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Material parameter identification for clinching process simulation using neural network metamodels

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***Abstract*—Clinching is a mechanical joining method in which two sheet workpieces are clamped and locked together using a punch and a die. Process parameters for such joint elements are often designed based on numeric simulation. Before this step, the identification of good material parameters is crucial to get validated computational results. In this paper, neural network metamodels are used for this specific task as a means to deal with large computation time. The identified material parameters reduce significantly the error between computational results and experimental results.**

Keywords—neural network metamodel, material parameters, finite element analysis, optimization, clinching

I. Introduction

In automotive industry, compared to conventional joining processes such as spot welding, mechanical joining offers many advantages such as less preparatory work, simpler and cheaper equipment, good environmental behavior, no thermal degradation and suitable for joining dissimilar materials [1, 2]. Clinching, also known as mechanical press joining, is a brand of mechanical joining.

During clinching, two sheets of same or different materials and thicknesses are clamped together by an impact extrusion between a punch and a female die. Additional elements such as rivets are not necessary. The two layers are locked as the upper layer is spread into the lower layer inside the gap at the bottom of the die called the die groove (Fig. 1).

Numerical simulation is often used for designing clinching process parameters to reduce the costs for the experiments. Simulation of such joining process has been performed by different authors using the finite element method [3, 4, 5]. One of the main difficulties is about the choice of material parameters, *i.e.* stress-strain relation at high plastic strains (up to 200%) and friction related parameters. For the former one, the tensile curve at low strain (< 10 %) is often fitted into a strain hardening law, such as power law model which in turn is used to extend the stress-strain curve to a wider range of plastic deformation. This extrapolation method does not ensure a correct material behavior at high strain. For the latter one, the coulomb friction model is assumed in most cases. The friction coefficients between different parts are often selected within the logical range in a rather arbitrary way without solid experimental supports for the exact materials and configurations. Shear stress limits, if applied, remains also a subjective choice.

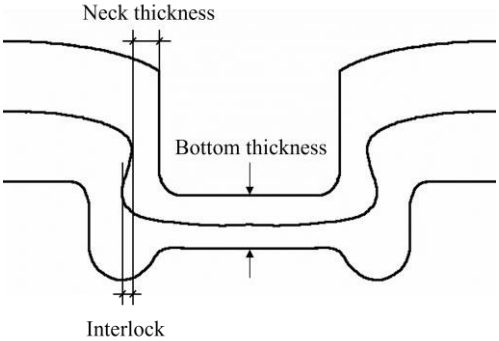

Fig. 1. Typical clinching joint geometry.

In order to select an acceptable combination of parameters which produces comparable results to the experiments, one must run a large amount of simulations. This routine quickly becomes intractable when the number of variable parameters increases and if the computation time is at the range of few hours which is the case for clinching process simulation.

In this study, the application of neural network metamodels is examined to tackle the cumbersome task mentioned above. Specifically, the metamodel replaces computationally expensive simulations in the optimization loop. It will be shown that a neural network can be used to reproduce the effect of material parameters on the punching force and the final joint geometry. It also gives an inside perspective into the unknown material behaviors.

In this paper, the experiments and the simulation model are described in Section 2. The metamodel construction is detailed in Section 3. Its use for the identification of material parameters is then discussed in Section 4.

II. Numerical Simulation

A. Materials and experimental process

In this study, two identical AA5052 aluminium alloy sheets with a thickness of 1.6 mm are joined. During the process, the die is fixed. The punch is driven by a hydraulic machine. At the initial stage, the punch is supported by a solid polyurethane (PU) holder in the form of a ring. The rubber-like holder is deformed as the punch moves downward and guarantees the position of the metal sheets. During the process, the maximum punching force is registered.

