COMPUTERISED CALIBRATION OF THERMO-MECHANICAL WELDING MODELS

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ABSTRACT

Welding models based on fundamental physical mechanisms have to be calibrated against measurements in order to compensate lack of understanding of process details, incomplete information on material properties or imperfections in formulating the computational model. Therefore, adjustment parameters are introduced into these models which cannot be directly derived from the parameters of the simulated technical process. Normally, time consuming intervention by a human operator is needed in order to adjust these tuning parameters and typically the calibration is performed against a single or very few measurements only. Obviously, such a procedure subsequently does not allow performing simulations for deviating process parameters at least with the accuracy normally demanded. Recent developments improve the situation by an automatic mapping of experimental parameters to tuning parameters, but require a-priori defined relationships between these parameters. If new effects are investigated, these relationships are usually unknown and interference by an operator is again necessary for modifying them in an iterative manner. In comparison to the enormous efforts in the field of numerical modelling based on the laws of physics, more focus on the calibration issue seems to be necessary. Otherwise new sophisticated models will theoretically provide detailed information, but cannot increase accuracy and reliability of predictions compared to existing models of lower complexity.

A contribution to adjusting theory-based models with their calibration to multiple measurements is made based on a unique Hybrid Simulation Technique (HST). The basic idea of the underlying algorithm is to compose the model of a theoretical model part that describes the physical phenomena and an empirical part based on artificial intelligence which is capable of managing measurements acquired from multiple welding experiments. To demonstrate the HST concept, the algorithm is applied to the simulation of the cross-sectional melting zone border shape in hybrid LB-GMA welding of aluminium. The results prove that even a simple hybrid model comprising neural networks and an analytical heat conduction model can provide results of an accuracy which corresponds to the quality of the experimental data. In addition, it can be concluded that the application of HST will allow to make better use of the improved features of more advanced analytical or numerical models.

1 INTRODUCTION

Mathematical models have been successfully applied for simulating various phenomena of the highly complex, dynamic, non-linear and multi-variable welding process that even contains chaotic elements. Essential contributions to the detailed understanding of the physics of welding were made and it is proven that the investigation of a flexible virtual process (gained by simulation) instead of the real one is an efficient alternative to laboratory experiments when adapting or optimising joining operations.[1,2]

Principally, welding models can be classified either as empirical data-based or as theory-based. Popular data-based techniques are empirical models such as artificial neural networks and regression analysis. They are the preferred solutions for control applications and especially interesting in situations where physical background knowledge is rare, time for model creation is limited or execution speed is an issue. Such models are robust, real-time capable and relatively easy to apply. However, empirical models are unqualified to fully substitute theory-based approaches due to essential disadvantages:

- limitations in filtering of inaccurate experimental data due to lack of physical background knowledge,
- difficulties to differentiate between significant and insignificant input,
- the limitation of the number of result variables to the experimental output,
- the inability to reflect drastic qualitative changes of process output due to a change in the process mode, e.g. mode of drop transfer in arc welding.

Opposed to that, theory-based approaches derive knowledge-based process models from fundamental physical mechanisms and use measurements primarily for model calibration and validation.[3] They provide the following advantages:

- flexibility with regard to changes of geometry, material, boundary conditions etc,
- the possibility of taking into account qualitative changes in process output,
- information for all unknowns at any location and possibility of simulating on small/large space scale and short/long-time scale,
- isolation of particular phenomena, e.g. influence of gravity.

However, the computational requirements of theoretical models are typically high even if simplifying assumptions are made. Consequently, the model creation process is very expensive if the series of simulation runs necessary for model calibration has to be interrupted by manual corrections. The calibration of theoretica1 welding models is almost always necessary in order to compensate lack of modelling or understanding of process details, incompleteness in measuring material properties or inaccuracies in formulating the computational model.[4,5] Therefore, adjustment parameters are introduced into these models which modify the influence of certain physical parameters of the technical process (e.g. the correction factor of the net heat input by a particular weld source). It should be noted that the potential of quantitative correct reproduction is very limited if the model calibration is not performed against a substantial number of experiments.

Traditionally, time consuming intervention by a human operator is needed in order to adjust the tuning parameters and typically the calibration is performed against a single or very few measurements only. Obviously, such a procedure subsequently does not allow performing simulations for deviating process parameters at least not with the accuracy normally demanded. Recent developments improve the situation by semi-automatic mapping of process parameters to model tuning parameters, but still require a-priori defined relationships between these parameters.[6,7] If new effects are investigated, these relationships are usually unknown and interference by a human operator is again necessary for modifying them in an iterative manner.

