Penetration and Quality Control With Artificial Neural Network Welding System

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Penetration and Quality Control with Artificial Neural Network Welding System

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ABSTRACT

In this paper an Artificial Neural Network (ANN) controlled intelligent GMAW system is created and experimentally verified. A three-layer neural network with 2 inputs, 14 nodes in each layer and 2 outputs is used to control the weld parameters. The objective is to reach quality level B weld with full penetration when joining 5 mm thick S355 steel plates with a butt weld. In the experiments, the input information for the neural network were extracted from the thermal distribution of an IR sensor and seam information (root gap, volume, shape) from a laser sensor. The output parameters of the neural network were planned to be wire feed and arc voltage. In the experimental part, the neural network control system is trained and verified using welding tests. It can be concluded that neural network weld parameter control suits well the butt weld case and full penetration and quality level B weld can be achieved.

KEY WORDS: Neural network; intelligent; penetration; adaptive; S355; GMAW, butt joint.

INTRODUCTION

The future challenges drive the manufacturing industry to use lighter, cost efficient and more environmentally friendly manufacturing. As lighter and optimized structures (structural and fatigue strength is mostly restricted by quality of the weld) require precise weld control (penetration, bead shape and size, tack weld, heat input and misalignment control), welding industry is driven to respond these challenges and create a way to control welding process with precise and deliver constant product quality. Companies are eager to develop fully automated and self-learning welding as it holds the key to get welding industry to the next level and respond to requirements set by the customers. (Kah et al., 2015)

The objective of the study is to find the possibilities, restrictions and suitability of Artificial Neural Network based adaptive welding in practice. Weld control includes seam tracking (workpiece or seam misalignment control), penetration control, tack weld control and bead width, height and shape control. Intelligent GMAW system used in the study is based on the artificial neural network, which is using back propagation method with a 2-14-14-14-2 configuration (2 input neurons, 3 hidden layer with 14 neurons and 2 output neurons). Supervised off-line adaptive welding system is trained and verified in practice with different pilot product cases. Different study cases are used to determine the suitability of the system in different welding conditions and environments, penetration control being the main module of review. Based on previous studies and the empirical case presented, the challenges, suitability to welding and weld control in practice is observed from a product-centered point of view and ability of the system to adapt to different welding various conditions is analyzed.

Weld control in intelligent welding

In adaptive and intelligent welding there are some requirements for a weld control system to work properly and accurately. Effective and continuous weld control requires reliable sensing of welding interference. The control or decision making system needs to identify the interference and defects in welding and give correct feedback to the system. With precise sensing, reliable feedback and decision making system it is possible to control the welding process. Some of the goals of weld control are to repeatedly ensure constant welding quality and make remote repair welding possible for special cases. Increased ability to ensure constant quality also reduces the need for Non-Destructive Testing (NDT). In following subchapters, the decision making characteristics, training process and weld control mechanism of the artificial intelligence system are introduced. (Chokkalingham et al., 2012; Chandrasekhar et al., 2015)

Seam tracking and workpiece misalignment control, penetration control, bead width height and shape control and tack weld control have been studied in various researches with different weld parameter control systems. Misalignment control has been studied by Oshima et al. (2003) and Ebert-Spiegel et al. (2013). Ebert-Spiegel et al. (2013) created a system which controls the weld parameters with variating gap between the plates. Constant quality weld was achieved with gap variation from 0 to 3mm. Oshima et al. (2003) welded a root pass with varying root gap and misalignment. Acceptable weld quality was reached while root gap was changing from 2.3 mm to 4.9 mm and plate misalignment was changing between 0.1 and 2.8 mm.

Penetration control and bead width height and shape control have been studied in Chokkalingham et al. (2012), Chandrasekhar et al. (2015), Rios-Cabrera et al. (2016). Welding control systems were based on various types of neural networks with different kind of layer configuration. Penetration and bead width prediction was based on the training data and the system was evaluated by simulating the system performance. Control of welding process at the tack welds has been studied and experimentally tested in Kim & Lee (2008). Tack welds can be detected and precisely measured, and the reinforced height and shape of the weld can be controlled. The control system was empirically tested with and without the parameter control to determine the effect of the control system.

ARTIFICIAL NEURAL NETWORK LEARNING METHODS AND DEFINITIONS

Artificial Neural Networks (ANN) imitates the way biological brains work. During the training phase ANN optimizes the connections between neurons based on the input targets. ANN creates interrelated links and new connections between the data recorded. Once the training process has been done, ANN is capable of classifying data resembling the training data. ANN can generate solutions which are different than the training data and therefore adapt to previously unknown situations. (Dhas et al., 2012; Kumar et al., 2013; Nagesh & Datta, 2002)

Welding process is not an easily predictable or controllable process. Therefore, increased adaptability is needed to reach the objectives of this study. The intelligent welding robots requires a training process to be able to adapt to the variation in the welding process. Different adaptive methods require different learning patterns and learning strategies to achieve robust outcomes. The training process of an adaptive welding system takes considerable time and therefore robotics companies have been studying automatic and self-adaptive systems for robots in manufacturing industry. Even today, the ability of robots, sensors and software are capable of self-adaptive welding with considerable quality. Examples of unsupervised learning or adaptive training without previous knowledge of the process has been demonstrated in research papers. ANN has four different types of learning modes: supervised, unsupervised, recording, and reinforcement learning. The most commonly used are explained in next subchapter.