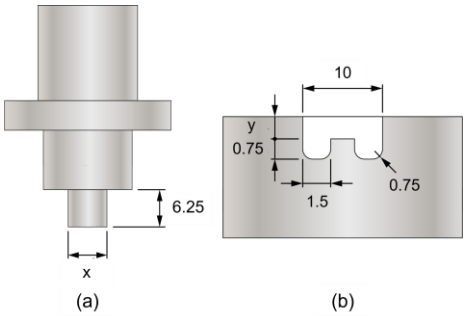

Fig. 2. Punch (a) and die (b) geometry where punch diameter and die depth are denoted as x and y respectively.

The formed clinching joint is then cut into halves so that the cross section dimensions can be measured. The geometry of the punch and the die is illustrated on Fig. 2. A typical joint geometry can be found on Fig. 1.

Three experiments have been conducted with three different configurations of process parameters. The punch diameter, the die depth and the final bottom thickness of the joint are varied. The details of each experiment and the produced joint geometry dimensions are provided in Table 1.

In this study, The tests A and B will be used to determine the material parameters. The test C is reserved for the validation. The idea is that an unique combination of material parameters should be able to give good numerical results for all experiments.

B. Numerical model

A finite element model is built by the help of the commercial software ABAQUS in order to simulate clinching process. Fig. 3 shows the schematic of the initial configuration. Assuming the axisymmetric nature of the problem, a two-dimensional axisymmetric model is adopted. Thus, only half of the structure is simulated. The punch and die are defined as analytical rigid.

The two metal sheets and the holder are meshed using the quadrilateral bilinear axisymmetric element with reduced integration and hourglass control (CAX4R). There are 5000 and 3277 elements in each metal sheet and in blank holder respectively. Remeshing is used to prevent excessive element distortions.

The axisymmetric boundary condition is imposed on the center line of the two metal sheets. The loading is applied by imposing the punch linear motion along the symmetry axis. The initial gap between the punch's lowest surface and the upper surface of the upper metal sheet is 3.75 mm. The

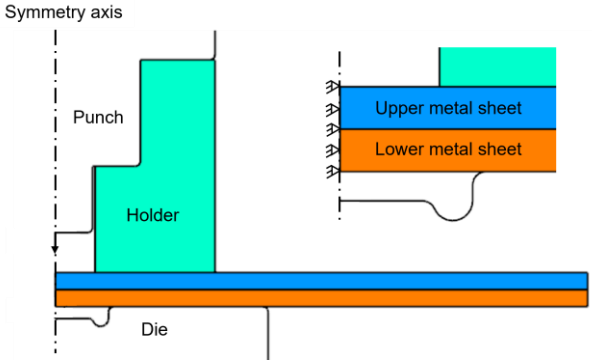

Fig. 3. Illustration of the initial configuration of the FEM model.

maximum displacement of the punch is chosen in order to reproduce the experimental final bottom thickness of the joint. The entire loading time is fixed within 1 second.

An isotropic elasto-plastic model is used to simulate the mechanical behavior law of the two sheets. The data are derived from an uniaxial tensile test of a reference sample. The Young's modulus and Poisson's ratio are 69 GPa and 0.33 respectively. A power law hardening model is chosen to extend the stress-strain curve to a higher plastic strain :

$$R(p) = R_0 * (p + p_0)^n \quad (1)$$

where R ang p are the true flow stress and true plastic strain respectively. Using least square fitting, the material constants are determined as R_0 = 330.5 MPa, p_0 = 0.478E-3 and n = 0.128. The fitting results are shown on Fig. 4. For simplicity purposes, the PU holder is modelled as elasto-plastic materials whose data are also derived from an uniaxial tensile test.

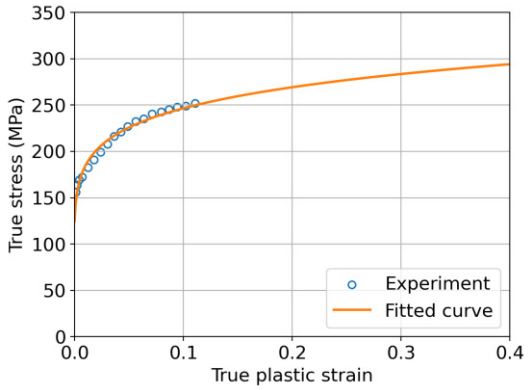

Fig. 4. Fitted stress-strain curve based on experimental data.

