PROGNOSIS OF SEAM GEOMETRY DURING LASER BEAM WELDING

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ABSTRACT

Data evaluation is of great importance for quality assurance and control loops. Components and process parameters involved in the production process can be networked and evaluated using all relevant information and controlled in real time. Thermal joining processes are complex; so is laser beam welding (LBW). The numerical description of the processes provides good approximations for partial aspects. However, experiments are still the basis for determining optimal process parameters. This is time-consuming and cost-intensive.

For the evaluation of experimental data there are some AI approaches; e.g. response surface method, Taguchi method, KNN models, Kriging models, principal component analysis (PCA). Systematic backup, analysis and visualization of welding and quality data using database systems and analysis algorithms is not currently taking place on a wide scale. Expert knowledge is a mandatory prerequisite for the preparation, execution and evaluation of LBW processes. Therefore, the potentials of the process are often not fully exploited. The consequences are e.g. long commissioning times, low flexibility for new tasks and missing objective knowledge management.

In the lecture a tool based on PCA will be presented. The interdependencies between process parameters and the welding result in the form of the 2D weld geometry are mapped in a statistical model. The system is learned from experimental data sets. The weld geometry can contain further characteristic values; e.g. weld penetration depth, weld width or load-bearing weld cross-section. These characteristic values can be linked to the quality of the welded joint. The two-dimensional weld formation and all contained spatially resolved result variables can be represented; e.g. width of heat affected zones and grain size distribution. This requires the analysis of multivariate data; e.g. micrographs with a pixel number of several million, as dependent result variables with all nonlinear dependencies. To realize the spatial resolution of the result variables, the full pixel resolution is used for image analysis. From the formed statistical model, the seam geometry with all properties can be predicted ad hoc within the learned data space for arbitrary parameter combinations, or local target variables can be specified and an optimization algorithm searches for the best possible parameter combination from many model queries. Using an LBW task as an example, the evaluation principle and the GUI are shown. Key points are the permanent accumulation of knowledge, usable control strategies, quality proofs and thus time and cost savings.

Keywords: Seamprognosis; measurement data; principal component analysis; spatially resolved result variables

INTRODUCTION

Individual operations or several operations in a process chain always have influencing variables; some can be easily influenced (controlled variables) and some are difficult to influence. In the complex operation of laser welding LBW, controllable influencing variables are e.g. feed rate, focus position and power; difficult to influence is usually the task, i.e. the materials to be welded. At present, theoretical control of the LBW-process is not sufficient to dispense with experiments. Therefore, the welding parameters are mainly determined experimentally (Fig. 1).

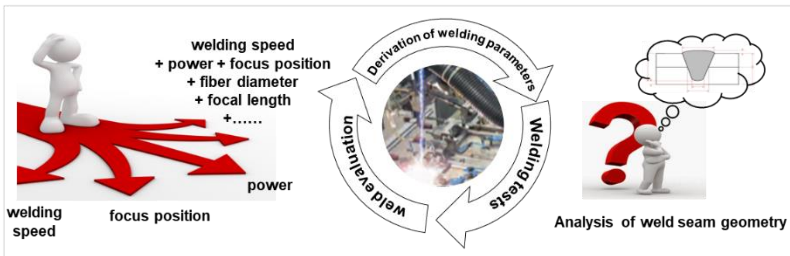

Fig. 1 Iterative approach to experience-based welding parameter determination

There is not always sufficient time available for test series. Technological decisions often have to be made on the basis of subjective empirical values. Potentials of the processes are not exploited to the full extent. For manufacturing companies, problems arise during preparation due to long commissioning times and during processing due to non-optimal parameters.

This situation is exacerbated by the increasing individualization of production. The development is characterized by the increase of small series, one-off productions or changing component derivatives within a series production. Rapid adaptation of technology parameters to new production tasks is required. This flexibility demanded by customers poses great challenges for plant manufacturers as well as for the supply industry and contract manufacturers.

Therefore, the following objectives are pursued:

- Predict welding parameters for desired seam geometries without time-, material- and energy-intensive welding tests; that leads to fast, efficient, accurate planning processes
- improvement of quality through optimal parameter selection
- fast commissioning of welding systems even for batch size 1; making uneconomical orders profitable
- Process stabilization in automatic control loops
- make welding knowledge independent of people; constantly expand know-how.

