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Procedia Manufacturing 38 (2019) 702–714

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

29th International Conference on Flexible Automation and Intelligent Manufacturing (FAIM2019), June 24-28, 2019, Limerick, Ireland.

Survey on artificial intelligence (AI) applied in welding: A future scenario of the influence of AI on technological, economic, educational and social changes

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Abstract

The application of artificial intelligence (AI) in the field of welding is an increasingly important area of research and a large number of journal publications on the topic have been published. A keyword search for AI in welding in the leading scientific journal databases Elsevier and Springer reveals more than 3,000 related articles. The large publication volume shows the importance being attributed to AI in welding and the breadth of the contributions of researchers utilizing AI approaches to tackle challenges and problems in welding. Such challenges include poorly controlled welding parameters and weld geometry, which lead to weld quality problems. This paper reviews previous studies on AI systems utilized in welding process control and welding robot control. Case studies on the utilization and development of AI systems in the Finnish welding industry are also presented. Analyses of the findings provide the means to predict future scenarios for a 5–10 year time frame on the impact of AI in the welding industry in the era of Industry 4.0. The changes that AI bring will drive a need for new technological, economic and social policies as well as reform of educational curricula and skills training in the sphere of sustainability and quality of life. Consideration of trends and scenarios is important for both academia and industry, where new research ideas and developmental trends on AI systems will emerge for practical implementation.

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Peer-review under responsibility of the scientific committee of the Flexible Automation and Intelligent Manufacturing 2019 (FAIM 2019)
10.1016/j.promfg.2020.01.095

Keywords: Artificial intelligence; digitalization; human-robot collaboration; industry 4.0; welding monitoring; weld control

1. Introduction

Welding operations involve consideration of many process parameters and joint geometry parameters. Process parameters include arc voltage, arc current, welding speed, while joint geometry parameters encompass base material thickness, joint profile (fillet joint, butt joint or corner joint), joint grooves and gap, weld bead height, and weld penetration. Establishing relationships between these parameters and variables is difficult due to the nonlinear attributes of welding. Control of an entire welding process becomes even more complex, especially when adapted to "teach-and-playback" robots. In recent years, systems such as sensors and monitoring devices have been adapted to robots to provide wide range of data to address the complexities in process control of welding.

Despite the availability of more data, common challenges and problems that arise due to difficulties in establishing accurate relationships between welding parameters and variables still exist. These challenges include: too high heat input, too low heat input, arc instability, joint position errors, distortion, weld undercut, porosity, irregularities in the weld bead, lack of weld penetration, lack of fusion, heat affected zone (HAZ) softening, microstructure deterioration, crack susceptibilities, and loss of mechanical properties in the weld metal and other weld zones [1-4]. Fig. 1 illustrates some common weld joint defects.

Earlier studies in sensing and monitoring have helped to reduce the occurrence of weld defects through seam tracking, thermo-profile measurement and welding control [5]. However, complete elimination of weld defects has not been fully realized, which leads to weld product quality problems in the welding industry. As these earlier systems do not fully harness real-time sensing and control, there is a need to explore the potential of real-time sensors and monitoring devices, together with nonlinear methods like artificial intelligence (AI), for efficient adjustment, monitoring, prediction and control of welding and joint geometry parameters. In general terms, AI can be described as the intelligence of machines and systems that mimics the natural intelligence of humans or animals. Machines and systems with such intelligence should be able to be taught, learn, reason and plan under conditions of uncertainty, solve problems, and remember past occurrences in their environment. Fig. 2 shows a schematic of seam tracking and thermo-profile measurement of welding parameters for AI control.

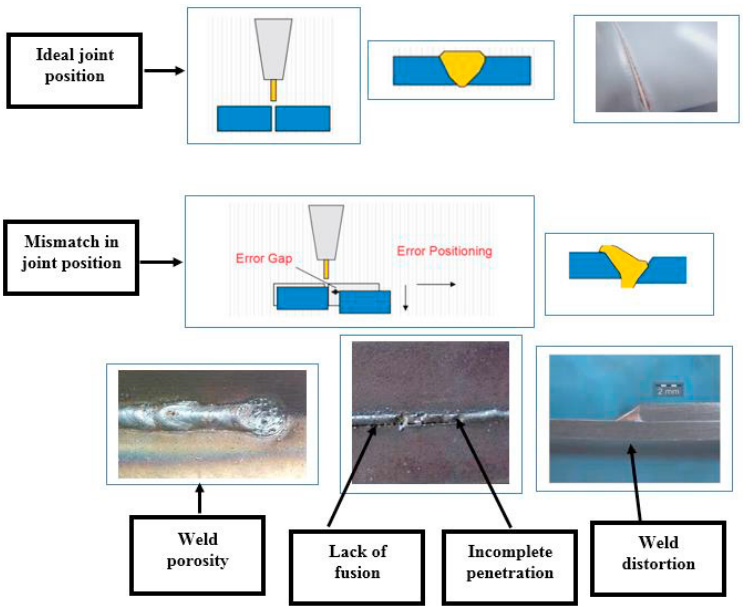

Fig. 1. Common weld defects that may be addressed by AI in welding automation.

