance, human interaction, control algorithms, adaptability, data utilisation, computing infrastructure, sensor integration and challenges. It helps to put them into a hierarcy for a better understanding of relations and dependencies between them. We have designed an high level architecture based on relevant data from recent scientific resources [1,5, 20-25] (see Fig. 3).

To do an intermediate conclusion – the intelligent welding control systems hierarchy above represents a comprehensive five-level architecture that transforms traditional welding automation into truly adaptive, AI-driven manufacturing systems. At the strategic apex, *System Integration* orchestrates unified manufacturing execution systems (MES) and digital twin frameworks, coordinating all subsystem interactions through IoT-enabled multi-agent architectures. The operational level encompasses *Quality Assurance* and *Human Interaction*, where proactive AI-driven defect prediction replaces reactive inspection methods, while augmented reality interfaces enable collaborative human-robot supervision. The control level integrates *Control Algorithms*, *Adaptability*, and *Data Utilization*, forming the intelligent decision-making core that employs real-time AI control loops, self-learning adaptive controllers, and machine learning-driven process optimization. The infrastructure level provides the technological foundation through *Computing Infrastructure* (edge computing, cloud integration, 5G/6G networking) and *Sensor Integration* (multi-modal fusion of vision, thermal, laser, and force sensors). Finally, the foundation level addresses critical *Challenges* including AI model verification for safety-critical applications, data security standardization, and workforce upskilling requirements. This hierarchical structure reflects the evolution from isolated, pre-programmed welding robots to interconnected, intelligent systems capable of autonomous learning, real-time adaptation, and collaborative operation with human operators, supported by extensive peer-reviewed research in intelligent manufacturing and welding automation.

Comparison between present and anticipated intelligent welding control systems

Welding automation is transitioning towards an intelligent adaptive paradigm which will replace traditional deterministic control methods by offering real-time optimization and self-modification functions for enhanced human-machine collaboration. The current intelligent welding system technologies include artificial intelligence, intelligent sensor technologies, and cyber-physical systems consisting of virtual simulation (digital twins) and Internet of Things (IoT) technologies that are used to form smart interconnected manufacturing systems. The shift in technology represents a qualitative change from stand-alone reactive welding systems to advanced interconnected welding systems that learn and work together with human operators. The distinction between the current (until 2025) and the future (2025–2030) is based on both the status of current technology development and imminent breakthroughs such that current implementations of artificial neural networks, fuzzy logic systems, and image processing systems are implemented mainly for offline optimization while the complete shift to the future will see a comprehensive integration of artificial intelligence in online control systems, reinforcement learning for self-adaptation, and multi-agent systems for coordinated manufacturing. The transition between the existing and the future is important for manufacturers and welding engineers looking to shift from automation to intelligent manufacturing.

The summary for each of the intelligent system technologies, comprising the existing and the future state, is given in Table 4. The table makes it clear the field is moving from primarily static, isolated systems to adaptive, interconnected intelligent systems.

Table 4 – High-level comparison of intelligent welding control systems: present (up to ~2025) vs. anticipated future developments (2025–2030)

Aspect	Up to 2025 (State of the Art)	2025–2030 (Future Outlook)
System Integration	Welding robots largely stand-alone. No holistic optimization – each cell optimized locally if at all. Digital simulation models exist but are not linked live to operations.	Welding cells are part of a unified manufacturing execution system (MES). Digital twins of welding processes run in parallel with real operations, providing real-time simulation feedback and what-if analysis [1]. Multi-agent control: multiple robots or stations coordinate via an AI supervisor agent to optimize line throughput and energy usage [5].
Quality Assurance	Largely reactive – defects are detected after the fact (using NDT methods or final inspection). Quality control relies on fixed welding procedure specifications (WPS) that must be pre-qualified.	Proactive and adaptive - AI models predict potential defects in real time and adjust parameters to avoid them [3]. WPS evolves into flexible adaptive procedures where the system can prove equivalence to standards via data. If a defect is unavoidable (e.g. due to material), the system flags it immediately and perhaps auto-repairs or marks the spot for automated post-weld repair.
Control Algorithms	Predominantly PID and simple feedback for real-time control. AI (ANN, GA) used mostly for off-line parameter optimization or advisory systems [2].	Widespread integration of AI in control loops: real-time control decisions guidance [1]; policies for robot motion and parameter tuning [1].