Complex theoretical models are usually so computer intensive that it is impractical to use them in process control, inverse problem solution (finding of parameter sets guaranteeing the result set desired) or process optimization. In order to improve the execution speed of such process models, meta-models[‡] have been introduced for real-time computations or fast initial guesses in design chains.[9,10] By training of neural networks with the computational results of complex theoretical models, very fast substitutes of the original model can be provided. However, accurate model calibration as the creation of the missing link between unknown model parameters and known experimental parameters is again a major issue because quantitative correct predictions of the theoretical model are needed in a wide range of process parameters.

Therefore, more focus on the calibration issue seems to be necessary for both using the original theoretical model and approximating the model response with meta-models. In this paper, a new way of providing reliable welding models is proposed which has benefit-potentials in research and development through

- fully automatic and objective calibration of thermo-mechanical welding models capable of competitive modelling trials for a particular application
- improving the reliability of process models by combination of a theoretical model with an artificial intelligence based empirical model which complexity can be adjusted to varying qualities and quantities of measured data.

2 MODEL CALIBRATION

The calibration task of finding the relationships between given sets of experimental parameters $\boldsymbol{p}_{\mathrm{exp}}$ and unknown calibration or tuning parameters $\boldsymbol{p}_{\mathrm{tun}}$ is indicated by the dashed arrows in Fig. 1. The intersection of the explicitly known experimental parameter set $\boldsymbol{p}_{\mathrm{exp}}$ and the model input $\boldsymbol{p}_{\mathrm{mod}}$ is classified as the input common to model and experiment and denoted as the intersection $\boldsymbol{p}_{\mathrm{com}} = \boldsymbol{p}_{\mathrm{exp}} \cap \boldsymbol{p}_{\mathrm{mod}}$. Non-model related experimental parameter sets $\boldsymbol{p}_{\mathrm{mnr}}$ are not considered as model input and defined as the complement $\boldsymbol{p}_{\mathrm{nmr}} = \boldsymbol{p}_{\mathrm{exp}} - \boldsymbol{p}_{\mathrm{com}}$. The model input, then, is the union of common and tuning parameter set $\boldsymbol{p}_{\mathrm{mod}} = \boldsymbol{p}_{\mathrm{com}} \cup \boldsymbol{p}_{\mathrm{tun}}$. The set of common result variables $\boldsymbol{r}_{\mathrm{com}} = \boldsymbol{r}_{\mathrm{sim}} \cap \boldsymbol{r}_{\mathrm{exp}}$ is the intersection of the computational result set $\boldsymbol{r}_{\mathrm{sim}}$ and the measurement result set $\boldsymbol{r}_{\mathrm{exp}}$. The common result set is the only connection between model and experiment when starting the model calibration. In the

[‡] A model is an abstraction of phenomena in the real world. A meta-model is a changed abstraction, in the case considered above approximating the model response in a limited range of application.[8]

following, lower case $\boldsymbol{p}$ and $\boldsymbol{r}$ denote single parameter and result sets and upper case $\boldsymbol{P}$ and $\boldsymbol{R}$ denote arrays of $\boldsymbol{p}$ and $\boldsymbol{r}$ sets.

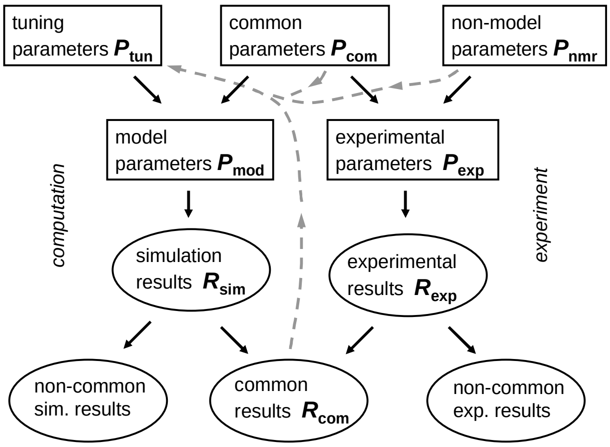

Fig. 1 Model calibration in respect of tuning parameters $\boldsymbol{P}_{\mathrm{tun}}$ based on common results $\boldsymbol{R}_{\mathrm{com}}$.

The result of the calibration process is the composition of the process model of a theoretical part (mathematical description based on physics) and an empirical part (application-specific information) based on information extracted from measurement results acquired from multiple welding experiments (Fig. 2). Starting with the objectives of

- reducing time and labour costs of model creation by automatic model calibration,
- eliminating subjective errors of human operators during the calibration,
- ensuring reliable simulations within wider parameter ranges by calibration against multiple experiments without pre-described parameter dependencies,

the employment of neural networks for providing the empirical model part should be discussed.

