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AI APPLICATION IN QUALITY ASSURANCE OF INDUSTRIAL LASER WELDING PROCESSES

Abstract: *The purpose of this paper is to explore conventional laser welding quality control methods and compare them with modern AI-based (Artificial Inteligence) testing solutions, highlighting the potential of AI in laser welding quality assurance. AI can effectively monitor various laser welding process signals and parameters to determine weld quality. Furthermore, AI image recognition can enhance weld error detection precision when monitoring laser welding with vision systems. In cases where conventional quality control methods, such as X-ray, are utilized, AI can be employed to process and interpret test results, reducing the time and effort required for a human operator. This paper presents and briefly discusses several successful AI application examples in laser welding quality assurance, as well as application possibilities, demonstrating the latest state-of-the-art non-destructive laser welding test solutions.*

Keywords: *Artificial Intelligence, Laser Welding, Quality Assurance, Non-Destructive Testing*

1. Introduction

Achieving a certain quality standard requires taking into consideration several factors – technical, technological, and economic[1]. Working conditions and equipment, production layout, as well as expenses of inspection, testing, and rework all affect the quality of the product. [2] The same criteria can be applied to the assessment of the quality of welded joints. However, when it comes to welding it is crucial to control and monitor the entire process, as errors can be frequent and consequences can turn out to be severe and costly [2].

The advent and improvement of artificial intelligence (AI) and its subfields, resulted in their rising impact on the manufacturing industry [3]. The advantages automated procedures hold over manual work increased the popularity of AI applications in manufacturing processes, especially quality control [3]. The implementation of machine learning (ML) models in industrial quality has proven to be of great use as it contributes to savings in resources, time, and money. A few examples of applied ML models in quality inspection procedures are stated hereinafter[4].

Faults and defects in laser welding evaluated during quality control can be classified either as internal or external [2]. External defects can be detected by the naked eye or with magnifying glasses, as they appear on the surface of the material [2]. Internal defects can only be detected after the metallographic preparation of the samples [2]. These defects occur under the surface of the material. Some of the most common welding discontinuities are:

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- cracks,
- cavities,
- solid inclusions,
- lack of fusion and penetration,
- imperfect shape and dimension.

Welding parameters should be closely followed during process as they affect the quality of the weld [19]. For example, by analyzing and controlling parameters such as the laser power, the welding speed, and the size of the laser beam, the formation of welding discontinuities can be predicted [12]. Also, process parameters determine the geometry of the keyhole which affects the weld geometry and quality[5].

1.1 AI application in industrial quality

AI-based methods are most commonly used for prediction, classifying a large amount of obtained data, and in optical inspection, when a high level of precision and accuracy is required for time-consuming and monotonous work.

An example of optical inspection based on a machine learning method is a blister defect detection for polymer lithium-ion batteries (PLB) performed by Ma et al. [6]. In this case, a widely used deep learning model, convolutional neural network (CNN), is employed to detect blisters in PLB sheets from images [4]. This can be regarded to as an image classification problem[6]. CNN uses a hierarchical structure to gradually extract advanced features from low-level features. It then uses these advanced features to do image classification and detect defects in PLB sheets from images [6].

Further use of machine learning methods is found in the identification of root causes of failures and quality deviations. Lokrantz et.al.[7] uses a Bayesian network, a form of a probabilistic graphical model, to represent dependence between manufacturing stages. This model uses expert knowledge and previously recorded data to perform inferences regarding the root causes of quality deviations [7]. Such framework provides a chance for the knowledge to be stored for further use and distributed to other manufacturing sites [7].

Another instance of employing machine learning tools is set by Sumesh et. al.[8]. They used two different classifier algorithms, J48 and Random Forest, to determine the quality of the weld based on the corresponding arc sound [7]. Input parameters for the classifier were sound signals recorded during experiments and later generated in Matlab software. The accuracy Random Forest showed was 88.69% and that of J48 was 70.78% [7]. Although the results turned out to be satisfactory there is still room for enhancing the performance of algorithms by bettering the conditions in which the sound arc is recorded, according to Sumesh et al. [7].