Supervised and unsupervised learning

Supervised learning means that the system is trained with human assistance. Desired response and output level, such as bead width are set by the user and the network is optimized by some criteria such as least mean square error to match the reference output. Supervised neural network control types can be found from fig. 1. (Rios-Cabrera et al., 2016; Jang et al., 1997; Jain et al., 2014)

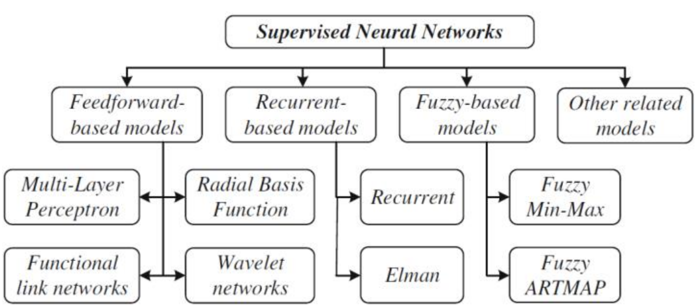

Fig. 1. Different control methods in supervised neural network. (Jain et al., 2014)

Unsupervised learning means that the experiment is done without human supervision, information or aid. The industrial robot is capable of learning and applying welding skills automatically. Therefore, less tests and time is needed to reach desired result. Also the output of the weld is more constant and accurate. With adaptive control methods (as in, “adaptive control system”, not “adaptive robot controller”) the system analyses the feedback from the sensor constantly, and can adjust input parameters and learn new patterns during the welding process. The output accuracy can be enhanced by combining the system with initial offline training to set the baseline for adaptive online training, achieving a shorter and more accurate learning process. (Rios-Cabrera et al., 2016; Jang et al., 1997)

Offline and online learning

ANN offline learning means that the learning is done by batch training. The training and operation phases are done individually as their own processes (Jain et al., 2014). The training and test phases are separate and learning only happens in training phase. Parameter updates are done after the whole training data or each training cycle (for example one weld) is processed. Optimized knowledge base is created from the training cases. Once the operation phase is activated, prior knowledge is used to adapt the welding parameters to the variation in welding conditions. In case of new and unexpected input not apparent in the training data, the behavior of the system cannot be completely predicted and a new learning phase is needed to collect knowledge and adjust for the case. (Jang et al., 1997; Jain et al., 2014)

Online learning means that the ANN learns and updates the neural network after each pair of input and output. In practice, the learning and operation phases are not separated, but the system adapts by itself to new cases as they are encountered. In case of new type of inputs, system has ability to adapt and create a knowledge database for the new case. The possible issue in knowledge base creation is if the system is making the right kind of knowledge base for the case. Constantly updating weights often provide more accurate prediction of the optimal parameters and it is more agile and adapts to new environment faster than off-line learning. (Jang et al., 1997; Jain et al., 2014)

EXPERIMENTAL SETUPS AND PROCEDURE

The objective of the experimental case study is to determine the suitability of neural network controlled welding process in practice. As there is no commercial or widely used neural network controlled intelligent welding system in the field, it is important to define the applicable domain of such a system. Experiments done in a laboratory may often be not so reliable in terms of actual industrial conditions with more sources for interference leading to repeatability issues or they might not fit the actual industrial welding cases. Therefore, the welding system in this study is kept rather basic and affordable for its possible implementation in production industry. The welding system is developed to also be suitable for mechanized welding commonly used in the industry. In the welding experiments conducted an automatic seam tracking system was used and the seam data (root gap, torch distance, seam volume etc.) and thermal distribution over the weld seam are used to extract the data to control the welding process. Using the information gathered from the sensors and knowledge of the weld material, the welding parameters to reach desired penetration as well as shape and size of the seam can be determined. In this study, off-line supervised learning system was used. Network configure (number of layers and neurons, output response speed) was optimized for the case study to reach optimal performance. Fig. 2 shows the experimental setup in the Lappeenranta University of Technology.

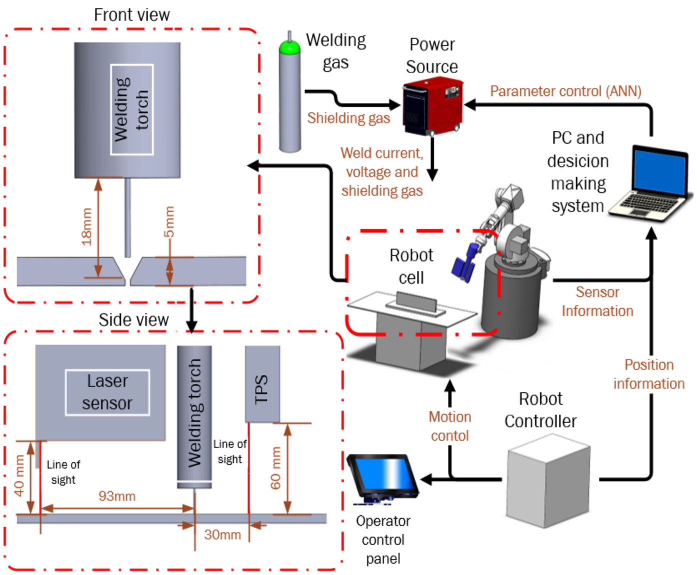

Fig. 2. Robot welding equipment in Lappeenranta University of Technology.

In the case experiments, welding equipment from Fronius was used together with an ABB welding robot system. Sensors and equipment of the robot system were calibrated so the system is capable of knowing its specific positions of each sensor constantly. In different cases the sensors were moved and recalibrated to reach optimal process control and behavior. The PC workstation was used to run both ABB RobotStudio software used to control the robot as well as a custom ANN control system running under Mathworks MATLAB environment.

Neural Network training process

The training process is the most important part of using a neural network as it defines the performance and reliability of the whole system. Training process includes data collection, data validation and neural network preparation.