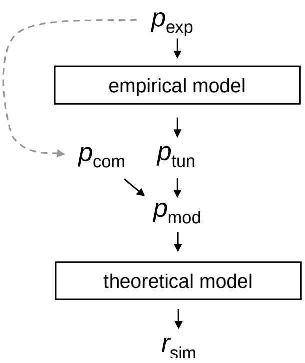

Fig. 2 Model composition of an empirical and a theoretical model part ($\boldsymbol{p}_{\mathrm{com}}$ is a subset of $\boldsymbol{p}_{\mathrm{exp}}$).

The basic idea of the proposed calibration algorithm is to train a calibration network with the arrays of experimental parameter sets $\boldsymbol{P}_{\mathrm{exp}}$ and corresponding tuning parameter sets $\boldsymbol{P}_{\mathrm{tun}}$, see Fig. 3.

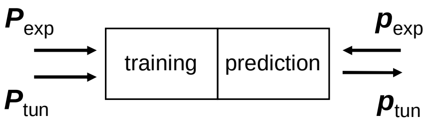

Fig. 3 Calibration network for prediction of a tuning parameter set.

After that, the calibration network can predict a single tuning parameter set as a function of a given experimental parameter set

$$\boldsymbol{p}_{\mathrm{tun}} = \boldsymbol{f}_{\mathrm{cal}}(\ \boldsymbol{p}_{\mathrm{exp}}\ ) \tag{1}$$

The union of this estimate with the known common parameters (extracted from $\boldsymbol{p}_{\mathrm{exp}}$) is the wanted model input

$$\boldsymbol{p}_{\mathrm{mod}} = \boldsymbol{p}_{\mathrm{com}} \cup \boldsymbol{p}_{\mathrm{tun}}\ . \tag{2}$$

The target $\boldsymbol{P}_{\mathrm{tun}}$ for the training of the calibration network is the collection of single predictions of $\boldsymbol{p}_{\mathrm{tun}}$ by local calibration networks for every experimental data set. Fig. 4 is a graphic illustration of the calibration algorithm, which comprises the following steps:

The calibration starts with the preliminary adjustment of the tuning parameters, see step a) in Fig. 4. For every experimental data set, the space of tuning parameters ($\boldsymbol{p}_{\mathrm{com}}$ is experiment-wise constant) is pre-scanned, an array of tuning parameter sets $\boldsymbol{P}_{\mathrm{tun}}$* is randomly selected and computations with the theoretical model are performed. A preliminary neural network is trained with the array of computed result sets $\boldsymbol{R}_{\mathrm{sim}}$* and the corresponding array of tuning parameter sets $\boldsymbol{P}_{\mathrm{tun}}$*. This preliminary network predicts a first estimate of the tuning parameter set $\boldsymbol{p}_{\mathrm{tun}}^* = \boldsymbol{f}_{\mathrm{pre}}(\ \boldsymbol{r}_{\mathrm{exp}}\ )$ as a function of the common part of the result set of the current experiment.

The calibration process proceeds with local domain training for the current experimental data set. A local domain of the tuning parameter space is selected around the initial estimate of $\boldsymbol{p}_{\mathrm{tun}}$*. Starting with a number of randomly chosen tuning parameter sets $\boldsymbol{P}_{\mathrm{tun}}$** selected from this local domain, the base of available tuning parameters and simulation result sets $\{\ \boldsymbol{P}_{\mathrm{tun}}^{**},\ \boldsymbol{R}_{\mathrm{sim}}^{**}\ \}$ is repeatedly adjusted by interpreting the prediction quality of an auxiliary network trained with this data and by performing of additional simulations in the neighbourhood of the worst reproduction of the training target $\boldsymbol{R}_{\mathrm{sim}}$**. After that, the location of the centre of the local domain in the global tuning parameter space is corrected based on a local calibration network trained with the final version of the $\boldsymbol{P}_{\mathrm{tun}}$** and $\boldsymbol{R}_{\mathrm{sim}}$** arrays. The moving of the local domain is terminated when a quality criterion with regard to the approximation of $\boldsymbol{r}_{\mathrm{exp}}$ by the result computed with $\boldsymbol{p}_{\mathrm{tun}}$** is met, see step b) in Fig. 4.

In the next step, the best local approximation of the tuning parameter set is selected and collected in the global arrays of experimental and tuning parameter sets { $\boldsymbol{P}_{\text{exp}}$, $\boldsymbol{P}_{\text{tun}}^{**}$ }, see step c).

Finally, the global calibration network is trained with the collected experimental and tuning parameter sets and so capable of making predictions of model parameter sets according to equation (1) and (2), see step d).