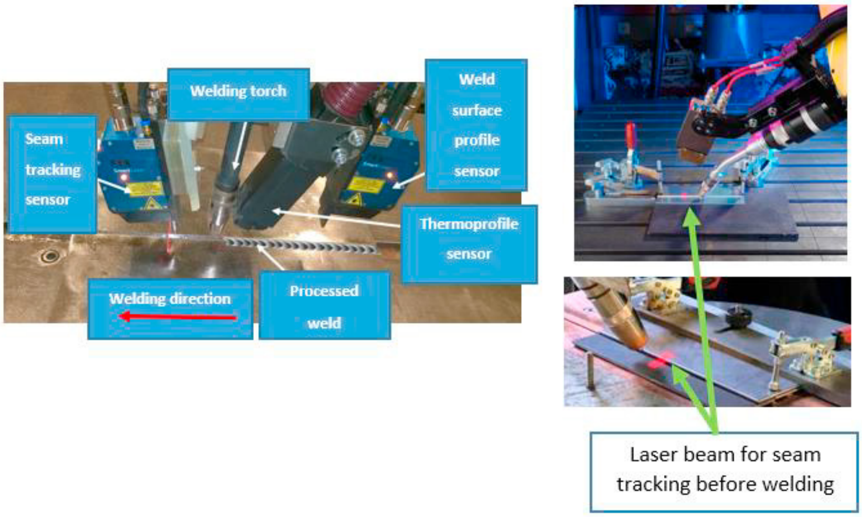

Fig. 2. Illustration of seam tracking and thermo-profile measurement of welding parameters for AI control.

The changes AI will bring to the welding industry cannot be under-estimated, especially in technology, economic, education and social policies. For these reasons, the advent of AI in the welding industry must be considered holistically.

2. AI used for welding process control

Recent studies in the field of welding have examined several nonlinear methods with AI capabilities, such as the Taguchi method, response surface method (RSM), artificial neural network (ANN), genetic algorithm (GA), fuzzy logic systems, adaptive neuro-fuzzy inference systems (ANFIS) and particle swarm optimization (PSO). The main aim of exploring such methods is to provide a platform to establish relationships between welding process input parameters and output variables, and on this basis, determine and control welding parameters that lead to desired weld quality and weld attributes. Table 1, referring to [6, 7], presents a simple comparison of key features of these AI methods. Table 2 presents system considerations when employing AI for welding control in a broader perspective.

The majority of previous studies use AI methods for static optimization of welding parameters where all parameters used are fixed [8], i.e., applications of AI in welding have been in the area of prediction and evaluation through experimental means. Kim et al. [9] performed a study on prediction of bead height in robotic arc welding. The work used ANN to predict welding parameters (welding speed, arc current, arc voltage) for weld bead height in butt joints. A backpropagation algorithm was used in training the AI on a data set obtained from empirical tests. Compared with regression models (linear and curvilinear), the ANN model gave more accurate prediction of weld bead height, and the model was able to be used for process control purposes.

Acherjee et al. [10] applied ANN using a backpropagation (BP) algorithm to predict weld quality in laser transmission welding of thermoplastics. It was concluded that the ANN was able to estimate lap-shear strength and weld-seam width using the given process variables. Zhang et al. [11] used ANN to identify the geometric parameters of a weld pool characterized by a polar coordinate. Using ANN to estimate and predict control of the weld fusion zone by using a neurofuzzy model has also been performed [12]. Kovacevic et al. [13] used ANN to predict weld penetration based on the weld pool geometric appearance. K. Zhang et al. [8], reported that ANN has stronger nonlinear mapping capabilities for almost all types of nonlinear relationships.

Table 1. Artificial intelligence methods investigated for arc welding.

Artificial Intelligence Systems	Principles	Advantages	Limitations
Artificial Neural Network Systems	- Operates on feed forward back propagation system. - Represents interconnected groups of artificial visible and hidden neurons. - Develops models that depict interrelation characteristics between input data and desired output data.	- Has learning and training capabilities for non-linear system modeling. - Has pattern recognition, signal processing, data prediction and control, and time series analysis capabilities. - Has adaptability abilities where free parameters can be adapted to changes in the surrounding environment. - Has knowledge discovery and data mining abilities. - Has uncertainty tolerance and imprecision abilities.	- Lacks linguistic/ explanatory ability. - Lacks knowledge representation abilities.
Fuzzy Logic Systems	- Operates on a set of linguistic fuzzy rules. - Relies on rule-based systems.	- Has linguistic/explanatory abilities. -Has good knowledge representation abilities, good uncertainty tolerance abilities, and good imprecision tolerance.	- Lacks self-learning abilities. - Lacks adaptive and pattern recognition abilities. - Has rather poor knowledge discovery and data mining abilities.
Neuro-Fuzzy Systems	- Operates by hybridizing a fuzzy logic qualitative approach and adaptive neural network systems capabilities.	- Combines the advantages of both paradigms and resolves their shortcomings concurrently to produce an improved intelligence system.	- Has limitations typical for a Mamdani fuzzy inference system with a single output defuzzification.
Adaptive Neuro-Fuzzy Inference Systems	- Uses a hybrid learning algorithm by combining least-squares estimators and the gradient descent method.	- Both antecedent and consequent parameters are optimized. - Has the ability to generalize and converge rapidly particularly in on-line learning. - Is applicable in adaptive control.	- Has limitations typical for a Sugeno system with constant and linear output membership functions and single output defuzzification.