Experiments explained in the text (A3, A8, C20, C21 etc.) represent the experiments done in laboratory. First letter stands for the welding case's identifier (A stands for Case 1, C stands for Case 2). The number after the letter represents the number of the test (for example A3 stands for case 1 experiment number 3).

Data collection

The training process of the neural network begins with the data collection. Data is collected from the welding process in different circumstances and situations to assess the effect of various welding conditions and setup errors. The data from a successful weld is important as the knowledge of the optimal conditions and parameters for various circumstances are important for maintaining optimal conditions and completeness of the target space. The neural network also requires the information from the failed or unstable welds as well as data from outside of the desired quality level of imperfections of the weld. Then the system can be used to detect and correct unacceptable weld parameters and estimate the boundaries for weld quality. Therefore, it is important to collect and define the unaccepted weld parameters. In this study, the welding data is collected by varying voltage and current (wire feed) while the other weld parameters remain constant. Voltage and current values are varied separately over the various kinds of gap geometries. Variation is done by defining a full experimental plan with middle points, that is voltage and current values which are too high, low and suitable. Other varied weld parameters (for example root gap) are defined individually with different welding cases. Raw data is gathered from the welding process and measurement errors and other outliers are filtered away. Data flow (refresh rate) from the sensors varies from 10-40 milliseconds. Because of the different and varying data flowrate, all data collected over a period of time is saved as a single half-second long sample. Medians from the 0.5 second timeframe is calculated to filter interference in the sample. After the median is calculated, the samples are prepared to be used for training or evaluation by the neural network and new measurement is started.

Data validation

After the data is collected from the welding experiments, it needs to be validated for training the neural network. Quality level B is chosen to be the minimum requirement for the weld quality. Suitable welding results are measured and marked on test plates for validation. Defined results are marked in data and unacceptable welding results are corrected with approximate corrections. Example of the data validation (experiment A8) can be seen on fig. 3. All gathered data is checked for measurement errors and other abnormalities. All unreliable data is discarded. For example, fig. 3 shows root gap as a zero at tack welds and the temperature raises at the point of tack weld due heat convection being directed to the top side of the plate. In order the tack welds can be dealt with, more training data is needed to achieve acceptable welding results; dealing with tack welds is ignored in this study.

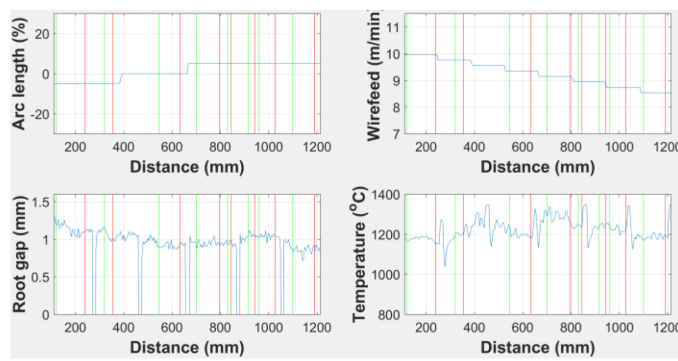

Fig. 3. Example accepted data points for the neural network (valid data area is marked from green line to red line), distance being the length of the weld (experiment A8).

For training, all valid samples are collected to a single matrix and fed to the neural network training program. Additionally, the neural network is used to assess the complete experimental data fed to it. Neural network computes a result for each case of the test samples and the results are compared to real welding data conditions. Fig. 4 shows all valid gathered data from the case A8 with neural network prediction compared to real values. Blue line is the training data set (tested "correct" values, validated acceptable data) for the case. The experiment number represents the correct value for each data point. Data point consists all the welding data (for example weld pool temperature, root gap, misalignment) however only the correct values and decision made by neural network is presented in the fig. 4. Neural network developed calculates its own decision from the welding data information in each experiment (plotted with red dots). The "correct" data defined and the decisions made by neural network are then compared and evaluated.

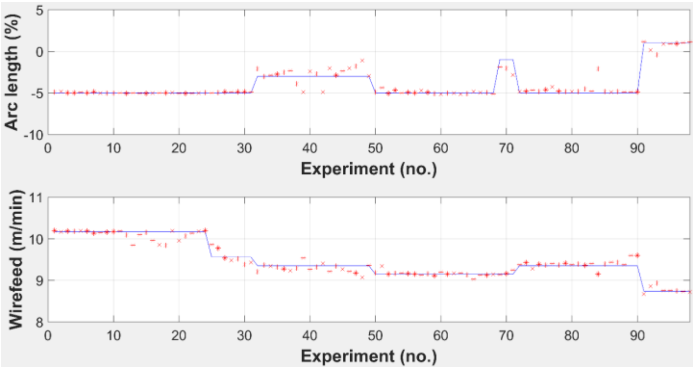

Fig. 4. Blue line is the training data set and red dots are neural network decision making results on specific point. Experiment number (samples taken every 0.5 seconds) represents collected data pack number over the successful weld.

All training data is combined for the neural network and the network is trained with all data gathered to get more reliable result. The more training data is gathered for the neural network the more accurate response is generated.

Neural Network preparation

Before the neural network training can be done, the input and output parameters, number of layers and neurons per layer need to be defined. In this study, input and output parameters are defined for closed-loop control. However, it was observed that output parameters cannot be directly connected to input parameters as there was a minor tendency of generating an open-loop controller which ignored some interference. Therefore, defining and preparing the neural network is one of the most important face. Incorrectly defined parameters will have significant effect on the welding quality and result. Simulation of neural network may suggest an excellent fit to training parameters but unless the cause and effect between the parameters can be determined, the practical results might be catastrophic. For example, if heat input is input parameter and current and voltage are output parameters, neural network will probably give excellent simulation results as the connection between current, voltage and heat input is directly proportional but the welding process in reality will not have preferred outcome. Optimal parameters need to be defined separately with different kind of weld circumstances (for example joint type, welding process etc.).