In contrast to conventional model calibration, the Hybrid Simulation Technique (HST) described above does not request interference by a human operator. Such full automation of calibration is especially welcomed in situations involving computation-intensive applications, because otherwise the task is extremely time-consuming and discouraging for humans.

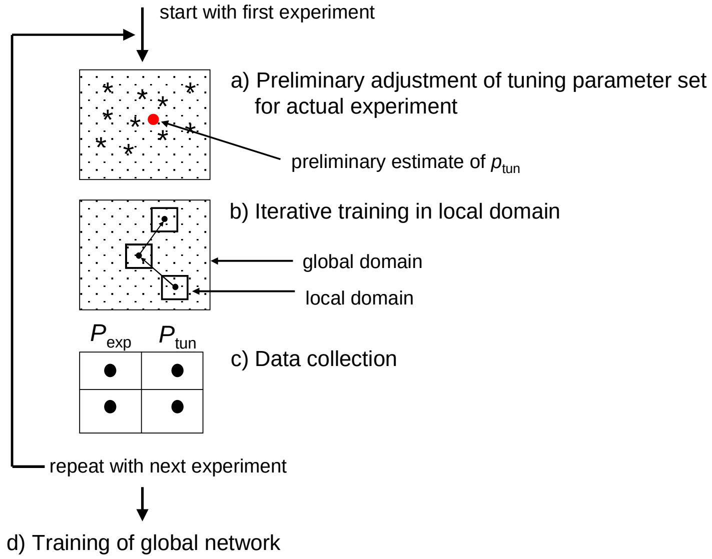

Fig. 4 Flow chart of calibration process.

3 COMBINATION OF EMPIRICAL AND THEORETICAL MODELLING

The current situation is characterized by a division of the simulation community into two camps, favouring either empirical or theoretical modelling in dependence of the given limits of experimental facilities, of human competence in modelling and of requirements regarding execution speed. Many implementations based on empirical or theoretical models have been presented as substantial progress from the view of the respective group. However, industrial applications of combinations of empirical and theoretical welding models besides meta-modelling (e.g. neural network representations of expensive simulation results) are not known. The high degree of specialisation necessary to apply theoretical or empirical models is seen as the barrier to such connections.

Deterministic models, such as conservation principles of energy, mass or momentum show generally good performance when predicting phenomena which are not too complex and almost free of chaotic influences. However, experience shows that purely theory-based approaches are not appropriate to a full simulation of the highly complex and non-linear behaviour of welding processes, and furthermore, no two joints welded under identical process conditions are exactly equal as experiments are not fully reproducible due to chaotic elements. Thus, the universal welding model extracting all needed information for model calibration directly from a few measurements is an idealistic goal, only. Besides, the quality of real data can be disappointingly low resulting in too noisy data or data of too little quantity for creation of reliable empirical models or proper calibration of theory-based models. On the one hand it is obvious that the purely deterministic welding models can be made more reliable by combining them with empirical models, and on the other hand entirely empirical models can be improved by getting corrective advices from a theoretical model part.

With the present proposal of HST, both types of models can be flexibly combined to models with a hybrid characteristic. Fig. 5 indicates how the weighting of the empirical model part influences the characteristics of the hybrid model. It allows adjusting of the model complexity economically to the actual needs regarding model execution speed, extrapolation quality and the existing resources for performing of experiments as well as the available time for model creation.

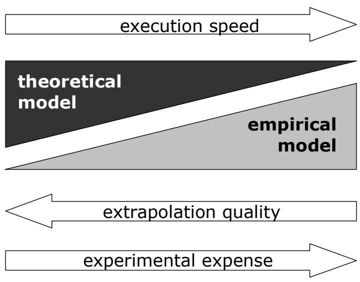

Fig. 5 Hybrid model characteristics in dependence of the weighting of the empirical model part.

Starting the hybrid model construction, an auxiliary neural network is trained with the measured data { $\boldsymbol{P}_{\exp}$, $\boldsymbol{R}_{\exp}$ }. During training of this network, a regularisation technique is used which reduces the sum of squared weights of the neural network. A pre-analysis of the experimental data can be performed by interpreting the structure of the trained network. Firstly, insignificant process parameters can be identified and the datasets recorded can be sorted with regard to their suitability for local calibration against the particular experiment. Secondly, it simplifies the filtering of erroneous data sets and planning of additional experiments. Besides, the structure and prediction quality of the network gives a first indication how complex the empirical and the theoretical part of the hybrid model should be. For instance, if high noise is detected, it is unlikely that a greater complexity of the theoretical model part can contribute substantially to the accuracy of the combined model. During the calibration, the selected theoretical model will be extensively employed. But, its weighting can be decreased by modifying the complexity of the empirical model if the process is significantly characterised by chaotic elements.