The analysis of complex data makes sense only if a large number of setting parameters are required and the user therefore has difficulty in keeping track of the interdependencies between input variables and welding results.

STATE OF THE ART

Data evaluation is of great importance for quality assurance and control loops. Components and process parameters involved in the production process can be networked and evaluated using all relevant information and controlled in real time.

Transforming the experiential knowledge of experts into usable algorithms has been the subject of research for years. For the evaluation of experimental data there are some AI approaches [1]; e.g. Response Surface Method [2], Taguchi method [3], Neuronal Network models [4], Kriging models [5], Principal Component Analysis (PCA) [6].

As parameter studies carried out on various manufacturing processes, PCA makes it possible to analyze multivariate data with a high number of input and dependent result variables - up to the range of millions [7]. Thus, complex nonlinear dependencies can be spatially resolved and mapped with good accuracy by statistical methods.

COUPLED PROCESS ANALYSIS

Coupled Process Analysis (CPA) is discussed in [8-10].

A number of 12 tests were performed to realise a prediction in this data space from experimental data with the CPA-Tool. In Fig. 2 the processing cycle of CPA is shown beginning with a Design Of Experiments (DOE).

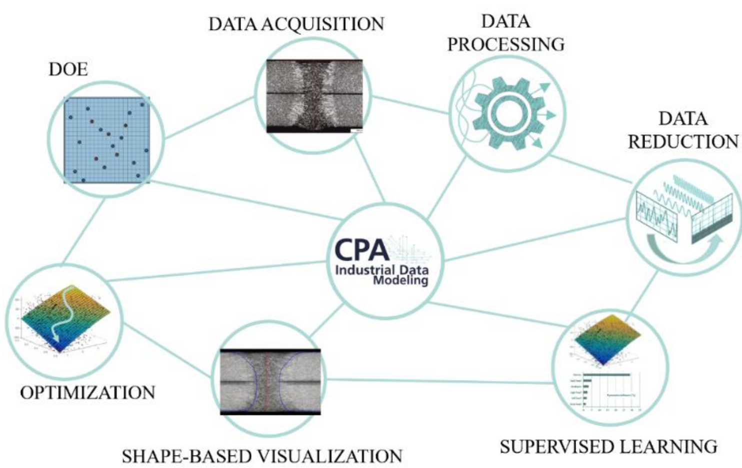

Fig. 2 CPA - processing cycle

There are indications that the acquisition of complex experimental data represents reality better and more efficiently than the attempt of numerical description. But, also targeted experiments to determine material properties [11] or serial measurements to describe processes are costly. This data acquisition incl. the preparation of the data for automatic machine readability are often 90% and more of the expenses for a successful AI project. Therefore, minimizing the experiments by maximizing the use of the data is an important criterion.

For the realized LBW task, the input variables with the selected data space are shown in Table 1; the fixed boundary conditions are shown in Table 2. As DOE a Latin Hypercube Sampling was used to determine the variable parameters for the 12 weld tests; see Table 3.

Table 1 Data space of the input variables

Input variable	min	max
welding speed [m/min]	1,5	5
Power [kW]	2	5
Focus position (mm)	-4	5

Table 2 Fixed boundary conditions

description	Value (const.)
Laser source	Disk laser Trumpf „TruDisk 10002“
Fiber diameter	0,4 mm
Welding optic	Trumpf MSO (focal length 200 mm)
Base material	Steel (DC04) / thickness 1,0 mm / uncoated
Weld configuration	lap joint in flat position

Table 3 Variable laser parameters

Test	Test Speed [m/min]	Power [kW]	Focus Position [mm]
1	2,83	2,83	2
2	3,17	2	3
3	4,5	3,13	1
4	1,5	4,62	-2
5	1,83	5	-4
6	4,17	3,37	0
7	5	3,37	0
8	1	2,62	5
9	2,5	4,12	-3
10	2,17	2,88	-1
11	3,83	2,38	5
12	3,5	4,38	4

Data acquisition is carried out on the prepared 12 cross sections in high pixel resolution. An example for a narrow seam, see Fig. 3, welded at higher speed and lower power. For a wide seam see Fig. 4, welded at lower speed and higher power.

