Closed-loop Control of Laser Power using the Full Penetration Hole Image Feature in Aluminum Welding Processes


Abstract

In contrast to other welding methods, laser beam welding still suffers from a lack of established quality control or even closed-loop control systems in industrial production. One promising solution is the observation of the image feature called “full penetration hole” indicating the penetration depth of keyhole welding processes. This article studies its stochastic behavior in aluminum. As a consequence of the nonlinear temporal response to laser power, a robust feedback strategy was developed to control penetration depth by adapting laser power to preset detection rates of the full penetration hole.

Keywords: Laser welding; Aluminum; Closed-loop control; Full penetration hole; Cellular Neural Networks; Quality control

1. Motivation

Laser beam welding is a joining technique frequently used in high volume applications, such as in the automotive industry. In so called keyhole welding processes, the laser beam is focused to intensities between $10^6$ and $10^7$ W/cm². In this regime, vaporization takes place on the surface of metals like steel or aluminum. This metal vapor forms the so called keyhole, i.e. a cavity within the melt, whose shape is defined by the balance between the vapor pressure and the surface tension of the surrounding melt. Within the keyhole, the laser light is reflected multiple times resulting in a high absorption efficiency. As the laser beam advances, the melt flows around the keyhole and solidifies after a certain time. Therefore, deep and slender weld seams at high feeding rates are achieved.

In the upper part of figure 1, such a keyhole penetration process in the full penetration state is sketched for an overlap joint. As the laser beam moves from left to right, it forms a keyhole whose diameter is slightly bigger than the one of the laser beam. If a sufficient laser power is used, the depth of the keyhole reaches the bottom of the work piece and the so called full penetration hole (FPH) opens on the bottom side. At lower laser power values, the FPH closes again. The lower part of figure 1 shows the thermal image where the FPH appears as a cool spot within the walls of the keyhole, which are at vapor temperature. Thus, the appearance of the FPH indicates that the keyhole extends to the bottom of the lower sheet. The welding depth is defined as the depth of the liquid-solid interface, i.e. the depth of the molten material. Since the keyhole depth is usually slightly less than the welding depth, the FPH can be considered as a measure for the welding depth.
The FPH is a well known image feature widely used for monitoring or closed-loop control of deep penetration laser welding processes [1, 2, 3]. However, the FPH exhibits rapid fluctuations and the reaction times are in the order of milliseconds or even below. Therefore, we introduced a novel camera technology based on the so called Cellular Neural Networks (CNN) in order to observe the statistics of the FPH with frame rates up to 14 kHz [4]. This closed-loop control system uses the FPH as a measure for the welding depth and the laser power as feedback parameter.

This article investigates the expansion of this concept to aluminum. The investigated welding geometry is an overlap-joint with aluminum of type AA 6014 which can be welded without any additives or shielding gas.

2. Cellular Neural Networks (CNN)

Conventional computing systems with the exception of FPGA are usually “Single Instruction, Single Data” (SISD) architectures [5]. Here, a program consists of a series of instructions which are applied sequentially to single data elements by one or few processor cores. Therefore the execution time of many algorithms lies in the order of N or N², where N is the number of pixels. One alternative are “Single Instruction, Multiple Data” (SIMD) computing architectures in which each instruction of a program is applied in parallel to a large number of data. Such SIMD applications are especially efficient for image processing applications which frequently apply the same operation on different pixels of the image. On SIMD systems, these operations can be executed simultaneously in a single step. As described in earlier publications, one possible application for CNN is to use this technology for the integration of a SIMD processor architecture in the electronic circuitry of the pixels in CMOS cameras [6].

Here, a CNN based system called Q-Eye developed by Anafocus [7] was used to execute the algorithms for the detection of the full penetration hole. It consists of 176 x 144 cells which are each interconnected to the 8 neighboring cells. The Q-Eye is part of the Eye-RIS 1.3 camera which contains an additional FPGA with a conventional NIOS II processor by Altera. For a closed-loop control system such an additional processor is crucial because the result of a CNN is always an image. Therefore, this processor is needed to analyze the information output of the Q-Eye, e.g. performing the decision making and actuation tasks.