At the time being, the existing post-priori estimates of the hybrid model characteristics allow only a qualitative consideration. However, tools for a-priori estimates of the optimal hybrid model composition are certainly needed and will have to be subject of future investigations.

4 EXAMPLE: FUSION ZONE WIDTH IN LASER/GMA HYBRID WELDING

The modelling effort when generating a hybrid model requires an appropriate empirical model as well as an application-specific theoretical model. As an illustrating example, the prediction of the cross-sectional melting zone border in Nd:YAG-laser/GMA hybrid welding is considered with focus on the fusion zone width at the plate surface.

Heat transfer is the dominating phenomenon in fusion welding, but normally also other effects as e.g. thermocapilary flow and (in arc welding) drop transfer and arc phenomena play an important role. Due to the complexity of the operation, modelling of the heat effects of welding requires strong simplifications or isolation of particular effects. In combination with the unsatisfactory knowledge about the thermo-physical properties of the materials, models of processes as the considered hybrid welding are characterized by great uncertainties. With regard to the complex effects occurring in the laser-arc interaction zone, several investigations have contributed to the understanding,[11,12] but relevant models are still limited with regard to their extrapolation capabilities, and many modelling issues are simply unsolved. The present example is focused on modelling of the heat transfer to the base metal and weld pool employing analytical heat conduction solutions of concentrated moving heat sources. Adaptation to the actual experimental results is achieved by superposition of the temperature fields of two point sources in a semi-infinite solid, one source above the other. It will be shown that the quality and quantity of the measurements justify the employment of such an analytical solution for the prediction of the melting isotherm and especially the fusion zone width at the surface of the plate. In addition, it will be demonstrated that even such a simple model can be automatically calibrated against multiple experiments with high reliability.

4.1 EXPERIMENTAL SETUP

A series of hybrid Nd:YAG-laser/GMAW flat position I-joint weld experiments (in total 36 welds) was conducted to obtain knowledge on how the significant welding parameters affect the fusion zone profile. A maximum 4.4 kW laser source DY044 from Rofin Sinar was used in combination with a LUD 450 W Aristo arc power supply from ESAB. The laser beam was delivered via a fibre optical cable of 0.4 mm thickness, the focal length was 200 mm, the work piece material was aluminium alloy (EN AW 5083-0) with a plate thickness of 8 mm, the gap width was zero mm and the wire was SG-AIMg5 with a diameter of 1.2 mm. Process parameters were varied in the following ranges: laser power: 2.4-4.0 kW, arc power: 2.94-6.41 kW, welding speed: 1.5-3.0 m/min and wire feed speed: 8-16 m/min. To quantify the geometry of the obtained fusion zone profiles, the data indicated in Fig. 6 were measured for each experiment. These parameters are the seam width *w* and the penetration *p*, as well as the characteristic tail widths *u*, *m*, and *l* at the positions of 0.75 *p*, 0.5 *p* and 0.25 *p*. [13]

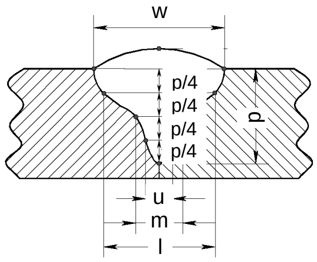

Fig. 6 Data measured for quantifying fusion zone profile.

4.2 EMPIRICAL MODEL

The employed multi-layer neural network is a highly complex, non-linear mapping function that transforms input to output in a given domain. Multi-layer feedforward networks with biases and at least one sigmoidal layer are widely recognised for their capability of approximating any function with a finite number of discontinuities.[14,15,16] Fig. 7 shows the structure of the neural network with one hidden layer. ***x*** denotes the network input and ***y*** the output of the particular layers.

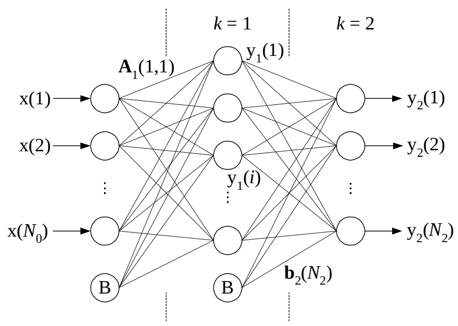

Fig. 7 Schematic diagram of two layer feedforward network

The mapping from input ***x*** to output ***y*** reads as :

$$\begin{aligned}&\mathbf{y}_0 = \mathbf{x}\\&\mathbf{y}_k = \mathrm{f}_k(\mathbf{A}_k\mathbf{y}_{k-1} + \mathbf{b}_k) \text{ for } k = 1,2,\cdots,n\end{aligned} \tag{3}$$

where $\mathbf{x}$ ($N_0 \times 1$) is an input vector and $\mathbf{y}_k$ ($N_k \times 1$) an output vector from the k^{th} layer; $\mathbf{A}_k$ is a weight matrix of dimension ($N_k \times N_{k-1}$), $\boldsymbol{b}_k$ a bias weight vector of dimension $N_k \times 1$, and n the number of layers. Finally, the sigmoidal function applied as the transfer function is expressed as:

$$\mathrm{f}_k(\mathbf{s}) = \frac{1}{1 + \exp(-\mathbf{s})} \quad (N_k \times 1) \tag{4}$$

