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Hybrid model for the threshold of deep-penetration laser welding

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Abstract

The development of reliable laser welding processes within a short time and with minimum experimental effort is an important aspect for small batch-size manufacturing. A physics-informed hybrid model was applied for the prediction of the threshold of deep-penetration laser welding. A "residual model" approach was used where a machine learning model was applied to learn and compensate for the deviations of an analytical model to the experimental results. Gaussian processes were used for the machine learning part. The results show an increase in model accuracy by using such a hybrid model compared to only using the analytical model. In comparison to only using a black-box machine learning model, the amount of required training data can be reduced and the extrapolation capability can be improved.

Keywords: modelling; hybrid models; machine learning; laser welding; deep-penetration threshold

1. Introduction

The development of reliable laser welding processes within a short time and with minimum experimental effort is an important aspect for small batch-size manufacturing. Quantitative prediction of process constraints, such as the threshold of deep-penetration laser welding, allows robust process windows to be developed more quickly and more reliably. The combination of physics-based models and machine learning in a so-called hybrid model, Gauger et al., 2022; Jarwitz et al., 2022, is a promising approach for this task. Such physics-informed hybrid models offer the potential to increase the model accuracy compared to only using a physics-based model, and to reduce the amount of required training data and increase the extrapolation capability of the model compared to only using a black-box machine learning model, Gauger et al., 2022.

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Therefore, we applied the combination of an analytical model, Graf et al., 2015, and a machine learning model for the prediction of the threshold of deep-penetration laser welding.

2. Hybrid model

A "residual model" approach, Gauger et al., 2022, was used for the hybrid model, where the machine learning part of the model learns and compensates for the deviations Δ of the physics-based model from the experimental results. For this purpose, Gaussian processes, Rasmussen and Williams, 2006, were used for the machine learning part. The threshold of deep-penetration laser welding is described by the value of P/d at which the onset of deep-penetration welding occurs, where P is the laser power and d the diameter of the laser beam on the sample surface. An analytical model for the description of this threshold condition, Graf et al., 2015, was used as the physics-based model. The hybrid model approach is illustrated in Fig. 1. The deviation of an experiment from the analytical model is schematically illustrated in Fig. 1(a), and a graphical representation of the hybrid model approach is shown in Fig. 1(b).

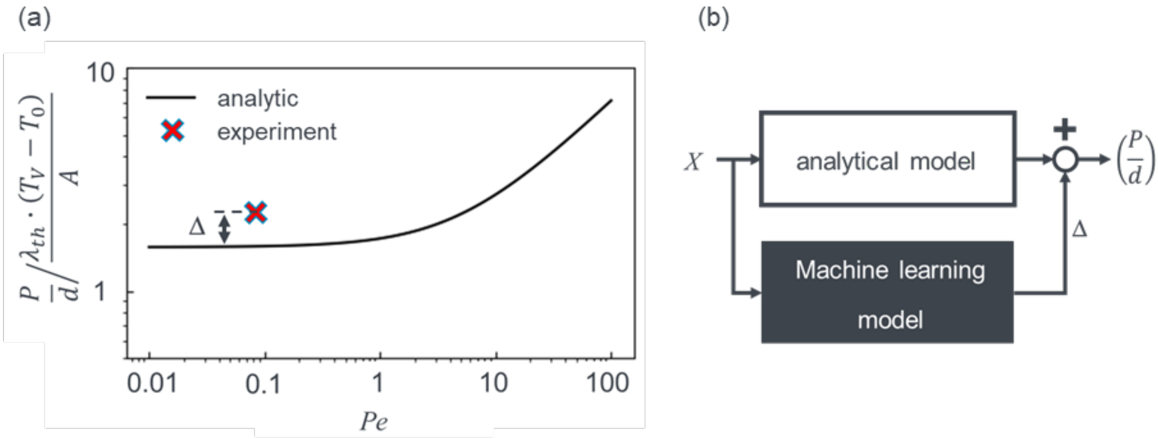

Fig. 1. (a) Illustration of the deviation of an experiment from the analytical model. λ_{th}: thermal conductivity, T_V: evaporation temperature, T_0: ambient temperature, A: absorptivity, Pe: Péclet number; (b) graphical representation of the hybrid model approach.

For the machine learning model, Gaussian processes were used with an RBF (radial basis function) kernel (sometimes also called squared exponential kernel) with separate length scales for each input feature. The experimental data to train and evaluate the model were taken from literature, Fabbro, 2010; Wagner, 2015, and comprise experiments with 1 µm lasers with a tophat intensity distribution and different materials (aluminum, copper, stainless steel, and bronze). In total, n_{exp} = 109 data points were gathered from literature and randomly split into the training and test data set. The number of training data points n_{train} was varied between 20 % and 80 % of n_{exp} in order to also investigate the influence of the amount of training data on the model performance. For comparison, also a black-box machine learning model was built, that directly models the threshold (P/d) of deep-penetration laser welding. A Gaussian process model was also used for this black-box machine learning model.

