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Laser welding: high volume manufacturing for E-mobility

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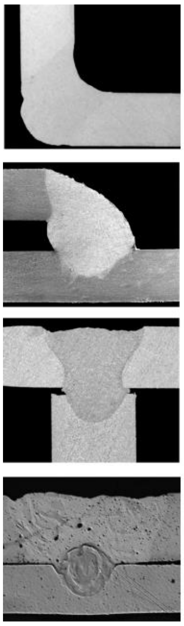
ABSTRACT

Motivated by the growth of the e-mobility sector and the fact that large arrays of welds are required for each finished assembly, this article first reviews some of the most established and adopted sensor technologies and closed-loop control strategies for laser beam welding; and, then discusses current challenges and future perspectives towards the full digitalisation of the laser beam welding in line with the current trend of Industry 4.0 and Industrial Internet of Things.

LASER WELDING IN E-MOBILITY: SITUATION TODAY



Material/thickness: AA6060, 2.5 mm
Joint geometry: corner weld
Application: battery enclosure (corner node)
Process speed: 80 mm/s

Material/thickness: AA6060, 1.5 mm
Joint geometry: fillet weld with gap bridging
Application: battery module/enclosure
Process speed: 100 mm/s

Material/thickness: AA1050, 1.5 mm to 2 mm
Joint geometry: through thickness weld
Application: battery bus-bars
Process speed: 120 mm/s

Material/thickness: AA1050 450 μm to Cu 300 μm
Joint geometry: lap weld
Application: battery tab
Process speed: 300 mm/s

Figure 1. Typical weldments (both similar and dissimilar materials) obtained by remote laser welding technology.

Laser Beam Welding (LBW) currently covers between 60% to 80% of all joining for e-mobility manufacturing for high-volume production above 150k vehicles/year [1]. Typical battery systems comprise hairpins, contact and terminals, bus-bars, modules/pack and enclosures. These are complex assemblies that involve multiple layers of dissimilar materials (copper, aluminium, nickel, steel) with a wide range of thicknesses (from tens of microns to few millimetres), and multiple fabrication processes (forming, casting, extrusion). Figure 1 shows typical weldments obtained with remote laser welding (no filler wire and no shielding gas). The high flexibility of current LBW technologies allows to introduce sophisticated welding patterns, fast beam re-positioning, laser power modulation and beam shaping. The combination of these features has been proven successful to weld challenging materials such as non-ferrous alloys and highly reflective materials. The manufacturing of each battery pack requires joining a large number of connections - up to 20,000. One single defective weld can cause the scrap of the whole battery pack [2]. Re-weld of a defective weld though possible, nonetheless, increases the tendency of cracks formation and brittle intermetallics - the latter applies especially to dissimilar material welding. Therefore, monitoring and control of the weld quality can significantly reduce scrap rate. Additionally, control strategies can help to increase weld durability and prevent weld degradation. Reports have indicated that weld degradation can ultimate in the catastrophic event of thermal runaway [3]. It is therefore clear that the classical 6-sigma approach currently in use in automotive industry for quality control must be revisited to accommodate for zero-defect manufacturing strategy.

AUTONOMOUS ASSEMBLY SYSTEMS: WHERE DO WE STAND WITH LASER BEAM WELDING?

There is undoubtedly a gradual transition towards autonomous assembly and welding systems brought on by tools from Industry 4.0 such as Machine Learning (ML) / Artificial Intelligence (AI) and computer-aided physical simulations [4]. Those tools hold promises of improving productivity and

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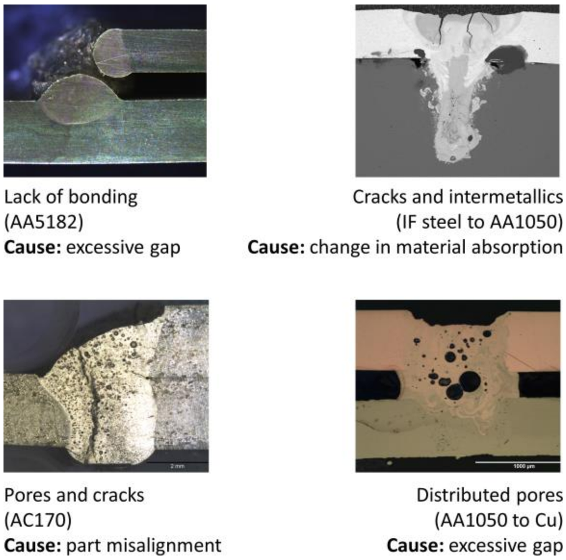