TABLE 1. PROCESS PARAMETERS OF THREE REFERENCE EXPERIMENTS AND COMPARISON TO SIMULATION RESULTS

Configurations		Punch diameter (mm)	Die depth (mm)	Bottom thickness (mm)	Punching force (N)	Interlock (mm)	Neck thickness (mm)	Lower sheet bottom thickness (mm)
A	Experiment	7	1.1	0.8	64 400	0.32	0.68	0.56
	Simulation				67 530	0.47	0.59	0.56
	Error				5%	47%	13%	0%
B	Experiment	6.5	1.1	1.0	50 600	0.12	0.75	0.66
	Simulation				53 680	0.31	0.65	0.67
	Error				6%	158%	13%	2%
C	Experiment	7	0.7	1.0	51 800	0.03	0.88	0.66
	Simulation				59 660	0.22	0.78	0.68
	Error				15%	633%	11%	3%

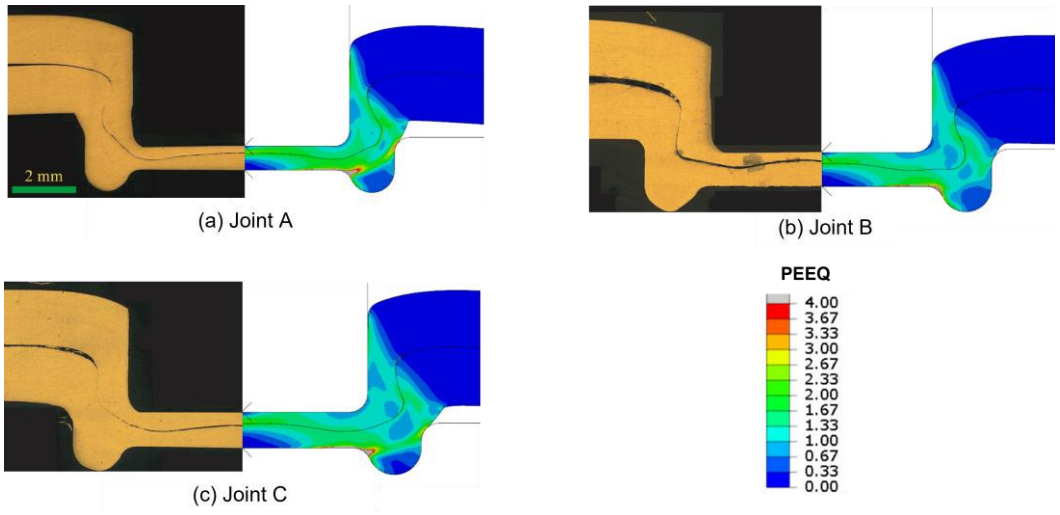

Fig. 5. Comparison between experimental and numerical cross section of clinching joints. The field color represents the equivalent cumulated plastic strain in two metal sheets.

All contacts are defined as surface-to-surface contact pairs. No penetration is explicitly allowed (hard contact). This contact constraint is enforced by the kinematic contact algorithm. The rigid body (tools) surface is always the master surface. A balanced master-slave contact pair is used for the contact between the two metal sheets.

The Coulomb friction model is assumed to model the tangential behavior. The friction coefficient between the different parts is chosen as follows: 1.0 between two metal sheets, 0.25 between sheet and punch/die and 0.1 between sheet and black holder. Furthermore, a shear stress limit of 75 MPa which is roughly half the yield stress of the aluminium alloy is applied to the friction between the punch and the metal sheet. One must note that even if the friction parameters taken in the model are within the logical range based on the literature, they are taken in a rather arbitrary way.