For training this feed-forward neural network, the Levenberg–Marquardt algorithm for non-linear least square error minimisation is used with the back propagation algorithm. Minimising the risk of inexpedient overtraining by employing a regularisation technique is more important than guaranteeing a fast rate of convergence. Instead of minimising the sum of squared errors $F = E_D$, which is the traditional approach for network training, the objective of this technique is to minimise a performance function with an additional term (for training based on a set of weld data of size m containing $\{\mathbf{x},\mathbf{t}\}_{(1)}$, $\{\mathbf{x},\mathbf{t}\}_{(2)}$, …, $\{\mathbf{x},\mathbf{t}\}_{(m)}$):

$$F = \beta E_D + \alpha E_W$$

where

$$E_D = \sum_{i=1}^{m} (\mathbf{t}_{(i)} - \mathbf{y}_n^{(i)})^T (\mathbf{t}_{(i)} - \mathbf{y}_n^{(i)}). \tag{5}$$

The optimal setting of the regularisation parameters α and β is based on Bayesian theory and known as Bayesian regularisation. Modification of the performance function by addition of the term E_W representing the square sum of the network weights improves the network generalisation so that any modestly oversized network has the ability to represent sufficiently the true underlying function. The technique consistently produces networks with good generalisation abilities by constraining the size of the network weights.

4.3 THEORETICAL MODEL

The choice of the theoretical model part is very much dependent on the available time for calibration and simulation runs as well as on the quantity and quality of the experimental data. Theoretically, any kind of deterministic model reaching from analytical solutions to sophisticated finite element codes could be applied. If time for problem analysis is an issue, it is often more efficient to calibrate a model of lower complexity with a high interpolation capability instead of adjusting a theoretically better model less reliable to a few measurement results. The opportunity of frequently repeated calibration and analysis cycles within a given time limit can compensate the partly reduced accuracy of simpler theoretical models by far in industrial applications.[17] This cost efficiency is especially interesting in the case of inverse problem solutions and process optimisation where a larger number of simulation runs is naturally required. The following example of simulating the cross-sectional melting zone border was selected in order to demonstrate the potential of hybrid models based on theoretical models of lower complexity. It should be noted that use of HST is not limited to such simple theoretical models and that even very detailed process models benefit from the proposed combination with an empirical model part.

The equation of conservation of energy reads as

$$\rho \frac{\partial h}{\partial t} = div(\lambda \; grad \; T) + \dot{q}_{vol} \tag{6}$$

if heat convection and dissipative effects are neglected. ρ denotes the density, h the enthalpy, t the temporal variable, λ the thermal conductivity, T the temperature and $\dot{q}_{vol}$ the volume-specific heat source. The initial condition is given by the preheating temperature T_0. Boundary conditions describe the heat flux into the work piece and heat loss by evaporation, spatter, radiation and others.

Rosenthal[18] has proposed to approximate the temperature in seam welding by a simplified heat conduction model, e.g. assuming a semi-infinite homogenous solid, a continuously acting heat point source, constant travelling speed of the heat source and neglecting microstructural phase changes and heat loss at the surface, the resultant temperature field being:

$$T(x,y,z) = \frac{\dot{Q}}{2\pi\lambda r_{xyz}} \; \exp\left(\frac{v(x - r_{xyz})}{2a}\right) + T_0 \tag{7}$$

where $\dot{Q}$ denotes the heat input from a point source, r_{xyz} is the radial distance from the heat source origin, v the travelling speed of the heat source and a the thermal diffusivity.
Obviously, equation (7) is not directly capable of representing the temperature field of the hybrid welding process described above because point source and semi-infinite solid are two rough approximations. Therefore, the more complex heat effect of the hybrid welding heat source will be considered through superposition of the effect of two simultaneously acting point heat sources, one above the other with modification of two superposed solutions according to Equation 7. Tuning parameters are the heat input $\dot{Q} = \dot{Q}_1 + \dot{Q}_2$, the scaling factor ξ_Y for scaling the y-coordinate $y' = \xi_Y \; y$ in equation (8), the scaling of the z-coordinate $z' = \xi_Z \; z$ in equation (9) and the offset Δz of the origin of source 2 (see Fig. 8).