The model performance was evaluated by means of the mean relative error $MRE(y_{exp}, y_{model}) = (1/n) \cdot \sum_{i=1}^{n} \left|(y_{exp,i} - y_{model,i})/y_{exp,i}\right|$ between the model results y_{model} and the experimental results y_{exp}.

3. Results

The MRE of the analytical model over the entire data set is 0.48. For a split of the experimental data into 80 % training data and 20 % test data, the MRE of the hybrid model is about 0.13, which is a reduction of the MRE by about 73 % compared to the analytical model.

Fig. 2 shows the difference in the mean relative error $\Delta MRE = MRE_{black\text{-}box} - MRE_{hybrid}$ between the black-box machine learning model and the hybrid model, as a function of the number of training data points. With a decreasing number of training data points, the difference in MRE between the black-box model and the hybrid model increases. The MRE of the hybrid model is always lower than the MRE of the black-box model, and therefore the accuracy of the hybrid model is higher than that of the black-box model, especially for a small number of training data points.

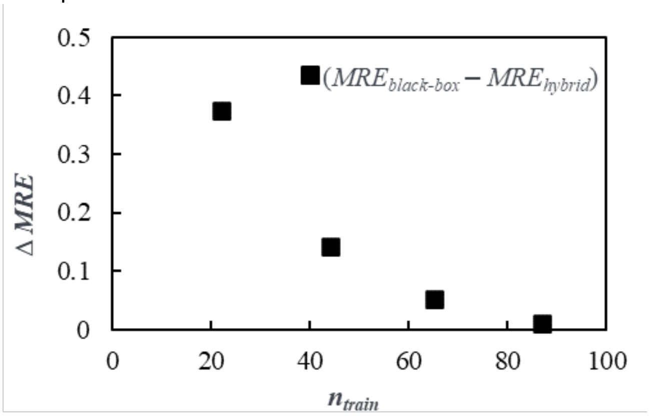

Fig. 2. Difference in MRE between the black-box model and the hybrid model as a function of the number of training data points.

Furthermore, the extrapolation behavior was investigated for the black-box model and the hybrid model. For this purpose, experimental data in a certain parameter range were intentionally excluded from the model training and then used as the test data set for the model evaluation. Results are shown for and discussed at the example of the input parameter laser beam diameter d. The models were trained with experimental data including d = 100 µm – 600 µm and the model performance was evaluated for predictions of the models for d = 1680 µm, which can be considered “far outside” of the parameter range that was applied during training. Fig. 3 shows the results for the deep-penetration threshold (P/d) for the test data set with d = 1680 µm. It can be seen that the agreement between the results from the hybrid model (green) and the experiments (black) is much better than between the results from the black-box model (purple) and the experiments. This indicates that the hybrid model performs better at extrapolation than the black-box model.

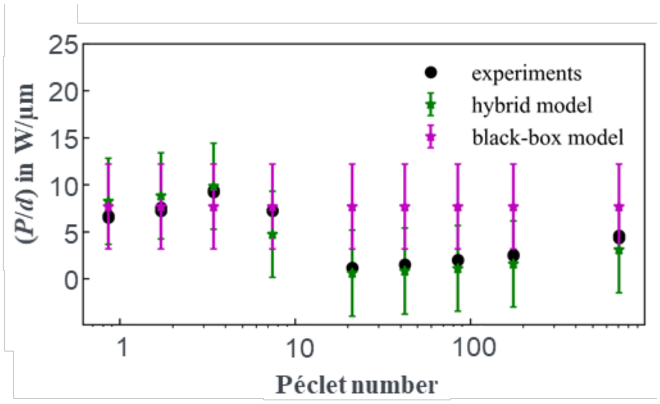

Fig. 3. Model results for the deep-penetration threshold (given by P/d) at extrapolation. Black: experimental results; green: hybrid model; purple: black-box model. Shown are the results for the test data set with d = 1680 µm and the models were trained with data comprising d = 100 µm – 600 µm. Error bars represent the standard deviation obtained from the Gaussian process models.

4. Conclusion

The approach of a physics-informed hybrid model was applied to the prediction of the threshold of deep-penetration laser welding. A “residual model” approach was used, where a machine learning model learned and compensated for the deviations of an analytical model to the experimental results. For this purpose, Gaussian processes were applied as the machine learning method.

The results show an increase in the model accuracy when using the hybrid model compared to only using the analytical model, leading to a reduction of the MRE by about 73 %. Furthermore, the accuracy of the hybrid model is higher compared to only using a black-box machine learning model, especially for small numbers of training data points. This indicates that using a hybrid model can significantly reduce the amount of required training data, and with this also the number of experiments required to train the model. This is especially beneficial when acquiring the training data is very expensive, as can be the case in laser materials processing. Moreover, the hybrid model showed a better performance at extrapolation than a black-box machine learning model. In conclusion, the results indicate that it can be highly beneficial to use a physics-informed hybrid model for laser materials processing.

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