The explicit solver is chosen to solve this problem. Fig. 5 shows the simulated geometry of the joints and the experimental cross sections. The dimensions are detailed in Table. 1. Even if the overall shape of the simulated joints is rather good, the exact values of important features, *i.e.* interlock, neck thickness, punching force, do not answer to our satisfaction. Notes that the equivalent plastic strain in two metal sheets can reach up to 200%.

III. Neural Network Metamodels

One can simply try to simulate on a large number of possible values of material parameters, in order to find a good combination which is able to approximate the experimental results of all experiments. However, one FEM simulation takes about one hour on our computer. This level of computation time makes this routine intractable. Instead, a metamodel can be constructed in order to reproduce the relation between the material parameters and the results as predicted by the simulations, within a reasonable amount of simulation runs.

This section described the construction of a such metamodel on the configuration A. The same applies for the metamodel on the configuration B which is not detailed here for repetition.

A. Data generation

The inputs of the model should represent the material parameters we want to determine which are the stress-strain curve at high strain level and the friction behavior between contact surfaces.

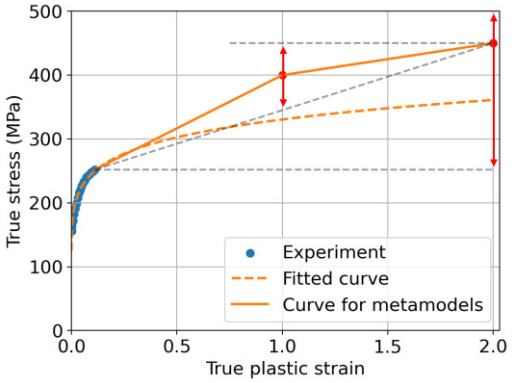

Fig. 6. Stress-strain curve used for metamodels. The arrows illustrate the range and the constraints on the two input parameters.

The following contacts are considered : between punch and upper metal sheet, between die and lower metal sheet and between two sheets. For each contact, two parameters of the Coulomb model are considered : the friction coefficient and the shear stress limit. In this study, the range of the friction coefficients is from 0 and 1. The shear stress limits can range from a fifth to the “full” yield stress limit of the aluminium alloy 88 MPa. Their value is normalized by the latest before fed into the metamodel.

It is decided to model the extrapolation of the stress-strain curve using two values: the stress at 100% plastic strain and the stress at 200% plastic strain (Fig. 6). The curve is the linear interpolation between the last experimental data point and these two points. Despite its oversimplification, this representation offers flexibility of the curve and avoids the limitation of using a specific work hardening law. However, some constraints must be applied to ensure physical common sense. First, the stress at 200% strain must be greater than the stress at 100% strain which in turn must be greater than the last experimental measured stress. Second, as a stress-strain

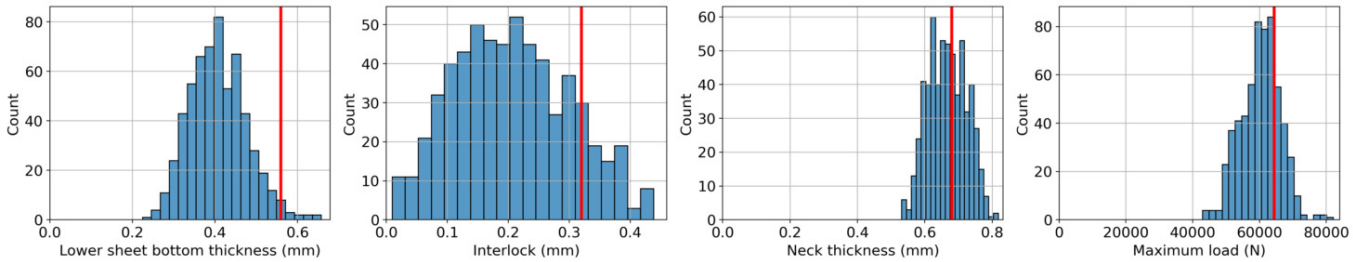

Fig. 7. Histograms of outputs in the dataset. The red lines represent the experimental results.

curve must be convex, the stress at 100% strain must be greater than the linear interpolation between the stress at 200% strain and the last experimental measured stress. In this study, the stress at 200% strain is considered up to 500 MPa.

