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THE APPLICATION OF ARTIFICIAL INTELLIGENCE IN WELDING AND RELATED TECHNOLOGIES

L.M. Lobanov, O.V. Makhnenko, O.S. Milenin, M.G. Malhin, G.Yu. Saprykina, O.M. Savitskaya

E.O. Paton Electric Welding Institute of the NASU.
11 Kazymyr Malevych Str., 03150, Kyiv, Ukraine

ABSTRACT

The use of Artificial Intelligence (AI) systems based on Large Language Models offers significant opportunities for welding specialists to analyze vast amounts of information available online when preparing scientific articles and reports, as well as for solving standard tasks in mathematics, physics, chemistry, etc. But the implementation of specialized AI models in welding is highly advisable. These models can effectively address challenges such as optimizing welding parameters, analyzing weld quality using computer vision methods, automating welding for repetitive tasks, monitoring the condition of critical welded structures, creating digital twin systems, and in the field of welder training. The utilization of AI systems in welding and related technologies can provide substantial advantages in the development of new welded products and welding technologies through optimized processes.

KEYWORDS: welding, artificial intelligence, neural networks, welding parameter optimization, weld quality control, robotic welding, monitoring systems, welder training

INTRODUCTION

Welding is a complex multifactorial technological process which is successfully used in many sectors of industry. The volume of welded structures which is constantly growing, widening of the range of structural and welding materials, appearance of new welding technologies, increase of the requirements to the quality of products and reduction of development time requires application of effective methods of solving the complex weldability problem in combination with ensuring the mechanical and operational characteristics of the welded joints and structures required by the specifications. At present, considering the high existing level of computerization and informatization of the society, it is rational to solve the problems of development and optimization of the technological cycles of welding, welded structure design, planning of their operation and maintenance using modern methods of mathematical and numerical modeling. This allows taking into account the complex spatially inhomogeneous nature of the nonstationary physical phenomena in advanced materials, which determine the joint quality and weldability and performance of the welded structure. These phenomena include the temperature field kinetics, development of the stress-strain state, hydro- and gas-dynamic phenomena, electromagnetic phenomena, microstructural transformations, material damage and destruction, etc.

For numerical prediction of such complex physical phenomena it is customary to use two fundamentally different approaches, namely: deterministic or statistic modeling. Deterministic modeling is a process of construction of the mathematical models, in which the system condition at any moment of time is uniquely determined by the set initial conditions, parameters and certain laws of physics. Such models are based on deterministic physical or technical laws (for instance, thermal conductivity equation, Navier–Stocks equations, Maxwell equations, etc.), and under the same conditions the calculation result is always the same. The main mathematical objects here are ordinary and partial differential equations, integral equations, and systems of algebraic equations.

However, both the complexity of the actual technological processes and the multiscale nature of the respective physical phenomena determine the emergence of natural uncertainty in the initial data as to the system condition and modeling results based on deterministic mathematical models. In this case, it is rational to use the so-called statistical modeling — the process of construction of mathematical models, describing the dependencies between the variables based on selective data, taking into account the randomness, variability, incompleteness or uncertainty in observations or in physical phenomena. Such an approach is particularly important in the case of uncertainty in the tendencies of running of the physical processes, but it allows determination of the required regularities based on analysis of large arrays of available data. One of the ways to implement the statistical modeling methods is the use of artificial intelligence (AI) systems, which are becoming ever wider applied for solving the practical problems [1]. Within this work, a critical analysis was performed and the main tendencies of AI application in the field of welding and operation of critical welded structures were determined.

Artificial intelligence are systems or programs capable of performing the tasks, which usually require human intelligence, such as: learning, logical thinking, information perception or decision making, often by using data, knowledge and experience for effective actions in new or uncertain situations [2–4]. The typical tasks, solved by AI systems, include: analysis of large volumes of information; looking for solutions of mathematical, physical and other problems; language or image recognition, generation of images or sounds; computer vision, etc.

The history of AI development as a scientific discipline started in 1956 in the Dartmouth seminar, in which the "artificial intelligence" term was introduced for the first time. Since that time AI has passed a series of development stages [5, 6], which were followed by periods when the interest in AI deceased, which was associated with a lack of computer power and insufficient level of development of computer technology.

Some of the first AI researchers in Ukraine, who laid the foundations of computer informatics and scientific approaches to AI problems, were academician V.M. Glushkov, outstanding mathematician and cyberneticist, founder of the Institute of Cybernetics of the NAS of Ukraine; academician M.M. Amosov, famous surgeon, as well as academician O.G. Ivakhnenko, well-known scientist in the field of informatics, automatic control and mathematical modeling. In the 60s of the previous century a number of scientific works were published [7–12], which set forth the main principles of information processing and intellectual system modeling used today in AI systems. Note that the monograph by M.M. Amosov "Modeling of Thinking and the Mind" was published in the English translation, in particular, by Springer Publishers [13] (Figure 1).

One of the stages of development in the field of AI was development of powerful computer systems known as expert systems (ES). ES is a computer system imitating the human decision-making ability [14]. It is designed for solving complex problems through reflection based on knowledge, presented mostly in the form of "if-then" rules, and not the traditional procedural code. ES consists of two main subsystems: logical conclusion mechanism and knowledge base. The knowledge base incorporates the facts and rules, while the logical conclusion mechanism applies these rules to known facts, so as to obtain new ones. The logical conclusion mechanisms can also include functions for clarification and adjustment. The first expert systems were developed in 1970s, and in 1980s they became widely accepted, also by welding-engineers and researchers, dealing with the problems of welding and related technologies. In order to prepare and plan the welding operations, means were created which were based on computer technology. In terms of information processing and presentation, these devices can be conditionally divided into two kinds: expert

Figure 1. First works on research into the problem of AI in Ukraine (top row, from left to right: [7], [10], [9], [8]; bottom row, from left to right: [12], [11], [13], [8])

systems and traditional programs. ES using symbolic logic and heuristics (empirical rules) when solving the problems, make certain conclusions even with incomplete or "noisy" input data. Program packages were developed within group funding projects on ES investigation and development. The best known of them is the TWI project "Expert System in Welding", American Welding Institute "Welding Information Network", German Welding Society "Schweisstechnik", joint work of The Welding Institute and Department of Energy of Great Britain, Babcock Power, British Nuclear Fuels & ESAB Companies. At the same time, works on creation of expert systems designed for different kinds of welding were conducted at PWI under the leadership of V.I. Makhnenko: resistance spot welding, brazing, electroslag casting, surfacing, submerged-arc welding. Some of these systems were brought to the level of research prototype [15, 16].