Genetic algorithms (GA) have been used to optimize process parameters such as laser power, welding speed and wire feed rate taking into account weldability and productivity factors. Correia et al. [14] optimized the welding process in gas metal arc welding using a GA and response surface methodology (RSM). It was found that the GA was a more effective method for optimizing the parameters of the welding process. Sathiya et al. [15] developed an ANN model to determine the relationship between laser welding parameters and the response of depth of weld penetration, bead width and tensile strength for three different shielding gases. It was concluded that the established models based on the relationships created were suitable for optimizing the process parameters by adopting the GA. A back propagation neural network (BPNN) and GA has been used to predict the tensile strength for laser welding of AA5182 aluminum alloy with AA5356 filler wire [16]. Katherasan et al. [17] studied weld bead geometry of flux cored arc welding (FCAW) and the effects of input variables (wire feed rate, voltage, welding speed, torch angle) using Taguchi design, an ANN and particle swarm optimization were ascertained.

The capabilities demonstrated by static optimization of welding parameters show evidence for the feasibility of employing AI methods for real-time welding situations where weld defects, positional changes and errors can be detected and avoided. However, utilization of AI methods together with adaptive systems like sensors and monitoring devices to dynamically optimize and control welding parameters and geometric parameters in real-time is rare, as are practical implementations in welding industries. However, the few studies performed within this domain have yielded good results.

Adaptive filling modeling of butt joints using a genetic algorithm and neural network for laser welding with filler wire was performed in [8]. A set of empirical data of welding parameters suitable for different joint gaps and mismatches were used to develop a back propagation neural network model. The model was further optimized using GA, especially on the initial weights and thresholds of the BPNN. Joint gaps, mismatch, bead width and reinforcement were used as input parameters, while laser power, wire feed rate and welding speed were used as output parameters. A hidden layer with six neurons was established. The process setup had real-time capabilities. The Levenberg-Marquardt learning algorithm was used, which has excellent convergence speed. It was observed that by optimizing the initial weights and threshold values of the BPNN, the GA enabled the BPNN to avoid falling into local optima values, especially when the welding sample data are relatively few.

Table 2. System considerations when employing AI for welding control

Welding process control	**Robot control**	**Joint geometry control**	**Sensor control**	**Monitoring control**	**Machine setup control**
Heat input (voltage, current, wire feed rate, welding speed)	Manipulator dexterity	Joint fit-up Eliminate joint fit-up errors	Weld shape	Weld shape	Grounding of the machine and the work-piece
CTWD (electrode stick out)	End effector maneuvering	*Joint position *Eliminate position errors	Weld profile (throat thickness)	Weld profile (throat thickness)	Work cable stability
Shielding gas flow rate	Motion and trajectory planning		Weld penetration (weld root)	Weld penetration (weld root)	Long welds and tandem arc welding
Mode of metal transfer	Axis control		Weld distortion	Weld distortion	vibrations
	Linkages control		Weld spatter and porosity	Weld spatter and porosity	
	synchronization		Compliance with welding procedure specifications (WPS)	Compliance with welding procedure specifications (WPS)	
	Torch angle				
			Big Data Analysis		
Welding data analysis	Robot motion analysis	Joint geometry analysis	Sensor control analysis	Monitoring control analysis	Machine stability analysis

3. AI for welding robot control

Current developments in AI for welding robot control have made AI approaches feasible for addressing challenges in motion planning, path optimization and trajectory reach enhancement. Widely used AI methods such as fuzzy logic control, ANN and GA are becoming increasingly prominent in welding study. Chao and Sun [18] performed motion planning and simulation of multiple welding robots based on a GA. In the experiment, a three-dimensional model of a welding assembly was designed in virtual eM-power software and the algorithms used for welding simulation. It was established that there were no collisions between the robots and the robots were able to find the paths planned according to the simulation performed. The work demonstrated that the AI method used not only shortens the time of path planning, but also improves welding efficiency. In addition, it was concluded that, by means of path simulation, damage to robots and equipment could be avoided in real-time.

Other research has used either one or a combination of AI methods for welding robot control. Mendes and Neto [19] developed an adaptive fuzz control method to control the motion and force of an industrial robot. Castillo et al. [20] employed a GA for the problem of offline point-to-point autonomous mobile robot path planning. Pashkevich et al. [21] proposed a collision avoidance path planning approach for robots based on a topologically ordered neural network model. Panda and Choudhury [22] presented an approach to dynamic path planning problems of robots in uncertain dynamic environments based on GA. Kim et al. [23] further addressed welding task sequencing for robot arc welding process planning using GA.

The capabilities of AI methods for welding robot control have to be verified in a production environment. Despite it being an initially time-consuming task, using AI methods for real-time operations could provide avenues for flexible off-line welding. The use of sensors alone to guide and control welding robots in real-time have encountered some drawbacks leading to real-time malfunctions where the welding robot moves out of joint limits, collides with objects in the work space and moves into singularities due to robot configuration changes [24]. Arc sensors with a semiconductor charge-coupled device (CCD) camera or complimentary metal-oxide semiconductor (CMOS) have been employed for guiding the robot during welding [5]. Laser scanners and other arc contact sensors like tactile sensors are also used in guiding the robot during welding [24]. Therefore, as most welding robots are controlled or guided by sensors, incorporating AI methods would ensure high accuracy in control. With AI in place, the welding robot can be controlled remotely by planning its motion and optimizing its path and trajectories, and the robot can adapt to changes and unforeseen situation.