The images were taken in a high resolution with millions of pixels; each with a gray value between 1 and 256. Suitable algorithms for image preprocessing and feature extraction are available open-source [12] as well as commercially. For supervised learning classifiers up to complex neural networks, a wide range of methods exists [13].

In addition to the gray values, color and texture features can also be recorded in order to make statements about the microstructure; e.g. about the grain size distribution.

Data processing means make the data machine readable. The LBW-micrographs will be formatted to the same size, i.e. to an identical number of pixels.

Classically, the relationship to the input variables could be mapped in an extra metamodel for each pixel. This does not make sense with current computing technology. So data reduction based on PCA is used.

Supervised learning on the basis of Python-based engines determines the best mathematical approximations for various relationships. Automatic model building takes place in the reduced data space. Often simple polynomial approaches are sufficient for the description. In the case of the LBW task, 5 modes with maximum quadratic terms resulted. Based on the created analytical model, input variables with only minimal influence can be sorted out in a sensitivity analysis. In the present case with only three input variables, no parameter was sorted out.

A dynamic shape-based visualization for arbitrary parameter combinations is performed. This GUI of the relationships can be automated by analytically calculating a large number of variants for a desired target variable in an optimization run and determining the parameter combination that best satisfies the target variable.

The whole cycle can be repeated if the model quality does not meet the set requirements. In this case, a new DOE is created with a serial Latin Hypercube Sampling, whereby only new values for the variables are specified.

LASERTOOL

In [14] the LBW-example was published for the first time. In the following the evaluation principle and the GUI are shown.

The 2D virtual micrograph is represented by different gray values, the fusion line - the boundary between laser weld seam and heat affected zone - by two blue lines. The data for the blue lines were determined manually in the 12 micrographs and then approximated. See Fig. 3 and 4 to compare the real micrograph with the image from the virtual model.

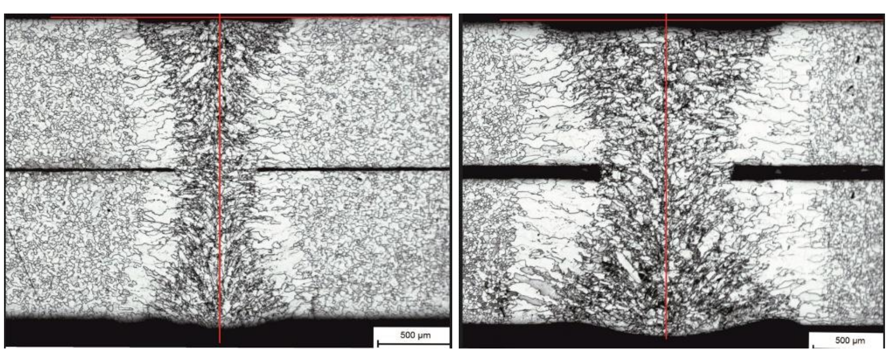

Fig. 3 Cross sections from experiment; Test 7 left; Test 12 right

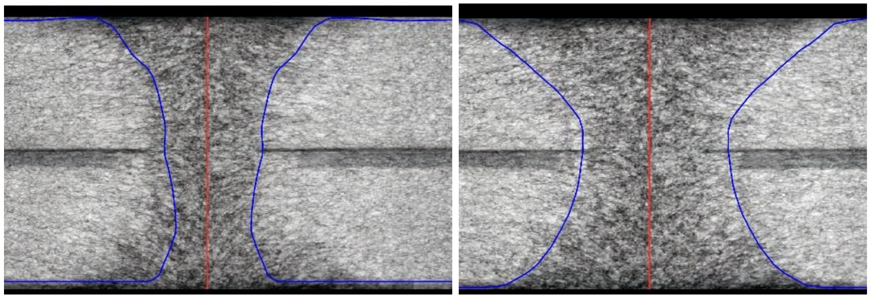

Fig. 4 Shape-based visualization with grey values and blue fusion line from metamodel; Test 7 left; 12 right

Fig. 6 shows the Graphic User Interface.
The two target variables – grey values and blue lines - are each represented by a separate metamodel.