Within the mentioned ranges, input samples are generated pseudo-randomly using Halton sequence, which is one of Quasi-Monte Carlo methods, in order to maximize the coverage of the parameter space. This method offers an advantage over other methods like Latin Hypercube sampling that one can incrementally add more points to the data set without forming clusters.

Once input samples are generated, they are fitted into the FEM simulations which return outputs. Four outputs are considered in this study : maximum punching force, interlock, neck thickness and lower sheet bottom thickness. The computation routine and the extraction of interested features are executed automatically using Python scripts and the Abaqus Scripting Interface. Fig. 7 shows the histogram of the four outputs. The experimental results are within the covered domains.

In order to speed up learning, the simulation outputs are scaled using their minimum and maximum values such that all feature values are in the range (0, 1). The last 2 input (stresses) features are also scaled by using two limits 250 MPa and 500 MPa. The first 6 input features are naturally within this range.

B. *Neural network architecture*

A fully connected neural network with only one hidden layer is chosen for the metamodel. Its architecture is illustrated in Fig. 8. There are 8 (hidden) nodes in the hidden layer (and one bias node). This architecture choice is later explained in Section III.C.

Each hidden node represents a neuron of the network. It is connected to every node in the previous layer. Each connection is assigned with a weight which is a trainable parameter of the model. A hidden node calculates the weighted sum of the values from the previous nodes and passes it to the sigmoid activation function which outputs values in between 0 and 1. No activation function is used for the output nodes.

C. *Training*

The first hundred samples in the Halton sequence are selected for the validation set which is used to evaluate the

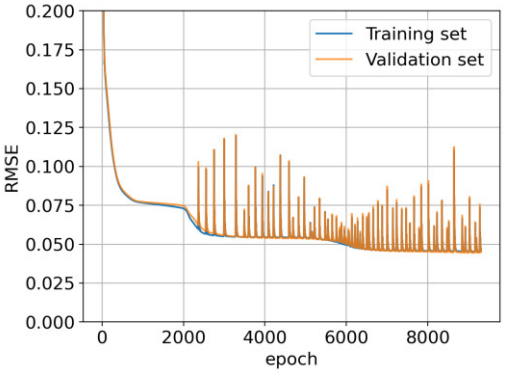

Fig. 9. Root mean squared errors (RMSE) on the training set and the validation set against the number of epochs during the training.