Continuation Table 4

Aspect	Up to 2025 (State of the Art)	2025–2030 (Future Outlook)
Adaptability	Limited adaptive behavior. Systems can handle expected disturbances. Most "intelligence" is pre-programmed or requires re-training offline if conditions change [2].	High adaptability and self-learning. Controllers adjust on the fly to variable conditions using AI. Robots are more general-purpose, able to weld new parts with by learning from simulation or operator demonstration rather than manual coding [1][4].
Data Utilization	Data from welds is used mostly for quality documentation or off-line analysis. Little sharing of data between machines.	Data-driven optimization at scale. Machine learning models analyze aggregated data from many welds to find optimal practices and feed improvements back to controllers [5]. Trends prediction triggers preventative maintenance.
Computing Infrastructure	Traditional industrial controllers (PLC/embedded PCs) with limited AI capability; heavy computations done on offline computers if at all. Minimal use of cloud or edge computing in real-time due to latency concerns.	Hybrid computing approach: edge computing becomes common at the cell level [1], non-critical data processing and machine learning training are offloaded to the cloud or central servers. Networking standards (5G/6G) allow data to be usable in closed-loop control and remote supervision.
Sensor Integration	Single primary sensor driving automation; through-the-arc sensing with known reliability issues in complex joints [2]. Additional sensors (laser, thermal, etc.) used mainly in research or high-end systems.	Welding robots combine data from vision (visible & IR), laser profilometers, sound, and more to gain a comprehensive view [1]. Sensor data is fused using AI. Real-time 3D sensing is utilized for adaptive path correction and quality control.
Challenges	Ensuring weld consistency with limited adaptation; dealing with noise in sensor signals; lack of interoperability (proprietary systems); obtaining sufficient training data for AI; conservative industry acceptance due to safety/quality risks.	Handling the complexity of AI models (verification and validation of AI-driven decisions for safety-critical welds); managing data security and standardization across IoT devices; maintaining human oversight and expertise in an AI-dominated process (avoiding over-reliance on automation); workforce upskilling to work alongside intelligent machines [2].

The above comparisons show an overall shift: from fixed automation to adaptive intelligence in welding robotics. To realize this shift, cooperation between welding engineers, AI and control system experts will be required in order to achieve safe, efficient and user-friendly solutions. Industries with high regulatory barriers, such as aerospace or oil & gas, may be more conservative and require AI applications to show consistently high-quality results at scale. High-volume industries such as automotive may adopt these new technologies earlier on, since potential cost savings may be larger.

Case studies already show the benefit of AI: a case study found fewer weld defects and more consistent welds when using an AI-based feedback control [4], and another reduced programming time by 40% using AI-assisted path planning [2].

Robotic welding systems are expected to be fully integrated in smart manufacturing in 2025-2030. They will be able to learn and autonomously adapt in real-time. Human operators will be responsible for mainly supervision, training and personalization. This development has the potential to mitigate the shortage of skilled workers and can further increase safety. Better understanding the current limitations may help to guide the AI development, so that in the future, welding control systems are truly smart, robust and reliable.

Conclusion

We presented an overview of the development of intelligent controls for welding robots from the early first automatic devices to the state of the art of today with AI-based approaches. Neural networks, fuzzy logic, and genetic algorithms have been successfully used to find optimal process parameters and support human decisions to enhance weld quality and process efficiency [2]. However, most current systems can still only execute predefined procedures with simple feedback from physical sensors. Advanced applications of AI for closed-loop control to operate in real-time are still the exception.

AI represents a major opportunity but also a big challenge for the future of welding robot controls. On the one hand, there are exciting new capabilities with the novel technologies, such as real-time weld defect detection and classification with deep learning vision systems [3], dynamic path planning and parameter adjustment with reinforcement learning, or collaborative operation with other robots and human operators as IoT-enabled multi-agent systems [5]. On the other hand, there are important open questions for a reliable implementation to be able to deploy it industrially. These include the generalization of AI models to different welding conditions [3], the necessary computational speed for real-time operation [1], or the interpretability of the AI-based decision-making for proper human supervision.

The potential benefits from further development of intelligent controls for welding robots are huge. Near 100% weld quality with very low defect rates could be achieved for significant cost savings and improved product quality. Intelligent robots could be adapted more easily for different production scenarios, thus mitigating skilled worker shortages or reducing safety hazards by reducing human exposure to welding tasks. In addition, AI-based optimization of material and energy consumption can support sustainability goals.