Most industrial robots are said to operate on CAR (Computer Aided Robotics) software that enables modeling, simulation and programming of robot operations within CAD environments. To ensure optimum performance of real-time sensors with AI methods, a virtual sensor model of the real sensor must be created and implemented in the CAR virtual operating environment [24], as shown in Fig. 3. The virtual sensor must be validated through static and dynamical approaches. The static approach matches the virtual sensor with the real sensor through measurements in the process setup and the dynamical approach is done by comparing a welding application performed in a real and a virtual work-cell created with a CAR application.

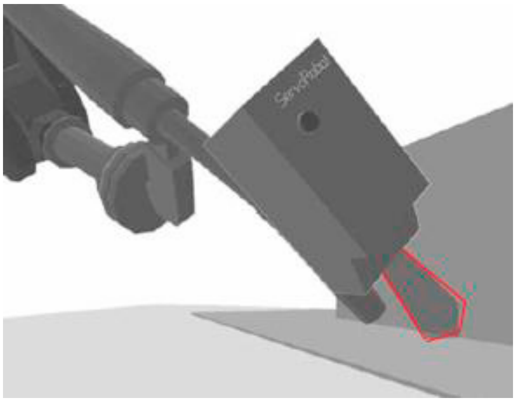

Fig. 3. 3D model representation in the CAR system of a welding torch with attached seam tracker [24].

Objects like features on the real time robot and the working environment are, therefore, updated based on information provided by the virtual/real sensor in real-time [24]. By going through static and dynamical approaches, the feed-back loop makes full use of the sensor information (specific instructions used to define the robot task as set of motions) and integrates it to the world model and application process models. Real-time sensor feedback to the world model means that the information from sensors will update the world model, including updating object positions in real time as required or creating objects not included beforehand. Through this mechanism, the use of sensors can be validated in a CAR environment as similar tests should be made in a real, physical set-up [24]. The controller unit maintains the camera head at its optimal operating point, image-processing algorithms are used for standard joints, and the weld joints can be recognized and features from the weld profile extracted and matched against predefined templates.

4. Case study on AI in the Finnish welding industry

Finnish industry is characterized by major large companies whose operations cut across diverse industries as shown in Fig. 4. Welding operations are a prominent manufacturing activity across the value chain of these Finnish industries and Finnish SMEs in the welding industry are subcontracted to provide welding services to these large companies. Welding SMEs Finland and even large companies face challenges remaining competitive and providing desired welding quality due to variations in product supplied by contractors, small product batch sizes, fast product changes, dimensional changes and new materials, tight tolerances, equipment setup, workshop ergonomics and strict environmental legislation. Even if compliance to welding standards is observed, other aspects related to welding data management systems pose challenges as well.

With the trend to smart manufacturing and Industry 4.0, it has become imperative to identify how Finnish welding industry intends to unlock the potential of AI for welding robots and to consider technological, economic, educational and societal changes that a transition to Industry 4.0 will bring.

To respond to challenges arising from industrial transition, the Finnish welding industry requires AI platforms that are tailored to provide specific solutions in welding. Some companies offering AI platforms for welding solutions utilize open architecture that needs to be customized to fit the operations of welding companies. Delfoi Oy and Visual Components Oy are leading Finnish companies in the field of AI for welding robotic operations. Delfoi operates on VC platform having AI offline capabilities that solve robot collision challenges, manipulator and end-effector reachability problems, and weld joint limit issues. Such platforms are capable of providing different robot arm configurations and support most weld types (horizontal straight welds, vertical straight welds, beveled straight welds, U-shaped welds and welding around a sharp corner). Despite their open architecture, the actual AI used in developing such platforms nevertheless remains confidential and proprietary information. To provide an overview of AI in the Finnish welding industry, some companies are presented as case studies.