Figure 2. Example of defective welds.

quality (towards zero-defect), optimise energy consumption and reduce scrap. Rather than relying entirely on the open-loop nature of traditional welding process development – meaning robust design optimisation and then "reactive" adjustment of the process parameters on the production line to satisfy the design tolerances - autonomous production systems leverage a number of digital twin assets which gather in-process data and in real-time, and provide continuous feedback information for "predictive" decision making. Sensor technologies play a pivotal role since they serve as the "surveillant" of a process. The need for sensor technologies is very timely indeed for the explosive growth of the e-mobility where large number of joints are generated for each assembly. While LBW has been rapidly absorbed by the industry, the sensor technology itself is lagging for industry 4.0 requirements especially when it comes to providing closed-loop feedback.

WELD QUALITY AND SENSOR TECHNOLOGY

The quality of laser weldments is assessed by measuring multiple features such as: (1) surface features – for example, melt pool width, concavity, convexity; and, (2) sub-surface features – for example, weld depth, interface width, weld pores and cracks. Figure 2 shows typical weld defects which are encountered while welding similar and dissimilar materials. Direct measurement of surface features is a well-established area and comprises of CMOS/CCD camera-based or laser-based sensors. While multiple sensors can be installed on the same laser welding head to measure multiple features, direct measurement of sub-surface features remains an un-solved problem. Sub-surface features are ultimately what drives the functional performances of the weld, along with mechanical, durability and electrical resistance (in those applications involving electrical connectors). There have been few efforts in recent years to address sub-surface feature monitoring. High-speed X-ray [5] offers the superior capability to detect weld pores (and eventually micro-cracks) at high spatial and temporal resolution (below 500 µm). However, X-ray inspection is only used for off-line process characterisation – applications to full scale in-process monitoring are currently disregarded owing to high implementation costs and safety hurdles. Latest advancements in Optical Coherence

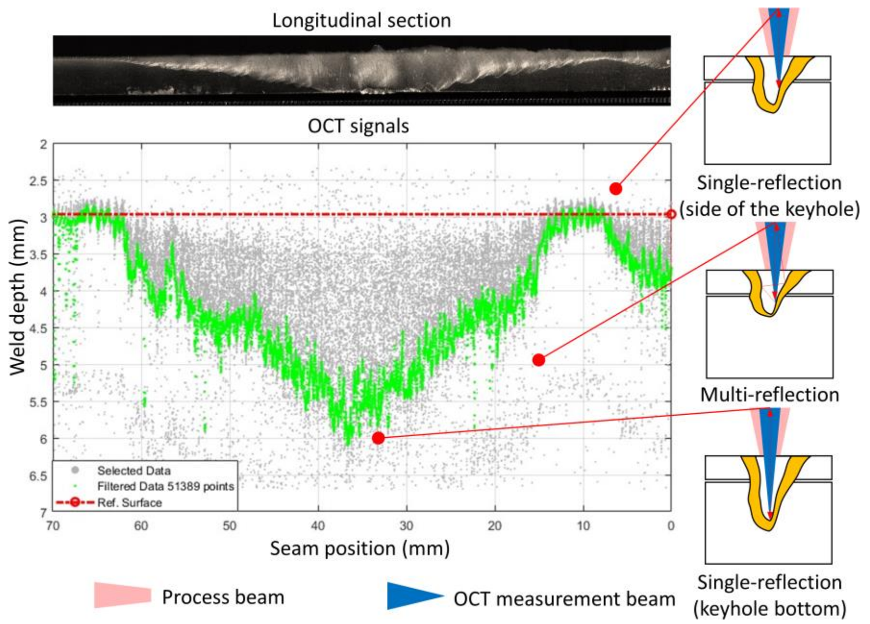

Figure 3. Typical signal generated by OCT technology. Adapted from [10].