3. System setup

The welding experiments were carried out with a 2D laser scanner setup sketched in figure 2. Without closed-loop control system, one needs the laser itself which is connected over a laser fiber with the welding head. For our experiments, the laser source was a 5 kW, 1030 nm Trumpf TruDisk 5001 Yb:YAG thin disk laser with a 200 μm transport fiber. The 2D laser scanner is integrated in the laser head (Trumpf PFO-33) which was equipped with a 450 mm focusing optics resulting in a focal diameter l of 600 μm. The welding head provides an optical window for coaxial surveillance of the laser interaction zone. The corresponding control unit provides a 24 V digital start/stop signal and a 10 V analogue input to control the laser power with a bandwidth of 10 kHz.

In order to add the closed-loop control functionality, this standard system is extended with several components which are marked in figure 2 by the dashed line. The optics unit is mounted to the coaxial process window of the welding head in order to create the thermal image in the spectral range of 820 to 980 nm.

The laser head is placed within a production cell for safety reasons, whereas the other components are mounted outside. Therefore, the required cable length between the camera and the CNN control unit is about 20 m and these...
cables must comply with drag chains in order to be compatible with robot welding systems and the rather harsh electromagnetic environment. Therefore, the camera unit contains the CNN camera and some signal conditioning electronics necessary to exchange commands and signals over optical fibers.

The CNN control unit at the other end of the optical fiber contains the interface to the laser control unit on the one hand and the PC on the other hand. This PC runs the control software which serves as the user interface. On this PC, signals and some of the images acquired by the CNN camera are stored. The most important signals are the laser power $P$ and the algorithm result $s_{FPH}$. The images are needed to train the algorithm.

4. CNN algorithm

In the setup described above, the CNN camera is the key component to achieve a robust FPH detection at a multi kilo Hertz frame rate. Two algorithms for different constraints have been implemented in the CNN-camera system. However, the intensity of the thermal images acquired from aluminium welding processes varied much more than on steel based materials. Therefore, only the so called omnidirectional algorithm worked. The flowchart is sketched in figure 3. The first step is a contour enhancement by adding a sharpened version of the grey image to the original one. The combined grey image is binarized by a global threshold. The second step consists of morphological closing operations, i.e. the subsequent application of dilation and erosion in order to fill the FPH area in the binary image. Several iterations of the closing operation allow connecting the objects which present holes or concave shapes, e.g. the FPH, leaving unchanged the shape of possible artefacts around the interaction zone. The subtraction between the last resulting image and the original binarized image provides the only “closed” area. It is obtained by a pixel wise application of logical XOR and AND functions. The result is a binary image containing the FPH area plus some additional artefacts considered as noise. Therefore, smaller artefacts are removed by an opening step and the area of the FPH is restricted by a circular mask. Despite these measures, some noise might still remain in the image. Therefore, the number of white pixels is counted. If it exceeds a certain threshold, the result “1” for “FPH detected” is returned and “0” for “no FPH detected” otherwise.

With this algorithm a maximum frame rate of 6 kHz was achieved in closed-loop control mode including image sensing, evaluation, and laser power control. Image saving interrupts this procedure for about 300 µs. Therefore,
saving every 20th image reduces the frame rate to 5.5 kHz. For every thermal image acquired at time \( t_i \) the algorithm returns a binary signal \( s_{FPF}(t_i) \) alternating between the values “1” if the FPH is found or “0” otherwise. For a further increase of the robustness, the mask is shifted automatically to the laser interaction zone at the beginning of the process [8].

5. Stochastic model of the FPH

Figure 4 sketches the important elements from the control system point of view. These are the laser system, the weld process, the FPH detection by the CNN algorithm and the feedback generation for the laser. Both, the laser system and the welding process are continuous in time and linked by the laser beam. The thermal image of the laser interaction zone is acquired by the CNN camera. These images represent discrete time steps \( t_i = i/f \), where \( i \) denotes the image number and \( f \) the sampling rate of the camera. They are evaluated on the CNN for the presence of a FPH, resulting in the signal \( s_{FPF}(t_i) \). From this signal, including its history, a feedback \( \Delta P(t_i) \) is generated in order to adapt the laser power to the current state of the process. In the open-loop system, the feedback is omitted. In this case, the laser power signal \( P(t) \) forms the input and \( s_{FPF}(t_i) \) the output. In this way, the system can be regarded as a discrete time “Single Input, Single Output” (SISO) system.