Next step is to define the number of hidden layers and neurons in them. Neural network decision-making performance, accuracy and speed is related on the defined layers and neurons via various processes. In this study, the optimal number of layers and number of neurons were simulated by training with various combinations and best solution is defined with the best simulated performance. To reduce the effect of chance, actual performance is computed as the average performance in five simulations.

Neural network is next trained and saved with defined parameters, hidden layers and neurons. Before empirical tests, a simulation of the decisions over the entire expected parameter space is computed to make sure that the solutions of the neural network are rational, as verified by a human expert. Example solution figures from the input and output parameters can be found in fig. 5, which contains arc correction percentage and wire feed value over the root gap and weld pool or joint temperature.

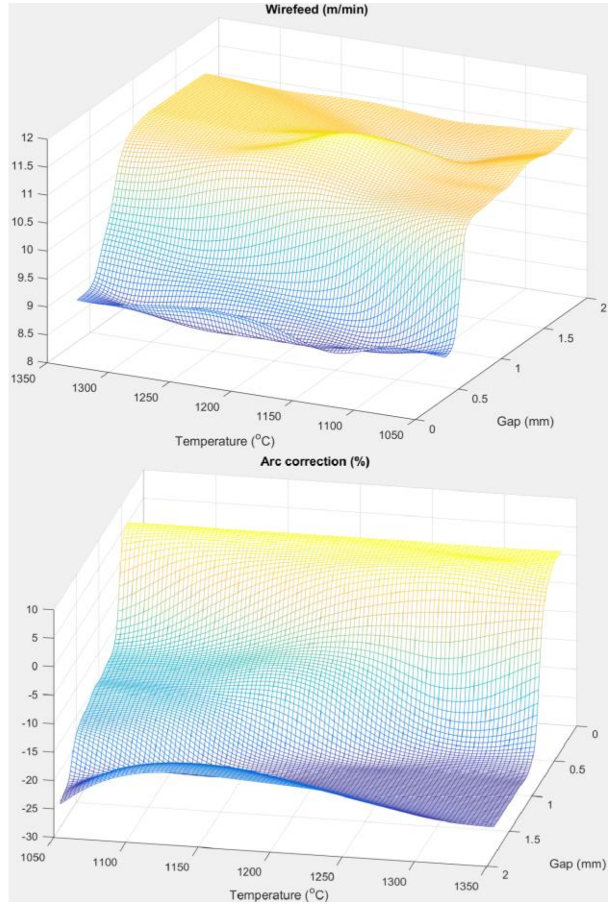

Fig. 5. On the top: Wire feed (vertical) variation decision over the root gap and weld pool/joint temperature. On the bottom: Arc correction (vertical) variation decision over the root gap and weld pool/joint temperature.

In practice, well-trained neural networks are usually capable of interpolation between related cases. Neural networks may be capable of doing extrapolation, but results may be unpredictable and unstable so they are not suitable for welding cases. To get a large scale solution basis for the welding cases, parameter window for data values of acceptable weld (quality level b) in both low and high extreme welding conditions is important to be defined. During the training phase, the test and validation sets of data are used to guard against “overfitting” the network to the data, generating possibly unstable NN models of the desired response.

After the simulation process is done and results are acceptable and rational, neural network is tested in practice. In practical tests the welding conditions are modified to respond industrial cases in practice. Neural network systems response to welding conditions are measured and results are compared to quality requirements (quality level B) of the weld.

The object of the case study was selected from a set of suggestions from industrial partners, because it is widely used and represents commonly used sheet metal example. The first case consists of a long and continuous butt weld between large 5 mm thick metal sheets. Complete penetration from one side in one pass is required. Despite the joining operation adding considerable value to the product, the plate handling takes lot of time. If the product can be consistently and reliably welded with complete penetration, remarkable amount of handling time can be reduced.

Materials and system layout

Material, weld parameters and system layout parameters can be found in table 1. Tests were performed on v-groove; the groove angle was 60°. Test plates used were 200 mm wide and length ranged from 400 mm to 1200 mm. The thermal profile scanner was positioned 30 mm behind and laser scanner 93 mm in front of the weld torch. Material used was Ruukki Laser 355 MC.

Table 1. Materials and system layout of the case 1.

Material	Ruukki Laser 355 MC
Material thickness	5 mm
Weld material	Esab OK Autrod 12.51, Ø 1 mm
Joint type	Butt weld
Groove angle	60˚
Root gap variation	0 mm to 1.5 mm
Torch distance	18 mm
Welding speed	7 mm/s
Welding gas	Ar 88% + 12% CO2, Woikoski SK-12
Welding gas flow speed	19 l/min
Root height	1 mm
Optical sensor position	93 mm in front of torch
Thermal profile scanner position	30 mm behind the torch
Other remarks	No torch weaving
Neural network type	Back propagation neural network
Neural network configuration	2-14-14-14-2
Neural network input parameters	Root gap, weld pool/joint temperature
Neural network output parameters	Wire feed/power, arc voltage

In order to ensure that the positioning of the torch was consistent between experiments, an automatic seam tracker device installed on the robot was used. Start and end points of the seam were scanned to recognize the correct start point and path. During the welding, the torch will follow the groove once the seam tracking from the laser scanner data is available, i.e. after 93 mm of distance has elapsed.