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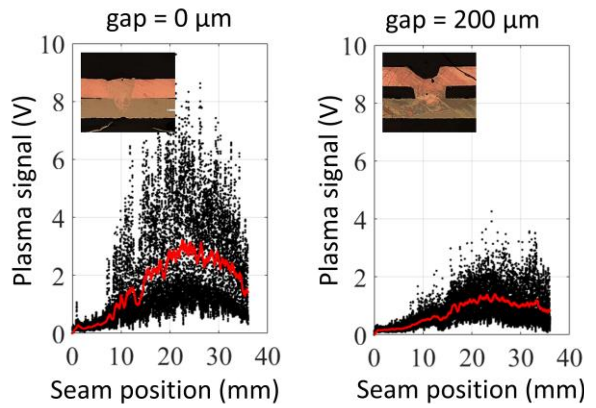

Figure 4. Example of plasma signals - variable part-to-part gap for 200 μm Cu to 300 μm steel (the red curve is the filtered signal, while black dots are raw data).

Tomography (OCT) have shown promising results towards direct measurement of weld penetration depth (Figure 3 shows typical OCT signals). For example in [6], OCT has been combined with Adjustable Ring Mode laser for battery tabs connectors (450 μm aluminium to 300 μm copper). Results showed that the OCT sensor was capable of direct measurement of the weld penetration depth with accuracy within 100 μm, when compared to off-line/off-process metallographic analysis. However, the study concluded that the accuracy was highly sensitive to the selection of the welding process parameters. As such, the sensor needed to be re-calibrated every time any process parameter was about to be changed. Furthermore, the absence of the keyhole mode would have made the OCT sensor unsuitable for measuring the weld penetration depth. The sensitivity to welding process parameters is overcome by those sensors which passively observe process emissions. Photodiodes are the most established sensors in this category. While photodiode-based monitoring has been largely implemented for structural welds – such as, door closures, seat frames and side frames in automotive body construction - applications for welding of thin foils and dissimilar metals remain an uncharted area of investigation. We have recently demonstrated that both part-to-part gap and laser power variations can be diagnosed by observing the step-change in the plasma signal. Figure 4 illustrates representative plasma signals with varying part-to-part gap. However, those results have limitations due to the fact that the photodiodes only provide indirect measurements in the form of correlated signals (plasma, temperature and back-reflection) to the actual welding features. A good example which re-affirms the inefficiency of indirect measurements is shown in Figure 5 (class[1]: lack of bonding; class[2]: over-penetrated weld; class[3]: sound weld). Though the correlation between plasma and weld depth is approximately 90% and the cases with over-penetrated welds are well diagnosed (i.e., weld (5) and (6)), this is not sufficient to provide full diagnosability of weld defects. For instance, weld (1) – clear lack of bonding but total fusion of the bottom plate – shows comparable level of plasma generated in weld (2) – which is a sound weld. Additionally, determining the correlation demands lengthy metallographic