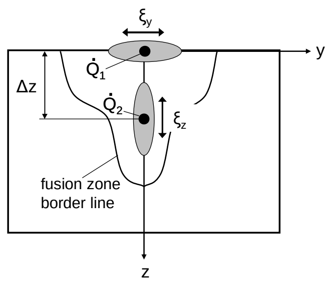

Fig. 8 Superposition of two simultaneously acting heat sources and introduction of tuning parameters in cross-sectional plane at $x = 0$.

Consequently, the set of governing equations reads as

$$T_1(x,y,z) = \frac{\dot{Q}_1}{2\pi\lambda r^*_{xyz}} \exp\left(\frac{v(x - r^*_{xyz})}{2a}\right) \tag{8}$$

with $r^*_{xyz} = \sqrt{x^2 + \xi_Y \cdot y^2 + z^2}$

$$T_2(x,y,z) = \frac{\dot{Q}_2}{2\pi\lambda r^{**}_{xyz}} \exp\left(\frac{v(x - r^{**}_{xyz})}{2a}\right) \tag{9}$$

with $r^{**}_{xyz} = \sqrt{x^2 + y^2 + \xi_Z (z + \Delta z)^2}$

$$T(x,y,z) = T_1 + T_2 + T_o \tag{10}$$

In order to restrict the tuning parameter set to the three components $\boldsymbol{p}_{\text{tun}} = (\xi_Y, \xi_Z, \Delta z)$, the heat flux by point source 1 will be fixed as a 60% share of the total heat input (sum of laser and arc power) based on experimental evidence. The heat input by source 2 is the remaining 40% of the gross input. The maximum extension of the melting isotherm in *y*-direction is the simulated fusion zone border line from which the common result set $\boldsymbol{r}_{\text{com}} = (w, l, m, u)$ is derived. *w* is the pool width and *l, m, u* are the tail widths according to Fig. 6. The choice of 3 tuning parameters and 4 result variables ensures an economic size of $\boldsymbol{p}_{\text{tun}}$ and $\boldsymbol{r}_{\text{com}}$.

4.4 RESULTS

Fig. 9 shows the extension of the process parameter space. The measurement results were separated into 24 training sets for model calibration (indicated by the dashed circles in Fig. 9) and into 12 test sets (dotted circles) for testing the performance of the constructed hybrid model.

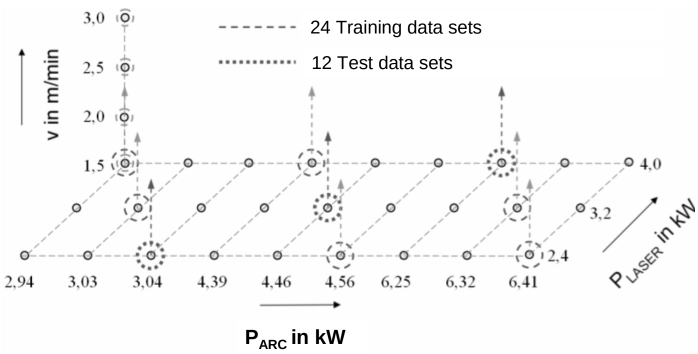

Fig. 9 Process parameter space and data separation for model training and performance test.

During the calibration process, the model is first locally calibrated to each experiment. Two such local calibrations are shown in Fig. 10. The degree of correspondence between the experimental findings and the simulation results is acceptable considering the fusion zone border shape.

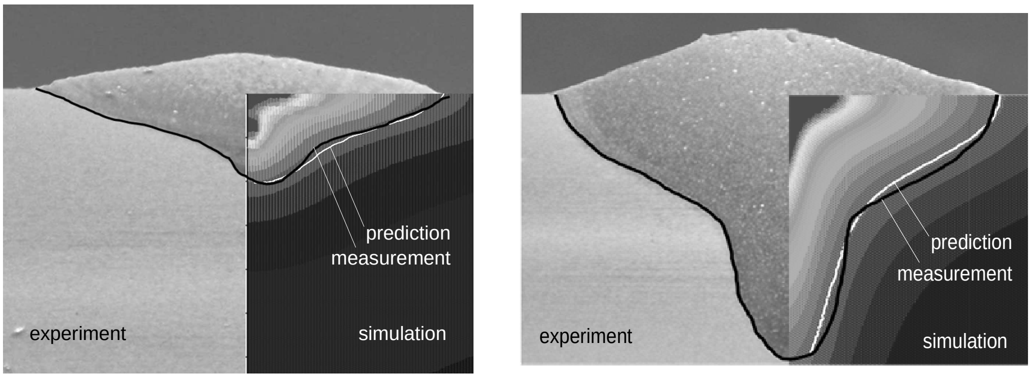

Fig. 10 Comparison of computed fusion zone border profile after local domain training (white line) with measured profile (black line).