Thus, ES are aimed at providing specialized knowledge and capabilities to solve the problems that helps the users to take decisions or solve complex tasks. However, the interest in ES decreased somewhat because of manual encoding of thousands of rules for complex tasks, and it became impractical. Moreover, the problem of uncertainty arose: confidence coefficients do not cope well with probabilistic scenarios, and competition also arose from the side of the statistical methods: machine learning (regression trees, support vector method). It showed that ES are effective only in limited areas.

Combining ES with machine learning, development of the big data area, neural networks (NN) and computing power allowed upgrading them, while preserving the logical transparency and adding adaptability.

ES evolution is a path from strict rules to symbiosis of logic and data. Modern hybrid approaches allow overcoming the limitations of classical ES, while maintaining their main advantage — solution transparency. In the future, the neurosymbolic AI can become the base for systems, which not only imitate the experts, but also learn from them, adapting to the dynamically changing world [5, 17, 18].

A real breakthrough in AI field occurred at the start of 2010s, which was associated with development of deep (machine) learning. This was promoted by increase of computing power, particularly appearance of graphics processors and accessibility of large data volumes. A real boom in neural network application in AI systems is observed now [19].

At present AI systems based on general language models have become widely accepted. The most well-known are the following developments of such AI systems:

- ChatGPT — chatbot with artificial intelligence from OpenAI Company, based on a large language model; capable of operating in a dialogue with natural conditions;
- Gemini — conversational chatbot with generative AI, developed by GoogleAI Company, based on language models;
- DeepSeek — a neural network developed by a China company of the same name, writes texts, analyzes documents, programs, etc.

MOST WIDELY USED AI METHODS IN THE FIELD OF WELDING

Rapid development of AI demonstrates the huge potential for improvement of the traditional industrial processes. AI integration into the welding production reflects a general trend to introduction of advanced technologies for solving the following tasks: shortage of skilled labour, need for high quality of welded products and need to increase the level of industrial process automation [20].

AI can analyze data on a scale no human can. AI methods and their application are expanding gradu-

Table 1. AI methods in the field of welding

Artificial neural networks	ANN are mostly oriented to training and are used for taking decisions in nonlinear systems or systems, in which the information about the system itself is incomplete or inaccurate. The complexity of transferring the available expert knowledge to solve a problem of retooling a task during training is an important drawback of ANN
Fuzzy logic	A conclusion is made based on logical operations, due to rules created using FL, while adhering to the causal relationship. The strongest aspect of FL is the use of available expert knowledge, which a serious drawback in the case, when expert knowledge is inaccessible in its full scope.
Optimization algorithm	OA are the optimal solution search algorithms These algorithms functioning on the base of the laws of probability, need only a target function. A certain part of the solution space is considered. Thus, they reach a solution through active search in a shorter time.
Machine learning	ML is a subfield of artificial intelligence which consists of modeling and algorithms, as well as prediction/clusterization/classification. Its main advantage is the ability to produce very good prediction results with minimal training data, in the shortest processing time and without retraining.
Hybrid systems	FL, ANN, etc. can be used separately, and also as hybrid systems, considering the advantages and disadvantages of each method. Thus, much more effective methods can be developed.

ally. Note that the following methods are singled out in the applications for using AI: artificial neutral networks (ANN), machine learning (ML), metaheuristic and hybrid methods, etc. These methods are aimed at different goals. The Table 1 briefly describes the advantages and disadvantages of these popular AI methods used in welding [21].

NEURAL NETWORKS. METHODOLOGY AND BASICS OF BUILDING THEM

Artificial neural networks (ANN), usually called just neural networks (NN), are a mathematical model, as well as its software or hardware realization, built by the principle of organization of nerve networks — networks of nerve cells of neurons of a living organism. NN are used for recognition of hidden regularities in unprocessed data (regression tasks), classification, as well as solving tasks in the field of AI and machine learning. An artificial neuron is a fundamental building block of neural networks, and it serves as information converter in the neural networks. It is named by analogy with the biological one, but it realizes its functions through mathematical operations.

Functioning of the artificial neuron (Figure 2) can be described by the following mathematical equations [22]:

$$u_k = \sum_{i=1}^{n} w_{ki} \cdot x_i \,,\; y_k = f(u_k + b_k),$$

where w_{ki} is the synaptic weight which determines the strength of the connection; b_k is a significant bias added to the weighted sum; u_k is the result of summing up the weighted input signals and bias; x_i is the i-th component of the input vector (input signal); y_k is the output signal of the neuron; n is the number of neuron inputs; f is the nonlinear transformation or activation function.

Weights are the numerical values, associated with each connection between the neurons in the neural network. They determine the strength and importance of this connection, indicating how much this input feature influences the output forecast.

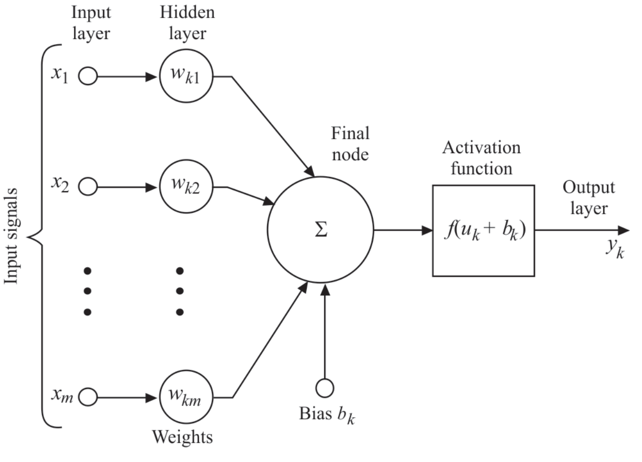


Figure 2. Schematic of plotting a nonlinear neuron model [22]

Biases are additional parameters, which are learned in the machine learning model, and allow accurate adjustment and correction of the predictions. They enable the model to take into account the factors, which cannot be completely covered by just the input features, and allow the neural network to make predictions even when all the input features are equal to zero.

Layers. In multilayer neural networks the neurons are grouped into layers. Each neuron in the previous layer is connected with all the neurons of the next layer (so called fully connected or dense layers), the bonds between the layers being absent inside the neurons. Neural networks consist of several layers of neurons, each of which is connected with neurons of the next layer, forming their complex nonlinear dependencies between the input and output data. With correct adjustment of hyperparameters (such as number of layers, number of neurons in each layer; functions of activation and speed of learning) the artificial neural networks are capable of detecting and effectively modeling the complex dependencies in the data. This process can be represented as a complex spatial multicomponent interpolation.