Quality requirements

Quality level B was determined as a requirement for quality level for the weld with full penetration through the plates. ISO 5817 (2014, p. 19-31) defines limits for the excess penetration, weld metal, undercut, root concavity, overlap, sagging, and the cracks for quality level B weld, which was used as a limit for the acceptable weld. All weld experiments were inspected for any defects and acceptable and unacceptable weld was marked and filtered away for the neural network training. Weld tests welded with neural network control were tested for imperfections by x-ray and welding procedure test.

Welding parameters

Neural network was optimized and input and output parameters for the networks were chosen. Optimal input parameters were root gap and weld pool/joint temperature. Output parameters were chosen to be wire feed/power value and arc voltage. In specimen A3 (fig. 6) wire feed value was varied while the other parameters were kept constant. Optimal weld parameters were estimated beforehand by a human expert. Wire feed parameter was varied from too low to too high values so the parameter window can be determined for the specific gap.

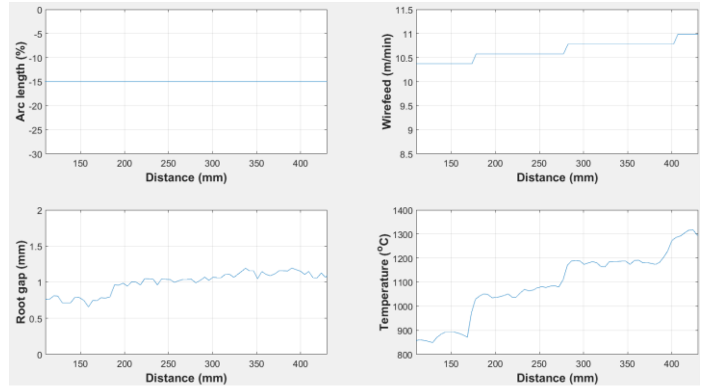

Fig. 6. Data variation in A3 welding experiment, distance being the length of the welded seam starting from arc ignition.

In experiment A4 (fig. 7) other weld parameters were kept constant while the arc voltage was varied. Beforehand determined optimal arc voltage parameters were kept in the middle of the arc voltage variation so the too high and too low arc voltage values can be determined. Acceptable weld parameters can be determined from the all data gathered.

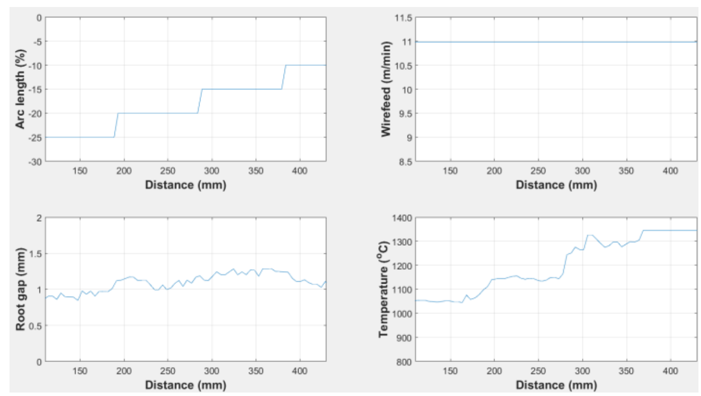

Fig. 7. Data variation in A4 welding experiment, distance being the length of the welded seam starting from arc ignition.

All experiments were done by similar test patterns to determinate the different welding parameter windows for the different root gap and weld pool/joint temperature values. The window for the root gap was determined by defining minimum and maximum values of root gap for acceptable weld. Also cases between the maximum and minimum values were determined for more consistent and reliable decision making accuracy. Test patterns were done from 0.0 mm to approximately 1.5 mm root gap. Number of hidden layers and neurons in neural network was optimized as explained before. Optimal layer configuration was discovered to be 2-14-14-14-2.

RESULTS AND DISCUSSION

The results of the practical experiments are introduced and discussed in detail. First the case is introduced and in the last subchapter the conclusion of overall performance of the welding system is determined. Also in the end of the chapter suitability and challenges of the welding system is discussed.

Case study

Neural network was trained from the data with layer configuration of 2-14-14-14-2. Solution figure was created from the trained network.

Neural network solution figure of arc correction (voltage correction) and wire feed over the root gap and weld pool/joint temperature can be found in fig. 8.