After collection of all local calibration data, the global calibration network is trained. In Fig. 11, the measured fusion zone widths at the surface are compared with the simulated ones based on the tuning parameter sets predicted after local and global domain training. While the results computed with the locally estimated tuning parameters almost coincide with the experimental data, the predictions of the hybrid model show small deviations due to the generalisation feature of neural networks with Bayesian regularisation. However, this smoothing is a desired effect because it compensates possible measurement errors and improves so the reliability of the model.

In order to quantify the prediction quality of the hybrid model, the 12 test data sets (experiments which are not used for model training) should be reproduced. Fig. 11-13 prove that accuracy of the prediction of fusion zone border width at plate surface, penetration and middle waist width for the test data sets is acceptable. The degree of result approximation presented qualifies the theoretical model (equations (8)-(10)) to be a sufficient theoretical model.[19]

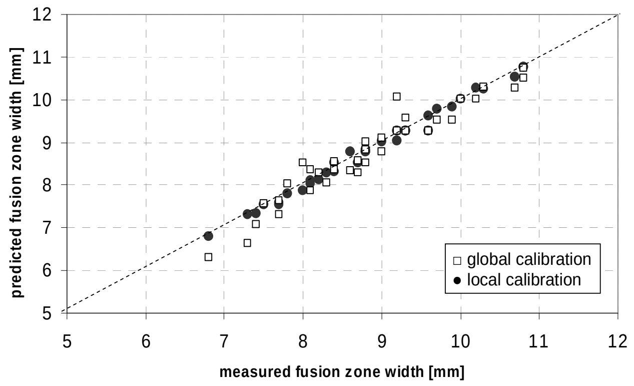

Fig. 11 Comparison of measured fusion zone width on plate surface with model results based on local and global calibration.

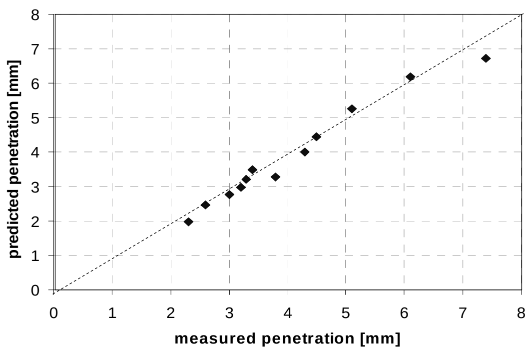

Fig. 12 Comparison of measured and predicted penetration

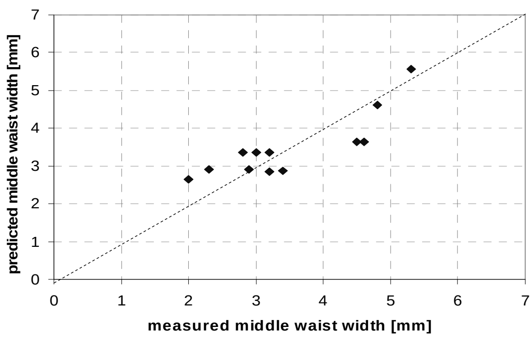

Fig. 13 Comparison of measured and predicted middle waist width.

5 SUMMARY AND OUTLOOK

Theory-based models of welding have been proven to be very efficient tools for prediction of several physical phenomena and to aid in product design and process optimisation. However, models based on fundamental physical mechanisms have to be calibrated against measurements in order to compensate lack of understanding of process details, incomplete information on material properties or imperfections in formulating the computational model. In the present work, a method for automatic calibration of theoretical models against multiple measurement results has been proposed. The Hybrid Simulation Technique (HST) is a generic concept with flexibility regarding the quality and quantity of measured data on one hand and the existing resources for model construction on the other hand. It identifies significant correlations between tuning and process parameters objectively and eliminates the need for interaction by a human operator.

Exemplarily, it was demonstrated that even simple analytical solutions can serve as theoretical models for the prediction of the shape of the fusion zone border in Laser-GMA welding over a relatively wide range of process parameters. An acceptable accuracy could be achieved after being complemented with a neural network of sufficient complexity.

Future work will focus on development of an a-priori estimator for an optimal share of the empirical model part and on introducing a robust detection of erroneous experimental data sets. So, an immediate feed-back to the experimental investigation of a process might be provided and costs of model training will be significantly reduced.

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