Neural network learning is an iterative process of adjustment of its internal parameters (weights and biases) with the purpose of minimizing the difference (error) between the output data predicted by the network and the actual target values. First the required scope of data is accumulated in the data set. After that, the main stage of neural network training begins, the objective of which is deriving a trained model, which is a file with optimized neuron weights and biases. The basic learning process involves forward propagation, in which the output data is evaluated on the base of the input data, and the back propagation of the error, during which the weights and biases are corrected to minimize the error. During learning the following parameters are selected: number of hidden layers; number of neurons in each layer; number of neurons, which are activated at each stage, as well as the number of training iterations, known as epochs. As a result of multiple iterations of training parameter selection, the model is optimized, until the best accuracy value is achieved. After that training can be completed, and the trained model is stored in the form of a file, which includes all the required weights and parameters for prediction. This model is ready for further use, for instance as part of the global ecosystem of the digital twin, where it can be integrated in the form of a plug-in module.

The future of intelligent control, will, probably, consist in synergy of the traditional control methods with the potential of systems, based on artificial neural networks [23, 24]. Such control methods offer significant advantages, namely: absence of linear system limitations, effectiveness under noise, possibility of real-time control after training and high adaptability to the real conditions. However, such challenges as ensuring the reliability also remain, as the artificial neural networks can be inaccurate even when functioning correctly, which requires their duplication by other systems for critically important tasks. New types of neural networks have been developed and are being applied, such as: cluster neural networks (CNN) and recurrent neural networks (RNN), which have their unique features, and their use allows avoiding the disadvantages of artificial neural networks. Ongoing investigations in the field of architecture, training algorithms and hardware optimization, will determine the development paths also in this field, which is rapidly progressing at present.

AI APPLICATION IN THE FIELD OF WELDING AND RELATED TECHNOLOGIES

Let us consider in greater detail the directions of AI application in the field of welding and related technologies. Application of AI systems based on general language models open up great possibilities for welding specialists to analyze large volumes of information available in the Internet, when preparing scientific papers and reports, and to solve typical problems in the field of mathematics, physics, chemistry, etc. It is rational to use in welding specialized AI models, which can effectively solve the following problems:

- Optimization of welding parameters in real-time mode, depending on the type of material, thickness and configuration of the joint.
- Analysis of welding quality using the computer vision methods for real-time defect detection.
- Cooperation with robotic welding systems for performance of repeated tasks.
- Development of systems for monitoring the condition of critical welded structures and digital twins.
- Welder training.

Use of AI systems in welding and related technologies can ensure significant advantages in development of new welded products and welding technologies due to optimized processes of design and manufacture.

USE OF LOCAL LANGUAGE MODELS

At present the local large language models are becoming ever more accessible for practical application due to open developments and active community growth. Such models as Minstral, LLaMA, Gemma, Phi, Qwen, GPT-OSS and others can be deployed on local hardware such as personal computers or work stations with GPU. This allows their local use without accessing external cloud services. At the same time, it should be noted that these models were taught on generalized external data sets, and they do not contain the full extent of the user's field specifics, such as welding processes and modes, quality control, robotization, systems of welded structure condition monitoring, welder training, etc. Therefore, additional model training is required for a productive interaction of the user with large language models in professional problems. This process, however, is lengthy, and technically complicated, and it requires significant computing power. The most effective alternative in such cases is use of Retrieval-Augmented Generation (RAG) approach, which assumes that the language model does not try to "remember" all the information, but extracts it from the external knowledge sources [25]. This is especially useful, when it comes to working with large arrays of one's own data: technological manuals, scientific reports, models, calculations, interpretation result bases, etc.

RAG application with LangChain framework, integrated into various large language models with test data bases, vector stores and external utilities was studied [26]. LangChain supports processing of various data formats: text, PDF, Excel, image with text, SQL-bases, and it allows creating your own data base, which is continuously enhanced and updated by the user. The capabilities of action chaining were studied, which include:

- natural language query generation (through text);
- extracting relevant information from documents;
- running specialized utilities or calculation software;
- access to parameterized data bases;
- ceneration of text and graphic report through LLM.

A working process is established in the form of how the scientific reports in PDF format are first processes: each document is divided into text fragments, which go through a stage of vectorization. This process generates numerical embeddings, which preserve the semantic content of each text block (Figure 3).

All these vectors are stored in the vector database. When the user asks a question in the natural language, for instance "Which welding process should be used for joining 6 mm sheets from 2219-T81 aluminium alloy"), the system turns this question into a vector representation and performs a semantic search in the database. The most relevant fragments are extracted, ranked by similarity to the request and transmitted to LLM. Based on these fragments, the language model forms the response that the user receives. Thus, the image demonstrates how a dynamic database, working in an interactive mode, is created form conven-

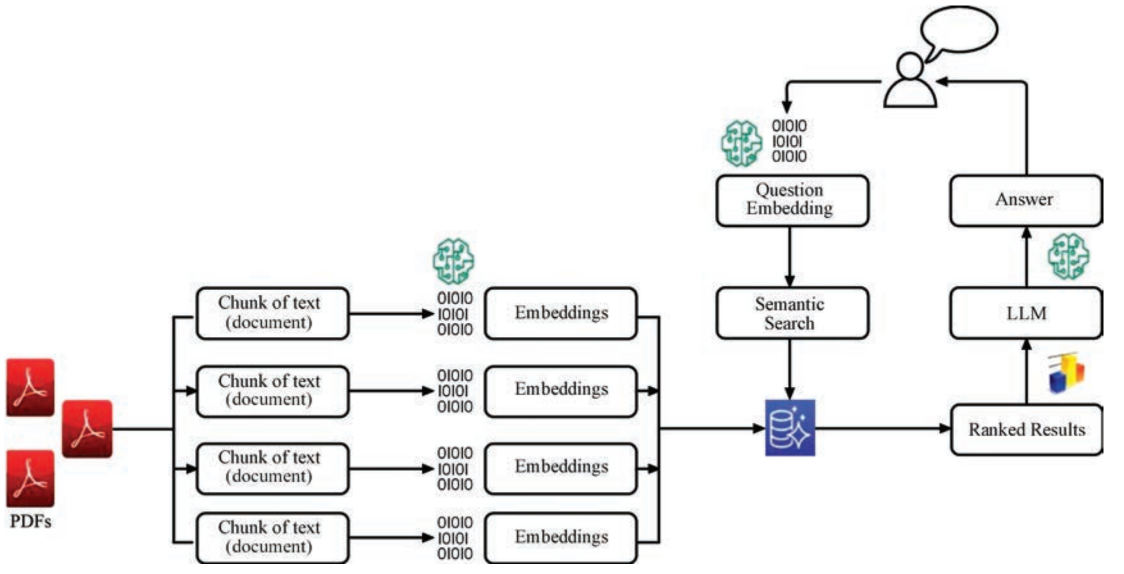


Figure 3. General schematic of interaction of the vector database with large language models based on LangChain framework [26]

tional technological manuals or scientific documents, LangChain acts as a coordinator of all the stages — from preparation of the data, search, calling the LLM and returning the result to the user. Such an approach allows integrating even large archives into a single knowledge system.