1.2 Conventional laser welding quality controls

Laser technology has been present in the industry for more than 40 years, and it has contributed greatly to the improvement of welding efficiency and accuracy [9]. These developments enable greater manufacturing flexibility (control over design) and therefore increase the range of useful material properties that can be achieved [8]. However, laser welding requires rigorous control and constant process monitoring to achieve a high-quality standard [2]. Conventional methods used to evaluate the quality of a welded joint can be destructive or non-destructive [1].

Destructive tests are achieved through mechanical and structural tests and they provide quantitative indicators of the quality of the welded joint [2]. To determine the mechanical properties of welded joints, it is necessary to make test samples under the appropriate standard [1]. These samples are obtained by cutting a small part of the welded piece that was intentionally left there, or by making special pieces (test plates) that are welded using the same procedure and welders as the planned construction [10]. Some mechanical tests include testing by tension, bending, measurement of hardness, etc[10].

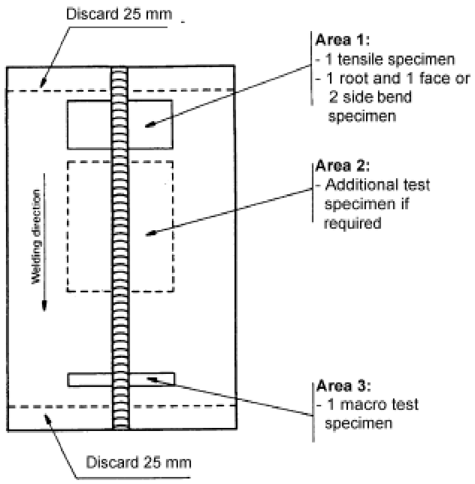

Figure 1. Test plate

To determine the structure of the welded joint, structural (metallographic) tests are performed [10]. Samples used for these tests are prepared by grinding and polishing, after which the surface of the sample is etched [9]. The choice of the chemical reagent used for etching is based on the material of the tested object [10]. This procedure lets us see the macroscopic appearance of the welded joint as well as the microstructure in the thinned zones of the welded joint [10].

On the other hand, non-destructive evaluation involves the detection and assessment of deviations on both the surface and interior of the material [2]. Considering the fact that achieving a welded joint without any discontinuities is almost impossible, it is important to determine their shape and dimensions [1]. Discontinuities aren't considered errors if they are evaluated to be within the permitted limits, prescribed in the quality requirements of the welded joint [1]. During these tests, the material is not damaged in any way. Some of the most common non-destructive tests are visual tests, testing with liquid penetrants, magnetic flux testing, ultrasound testing, and radiographic examination [10].

Both destructive and non-destructive methods usually require a lot of time and additional workstations, specialized equipment and materials, and trained staff, resulting in a high cost [11].

2. Smart laser welding quality assurance systems

An alternative to conventional quality assessment methods is found in the development and integration of process monitoring systems. These systems detect welding errors during the process and the negative impact of uncertain interfering factors can be effectively reduced and flawed parts can be separated [11].

When it comes to laser welding, process monitoring is conducted in three stages. In the first stage, during the pre-process, the weld seam is tracked [12]. After that, the melt pool, weld defects, spatter, etc. are monitored during the process. Lastly, the geometry of the weld and visible defects are examined post-process [12].

Using AI-based methods, weld features, defects, and the state of the weld can be predicted and adjusted [13]. Also, corrective measures are proposed through feedback to system control if needed, and the entire process becomes more efficient over time, as more data is collected. There are different methods used for process monitoring and quality assessment.

2.1 Signal monitoring sensor techniques

During process monitoring, the most commonly monitored signals are acoustic, optical, and thermal.

Acoustic emission signal is one way to monitor the laser welding process. The plasma ejected from the keyhole leads to pressure fluctuations which bring about the acoustic signal [13]. This signal can be measured without contact, by using a microphone or a resonant sensor [14].

Acoustic signatures, such as sound pressure deviation and band power, can be used to specify the weld penetration by applying a neural network algorithm and regression analysis methods [15]. The algorithms effectively separated full penetration from partial penetration. An automatic measure and control system designed by Lv et al. [16] proved that acoustic signals are also helpful in controlling arc length in real-time, based on the linear relationship between the arc sound and arc length. The linear fitting model was used to predict the surface height of the molten pool. Achieved prediction results were successful [16].