Model-based generation of a 2D virtual micrograph with the geometry of the heat-affected zone and the fusion area of the laser weld seam for various parameter combinations is possible in real time – see Fig. 5 and 6 for process chain and GUI.

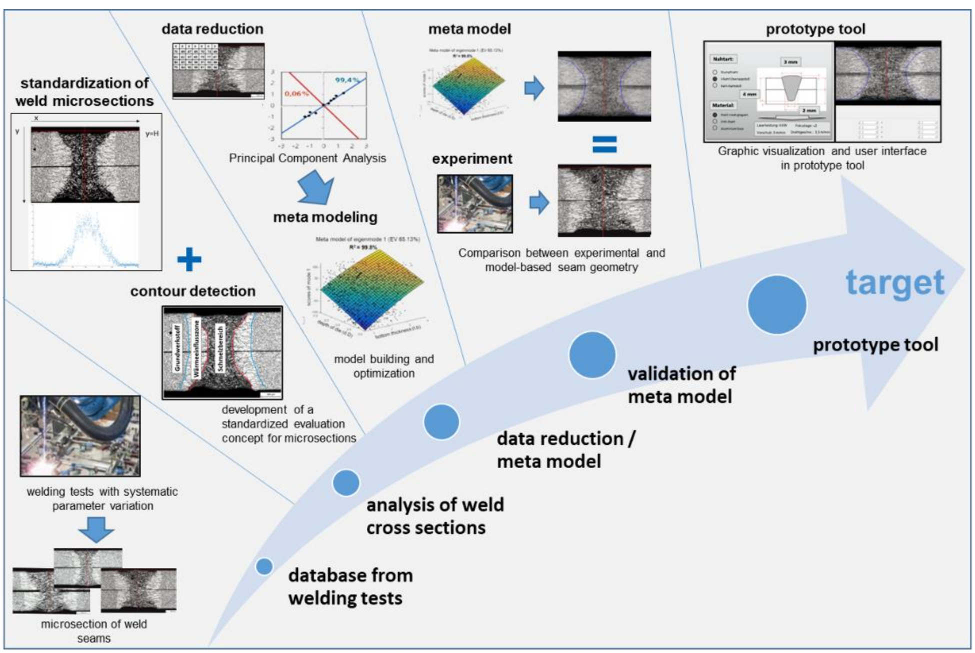

Fig. 5 Shape-based visualization with grey values and blue fusion line from metamodel; Test 7 left; 12 right

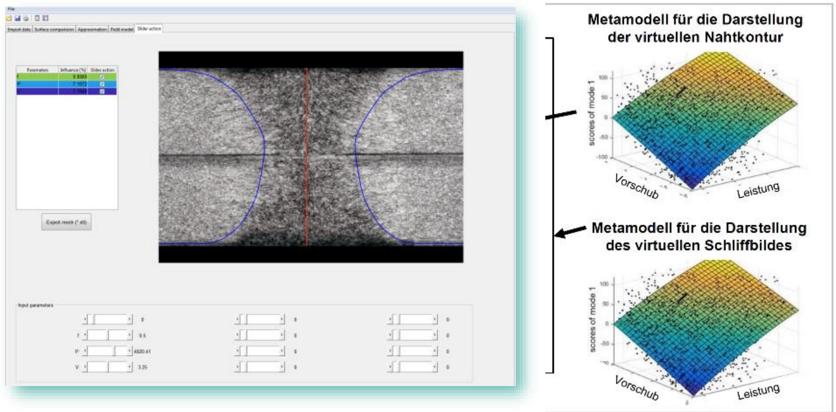

Fig. 6 GUI Virtual, shape-based visualization

OUTLOOK

Many other influence parameters have an impact on the process; e.g. process gas or laser parameters (e.g. laser beam wavelength, fibre diameter, spot diameter, power distribution in the beam ...). These variables multiply the solution space and the effort. Especially the material combination can hardly be parameterised.

Further characteristic values can also be evaluated for the target variables; e.g. weld penetration depth, load-bearing weld cross section or grain size distribution. These characteristic values can be linked to the quality of the welded joint.

Based on the described approach, the goals stated in the introduction can be achieved.