OPTIMIZATION OF THE WELDING PROCESS PARAMETERS

Light and strong materials are becoming ever wider applied in modern industry, which is due to the orientation to reducing the greenhouse gas emissions. Friction stir welding can be called one of the most ecologically clean welding methods, which requires much lower energy costs compared to the traditional welding methods, in particular, arc and electroslag. It can be used for welding alloy steels, light non-ferrous metals and alloys (similar and dissimilar), in particular titanium, magnesium, copper and aluminium alloys.

The friction stir welding process (Figure 4) is a solid-phase welding process, without material melting, using a rotating tool of a higher hardness than the material being welded. First the rotating tool is immersed into the butt of the materials, then the heat from friction

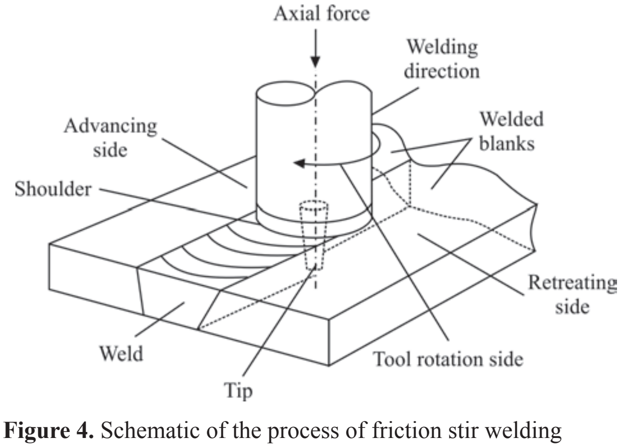


Figure 4. Schematic of the process of friction stir welding

softens the material being welded, and, finally, a strong joint is formed due to stirring. All the materials, which can be brought into a viscous state can be welded this way, and there is also the possibility of welding thermoplastic polymers to metals (welding dissimilar materials and metals — a mixed joint).

Authors of [21, 27–29] consider the key AI methods, which are used for optimization of the friction stir welding parameters, as well as prediction of the welded joint properties and improvement of the process quality:

1. Algorithms of Artificial Neural Networks (Figure 5) have become accepted for prediction of the mechanical properties (ultimate strength, hardness, wear), and welded joint microstructure.

The methods with AI algorithm application based on artificial neural networks demonstrated a high accuracy (up to 95–99 %), and ability to model the nonlinear dependencies, but their introduction requires a large volume of data for learning. The following parameters were used in a single-level model at the input level: tool rotation speed (TRS), welding speed (WS). At the output level we obtain the data on the mechanical properties of the welded joint material: weld metal hardness, HAZ hardness, relative elongation, yield point, and ultimate strength.

Application of a multi-level model of an artificial neural network (Figure 5, *b*) demonstrates a high accuracy of prediction of the vertical force (axial force) of pressing down the work tool, successfully allowing for the nonlinear dependencies between the process parameters [29]. The architecture of this network contains: network type (multi-level straight neural network with an algorithm of reverse error propagation); input parameters — the four nodes: tool rotation speed (ω, rpm); welding speed (v, mm/min); ratio of the tool

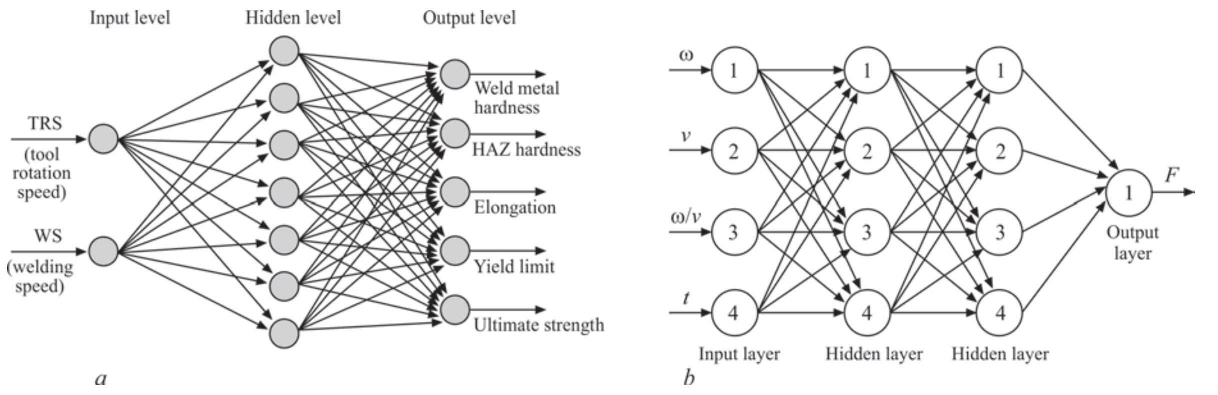


Figure 5. Schematics of artificial neural networks: single-layer [27] (*a*) and multilayer models [28] (*b*)

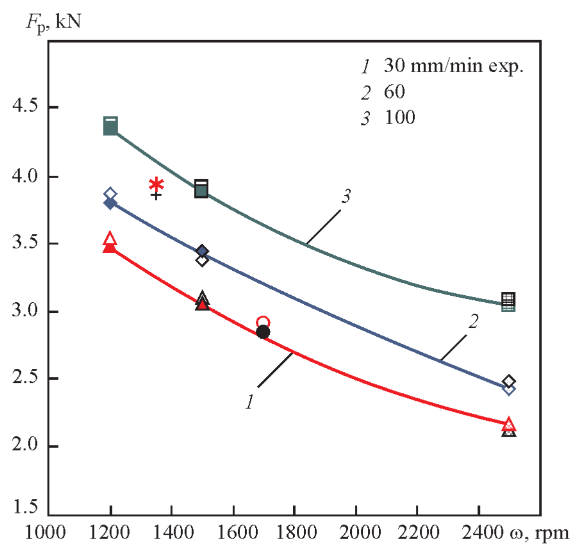
rotation speed to the welding speed (ω/*v*); processing time (*t*, s); output parameter — one node — vertical force (*F*, kN); hidden levels consist of two levels of four neurons each; activation functions — these are the hidden levels and the output level; learning algorithm — Levenberg-Marquardt algorithm; quality metric — root mean square error.

This example was used to check the model property to predict the vertical force under the conditions that are not included into the training set of conditions. Two approaches were used for this purpose: a method in which each experiment was excluded in turn from the training data, and a method when the model was tested on excluded data. The result showed the low error level and the high correlation (coefficient of correlation between the predicted data and the experimental data was $R = 0.9928$, which confirms a strong linear relationship). After testing with new data the model successfully predicted the vertical force curves for the parameters which did not participate in the training. The errors remained in the range of ±5 % for the welding stage and ±10 % for the tool immersion.