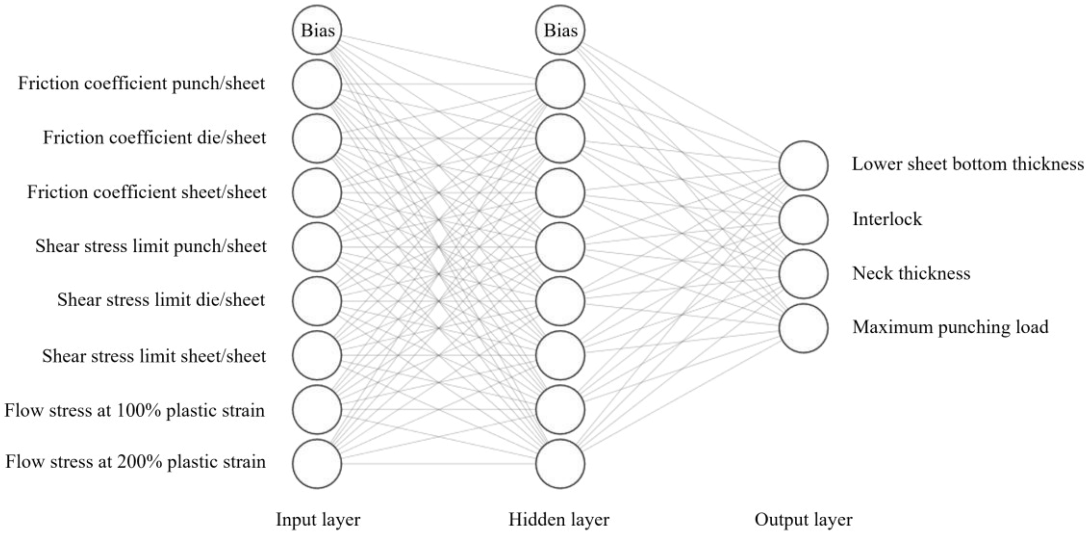

Fig. 8. Neural network architecture used for metamodels

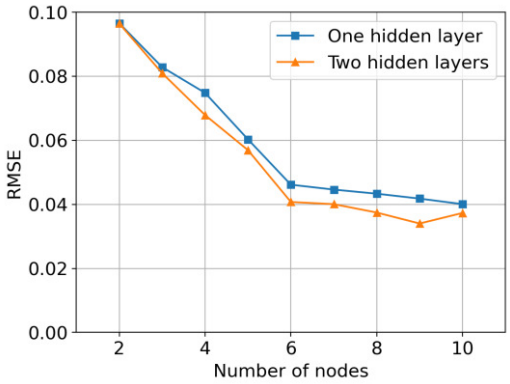

Fig. 10. Root mean squared errors on the validation set as a function of the number of nodes in each hidden layer.

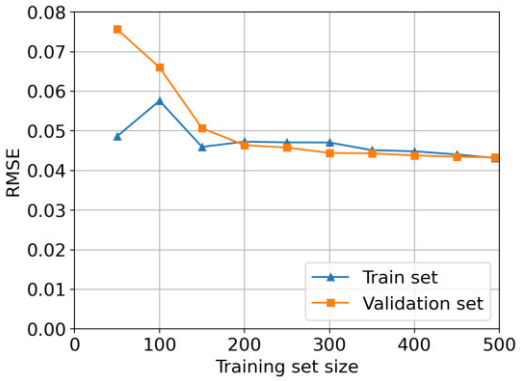

Fig. 11. Root mean squared errors on the validation set as a function of the training set size.

model's performance on unseen data. The next 400 samples are used as the training set.

For the training, the loss function is the mean squared error (MSE) averaged over 4 outputs. Backpropagation learning is performed with the Adam algorithm that involves gradient descent with momentum and adaptive learning rate. An epoch is comprised of only one batch which contains the full training set. In other words, the training is not stochastic. Early stopping regularization is used to stop the training before overfitting with the validation loss as the monitored metric. The model weights are initialized randomly from a normal distribution with mean 0 and variance 1. In order to get a good local minimum, different seeds are tested for weight initialization. Then the seed giving the lowest validation loss is chosen for the final results. The training history is shown in Fig. 9. The oscillation near the convergence is a typical feature of the Adam algorithm related to the adaptive momentum.

The necessary code was implemented in Python using Keras library with TensorFlow backend.

D. *Hyperparameters tuning*

The number of hidden layers and the number of nodes in each hidden layers are two important hyperparameters to be tuned for each problem. An oversimple architecture neural network cannot predict with good accuracy. A complex model is difficult to train and can suffer from overfitting. One must find a compromise between these two problems.

Fig. 10 plots the evolution of the error (loss) evaluated on the validation set in function of the number of hidden nodes for two cases: one hidden layer and two hidden layers. For simplicity, the numbers of nodes in two hidden layers are constrained to be equal. It is shown that a neural network with more than 8 hidden nodes does not offer a higher prediction accuracy. In addition, adding another hidden layer also does not significantly improve the metamodel performance.

E. *Effect of the training set size*

Fig. 11 shows the metamodel accuracy in function of the size of the training set. It can be seen that adding more data over 300 samples does not help to improve the prediction accuracy remarkably. Moreover, it is a good indication that the error on the validation set is close to the error on the training set.