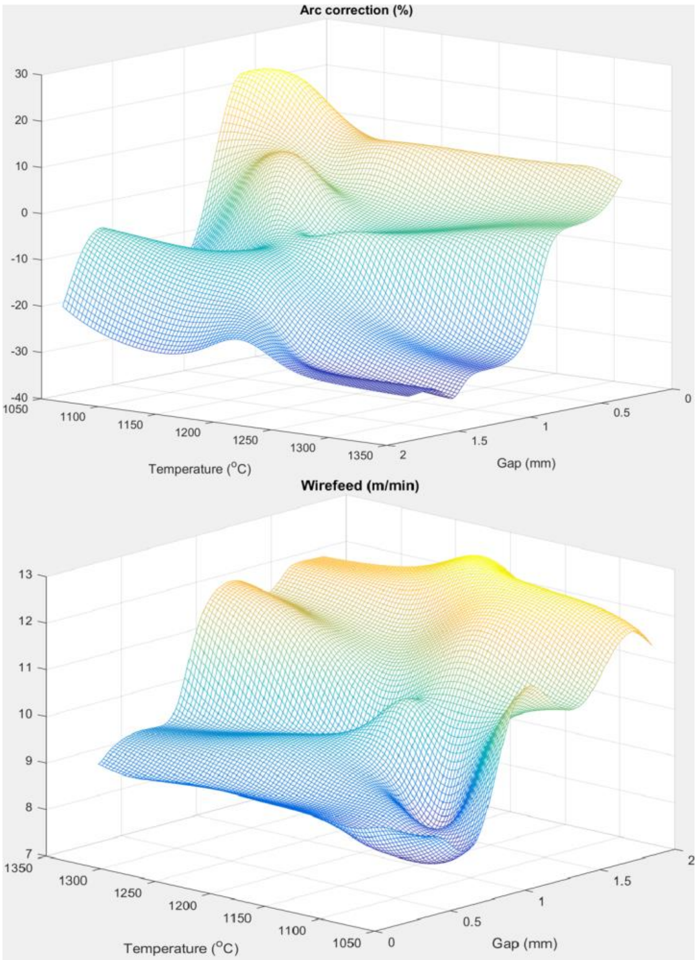

Fig. 8. Neural network solution figure of arc correction (vertical) over the root gap and weld pool/joint temperature (top). Neural network solution figure of wire feed (vertical) over the root gap and weld pool/joint temperature (bottom).

It can be seen that the solution figures are not smooth planes over the parameter window. Neural network combines the training data and has made interpolation between the values with its own decision making. Neural network was tested in practice with different gap variation to be sure that required weld quality (quality level B) is reached. In fig. 9, weld data is collected from the practical experiment (A22). Also, the pictures from the top side, back side and an X-ray image of the weld with the scale, is added in the same figure. In X-ray image, the darker areas mean less thickness and brighter areas mean higher thickness. For example, spatters can be seen as a brighter X-ray image (more material thickness at that point). Also a few small spores (little black spots) can be seen at the end of the weld, although the weld still managed to reach quality level B with a small margin.

The experiment A22 seemed to be surprisingly stable even though the weld process sounded like it was unstable. The cause of the instability sounds was swiftly variated weld parameters by neural network. Overall process stability was good and there was only some spatter even the parameters were varied straight from the neural networks decision making.

The weld reached the quality level B with a visual as well as the X-ray inspection. The joint was penetrated well trough, there was no excess weld metal, undercut, root concavity, overlap, sagging, or cracks. The quality level B was also confirmed with welding procedure test. Welding procedure test passed the bending test without any cracks. 489 MPa of ultimate tensile strength and 388 MPa of tensile strength was achieved from the tensile test. Test pieces were cracked from the base material and elongation at break was 22%. Welding procedure test was passed completely with the experiment A22. Fig. 10 above shows the macro picture done with experiment (A22) at the point of 295 mm.

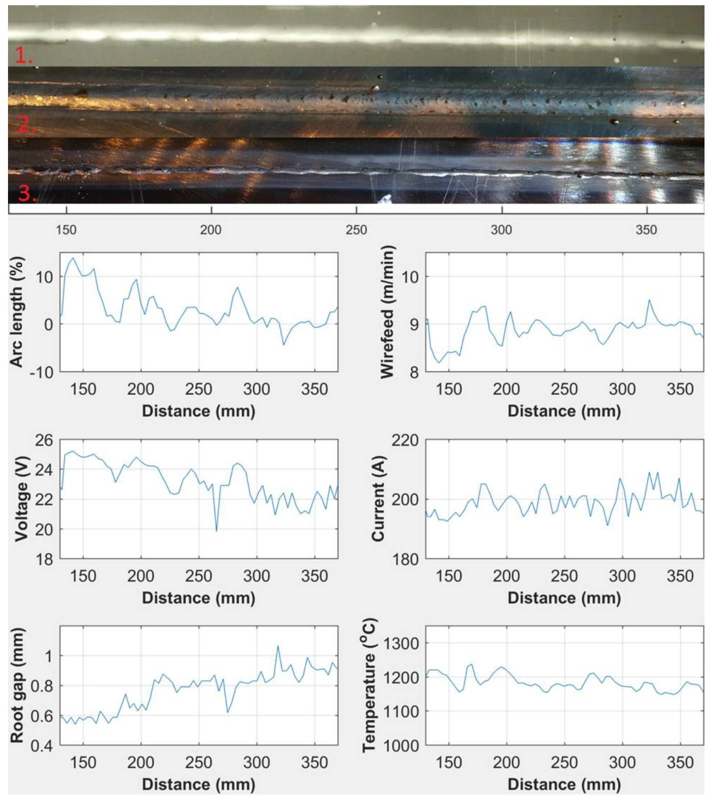

Fig. 9. Full neural network controlled weld test (experiment A22), welding parameters plotted over the weld. Distance being the length of the welded seam starting from arc ignition. On the top is the X-ray image of the weld (1.), in the middle top side of the weld (2.) and in the bottom, is the back side of the weld (3.). Weld profile is cut to fit the scale in the measurements.

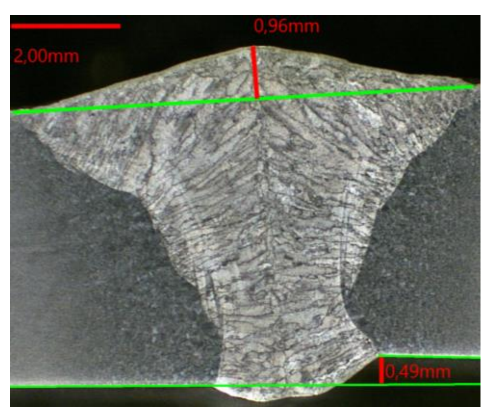

Fig. 10. Macro picture of experiment A22.