This model successfully predicted the vertical force even with a dynamic change of ω and *v* during welding. This demonstrates the possibilities for its application for *adaptive control* (real-time adjustment of the parameters for maintaining a stable force), *producing heterogeneous joints* — different welding zones can have different mechanical properties. Thus, prediction of the force allows avoiding defects and optimizing the welding parameters. Figure 6 gives a comparison of the peak values of the vertical force (*F*, kN) at the welding stage, predicted by the artificial neural networks and derived experimentally. *F* value in the graph corresponds to the anticipated behaviour of the vertical force as a function of the tool rotation speed ω and welding speed *v*, which confirms the effectiveness of the model based on the artificial neural network.

2. *Fuzzy logic* can be applied for controlling the welding process based on expert knowledge and application of linguistic rules. The advantage of this approach consists in that the uncertainty and simple interpretation of the rules are taken into account, but there exists a dependence on expert knowledge and complexity of setting up the membership functions.

3. *Machine learning* includes defect prediction and welding quality classification. For instance, the support vector machine used for the welded joint strength classification is effective when working with a small amount of data and it has a high learning rate, but also



ω, rpm	v, mm/min	Experiment	Prediction
1200	30	▲	△ ANN1
1200	60	▲	△ ANN2
1200	100	△	△ ANN3
1500	30	◆	◇ ANN4
1500	60	◆	◇ ANN5
1500	100	◇	◇ ANN6
2500	30	■	□ ANN7
2500	60	■	□ ANN8
2500	100	⊞	⊞ ANN9
1350	80	+	* ANN
1700	45	●	○ ANN

Figure 6. Comparison of experimental and predicted peak values of the vertical force during welding as a function of welding parameters

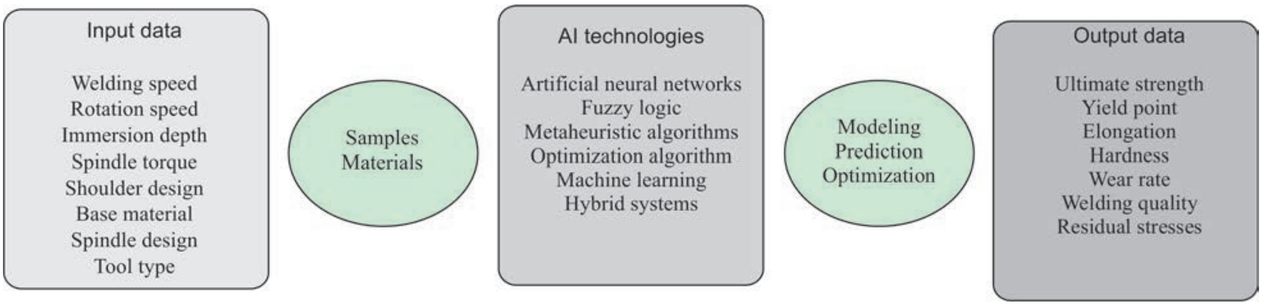


Figure 7. Stages of development (optimization of the technological parameters) of friction stir welding process

has certain limitations, so that a careful selection of features is required.

4. It makes sense to use the *heuristic algorithms* during optimization of the welding parameters, namely tool rotation speed and linear speed. The global search and adaptability can be called the advantages of this type of algorithms, but their drawback is a high computational complexity.

5. *Hybrid systems* are used with the purpose to enhance the accuracy and stability for acoustic signal analysis, joint strength prediction, as well as for optimization of the welding parameters. The advantages of these methods are error reduction and method synergy, but the setting up complexity can be called a disadvantage.

The stages of development of the process of technological parameters optimization in the case of friction stir welding are schematically shown in Figure 7.

DEFECT DETECTION AND QUALITY CONTROL AND OPTIMIZATION OF THE WELDING PROCESS

Using machine vision AI is capable of detecting defects in welds (for instance, porosity, cracks, undercuts and displacements). This will promote an increase in the welded joint quality, prevention of rejects, and, most importantly, detection of such problems at an early stage [29, 30].

The welding process is associated with controlling many parameters (voltage, current, speed, etc.) and geometry of the welded joint. The traditional methods run into such problems as weld defects (porosity, lack of fusion, deformations), arising because of process nonlinearity (Figure 8). Modern systems with sensors and with the use of robots improve the control, but do not solve the problem completely. AI suggests a solution for prediction and real-time adaptive control.

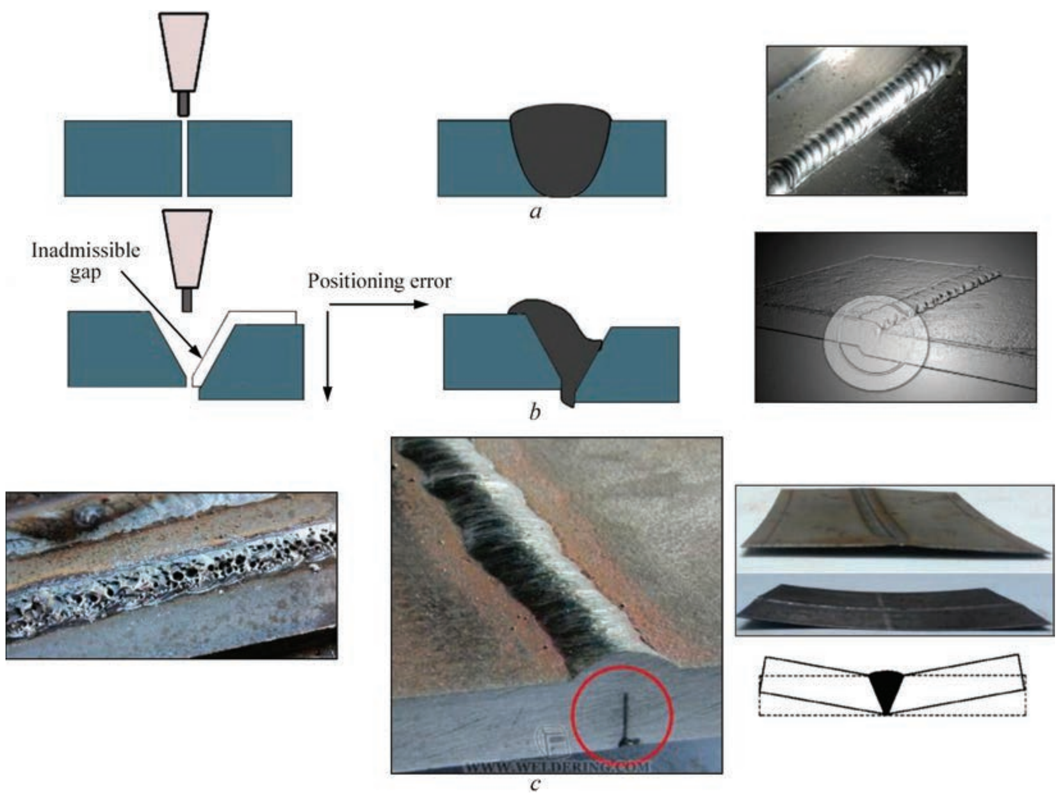


Figure 8. Common welding defects, which can be eliminated using AI and welding process automation: *a* — ideal position of the welded joint; *b* — mismatch of welded joint position; *c* — defects (porosity, incomplete penetration, deformation)