The main downside of this signal is its susceptibility to environmental noise. This interferes with the forthputting of acoustic signal monitoring[13]. However, this can be avoided by using noise reduction methods to reduce the background noise signals [17] or by using a plane microphone array system, composed of eight microphones [18].

Optical signal monitoring consists of optical radiation and optical vision monitoring [13]. The molten pool, spatters, and plasma emit strong optical radiation, and the optical radiation signal mainly comes from the laser beam and the welding area [19]. Based on a different wavelength, optical radiation signals can be divided into two categories – one is UV and VIS radiation, where the wavelength is 0.3 – 0.7 μm, and the other is IR radiation with a wavelength range between 1.1 μm and 1.6 μm [20, p.]. The equipment used to collect the optical radiation signals consists of, most commonly, spectrometers, photodiode sensors, high-speed cameras, CCD cameras, and CMOS cameras [13]. This monitoring method is widely used nowadays as it provides a large amount of reliable data. For example, [21] used the image processing method under different welding conditions to gain insight into the dynamic behaviors of the keyhole, and [22] measured the velocity and direction of the fluid flow inside the keyhole, by attaching a glass plate, very precisely. Results showed a connection between the fluid flow and laser power, feed rate, and welding gap [22]. Still, due to spatial restrictions, the signal camera sensor is limited in data collection[13]. To avoid this downside and to be able to extract enough features for proper evaluation of the quality of the weld seam, researchers opt for multiple camera sensors [13]. This way, the welding zone can be monitored from different angles and extensive information can be obtained [13].

Thermal radiation signal is especially strong in the keyhole, the molten pool, and the high-temperature metallic vapor, as the temperature and thermal radiation are very high in these parts of the welding zone [13]. Frequently used sensors for obtaining thermal signals are pyrometers and IR cameras [13]. While the pyrometer is cheaper and easier to assemble, the IR camera can reflect the temperature distribution of the welding zone more extensively [13]. IR images of the molten pool were used to estimate the width and depth of the weld seam[23], [24]. By analyzing the emitted thermal radiation, Weberpals et al. [25], examined the temperature distribution and geometrical structure of the welding zone. This approach could also be used to define the inclination of the keyhole [25].

2.2 Monitoring techniques

Traditional monitoring methods can be divided into two approaches, coaxial and paraxial [26]. The coaxial monitoring method monitors the welding zone by installing a spectroscope in the laser propagation path. [27]. Obtained optical and thermal signals are stable and undisturbed. The imperfection of this method is its lack of flexibility and complex installation of the monitoring sensor [13]. However, paraxial monitoring is characterized by easily adjusted monitoring distance and angle between the welding zone and the sensor [13]. These traditional methods commonly represent a basis for novel monitoring methods and multi-sensor fusion technology [13].

Novel monitoring methods, like X-ray imaging technique, inline coherent imaging (ICI), magneto-optical imaging (MOI), etc. have achieved good results in obtaining some welding features, which are normally difficult to get during the process [13]. These features, like the depth of a keyhole for example, are very helpful when evaluating welding quality since they are closely connected to it [13].

X-ray videography can obtain temporally and spatially defined information about the keyhole geometry during the welding process[5]. Furthermore, this method can also be used to identify the inner defects of the weld seam with high spatial and temporal resolution [13]. By using an X-ray diffraction system, the microstructure and mechanical properties of the weld seam can be investigated [28], and residual stress distribution in the weld seam measured [29].

Optical coherence tomography (OCT) is another novel technique. OCT is a 3D measuring technology for automated laser welding[13]. It can serve as a basis for an inline monitoring device used to extract the tomographical geometrical measurement data during the process of weld seam forming [30].

The MOI technique is based on the magnetic induction principle and the Faraday rotation effect [31]. An experiment showed that the microstructure of the weld joint can be investigated using the MOI method, and without the metallographic preparation process [32].

Automated monitoring of laser welding processes is often achieved using *weld watchers*. Analyzing the measured light emission, created from the interaction between the laser and the material, weld watchers can recognize errors in welding based on previously recorded error-free weldings[33] [32].