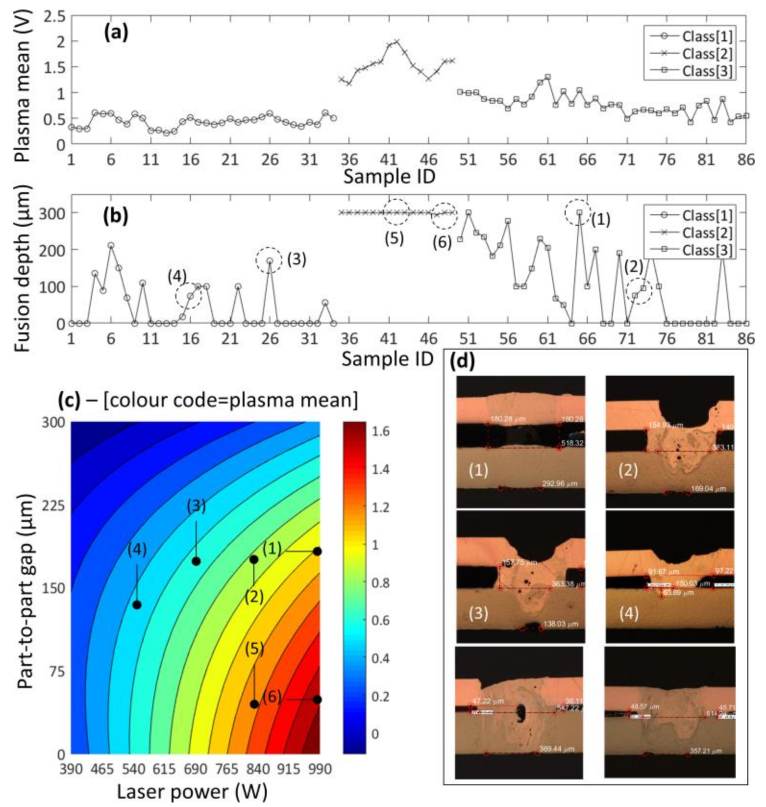

Figure 5. Example of process monitoring via photodiode-based signal (200 μm Cu to 300 μm steel). (a) plasma signal; (b) weld fusion depth measured via metallographic analysis; (c) process parameters mapped against plasma signal; (d) representative cross-sections.

analyses, which incur significant cost and manual labour.

FEEDBACK CONTROL SYSTEMS

Only single-feature control systems have been common for the control of LBW, where either the laser power or the focal position is used as control parameter to maintain a reference value of the weld penetration [7]. Other good examples are seam tracking and gap bridging control systems that cope with the intrinsic manufacturing tolerances (i.e., gap and trim edge variation). However, irrespective of the material quality and manufacturing tolerances, the LBW system needs to be manually re-optimised and re-calibrated every time a new scenario is introduced (i.e., new material alloy, part geometry, processing conditions, etc.). This incurs costly and lengthy optimisation loops. ML/AI principles offer the tools to overcome current limitations and set-up automated feedback control systems. Despite the potential, applications of ML/AI in LBW for closed-loop control systems are still at an infancy [8]. Major challenges arise first from the substantially limited amount of process data – ML/AI methods are data-hungry and they require large amount of data to train the models and determine predominant patterns. Large datasets are rare in LBW applications. This is due to cost and time required to generate experimental samples. Second, it can be argued that conventional ML/AI approaches can find complex non-linear patterns but they are only reliable in the subdomain in which they have been derived and trained, and therefore they may be unable to accurately characterise un-trained cases with a large variety of material property profiles (chemical composition, thermal and rheological properties), and product variants (part geometry, joint geometry, thickness, etc.). Third, it is also worth noting that while ML/AI-based models have showed outstanding performances towards the generation of actionable models for adaptive control, they fail to explain the causality between input process parameters and outputs variables.

The aforementioned challenges could be overcome by the model-driven controllers which, rather than inferring the control law from a "black-box" data-driven model, make direct use of the first-principle physical equations. Nonetheless, applications of physics-based controllers have been rarely reported owing to the inherent highly complex underlying physical phenomena [9] involved in LBW. These phenomena include multiple reflections (also known as Fresnel reflections), Marangoni and buoyancy effects and recoil pressure, and complex thermal-mechanical-fluid coupling. Those complex mechanisms have been widely studied by the applied physics community which has developed highly accurate models for the purpose of off-line optimisation of process parameters. The cost of such accuracy is the computational complexity and especially in time critical applications such as in-process monitoring and feedback control, the real-time evaluation of a complex physics-based model requires prohibitive amounts of computational power. Paradoxically the best feature of LBW, its speed (up to 4000 mm/s for extreme high-speed processes), is also the greatest threat when it comes to in-process monitoring and control – for instance, higher processing speeds and variable computational delays can affect the spatial and temporal resolution of the monitoring device, and the stability of the control architecture.

FUTURE PERSPECTIVES

Motivated by stringent requirements brought by the growing e-mobility sector and the fact that large arrays of welds are required to produce each finished assembly, novel methodologies and technologies are urgently needed to uplift current laser welding solutions to make them Industry 4.0-compatible. A bolder approach is to use a combined methodology, which makes use of the strength of both ML/AI-based methods and physics-based models, and fuse them with best-in-class sensors. Although this seems daunting, with the emergence of digital technologies and large computations available on multi-core Graphics Processor Units (GPUs), the time is now ripe to address the issues of in-process monitoring and adaptive feedback control of multiple weld features. Further developments are expected in the forthcoming years that will pave the way towards full digitalisation of the LBW technology in line with the current trend of Industry 4.0 and Industrial Internet of Things.

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