CONCLUSION

For the field meta modelling approach based on the sensitivity analysis of variances it will be necessary to automate the pre- and post-processing of experiments and data analytics.

In the presented example "LBW", a prediction of the seam geometry becomes possible on the basis of micrographs using the variance-based sensitivity analysis with field metamodeling. This makes it possible to find suitable parameters for welding processes.

Often the data acquisition can be the biggest cost driver. What is sought is the analytical model that achieves the best process description at the lowest cost for measurement. Such an analytical model is then used as a basis for the automatic control of processes based on the developed software workflow via suitable control variables; e.g. laser parameters.

References

[1] J. E. R. DHAS and S. J. H. DHAS: ‘A Review on Optimization of Welding Process’, *Procedia Engineering*, 38 (2012), S. 544-554; 2012.

[2] G. PADMANABAN and V. BALASUBRAMANIAN: 'Optimization of laser beam welding pro-cess parameters to attain maximum tensile strength in AZ31B magnesium alloy', O*ptics & Laser Technology*, 42 8, S. 1253-1260; 2010.

[3] E. M. ANAWA and A. G. OLABI: 'Using Taguchi method to optimize welding pool of dissimilar laser-welded components', *Optics & Laser Technology*, 40 2, S. 379-388; 2008.

[4] J. MIRAPEIX, P. B. GARCÍA-ALLENDE, A. COBO, O. M. CONDE and J. M. LÓPEZ-HIGUERA: 'Real-time arc-welding defect detection and classification with principal component analysis and artificial neural networks', *NDT & E International*, 40, 4, S. 315-323; 2007.

[5] Y. YANG, Z. GAO and L. CAO: 'Identifying optimal process parameters in deep penetration laser welding by adopting Hierarchical-Kriging model', *Infrared Physics & Technology*, 92, S. 443-453; 2018.

[6] S. DATTA, G. NANDI, A. BANDYOPADHYAY and P. KUMAR PAL: 'Application of PCA-based hybrid Taguchi method for correlated multicriteria optimization of sub-merged arc weld. A case study', *The International Journal of Advanced Manufac-turing Technology*, 45 3-4, S. 276-286; 2009.

[7] CH. SCHWARZ, S. KRIECHENBAUER, R. MAUERMANN, W.G. DROSSEL: *Field meta modelling for process design in complex sheet metal forming;* 41st International Deep Drawing Research Group Conference, Lorient-France, 2022.

[8] CH. SCHWARZ, P. ACKERT, T. FALK, M. PUSCHMANN, R. MAUERMANN, W.G. DROSSEL: 'Model-based joining process design for the body shop process chain', International Conference on Advanced Joining Processes, *Proceedings Engineering Mechanics*, https://doi.org/10.1007/978-3-030-95463-5_2, AJP 2022.

[9] CH. SCHWARZ, P. LINK; ST. IHLENFELDT, W.G. DROSSEL: 'Application of Fourier-related data reduction methods in sheet metal forming', *Procedia CIRP*, Volume 99, Pages 260-265, ISSN 2212-8271, Naples-Italy, 2021.

[10] CH. SCHWARZ, P. ACKERT, R. MAUERMANN: 'Principal component analysis and singular value decomposition used for a numerical sensitivity analysis of a complex drawn part', *Int J Adv Manuf Technol*; 94: 5-8. p. 2255-2265. DOI: 10.1007/s00170-017-0980-z.; 2018.

[11] D. MOHR: *Creating Big-Data on Sheet Metal Plasticity and Failure*, 41st International Deep Drawing Research Group Conference, Lorient-France, 2022.

[12] OPENCV*: Open Computer Vision Library*, http://opencv.org, retrieved: 31.07.2018.

[13] R. O. DUDA, P. E. HART and D. G. STORK: Pattern Classification. s.l.*: Wiley-Inter-science 2012.*

[14] CH. SCHWARZ, P. ACKERT, T. FALK, M. PUSCHMANN, R. MAUERMANN, W.G. DROSSEL: 'Model-based joining process design for the body shop process chain', International Conference on Advanced Joining Processes, *Proceedings Engineering Mechanics*, https://doi.org/10.1007/978-3-030-95463-5_2, AJP 2022.