However, risks such as the over-reliance on AI without adequate validation and error handling measures leading to unexpected failures must not be neglected. The associated need for appropriate standards and workforce training must also be taken into account in due time. By 2030 we expect welding robots with AI elements to usually operate autonomously by learning and adjusting while human operators will transition to supervisory and training roles. We view this development as a major advancement towards achieving fully autonomous manufacturing capabilities in welding robots.

Acknowledgements
None.

Conflict of interest
None.

References

1. Kahnamouei J.T., Moallem M. Advancements in control systems and integration of artificial intelligence in welding robots: A review. Ocean Engineering. 2024. Vol. 312. doi: 10.1016/j.oceaneng.2024.119294
2. Gyasi E., Handroos H., Kah P. Survey on artificial intelligence (AI) applied in welding: A future scenario of the influence of AI on technological, economic, educational and social changes. Procedia Manufacturing. 2019. Vol 38. pp. 702-714, doi:10.1016/j.promfg.2020.01.095
3. Li H., Ma Y., Duan M., Wang X., Che T. Defects detection of GMAW process based on convolutional neural network algorithm. Scientific Reports. 2023. Vol. 13(1). doi:10.1038/s41598-023-48698-x
4. Penttilä S., Lund H., Skriko T. Possibilities of Artificial Intelligence-Enabled Feedback Control System in Robotized Gas Metal Arc Welding. Journal of Manufacturing and Materials Processing. 2023. Vol.7(3). P. 102. doi: 10.3390/jmmp7030102
5. Liu Q., Chen C., Chen S. Key Technology of Intelligentized Welding Manufacturing and Systems Based on the Internet of Things and Multi-Agent. Journal of Manufacturing and Materials Processing.2022. Vol 6. P.135. doi: 10.3390/jmmp6060135
6. Ship Technology. The digital shipyard: robotics in shipbuilding. Available: https://www.ship-technology.com/features/feature-the-digital-shipyard-robotics-shipbuilding/
7. ResearchGate. WELDES: An intelligent defects expert system for aluminum welding process. Available:https://www.researchgate.net/publication/240305021_WELDES_An_intelligent_defects_expert_system_for_aluminum_welding_process
8. Path Robotics. Robotic Welding Systems by Path Robotics. Available: https://www.path-robotics.com/
9. Engineering.com. The AI Revolution has Arrived for Laser Welding. Available: https://www.engineering.com/the-ai-revolution-has-arrived-for-laser-welding/
10. ScienceDirect. Data-driven process characterization and adaptive control in robotic arc welding. Available: https://www.sciencedirect.com/science/article/abs/pii/S0007850622000920
11. ScienceDirect. Vision-based construction robot for real-time automated welding with human-robot interaction. Available: https://www.sciencedirect.com/science/article/abs/pii/S0926580524005181
12. Nature Communications. A physics-informed and data-driven framework for robotic welding in manufacturing. Available: https://www.nature.com/articles/s41467-025-60164-y
13. Nature Scientific Reports. A guidance system for robotic welding based on an improved YOLOv5 algorithm with a RealSense depth camera. Available: https://www.nature.com/articles/s41598-023-48318-8
14. Grand View Research. Digital Twin Market Size And Share | Industry Report, 2030. Available: https://www.grandviewresearch.com/industry-analysis/digital-twin-market
15. GlobeNewswire. Collaborative Robot Market Analysis Report 2025-2030. Available: https://www.globenewswire.com/news-release/2025/07/09/3112356/28124/en/Collaborative-Robot-Market-Analysis-Report-2025-2030-with-Universal-Robots-FANUC-ABB-Techman-Robot-Aubo-Robotics-Technology-Co-and-Kuka-Leading.html
16. Interesting Engineering. US firm's humanoid robot to perform welding in Korea's shipbuilding. Available: https://interestingengineering.com/innovation/us-humanoid-robot-in-korea-shipbuilding
17. Frontiers in Mechanical Engineering. Welding robot automation technology based on digital twin. Available:https:/www.frontiersin.org/journals/mechanical-engineering/articles/10.3389/fmech.2024.1367690/full
18. Wang Q., Jiao W.,Wang P., Zhang YuMing. Digital Twin for Human-Robot Interactive Welding and Welder Behavior Analysis," IEEE/CAA J. *Autom. Sinica*.2021. Vol. 8. No. 2, P. 334-343. doi: 10.1109/JAS.2020.1003518
19. IoT Analytics. The top 15 smart factory KPIs: Operational indicators most important for measuring performance. Available: https://iot-analytics.com/top-15-smart-factory-kpis-manufacturing-kpi/# AI-Driven Welding Robot Adoption Analysis: Market Data and Technology Transitions (2024-2030)
20. Zou, D. et al. Robotic welding system for adaptive process control in gas metal arc welding. *Welding in the World*. 2024. Available: https://link.springer.com/article/10.1007/s40194-024-01756-y