Macro picture shows that the weld has smooth connection without any undercut. Also, the root height is under 1 mm although the misalignment between the welded plates was 0,49mm, which was formed because of heat distortions during the welding. Weld still reaches quality level B by a margin. Because of the rapid parameter variation, the neural network output interface was modified to use mean of three last decisions. Therefore, the quick up and down variations of the output parameters can be filtered away and also the effect of possible misreading from the sensors can be reduced or even avoided completely. Updated interface was tested with practical experiment (A24), which can be seen in fig. 11.

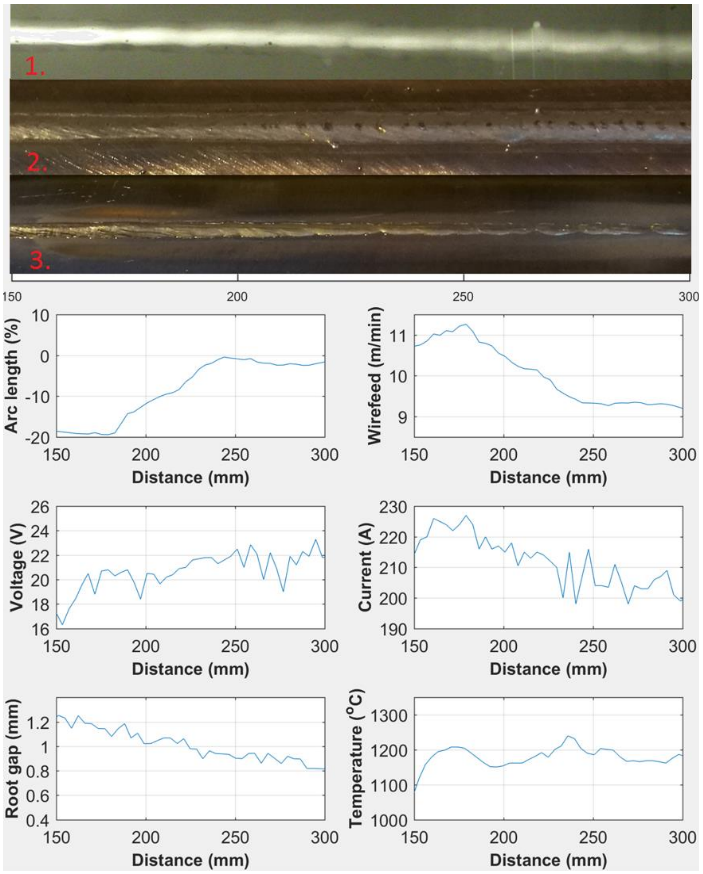

Fig. 11. Full neural control test experiment A24, welding parameters plotted over the weld. Distance being the length of the welded seam starting from arc ignition. On the top is the X-ray image of the weld (1.), in the middle top side of the weld (2.) and in the bottom, is the back side of the weld (3.). Weld profile is cut to fit the scale in the measurements.

It can be seen that the parameter variation was much smoother and the process sounded considerably more stable. After the visual inspection, it can be concluded that the weld had hardly any spatter. The weld reached the quality level B with a visual as well as the X-ray inspection.

The quality level B was also confirmed with welding procedure test. Welding procedure test passed the bending test without any cracks. 489 MPa of ultimate tensile strength and 411 MPa of tensile strength was achieved from the tensile test. Test pieces were cracked from the base material and elongation at break was 24.7 %. Welding procedure test was passed completely with the experiment A24. Macro image was taken from the point of 240 mm can be seen on fig. 12.

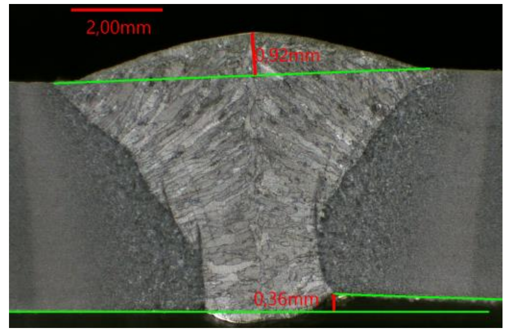

Fig. 12. Macro picture of experiment A24.

Smooth connection with no undercut was obtained from the macro picture. Bead height was 0.92 mm and plate misalignment was 0.36 mm. Weld reached quality level B. Bending test results from both of the experiments can be found in fig. 13 and tensile test results in fig.14.

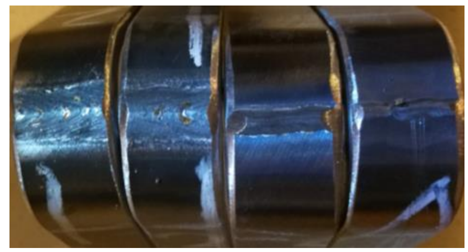
Fig. 13. Bending tests from both of the experiments. From the left, 1st and 3rd are from test A22 and 2nd and 4th are from the test A24.

It can be concluded from the neural network training data that the weld was impossible to reach quality level B with root gap greater than 1.2 mm. With this configuration, it was not possible to fill the whole seam while the penetration would not be excessive. Also, full penetration was not possible to reach when the root gap was under 0.2 mm. Therefore, the neural network works as well as it was trained in these extreme cases.

In conclusion of case study, the neural network worked well in all cases taught. Quality level B was reached with low spatter and with good consistency. In case of butt weld, the neural network can be used as reliable and effective tool for adaptive intelligent control. Optimal application for the system would be long butt welds (mechanized or robotized) in the industry where the full penetration is required to prevent extra handling of the product. Thermal disorientation often occurs with long welds where the material thickness is low even the seam is prepared with care. With use of neural network, effect of disorientation to welding result can be reduced.

Challenges

Challenges of using ANN based solution making for weld parameters are the determination of the ANN input and output parameters. Parameters should be not directly linked, but the output parameters should have some effect to input parameters (for example relations between current and temperature). In many cases this process takes quite a lot of practical testing until the system works as it was designed to work.