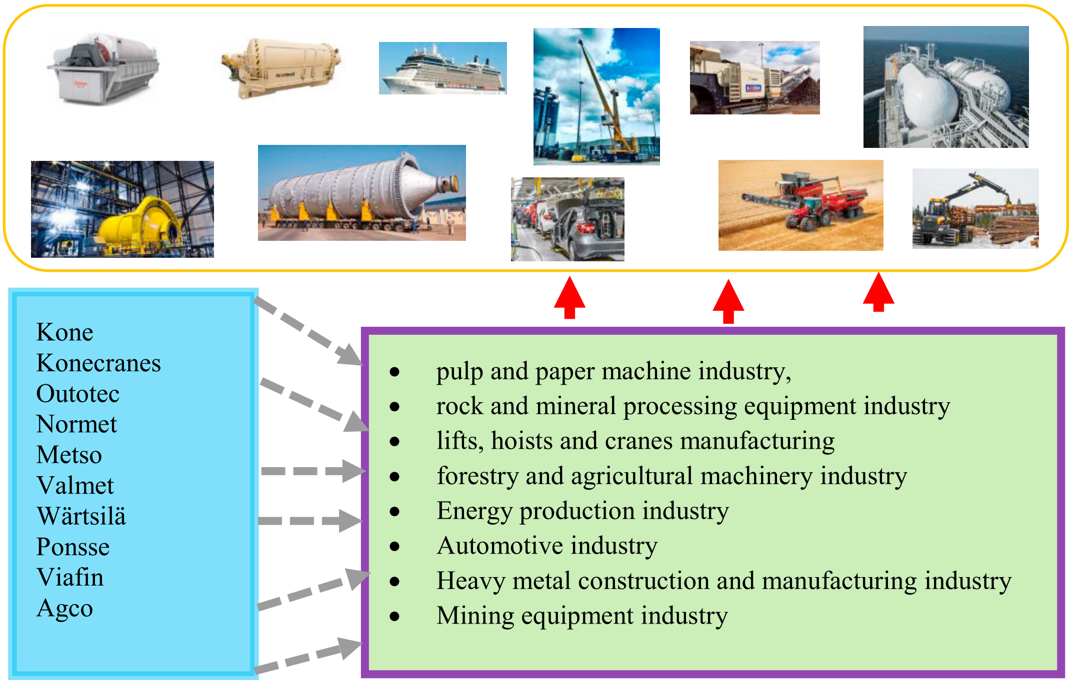

Fig. 4. Major Finnish companies and the industries in which they operate.

4.1. Case company 1 (SME welding firm)

The company (company name withheld) has plans to install an ABB robot welding cell that can weld 10 m straight welds. This investment in new welding equipment is because of weld quality issues and to prepare for changes envisaged for future manufacturing. The company wants to ensure consistency and equality in weld quality. However, implementing welding robotic systems also aims to reduce the number of welders on the welding jobs. These changes are a response to changes in the Finnish labor market and tax policies which have led the company to feel they can no longer hire freelance welders on a contract basis. The welding company would rather employ more plate fitters (EN 1090) who will prepare materials and set joints for welding by the robot. Nevertheless, the company aims to find other suitable tasks for welders who might lose their jobs.

One identified challenge to using a robot for welding long seams is the possibility of weld distortion; the joints must be tacked together to avoid large dimensional weld distortions. The tacked joints, however, pose some weld quality problems because the robot has to weld over these tacked joints and there is a high likelihood of lack of penetration at these positions. Consequently, the robot should be trained such that heat inputs at tacked joints are high enough to ensure complete melting.

In addition, the company plans to employ offline programming for the welding robot since there exists a need to automate their welding manufacturing and production. The need for CAD models of the products to be welded offline is an essential component. If such data are unavailable, for example, because contractors are unwilling to distribute such 3D models, the company has to design 3D models of the jobs they are contracted to perform. The company is trying to find solutions for this possible challenge.

4.2. Case company 2 (Visual components Oy)

Visual Components (VC) provide platforms for building welding robots via modeling, programming, simulation and controls. The practical steps are outlined below. Before modeling the robot, the key information needed includes 3D CAD data and kinematic information that shows the position and velocities of the robot joints, links and end-effector as a function of time. The CAD data contain geometry data of the robot, and the kinematic information provides information about the robot motion. All this information can be obtained from the robot manufacturer or through channel partners or customers. The CAD data come in multiple formats, either SolidWorks, Solid Edge, CATIA, Autodesk Inventor, 3D Studio, etc. The different phases required when modelling a robot is shown in Fig. 5.

Robot programming can be done online (in the production environment) or offline (outside a production environment). In the programming process, the robot normally has to go through teaching phases to learn how to perform a set of tasks. Using on-line programming, a teach pendant is used to manually move the robot manipulator and the attached end effector to different positions and orientations at each stage of the task. These steps are recorded by the robot controller and a robot program is written to command the robot to move through the recorded trajectory [25]. The offline program (OLP) uses 3D data to create a virtual model of the robot and work cell. Using simulation, the model allows the user to teach the robot virtually. As the OLP is a computer-based approach that uses digital models and advanced simulation, it is much faster and more accurate than online programming for many applications.

The VC curve-teaching tool (CTL) to generate paths relies on AI, which greatly simplifies robot path teaching/planning. The CTL analyzes object geometries, makes path predictions, and suggests robot paths. It then automatically generates the statement in the robot program code. When a CAD model is imported into the welding robot platform, an inbuilt 3D geometry engine analyzes the model and provides structured data of the geometry surfaces, curves and curve loops. The CTL uses such data to make its path prediction and suggest robot paths.

The virtual topology feature can also be accessed as a service through a topology application programming interface (API), and used to develop custom robot path planning and teaching tools. This is especially useful for users who want to create their own path generation tools for their organization's customized manufacturing processes [26].