Considering the time scales, the reaction time of the welding process is the most difficult element to be estimated because of the complexity of the physics involved. One obvious time constant is the value \( \tau_u = l/u \) where \( l \) denotes the diameter of the laser beam and \( u \) the feeding rate. This is the time during which the laser beam irradiates a single point on the weld seam. Thus, it is also the minimum time necessary for the welding process to reach stationarity after a stepwise change of the laser power \( P(t) \). For a beam diameter \( l \) of 0.6 mm and a feeding rate \( u \) of 5 m/min, the value of \( \tau_u \) is 7.2 ms. The transport processes within the melt and the gas phase are much faster. In steel, the velocity of the convection within the melt can exceed the feeding rate \( u \) by a factor of 10 and pressure waves within the gas phase travel at the speed of sound. Therefore, the process might reach approximate values of the equilibrium point much faster. Since the reaction times of the laser system on the signal \( P(t) \) and the delay of the CNN camera in the order of 100 µs are negligible, the reaction time of the whole closed-loop control system is dominated by the welding process and the value \( \tau_u \) might serve as a simplified measure for it.

Using the CNN algorithm described above as FPH detection, the welding process in combination with the CNN camera can be viewed as a discrete time and binary stochastic process with the output signal \( s_{FPF}(t_i) \). This signal alternates between the discrete values 0 and 1 denoting the events “no FPH” and “FPH”, respectively. Thus, the outcome \( \xi = s_{FPF}(t_0) \) at a distinct time \( t_0 \) within the process can be regarded as a random variable. The probability density function \( f(\xi) \) consists of two discrete probabilities \( p_{FPF}(t_0) \) for the events \( \xi = 1 \) and \( (1-p_{FPF}(t_0)) \) for the event \( \xi = 0 \).

\[
f(\xi) = p_{FPF}(t_0) \delta(\xi - 1) + (1 - p_{FPF}(t_0)) \delta(\xi)
\]

If the same process is repeated \( n \) times, the \( n \) outcomes \( \xi_1, ..., \xi_n \) can be treated as \( n \) independent Bernoulli trials [9]. In this case, the probability to observe \( k \) “FPH” events within the \( n \) trials is given by the Binominal distribution

\[
p_n\{k, t_0\} = \binom{n}{k} (p_{FPF}(t_0))^k (1 - p_{FPF}(t_0))^{n-k} \quad \text{with} \quad \binom{n}{k} = \frac{n!}{k!(n-k)!}
\]

The mean value of this distribution corresponds to the number FPH-events expected for \( n \) trials

\[
E\{n, \xi\} = \int_{-\infty}^{\infty} \xi f(\xi) d\xi = n \cdot p_{FPF}(t_0)
\]

The dashed line marks those components implemented in the CNN camera.
The term \( E[n] \) denotes the first moment of the random variable \( n \). Thus, the probability \( p_{\text{FPH}}(t_0) \) can be estimated as the relative frequency \( q_{\text{FPH}} \) of FPH events within a set of \( n \) thermal images

\[
q_{\text{FPH}} = \frac{n_{\text{FPH}}}{n} \approx p_{\text{FPH}}(t_0)
\]  

Here, \( n_{\text{FPH}} \) denotes the number of observed FPH events. This ‘observation’ is either a visual inspection of the thermal images or an automatic evaluation using the CNN algorithm described above. For the visual inspection, each image is shown on the monitor and the user has to divide the images into the categories “FPH”, “no FPH” or “uncertain”. The criteria are the visibility of the FPH and the welding result obtained at time \( t_0 \). Only the first two categories contribute to the number \( n \) of images. In the case of an automatic evaluation, the CNN algorithm is used to count the number \( n_{\text{FPH}} \) of FPH events. The results of the visual inspection serve as a base for the optimization of the algorithm parameters. To obtain a value for the uncertainty of this estimation, the standard deviation \( \sigma_{\text{BIN}} \) of the Binominal distribution can be used

\[
\sigma_{\text{BIN}} = \sqrt{n \cdot p_{\text{FPH}}(t_0) \cdot (1 - p_{\text{FPH}}(t_0))}
\]  