To control the welding process quality, the authors [29] came to the conclusion that it is rational to use *artificial neural networks* for prediction of the weld geometry (bead height, penetration depth), and *genetic algorithms* for optimization of the welding parameters (welding speed and wire feed) allowing for the weldability and productivity factors. In this work, it is demonstrated on examples that AI improves the accuracy of weld quality control, but the dynamic optimization in real time is used very seldom.

ROBOTIC WELDING

AI can be used to control the robotic welding systems, ensuring process stability and high weld quality. AI can also be used not only for changing the welding process parameters, but also for such tasks, as part loading and unloading.

Industrial robotization has numerous advantages: enhancing the efficiency and productivity, cost reduction, product quality improvement, increase of flexibility and safety. Paper [31] describes an intelligent and adaptive system, based on measurement of welded joints, using laser scanning and further analysis of the obtained set of points for welding trajectory adaptation. This study is focused on optimization of T-shaped joints under specific welding conditions, and it is the base for expanding the algorithm application to a wider range of welding problems (Figure 9).

AI methods and their effective application with sensors resulted in improvement of welding technologies. Welding robots have been introduced with integrated AI and adaptive systems, which can work with different workpiece types. Despite all these achievements, application of non-autonomous systems is still observed, when the operators manually set the welding points for robots.

Design and development of the welding robot using AI and machine learning methods for welding trajectory identification and tracking to reduce the operator errors and to improve the welding quality, is considered in [32]. Within this study, it is planned to develop and implement a robotic system, which will autonomously determine the welding trajectory using AI methods and will perform the welding process. A prototype was developed, incorporating a pen holder for initial experiments with trajectories. A torch holder was also designed and produced. The system was prepared for final testing, using a high-quality camera and AI for defining the trajectories. The high-quality camera will capture the images of the blanks, and the image processing methods will be used for welding path determination. The algorithms will improve the image quality in the presence of noise. The system will support 2D and 3 D movement for welding blanks of different shapes (for instance, S-shaped, zigzag-shaped).

Various AI and machine learning (ML) methods were used during the investigations:

● *Cluster neural networks* (*CNNs*). For reduction of the noise and trajectory recognition.

● *Faster-RCNN*. For weld tacking.

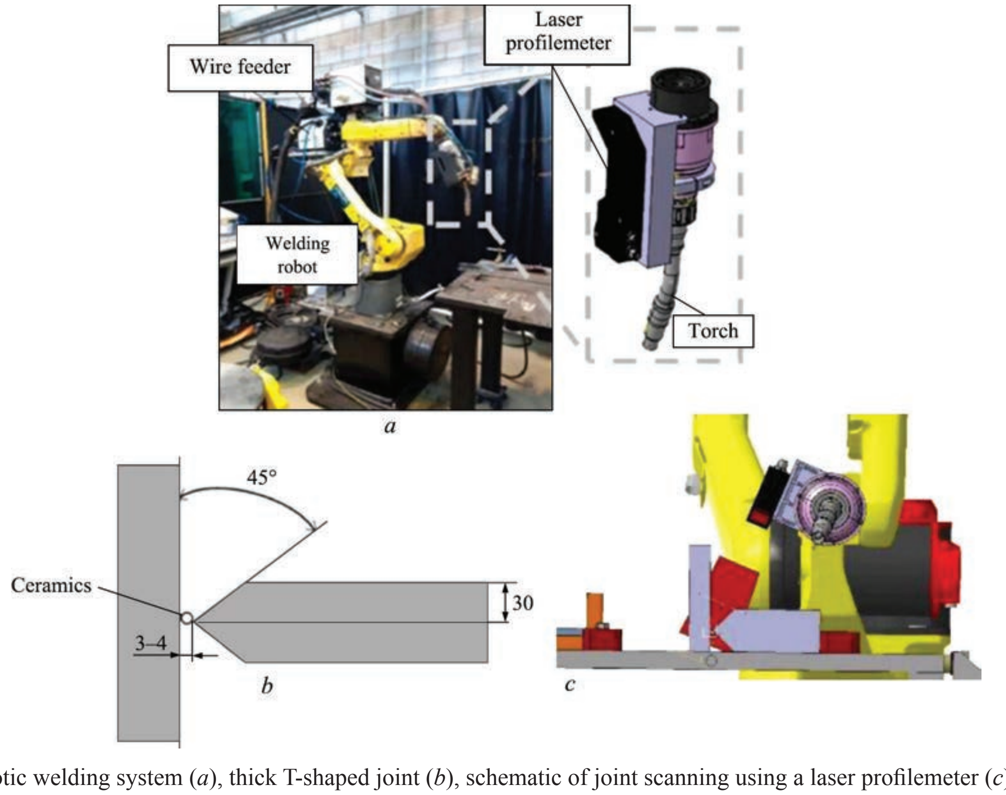


Figure 9. Robotic welding system (*a*), thick T-shaped joint (*b*), schematic of joint scanning using a laser profilemeter (*c*)

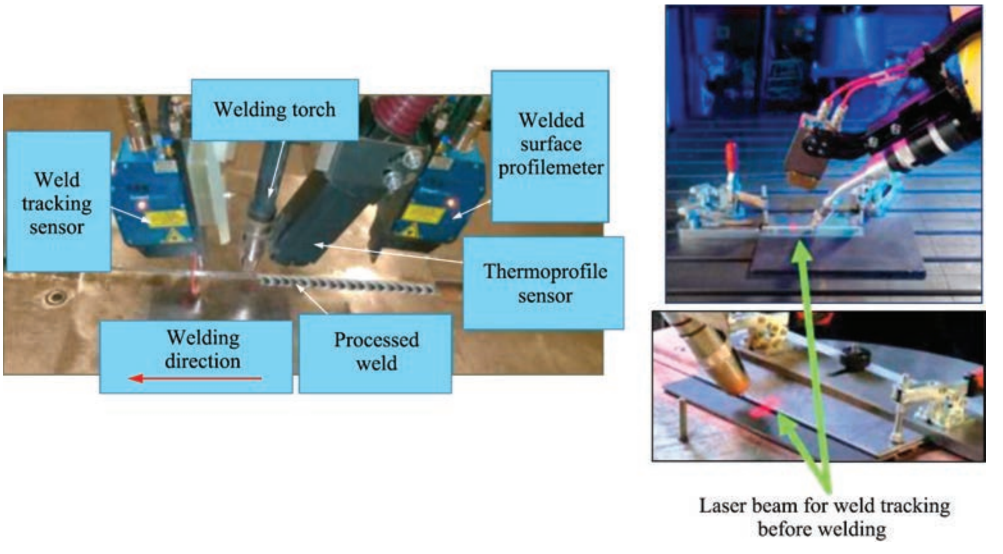


Figure 10. Weld tracking and analysis of the spectrum of the arc or thermal field

- *Generative adversarial networks (GAN).* For noise reduction and trajectory recognition.