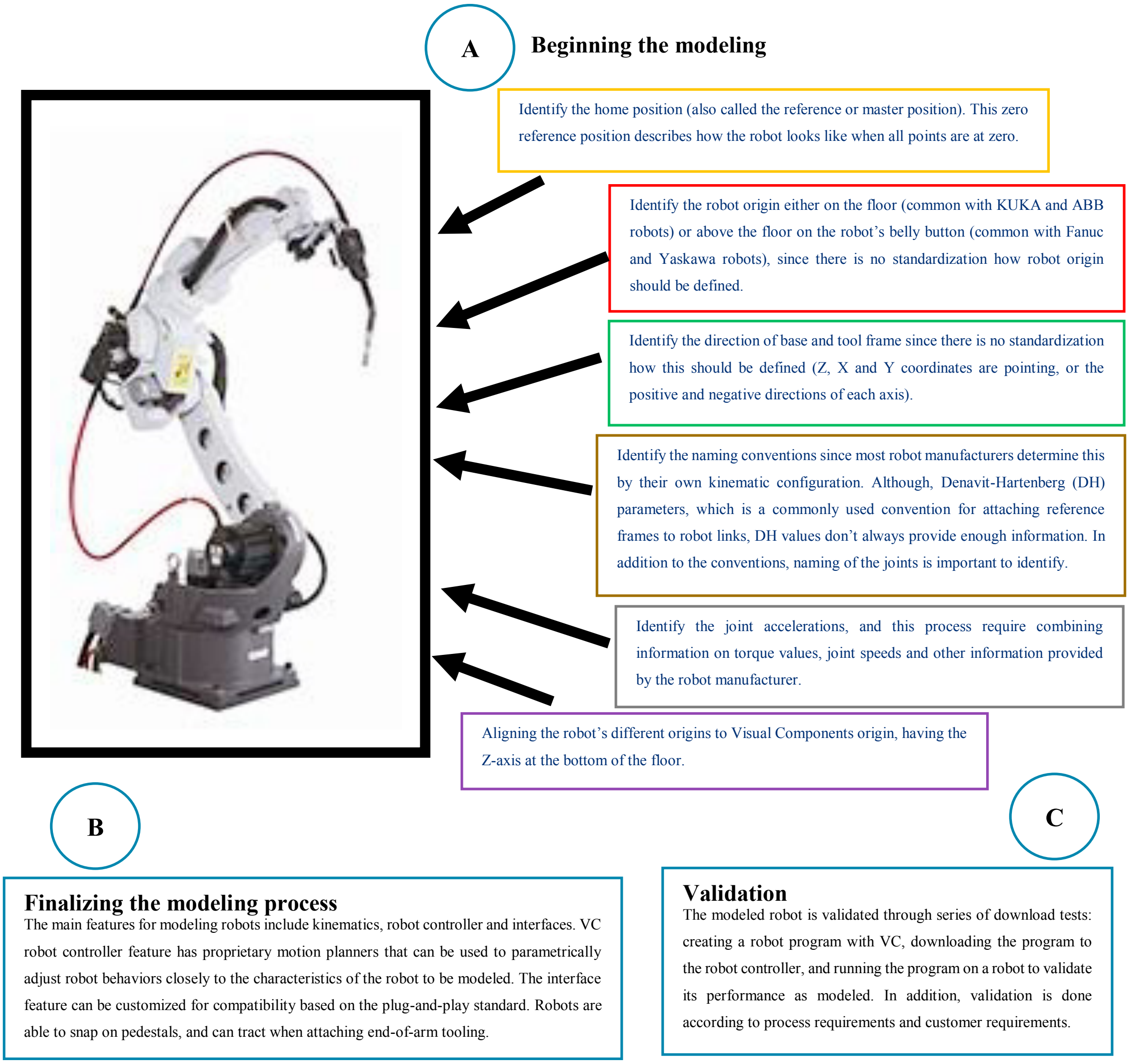

Fig. 5. Robot modelling phases.

4.3. Case company 3 (Delfoi Oy)

Delfoi Oy has developed an ARC 4.0 offline programming (OLP) software for arc and laser welding, including plasma and laser cutting processes. The visual welding platform, as shown in Fig. 6, provides easier programming for welding simulation and visualization. The platform is standardized for all major robot brands and paired with programming and trajectory/programs.

By using 3D search and weld features, the welding robot does not have to go through all the tool center points (TCP) during preprogramming. The robot is stationary, but only the points to be welded are selected and the welding robot does the welding. Consequently, the selected points are synchronized with the welding robot automatically and the robot identifies the joints to be welded with precision. Unlike in previous systems such as the ABB robot studio, the robot manipulator is moved around the joints to be welded, which is sometimes time consuming and cumbersome. Delfoi ARC 4.0 offline programming software operates on the Visual Components platform.