The standard deviation \( \sigma_{\text{BIN}} \) is a measure for the width of the distribution of the \( n_{\text{FPH}} \) values around the expectation value. Applying error propagation to equation (4), the standard deviation of \( p_{\text{FPH}}(t_0) \) becomes

\[
\sigma_{\text{FPH}} = \sqrt{\frac{q_{\text{FPH}}(t_0)}{n} \cdot \left(1 - q_{\text{FPH}}(t_0)\right)} \approx \sqrt{\frac{q_{\text{FPH}}(t_0) \cdot (1 - q_{\text{FPH}}(t_0))}{n}}
\]  

Since the number \( n \) of images is proportional to the sampling rate \( f \), the uncertainty of \( p_{\text{FPH}}(t_0) \) decreases with the square root of \( f \).

For the following measurements, the welding process is considered as a discrete-state stochastic process \( s_{\text{FPH}}(t) \), whose outcome at time \( t \) is characterized by the probability \( p_{\text{FPH}}(t) \) to observe an FPH at time \( t \). This probability depends on the process conditions and it changes when the bottom of the vapour capillary reaches a boundary of the work piece. To estimate it under open loop conditions, equation (4) is applied either to stationary conditions, where \( p_{\text{FPH}} \) is assumed to be constant, or to periodic input signals \( P(t) \). In the later case, images with the same phase \( \omega \) can be treated as independent if the duration \( \tau_p = 2\pi \omega^{-1} \) of the period is sufficiently larger than the reaction time of the welding process estimated as \( \tau_a \).

6. Open-loop characterization

The most interesting relationship is the one between \( p_{\text{FPH}} \) and the stationary laser power \( P \). Instead of a large number of measurements with constant laser powers, a slowly varying triangular input signal \( P(t) \) is applied. Afterwards, the images are classified into discrete laser power intervals of size \( P_i \). These measurements can be considered as “quasi-stationary” if the laser power variation within the time \( \tau_a \) is sufficiently smaller than the interval size \( P_i \). For example, if \( P_i \) is 100 W, the slope \( \dot{P}(t) \) of the triangular signal \( P(t) \) is chosen so that the product \( \dot{P}(t) \tau_a \) is sufficiently smaller. Images acquired within the same power interval are combined to a class. The number of thermal images with FPH is counted by visual inspection.

Figure 5: Relationship between the laser power \( P \) and the relative frequency \( q_{\text{FPH}} \) of FPH events. The hollow blue symbols mark the \( r_{\text{FPH}} \) and \( P_{\text{nom}} \) values from table 1.
The result, i.e. the relative frequency \( q_{FPH} \) of FPH events at a certain laser power \( P \), is shown in figure 5. The welding geometry was an overlap-joint as sketched in figure 1 with two sheets of an AlMgSi alloy of thickness 1.2 mm and without gap. The laser power interval \( P_i \) was 100 W in a range of 3000 to 5000 W. For each feeding rate, about 3100 images were evaluated, resulting in 20 power classes with an average of 150 FPH results per class. For every class, the probability \( p_{FPH} \) was estimated by calculating the \( q_{FPH} \) values according to equation (4). The values obtained for a feeding rate of 3 m/min show an almost linear dependency between the laser power \( P \) and the probability \( q_{FPH} \) to observe an FPH. This linear relationship is visualized by a straight line and the scattering of the measurement points is apparently caused by the limited number of observations. The behaviour of those measurement points obtained for the higher feeding rate of 5 m/min is slightly different. There, the linear relationship is only observed within the range of 3600 to 5000 W. At lower laser power values, a significant increase is observed. A comparison with similar measurements carried out on zinc coated steel indicates that this increase might be caused by the gap [10].

Figure 6 shows typical thermal images acquired from aluminum welding processes. The full penetration holes are clearly visible. In contrast to steel, the melt pool is much darker due to the lower melting temperature. Instead, bright spots appear on the front side of the keyhole which is presumably caused by the aluminum oxide. Fortunately, these spots do not influence the CNN algorithm. The most important difference is the fluctuating intensity of the keyhole walls. On steel, this intensity was almost constant in the thermal image because the keyhole walls are at vapor temperature. Therefore, the faster linear algorithm [11] did not achieve sufficient detection rates whereas the omnidirectional one was better than 90%.