The authors [30] consider AI application for controlling the welding robots in some Finnish companies for trajectory design, collision avoidance, and adaptation to changes in the operating environment. Figure 10 demonstrates weld tracking and measurement of the thermal profile of welding parameters for AI monitoring of the welding process.

PREDICTION OF WELDING EQUIPMENT FAILURES

AI application for prediction of the welding equipment operability and planning preventive maintenance is a key element of predictive maintenance concept. Such systems allow minimizing downtime, reducing repair costs and preventing emergency breakdowns.

Predictive maintenance differs from the preventive one in that prediction of the required maintenance time is based on the actual equipment condition, and not on the average or anticipated statistical data on the service life. Machine learning approaches are used to determine the actual condition of the system and prediction of its future conditions [33].

The following data types are used for prediction: sensor data (vibrations (accelerometers)), temperature (thermocouples, IR-sensors), arc current and voltage, pressure in the gas supply system, welding wire feed rate, sound signals (acoustic analysis), operational parameters(welding speed, torch nozzle wear, number of hours worked), data of previous failures (failure log, results of previous maintenance, data on component replacement).

Typical architecture of the forecasting system includes: collection of data from sensors and devices of the Internet of Things, preprocessing (data normalizing, noise reduction (Kalman filters, wavelet-transformations), creating temporary windows for analysis of the time series, designing the features (removal of features: average values, peaks, spectral characteristics, automatic removal of features using autoencoders), AI model training, predictions and recommendations on maintenance.

AI models used for failure prediction are divided into groups: failure probability prediction (for working with tabulated data and detection of the importance of the features; deep neural networks for complex nonlinear dependencies); for analysis of numerical series (for instance, vibration dynamics); prediction of the time-to-failure (regression) (survival models and gradient boosting with regression loss functions are used) and cluster networks (for analysis of vibration spectrograms), anomalies detection (autoencoders for highlighting hidden patterns and anomaly flags, isolating forest, uncontrolled algorithm, which learns the decision taking function to detect the novelty). For instance, the system detects the noncharacteristic voltage surges, not leading to immediate failure, but pointing to the failure risk after 2–3 cycles.

We will give some examples of implementation:

1. Prediction of the welding torch wear. Data: temperature, current, welding cycle number. Model: Hybrid architecture (LSTM+XGBoost). LSTM analyzes the time dependencies, XGBoost interprets the static parameters (material, thickness welded). Result: Prediction accuracy for wear is 92 %, saving on part replacement is up to 30 %.

2. Wire feed system failure. Data: vibration, pressure, welding wire feed rate. Model: Cluster neural network for vibration spectrogram analysis. Result: Detection of contamination 10–15 minutes before stopping.

Digital twins of the equipment for real-time simulation of wear are used for integration with the control systems. Optimization algorithms are proposed (for instance, a method used in AI with agent-based approach). They belong to reinforcement learning experiments to select the optimal time, taking into account the work schedule. In order to prevent downtime, the system recommends performing maintenance during the next shift.

Thus, this offers the following advantages: cost reduction by 25–40 % due to prevention of emergency repair, equipment operates 15–20 % longer between the scheduled maintenance, minimization of risks associated with sudden breakdowns. Thus, AI introduction for prediction of welding equipment failure is a necessity for modern production.

CREATION OF SYSTEMS FOR MONITORING THE CONDITION OF CRITICAL WELDED STRUCTURES AND THEIR DIGITAL TWINS

A classical strategy for maintaining the operability of critical structures for various purposes envisages systematic control of the technical condition and further expert analysis of the possibilities of continued operation under design load conditions. This requires compliance with certain design requirements, nondestructive testing and technological approaches to maintaining the equipment operability. In particular, in the case of a long-term operation under the impact of complex external force, temperature and corrosion factors, during design and assessment of the residual life, it is customary to take into account the worst possible scenario, namely maximal load, maximal material degradation and damage accumulation, and intensive corrosion-erosion wear. An additional factor to be taken into account is the human factor and safety of conducting the diagnostic and repair procedures. While taking each separate factor into account does not present any fundamental difficulties under the condition of sufficient conservatism based on standard approaches and experience of operation of the available facilities, it is quite difficult to predict the multifactorial influence. In order to guarantee the reliability of such objects, significant safety factors, the most unfavourable (including unlikely) scenarios of the operational influence and minimal admissible mechanical and physical-mechanical characteristics of the materials are used. As shown by practice, this leads to excessive material intensity, higher cost, reduction of the real parameters of structure reliability, as well as significant labour intensity during maintenance, in particular in difficult-of-access areas.

Modern development of fundamentals of analysis of the reliability and operability of critical structures and components, understanding the nature of structural material degradation, instrumental methods of nondestructive testing and technical diagnostics with due adaptation of interdisciplinary approaches to solve the specific fundamental and oriented to practical realization tasks opens up the prospects for rethinking the existing ideology of supporting the technological condition by transition from scheduled to predictive maintenance [34–36]. This can be realized, in particular, using a condition monitoring system, based on a set of sensors of different type: strain gauges, accelerometers, corrosion sensors, anemometers, thermometers, acoustic emission sensors, etc. Collecting this information and taking decisions on the actual technical condition of the structures, in particular, in the area of the welded joints, which are the locations of the possible defect initiation and further fracture involves using large data files, which change in time. Application of AI systems is rational for processing the statistically uncertain information collected from different sensors and implementing the decision taking system for planning the maintenance procedures [37, 38].

Digital twins (DT) are an advanced concept of simultaneous application of the monitoring systems and AI (DT) [39, 40]. DT is understood to be the virtual representation of physical essence (object, phenomenon, process or system), which ensures the real-time monitoring, analysis and optimization due to an active interaction between the digital and physical elements and intelligent decision taking. This concept has become widely accepted in realization of different smart systems, which are capable of independently reacting to external influences or changing their properties according to the operating conditions [41, 42]. This happens owing to built-in sensors, actuators, adaptive materials or controls. If we consider the infrastructure objects, creation of smart structures based on adaptive AI systems is realized for development of smart bridges, with integrated monitoring and decision making systems. Here are the following examples of realization of this concept.