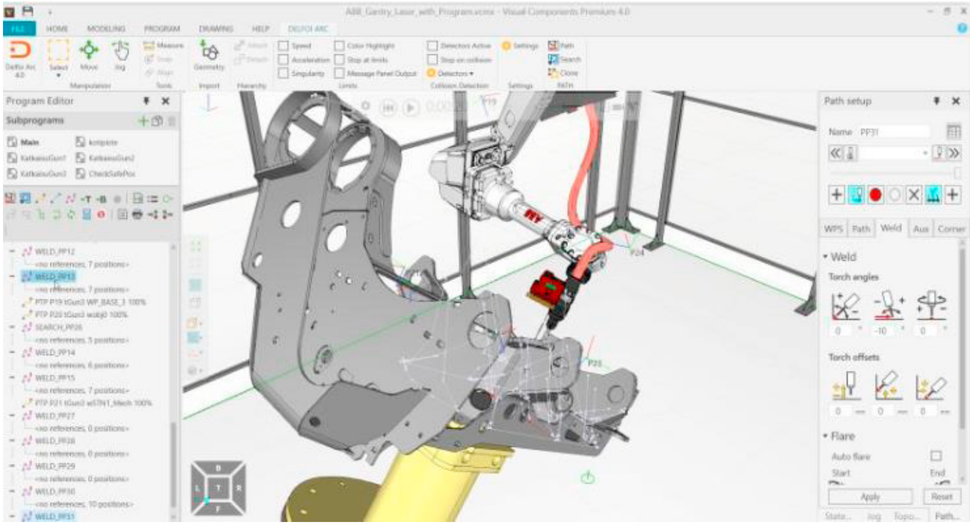

Fig. 6. Delfoi Arc 4.0 platform for robot simulation and offline programming [27].

Interview session

To get an insider view of the latest thinking on the future of welding manufacturing and possible effects on society and industry, an interview session was arranged with a senior executive of Delfoi Oy seeking his opinions and ideas regarding AI, robotization and Industry 4.0 in the Finnish welding industry. The questions on AI and Industry 4.0 were specifically crafted to tackle issues related to technological, economic, educational and societal implications. Key questions are considered below.

a) "**How will your technology change the welding industry within the next 5-10 years**"

In the opinion of the interviewee, one of the major changes is the ability to use welding robots to weld very small batch sizes, which typically have been unsuitable for robot welding. A robot welding program can be generated offline using the virtual/digital twin in the simulation software. The digital twin means that a virtual copy of the real robot cell has been made that includes the welding robot and welding peripherals like the positioners, etc. Thus, the welding robot does not need to be stopped for teaching since the robot welding programming is done remotely or offline. The welding robot consequently remains available for welding, as new welding programs are prepared offline, and production is not halted. The welding robot will have more operational welding time even if small batches of material are to be welded. The interviewee referred to the example of the automotive industry, where 1000's of new cars with varying parts are to be made at the same time. Using Delfoi software for such large variance of the products, there is no need to reprogram the robot, but the robot can be taught to adapt to changes in the models and part variants. The interviewee cited the construction industry as a further example. He pointed out that construction steel beams for buildings come in different sizes, and the sizes are selected depending on the building design. However, as standard length and size of beams cannot always be used due to the design of the building, there is often a need to weld small batch sizes of beams. The interviewee made references to companies using Delfoi software like Lindab in Luxembourg. In addition, he referred to Ponsse Oy, which uses Delfoi software for offline robot programming and welding robot teaching for welding of machine frames. The benefit is that with previous approaches Ponsse had to re-program their welding robot for each new product, which took about 40 hours or more. However, with the Delfoi offline software, this same task can be done in 4 hours. Consequently, the welding robot can now weld more frames having differences in dimension in less time. Following the offline programming, the robot movement points and trajectories are being monitored to ensure that the robotic welding operations are accurate. The interviewee pointed out that this is a technological change that is happening throughout the Finnish welding industry and will continue for the next 5-10 years.

b) “**How will the need for labor change in the given period**”

In the opinion of the interviewee, the need for manual labor will reduce because of AI and robotization. Even basic tack welding and pre-assembly welding can be replaced using robots. Moreover, welding of small batch sizes and single pieces of metal products which once required manual work will be replaced. On a broader perspective, he felt that AI and robotization will cause unemployment. In addition, he considered labor change in a general perspective and noted that people can do many different jobs that robots cannot do, which gives possibilities to educate people to do other tasks in the industry. The interviewee gave an example from the USA, where General Motors (GM) closed down a factory and moved it to Mexico. The US government, at the time presided over by President Barack Obama, decided to grant a loan to GM so that they would move the factory back to the USA. However, the outcome was such that the new factory was highly automated with only half of the number of staff previously employed because the company felt it could otherwise not survive competition from other producers in Mexico. The interviewee concluded by saying that AI and robotization will probably cause unemployment over the next 5-10 years.

c) “**How should professional education change to take account of the effects of robotization and AI**”

In the opinion of the interviewee, educational needs are such that educating people for work which is present today should be revised by including in education a vision for 5 or 10 years from now and educating people about what is happening in the industrial world. People should be educated and trained for future jobs. As automation systems are changing the world, the future will bring different kinds of working positions. So, institutions in Finland training people for manual work, for example, in welding, should rather consider training them how to work using the sophisticated systems of the future factory, where automation is the key driving force. Otherwise, Finland will be educating people to be unemployed. So different levels of education should be considered. He pointed out that this is a global concern and if we think that future factories will have more robots installed, then we have to educate and train people to be able to operate automated systems and be able to use the robots. He emphasized that people have to be taught about things beyond automation. So, an example is that if there is no need for manual welding, then the welder must be trained in using the robot to do other tasks. He concluded by saying that the level of education should prepare for the automation 5-10 years from now.

d) **What solutions should be implemented for social issues like unemployment because of the effects of AI and robotization**”