The second important issue is the characterization of the transient behavior of the probability \( p_{FPH}(t) \). For this purpose, a periodic rectangular laser power signal \( P(t) \) with period \( \tau_P \) is applied to the open-loop system. From the different periods, images with similar phase \( \varphi = \omega t \) with \( \omega = 2\pi \tau_P^{-1} \) are combined to a class. In order to obtain a sufficient statistics, the automatic evaluation result of the CNN algorithm was used. This algorithm was trained using the visual reference which was used in figure 5, too. Figure 7 shows the result of the automatic evaluation of 23400 images acquired with a rectangular signal \( P(t) \) with period \( \tau_P \) of 130 ms. This period is divided into 130 classes where the phase shift \( \Delta \varphi \) within each class corresponds to a time shift \( \Delta t \) of one millisecond: \( \Delta t = \Delta \varphi \tau_P / 2\pi = 1 \) ms. The resulting class size is 180 images per class. The probability to observe a FPH within each class is again estimated by calculating the \( q_{FPH} \) values according to equation (4).

Figure 7 shows the \( q_{FPH} \) values calculated for each of the 130 classes together with one period of the input signal \( P(t) \). The laser power drawn as black line alternates between 3500 and 4500 W. The red dots mark the \( q_{FPH} \) values calculated for each class. The length of the error bars is the standard deviation \( \sigma_{BIN} \) calculated after equation (6). Starting at the rising edge of the laser.
power signal, the graph can be divided into four regions: Between 40 and 48 ms, transient behavior of \( q_{FPH} \) is observed. Between \( t = 48 \) ms and the falling edge at 105 ms, the \( q_{FPH} \) values scatter around a stationary value of about 58 %. At the falling edge, a second transient region is observed. In contrast to the transient region at the rising edge, this region is significantly shorter. The mean \( q_{FPH} \) value of the second stationary region with a laser power of 3500 W is already reached after about 2 ms. Afterwards, in the range between \( t = 107 \) ms and 130 ms of one period and \( t = 0 \) to 40 ms of the next period, stationary behavior is observed again. Due to the lower laser power of 3500 W, full penetration holes are measured with an average probability of about 16 %.

In figure 7, the error bars are calculated using the assumption that the distribution of the number \( n_{FPH} \) of FPH events within a class of \( n \) images is given by the Binominal distribution. To test this assumption, the distribution of the \( n_{FPH} \) values within the stationary regions, where the probability \( p_{FPH}(t) \) can be considered to be constant, is compared to the probability of the number \( k \) in equation (2). To do this, \( n_{FPH} \) is treated as a random variable and the probability \( p_k \) is defined as the probability that \( n_{FPH} \) is smaller or equal than the number \( k \).

For the results shown in figure 8, those classes of figure 7 were evaluated which lie in the stationary regions. At the laser power of 4500 W, the 49 classes between \( t = 50 \) ms and \( t = 100 \) ms were evaluated. There, the average probability over all classes to observe an FPH was 58.3 %. For the stationary region at 3500 W, the 49 classes with \( t \geq 115 \) ms and \( t \leq 35 \) ms were evaluated. There, the average probability for an observation of an FPH was 16.1 %. For each number \( k \), the following empirical estimate for \( p_k \) was used

\[
p_k(k) = \frac{n_k}{n_c} \tag{7}
\]

Here, \( n_k \) denotes the number of those classes within a stationary region whose number \( n_{FPH} \) of observed full penetration holes is smaller or equal to \( k \); the number \( n_c \) is the total number of classes within a stationary region. In figure 8, the value of \( n_c \) is 49. The distribution of the measured values for each value of \( k \) was compared to the cumulative Binominal distributions with \( n = 49 \) and the probabilities \( p_{FPH} \) of 16.1 % in the 3500 W region and 58.3 % in the 4500 W region, respectively. The maximum deviations \( \Delta p_{\text{max}} \) are 11.0 % in the first case and 9.3 % in the second one. This shows that the Binominal distribution agrees quite well with the measured distribution.