Training process of the ANN takes considerably long time so the optimized system would have constant reliable and repeatable result. Also, the limitations (minimum and maximum parameter values) should be defined accurately in case of system instability. System needs to be configured to each case separately, which means the suitability in varying material thicknesses and weld positions can be tricky and time consuming.

Third disadvantage of the welding system is the reachability restrictions of the weld torch. The used sensors required to lock one axis from the welding robot to achieve consistent measurements, which restricts the movements of the robot a lot. Also, the reachability of the torch is restricted due to sensors attached to it. Corners and tight bends can be difficult to or even impossible to handle without collisions.

Suitability

The welding system tested above suits well for long straight welds, where full penetration with excellent weld quality (Quality level B) is required. In industrial case the use of root support in such of cases can be avoided. Root support often need to be removed after the welding, which can be hard because of the reachability (small space) or the size of the product for example huge metal sheets in the naval industry. The case tested above was adapted from a naval industry case where the root support removal required turning the sheet, increasing labor time and production cost. Optimal suitability of the system would be long, constant and continuous welds, for example sheet metals, profiles and beams with robotic welding system or mechanized welding system.

Because the ANN welding system can be taught in laboratory instead in the industry, implementation time can be reduced significantly. Also, the updates of the weld profiles can be updated online and system can be optimized and improved constantly.

CONCLUSION

Overall the sensor technology today provides reliable and accurate enough information for the GMAW. Artificial Neural Network can provide stable and reliable process control based on laboratory tests. It can be concluded that welding system tested is suitable for industrial implementation for long continuous welds with robotic or mechanized welding.

Full penetration with quality level B was reached with root gap varying between 0.2 mm to 1.2 mm. Quality level was verified by visual inspection, radiographic imaging, macro pictures, tensile and bending testing. Configured, and taught adaptive neural network system can reach quality level B constantly and work as a quality assurance based on the laboratory tests. Bending test were passed without any cracks and tensile test specimens cracked from the base metal. Ultimate tensile strength of 489 MPa was reached with 22-24.7 % elongation.

Challenges of using ANN based solution making for weld parameters are the determination of the ANN's input and output parameters and training process. Incorrectly set parameters can cause unreliable or even disastrous result. Training process of the ANN takes considerably long time so the optimized system would have constant reliable and repeatable result. Also the limitations (minimum, maximum parameter values) should be defined accurately in case of system instability.

The penetration of the weld can be evaluated from the weld pool temperature. Higher temperature in thermal profile scanner reflected deeper penetration and lower temperature caused decreased penetration. Keeping the weld pool temperature constant gave constant weld quality and penetration.

It can be concluded that the temperature variation after the weld changes around 100 degrees per millimeter. Therefore, the distance between welding torch and temperature profile sensor needs to be constant to reach reliable results. Even 1 mm change in the distance will be crucial to the weld quality and stability.

REFERENCES

Aviles-Vinas, J, Rios-Cabrera, R and Lopez-Juarez, I (2016). On-line learning of welding bead geometry in industrial robots, *Int J Adv Manuf Tech*, 83, 217-231.

Chandrasekhar, N, Vasudevan, M, Bhaduri, AK and Jayakumar, T (2015). Intelligent modeling for estimating weld bead with and depth of penetration from infra-red thermal images of the weld pool, *J Int Manuf*, 26:1, 59–71.

Chokkalingham, S, Chandrasekhar, N and Vasudevan, M (2012). Predicting the depth of penetration and weld bead width from the infra red thermal image of the weld pool using artificial neural network modeling, *J Int Manuf*, 23:5, 1995–2001.

Dhas, ER, Kumanan, S and Jesuthanam, CP (2012). Prediction of weld quality using intelligent decision making tools, *Artificial Intelligence Research*, 1:2, 131-148.

Ebert-Spiegel, M, Goecke, S and Rethmeier, M (2013). Efficient Gap filling in MAG welding by using optical sensors, *IIW Doc. XII-2124-13*, 1-9.

ISO (2014). *ISO 5817 Welding. Fusion-welded joints in steel, nickel, titanium and their alloys (beam welding excluded) - Quality levels for imperfections,* International organization for standardization, Geneva, Switzerland, 27.

Jain, LC, Seera, M, Lim, CP and Balasubramaniam, P (2014). A review of online learning in supervised neural networks, *Neural Computing and Applications*, 25:3, 491-509.

Jang, JSR, Sun, CT, and Mizutani, E (1997). *Neuro-fuzzy and soft computing; a computational approach to learning and machine intelligence,* Prentice-Hall, 614.

Kah, P, Shrestha, M, Hiltunen, E and Martikainen, J (2015). Robotic arc welding sensors and programming in industrial applications, *Int J Mech Mater Eng*, 10:13, 16.

Kim, J and Lee, J (2008). A control system for uniform bead in fillet arc welding on tack welds, *J Mech Sci Tech*, 22, 1520-1526.

Kumar A, Chauhan, V and Bist, A (2013). Role of Artificial Neural Network in Welding Technology: A Survey, *Int J Comp Appl*, 67:1, 32-37.

Nagesha, DS and Datta, GL (2010). Genetic algorithm for optimization of welding variables for height to width ratio and application of ANN for prediction of bead geometry for TIG welding process. *Appl Soft Comp*, 10:3, 897-907.

Rios-Cabrera, R, Morales-Diaz, A, Aviles-Vinas, J and Lopez-Juarez, I (2016). Robotic GMAW online learning: issues and experiments, *The Int J Adv Manuf Tech*, 1-22.