In the opinion of the interviewee, there should be a plan to educate unemployed people in automation as it is a preparation for future jobs. Also, the question of robots paying taxes to support social welfare systems is an issue being discussed. However, in his view, he thinks that such taxation is not possible because the system of robots paying taxes would have to be enforced globally. However, if one country decides not to follow the system, then the ability of other countries to compete on the global market will not be the same because the cost of robots is quite similar. He gave the example of China; if China decides not to follow this system, other countries cannot compete at the same level and will lose market share in the long term.

e) “**How will AI affect business in the welding industry**”

In the opinion of the interviewee, there is a big change towards using simulation software for digitalization as more and more jobs are being done using computers. These kinds of software tools and solutions are going to be more accepted than they used to be. People are not going to raise as many questions like should the system be used or does this system work, because they will see more references to and information about the systems. He pointed out that companies will more readily think of acquiring AI systems and will have return on investment as a primary concern. He stated that AI will drive a combined approach where there will be collaboration between humans and automated systems. With robotization, there will be a system of collaborative robots working with humans. Automated robots will do work which was traditionally a manual job, for instance, production of very small batch sizes, say one piece production. The interviewee ended by saying that improvements in the effectiveness of robots in industry is moving their utilization into smaller batch sizes and robots are going to be used in factories that have traditionally not used robots.

To validate claims made by the senior executive of Delfoi Oy, opinions of some experts captured in an interview and reported by Tanya M. Anandan (contributing editor of Robotic Industries Association) are presented. On the subject of “how offline welding technology will change the welding industry”, Rob House (director of sales at OCTOPUZ Inc.) indicated that using offline programming the user does not need to shut down welding production as peculiar to online programming of a welding robot. With offline programming, one can conduct research, development and testing to make sure a new part can be welded. Also, several welding programs for different parts can be made awaiting production while the robot is in operation, thus minimizing machine downtime as well as labor in programming (i.e. more time producing, less time programming). Garen Cakmak (senior director at Hypertherm Robotic Software Inc.) also emphasized that offline programming having easy-to-use software systems will aid welding robots to be utilized in a high-mix, low-volume environment. Therefore, SMEs can benefit from wider adoption of offline robotic welding due to less constraint, for example, welding of small batch part sizes [28].

On the issue of "how will the need for labor change for the next 5-10 years", a report produced by Georgios Petropoulos [29] indicates some salient points. He mentioned that technological innovations affect employment either by directly displacing workers from jobs they were previously doing (displacement effect) or by escalating the demand for labor in industries or tasks that arise or develop due to technological advancement (productivity effect). The previous statement corroborates with John Maynard Keynes technological unemployment theory postulated in the 1930s, i.e. technological change causes loss of jobs. Assessing the impact of artificial intelligence on employment, Georgios Petropoulos suggests that developing policies that promote efficient labor markets for the benefit of workers, employers and societies as a whole is crucial, as rapid technological progress and innovation can threaten employment.

In summary, the International Federation of Robotics positioning paper on "robots and the workplace of the future" provides meaningful perspectives and somewhat agrees with the claims and suggestions made by the senior executive of Delfoi Oy and experts from OCTOPUZ Inc. and Hypertherm Robotic Software Inc. The paper present ideas which suggest that robots and artificial intelligence will affect industries, business models, jobs, workers, education and social policies over the next 10 years. The paper further indicates that the quality of work and remuneration will improve. Thus, new job types will be created, and many more types of jobs will be available to people whose access to the job market has been limited by physical disability or by declining physical strength in old age. In addition, SMEs that account for over 90% of businesses in most economies, will have the edge to compete and to assume new roles in the value chain in global supply. Also, situations, where humans and machines will work collaboratively and make work safer and less physically demanding, will arise. On the other hand, the need for collaboration between industry, government and educational institutions is imperative to provide the needed training for the existing and incoming workforce for new jobs. Policy makers and industry players will need to develop policy frameworks and incentives to encourage corporate bodies to invest in training, and either inject more funding into education and training [30].

Conclusions

The application of AI methods such as ANN, PSO, ANFIS, GA, and FLS has become popular in experimental works involving welding process control and welding robot control. These methods can be used separately or in combination. However, information on the use of these AI methods for industrial welding purposes is limited in previous studies. Nevertheless, available flexible robotic simulation AI platforms enable these methods to be tested for use in industry. Moreover, new AI control systems can be developed through combination of the different AI approaches. AI can help solve welding industry issues as regards weld quality and productivity and some SMEs in the Finnish welding industry are beginning to embrace automated systems where welding robots with adaptive features are implemented. The impact of AI and robotization will have both positive and negative effects on the Finnish welding industry and the international welding industry in general. The changes AI will bring to industrial production should be countered with new technological and educational training curricula and increased social awareness to alleviate the downsides on the economy and society.

Acknowledgements

This research was carried out at LUT University, Finland. The work received initial financial support from an Academy of Finland grant awarded to LUT University, Laboratory of Intelligent Machines project 'Manufacturing 4.0 – Strategies for Technological, Economical, Educational and Social Policy Adoption'. The work was finally completed due to financial support received by the corresponding author from Post Docs in Companies (PoDoCo) grant funded by the Foundation for Economic Education (Liikesivistysrahasto). The authors would like to thank Peter Jones for his comments and assistance with the English language.

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