### 7. Closed-loop control

For the closed-loop control system sketched in figure 4, a robust feedback strategy is required. A simple strategy is to start with an initial value \( P_0 \) and to adapt this value after every acquired image. If no FPH is observed, a value \( \Delta P_{\text{up}} \) is added to the current laser power \( P(t) \); otherwise, a value \( \Delta P_{\text{down}} \) is subtracted. As shown in figure 5, the probability to detect a FPH rises with increasing laser power \( P \). Therefore, such a system reaches its operating point, i.e. the average laser power over a time interval \( T_{\text{S}} \) is constant when the following equilibrium condition is fulfilled

\[
r_s \Delta P_{\text{down}} = (1 - r_s) \Delta P_{\text{up}} \tag{8}
\]

In this equation, the ratio \( r_s \) denotes the relative frequency of FPH events within the images acquired over a time span \( T_{\text{S}} \). The left side of equation (8) describes the frequency with which the laser power is lowered, the right side the frequency of raising the laser power. The sign of both, \( \Delta P_{\text{up}} \) and \( \Delta P_{\text{down}} \) is chosen positive. Resolving equation (8) for \( r_s \), one obtains
This control strategy together with measurement results was described in [4]. It was shown that such a system oscillates around an average laser power $P_S$. One can use figure 5 to estimate the approximate value of $P_S$ if one equalizes the quantities $q_{FPH}$ and $r_S$. Both quantities measure relative frequencies, but $q_{FPH}$ is measured over several periods whereas $r_S$ is an time average. Thus, they can differ because the $q_{FPH}$ values represent ensemble mean values whereas the $r_S$ values are averaged over time.

Figure 9 shows the $P(t)$ signals and weld seams of two laser welding processes with different nominal set points $r_S$ under constant process conditions. Both start from the same initial laser power value $P_0$ of 3500 W, which is too low for full penetration. Therefore, the laser power is increased automatically until the process reaches a stationary full penetration state after about 150 ms. Afterwards, the process remains more or less constant until the laser is switched off after 900 ms. In this constant regime, the average laser power of the two processes differs by about 250 W. As figure 9e shows, this reduction in the laser power results in a reduced seam width on the bottom side.

Table 1 lists statistical results for six welding processes under constant conditions but different nominal set points $r_S$. The processes in figure 8 are the processes number 1 and 6 from table 1. For comparison, the relative frequencies $r_{FPH}$ of FPH events measured in the stationary regime between 180 and 880 ms are listed, too. These values are slightly lower than the $r_S$ values, what might be explained by the difference in transient behavior at the rising and falling edge of the rectangle signal (figure 7). The mean values $P_{mean}$ of the laser power in the stationary range rise about 250 W when the set point $r_S$ is shifted from 20 to 33 %. The standard deviation $\sigma_P$ of the laser power – which might serve as a measure for the quality of the closed-loop control system - lies in the range of 50 to 80 W. This is about 2 % of the average laser power.

Table 1: Statistical results from welding processes under constant process conditions. Sheet thickness is 1.2 mm and feeding rate is 5 m/min.