Tsing Ma bridge in Hongkong together with Ting Kau and Kap Shui Mun bridges, integrated into WASHMS system (Wind and Structural Health Monitoring System) — a complex system for monitoring the wind load and technical condition of the structures [43].

● Millau Viaduct (France), where the pylons, road surface and anchor cables are equipped with numerous sensors for monitoring the technical condition of the bridge [44]. These sensors are designed to detect the smallest viaduct movements and measure its resistance to wear over time. The network of measuring instruments uses anemometers, accelerometers, inclinometers and temperature sensors. In particular, twelve fiber optic strain gauges are installed at the base of the highest pylon. Electric strain gauges are distributed at the

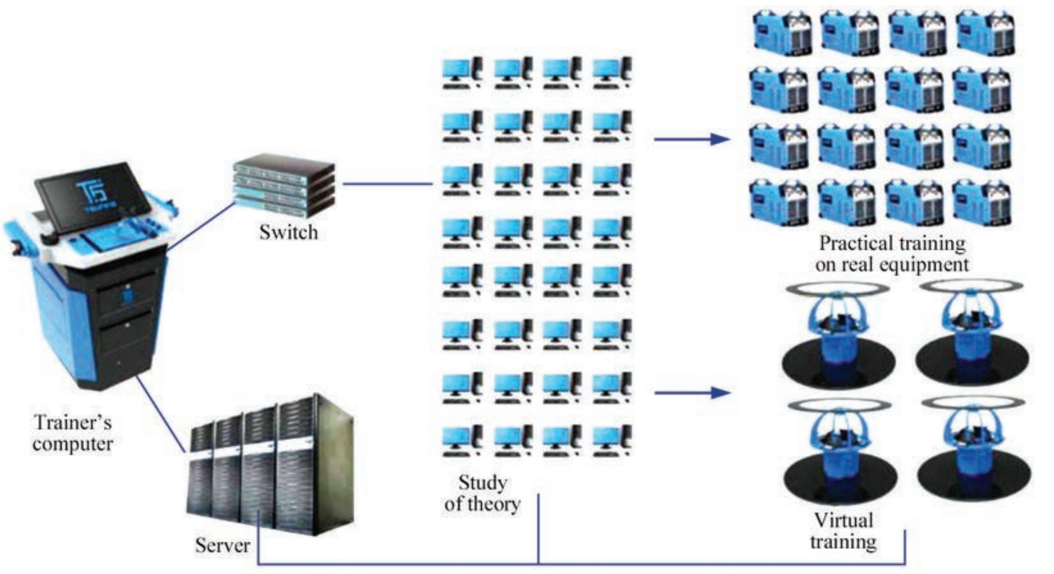


Figure 11. Concept of the welding training complex, incorporating real and virtual training sessions [46]

tops of other pylons and take up to 100 measurements per second. In the case of strong winds these devices continuously monitor the viaduct reactions to extreme conditions. Accelerometers, strategically placed on the road surface, measure the oscillations, which can affect the metal structures. More over, two piezoelectric sensors collect the data on transport movement: car weight, average speed, traffic density, etc. The data are transmitted via an Ethernet system to the computer system, where they are processed.

● Second Jingjo bridge in South Korea became the world's first bridge where an autonomous and full-scale wireless monitoring system was introduced [45]. The system was initially installed within the framework of the joint project of the University of Illinois Urbana-Champaign, Korea Advanced Institute of Science and Technology and Tokyo University. 71 node of the wireless sensor network with the total number of 427 sensory channels were mounted on the main beam, pylons and cables of the bridge. Each node consists of an Imote2 module (incorporating a built-in processor, radiomodule and power management chip), sensor boards and batteries.

WELDER TRAINING

AI can be used to create virtual welding simulators, which can be used to train welders. The simulators will be able to create realistic welding conditions and have feedback which will promote welder skill improvement (Figure 11).

The authors of [46] announced the creation of AI for welder training, which allows developing a virtual training system in real-time with the functions of prediction and modeling of the morphology, as well as intellectual assessment of the weld quality. It resulted in development of an AI system for the welding simulator network V60, which has the following advantages: possibility of modeling a realistic appearance and quality of the weld; possibility of modeling the stress-strain state of the welded parts and temperature fields in real-time; availability of a database for modeling the majority of welding technologies and materials; possibility of modeling the processes of 3D printing; availability of a system of virtual testing and analysis of the quality of the welded parts; presence of certification system; entertainment module; access to the Department of Experts; and high economic feasibility.

CONCLUSIONS

AI application can provide significant advantages in welding and related technologies, namely:

● Increase in productivity and effectiveness of development of new welded products due to optimized processes (of design and production).

● Improved control of welded product quality and reduction of the defect repair costs.

● Increase of the competitiveness and profitability of welding production due to increase of welders' qualifications, process automation, cost saving and product quality improvement.

AI development and integration into welding processes and related technologies require considerable investment, which is due to a complex nature of the tasks at each stage of implementation: investigations and development of algorithms; data acquisition and processing; integration with available systems; integration with the equipment already in operation; testing and validation; personnel training; maintenance and reconditioning (constant retrofitting of the models) as AI requires regular updating for adaptation to new materials or welding technologies, ensuring protection of the data and systems from hacking).

The prospects for AI integration into welding and related technologies are promising, particularly in the context of development of autonomous systems, 3D printing, additive manufacturing and new sectors. These areas can transform the industry, improving the accuracy, speed and safety of the processes: AI will become the basis for creation of completely autonomous welding robots, which will be capable of adapting to changes in real time; it will accelerate the introduction of additive technologies into metal processing, combining it with the traditional welding; will open up the possibilities for welding application under the extreme conditions (welding in space, underwater welding) and welding of ultra-small parts, which was impossible earlier. Despite the fact that the investments should be large, they will pay off due to reduction of rejects, increase in production rate and minimizing manual labour.

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ORCID

L.M. Lobanov: 0000-0001-9296-2335,
O.V. Makhnenko: 0000-0002-8583-0163,
O.S. Milenin: 0000-0002-9465-7710,
M.G. Malhin: 0009-0003-8159-8226,
G.Yu. Saprykina: 0000-0003-1534-7253,
O.M. Savitskaya: 0000-0002-9363-6184

CONFLICT OF INTEREST

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CORRESPONDING AUTHOR

O.V. Makhnenko
E.O. Paton Electric Welding Institute of the NASU
11 Kazymyr Malevych Str., 03150, Kyiv, Ukraine
E-mail: makhnenko@paton.kiev.ua

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