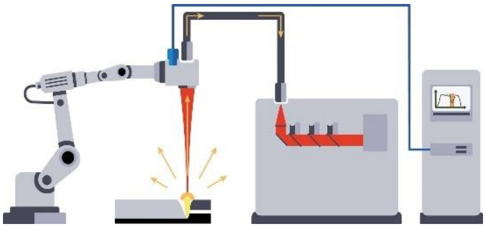

Figure 2. Weld watcher

Using smart evaluation methods, weld watchers can signal warning thresholds to the system control completely automatically [32].

Multi-sensor fusion technology combines various signal sensors and benefits from the advantages of each one [12]. It can, therefore, monitor the welding process effectively and comprehensively [13]. The main sensor of this technology is usually the vision sensor, as it provides extensive information about the welding zone [13]. The combination of sensors varies based on the desired outcome. For example, the X-ray system can be combined with the high-speed camera [34], the sound sensor with the vision sensor [35], etc.

3. Successful examples and possibilities of AI application in laser welding quality assurance

AI can be applied in many ways to ensure the quality of the welded seams, significantly reducing test costs, especially compared to destructive test methods. Possibilities are numerous, but some of the most significant would-be AI monitoring of various process parameters to determine weld quality, monitoring optical signals during welding and applying AI image recognition, and AI result processing and interpretation for some of the conventional control methods (such as X-Ray). A few successful application examples shall be presented and shortly discussed.

Image recognition can be applied in many ways in quality control of welded joints. Welding errors can be detected while observing the melt pool contour, (melt-on and the resolidification line) [11]. Various defects can be identified in this way, especially lack of fusion. In order to have a proper setup researchers have used a CMOS camera with an additional light source, and a robust algorithm for image analysis. Image recognition approach can be utilized to detect laser optical backlash during welding, a heat camera can be used to monitor thermal distribution patterns, or different light sources can be applied in order to have a visual inspection of the welded seam in form of a machine vision [6], [11], [19], [23].

Monitoring process parameters in order to determine weld quality can be a very promising approach. Non-visual process parameters could be monitored during the welding process. For example, AI can be trained to monitor temperature, voltage, electric current, sound, pressure, and many other parameters during welding and determine the outcome of the welding operation based on various combinations of parameter values [8], [11], [13], [35]. When possible, the most economical approach is to use existing process parameters measurement values, without investment in microphones or other measurement devices. An example of this approach is the utilization of an adaptive neuro-fuzzy inference system (ANFIS) and multi-gene genetic programming (MGGP) to predict the laser weld quality, such as surface roughness, weld strength and more [36].

AI result processing and interpretation is a useful method to eliminate long manual work, make the process cost-efficient, and get the testing results faster. Eddy current testing, ultrasonic testing, X-Ray, or CT (computer tomography) scanning can provide as an output a very complex result. For a human, it can be quite tricky to analyze, understand and interpret those results, and the process can take a long time. If a CT scan of a laser welded seam is analyzed for pores, on the output scan an operator should look for pores, measure them and make a report. Many scanning systems have a built-in AI feature for porosity analysis, but if porosity-induced fatigue damage should be calculated numerous calculations should be performed. Researchers have tried to predict porosity-induced fatigue damage of laser welded joints, where the AI algorithm could be a very beneficial tool to increase prediction accuracy and reduce testing time [37], [38].

4. Conclusion

This paper provides a rough overview of the AI application in industrial quality, with a focus on laser welding quality assurance. Basics of the laser welding process were given, followed by conventional laser welding control methods. Conventional testing methods can be quite costly and time-consuming, especially destructive testing methods. State-of-the-art technologies provide better solutions. AI prediction models or process monitoring solutions can be applied to provide real-time test results in a high-speed production environment with very low investments, and very low testing costs.

Through various examples of AI application in laser welding quality assurance, it is shown that there is a great potential to improve conventional quality control systems, shorten the test duration, reduce the test cost, improve defect detection precision, and much more. AI can be successfully applied to monitor various laser welding process signals or parameters to determine the weld quality, in cases where laser welding is monitored with some vision systems AI image recognition can be applied to enhance the weld error detection precision, or if a conventional quality control method is applied (such as X-ray), AI can be utilized to process and interpret test results as it might be a time-consuming process for a human operator.

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