21. Powell B.W. Adaptive weld control for high-integrity welding applications. NASA Technical Reports Server. 1993. Available: https://ntrs.nasa.gov/citations/19930065637

22. Dharmawan A.G. et al. Intelligent welding system technologies: State-of-the-art review and perspectives. *Journal of Manufacturing Processes*. 2020. Vol.56. P. 373-391. doi: 10.1016/j.jmsy.2020.06.020

23. Kumar R. et al. Robotic arc welding sensors and programming in industrial applications. *Journal of Materials Science: Materials in Engineering*. 2015. Vol. 10.No. 13. doi: 10.1186/s40712-015-0042-y

24. Stavropoulos, P. et al. Intelligent and Adaptive System for Welding Process Automation in T-Shaped Joints. *Metals*. 2023. Vol.13(9). P.1532. doi: 10.3390/met13091532

25. Papazoglou E.L. et al. Expert Systems - An Application to Welding Adaptive Control. *IFAC-PapersOnLine*. 2017. Vol. 50(1). P. 13586-13591. https://www.sciencedirect.com/science/article/pii/S1474667017494717

ІНТЕЛЕКТУАЛЬНІ СИСТЕМИ КЕРУВАННЯ ЗВАРЮВАЛЬНИМ РОБОТОМ НА ОСНОВІ ШТУЧНОГО ІНТЕЛЕКТУ: ПОТОЧНІ ТЕХНОЛОГІЧНІ ДОСЯГНЕННЯ ТА ПЕРСПЕКТИВИ МАЙБУТНЬОГО

Єгоров О. П.
Аспірант
Національний університет кораблебудування імені адмірала Макарова
54025, просп. Героїв України, 9, м. Миколаїв, Україна
https://orcid.org/0009-0009-6206-2956
e-mail: alex.yegorov@gmail.com

Анотація. З метою підвищення рівня автоматизації, стабільності процесів і якості зварних з’єднань у сучасній промисловості активно впроваджується концепція інтелектуального керування зварюванням. У статті проаналізовано поточний стан розвитку технологій зварювальної автоматизації та окреслено основні напрями їх еволюції на найближчі п’ять років. Особливу увагу приділено застосуванню методів штучного інтелекту, таких як експертні системи, нечітка логіка, алгоритми машинного та глибокого навчання, а також комп’ютерний зір. Ці підходи використовуються для оптимізації параметрів процесу, моніторингу стану зварювальної ванни, виявлення дефектів у режимі реального часу та підвищення точності формування шва. Проте більшість існуючих рішень залишаються вузькоспеціалізованими, не забезпечуючи повної інтеграції між етапами підготовки, виконання та контролю зварювання. Значною проблемою залишається обмежена здатність систем працювати в онлайн-режимі та адаптуватися до змін умов процесу, таких як коливання температури, положення деталі або нестабільність дуги. У статті підкреслюється важливість розвитку онлайн-адаптивного керування на основі багатосенсорних даних і штучного інтелекту. Зокрема, розглядаються перспективи використання глибокого навчання для аналізу відеопотоків і термографічних зображень зварювальної ванни, що дозволяє здійснювати автоматичне регулювання параметрів у реальному часі. Застосування навчання з підкріпленням відкриває нові можливості для оптимізації траєкторій руху зварювальних роботів і вибору стратегії зварювання в умовах невизначеності. Крім того, впровадження технологій Інтернету речей (IoT) дає змогу створювати інтегровані мережі сенсорів і пристроїв, які обмінюються даними для побудови цифрових двійників зварювальних процесів. Зварювальна автоматизація може значно покращитися в ефективності, гнучкості та якості за допомогою використання цих AI-технологій. Це пов’язано з можливістю безпечної співпраці з людиною, автоматичної адаптації до змін середовища та прогнозування та запобігання дефектам.

Ключові слова: інтелектуальне керування зварюванням, роботизоване зварювання, штучний інтелект (ШІ), машинне навчання, глибоке навчання, автоматизація зварювання.