<table>
<thead>
<tr>
<th>No</th>
<th>Parameters</th>
<th>$r_S$</th>
<th>$r_{FPH}$</th>
<th>$P_{mean}$</th>
<th>$\sigma_P$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\Delta P_{\text{up}} = 5 \text{ W}, \Delta P_{\text{down}} = 10 \text{ W}$</td>
<td>33.3 %</td>
<td>30.7 %</td>
<td>4054 W</td>
<td>57 W</td>
</tr>
<tr>
<td>2</td>
<td>$\Delta P_{\text{up}} = 5 \text{ W}, \Delta P_{\text{down}} = 10 \text{ W}$</td>
<td>33.3 %</td>
<td>29.8 %</td>
<td>4068 W</td>
<td>77 W</td>
</tr>
<tr>
<td>3</td>
<td>$\Delta P_{\text{up}} = 5 \text{ W}, \Delta P_{\text{down}} = 15 \text{ W}$</td>
<td>25.0 %</td>
<td>21.3 %</td>
<td>3887 W</td>
<td>56 W</td>
</tr>
<tr>
<td>4</td>
<td>$\Delta P_{\text{up}} = 5 \text{ W}, \Delta P_{\text{down}} = 15 \text{ W}$</td>
<td>25.0 %</td>
<td>21.5 %</td>
<td>3898 W</td>
<td>71 W</td>
</tr>
<tr>
<td>5</td>
<td>$\Delta P_{\text{up}} = 5 \text{ W}, \Delta P_{\text{down}} = 20 \text{ W}$</td>
<td>20.0 %</td>
<td>16.9 %</td>
<td>3851 W</td>
<td>72 W</td>
</tr>
<tr>
<td>6</td>
<td>$\Delta P_{\text{up}} = 5 \text{ W}, \Delta P_{\text{down}} = 20 \text{ W}$</td>
<td>20.0 %</td>
<td>17.0 %</td>
<td>3785 W</td>
<td>80 W</td>
</tr>
</tbody>
</table>
In order to compare these results with the \( q_{FPH} \) values measured under open-loop conditions, the \( r_{FPH} \) and \( P_{\text{mean}} \) values from table 1 are drawn in figure 5. Although the \( r_{FPH} \) values are measured as time average values under closed-loop conditions, they fit very well to the quasi-stationary curves measured under open-loop conditions. Therefore the open-loop measurement with a triangular laser power signal is regarded as a suitable method to characterize the closed-loop control system.

![Figure 10: Closed-loop controlled welding at two different sheet thicknesses and variable feeding rates. Laser power signal (a), upper weld seams on sheets with thickness 1.2 mm (b) and 1.5 mm (c), lower weld seams on sheets with thickness 1.2 mm (d) and 1.5 mm (f).](image)

The final test was a dynamic test where the feeding rate was decreased from 5 to 3 m/min during the welding process. In addition, the same welding process – an overlap-joint with nominal gap size 0 mm – was repeated with thicker sheets (1.5 mm instead of 1.2 mm). All control parameters with the exception of the initial laser power \( P_0 \) were the same. As the signals \( P(t) \) in figure 10a show, the laser power is adapted automatically to the increased sheet thickness as well as to the lowered feeding rate. The images of the weld seams on the right side show a slightly increased seam width on the bottom seam at 3 m/min. The difference in the sheet thickness is completely compensated by the closed-loop control system.

8. Conclusion

We have discussed the expansion of a closed-loop control concept as it was thoroughly demonstrated for zinc coated steel sheets [4, 12] to aluminum of type AA 6014. This alloy can be welded without additives or shielding gas. The setup is identical to the one used for steel welding. It uses a CNN camera as a fast and intelligent detector for the full penetration hole. The major difference found is the appearance of the full penetration hole in the thermal image. Due to the lower melting temperature, the melt is hardly visible on aluminum. Instead, bright spots occur which are presumably caused by the aluminum oxide. For the CNN algorithm, the most important difference is that the intensity of the keyhole walls varies significantly more than on steel sheet. These intensity variations are the reason why the fast linear algorithm did not work. Therefore the omnidirectional algorithm with a reduced frame rate of 6 kHz had to be used. Nevertheless, it was shown that the closed-loop control system is able to compensate variations of the feeding rate as well as different sheet thickness.

This paper presents for the first time a stochastic model for the relation between the probability to detect a full penetration hole and the laser power. Within this model the opening and closing of the full penetration hole at the bottom side of the keyhole is regarded as a stochastic process whose distribution is described by the Binominal distribution. Based on this model, methods for a quantitative open-loop characterization based on periodic laser power signals are presented. With these methods the relationship between the probability \( p_{FPH} \) for the occurrence of a full penetration hole and the laser power \( P \) is estimated by a quasi-stationary measurement method. The transient response of the probability \( p_{FPH} \) at the edges of a rectangle laser power signal indicates that the control system is
nonlinear. From this mode a robust control strategy was derived which allows to adapt the average laser power of the closed-loop control system despite the binary detection of the full penetration hole. The standard deviation of the laser power in closed-loop control mode was in the order of 2%.

These results demonstrate that the closed-loop control principle can be transferred from steel to aluminum for full penetration weld seams. Such a system maintains the full penetration state under an augmented range of welding parameters. The major benefit is a constant seam quality and an increased process stability because process drifts due to polluted protection windows, variable focus positions or feeding rates are compensated.

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