IV. Material Parameter Identification

Two metamodels have been constructed for two process configurations A and B in order to predict simulation results from 8 material parameters. The material parameters therefore can be optimized in order to minimize the difference between the simulation results and the experimental results. The loss is chosen to be the average of the mean squared error of the four outputs of the two metamodels. The optimization is performed using a gradient based algorithm. The gradient of the loss is calculated by automatic differentiation thanks to GradientTape API provided by TensorFlow.

TABLE 2. OPTIMIZED MATERIAL PARAMETERS

Solutions	**Friction coefficient punch/sheet**	**Friction coefficient die/sheet**	**Friction coefficient sheet/sheet**	**Shear stress limit punch/sheet (normalized)**	**Shear stress limit die/sheet (normalized)**	**Shear stress limit sheet/sheet (normalized)**	**Flow stress at 100% strain (MPa)**	**Flow stress at 200% strain (MPa)**
Global optimum	1.0000	1.0000	1.0000	0.2000	1.0000	0.3575	415.8707	391.7660
1	0.7410	0.5162	0.4858	0.3386	1.0000	0.3611	394.5972	372.5730
2	0.5881	0.4398	0.7545	0.3160	1.0000	0.2994	399.2369	371.1448
3	0.5959	0.7602	0.5231	0.3577	1.0000	0.2826	441.4521	351.3855
4	0.7469	0.4927	0.4655	0.3442	1.0000	0.3248	415.6395	360.2948
5	0.5983	0.5205	1.0000	0.2138	1.0000	0.3340	440.7345	382.0971
6	0.7800	0.5051	0.8045	0.2543	1.0000	0.3671	397.4937	386.2823
7	0.8225	0.6115	0.8042	0.3382	1.0000	0.2777	416.7320	361.1949
8	0.2781	0.6865	0.4518	0.3875	1.0000	0.2846	404.0742	355.6252
Mean	0.64	0.57	0.66	0.32	1.0	0.32	414	368

TABLE 3. SIMULATION RESULTS WITH OPTIMIZED MATERIAL PARAMETERS

Configurations		Punching force (N)	Interlock (mm)	Neck thickness (mm)	Lower sheet bottom thickness (mm)
A	Experiment	64 400	0.32	0.68	0.56
	Simulation	75 960	0.19	0.77	0.52
	Error	18%	40%	13%	7%
B	Experiment	50 600	0.12	0.75	0.66
	Simulation	49 400	0.12	0.75	0.60
	Error	2%	< 8%	< 1%	9%
C	Experiment	51 800	0.03	0.88	0.66
	Simulation	57 050	0.01	0.90	0.66
	Error	10%	67%	2%	< 2%

The Table 2 shows some material parameter combinations as suggested by the optimization which give approximately the same level of deviation from the experimental results as predicted by two metamodels (less than 10% than the variation range, see Fig. 7). Each solution results from a different initialization of the input variables at the beginning of the optimization process.

It is worth to mention that the global optimum in this problem stays at the border of the searched domain. We opted for slightly lower accuracy for more physical meanings. However, the shear stress limit at the contact between die and sheet still remains at its maximum which is the yield stress limit of the aluminium sheet. There may be a physical meaning behind this fact, but it is quite surprising that the contact between punch and sheet (basically the same materials) does not exhibit the same behavior. All other material parameters seem to fluctuate around and close to some means. However, a combination of these means does not give results comparable with the experiments.

The simulation results using the first solution are shown in Table 2. Even if the error in the interlock on the configuration A is still non negligible, the error levels are significantly smaller and more spread out over all outputs compared to the results obtained with non-optimized material parameters in Table 1. The observed high error indicates that the optimization algorithm has a hard time to satisfy two experimental results simultaneously, despite a rather high number (8) of variables.

Interestingly, even if no metamodel is constructed for the configuration C and their experimental results are not used to tune material parameters, we get a good comparison. The simulated joint geometry is shown in Fig. 12. The vanishing of the interlock is well simulated. This shows the generalizability of the determined material parameters on others process configurations.

V. CONCLUSION AND PERSPECTIVES

In this paper, the authors explore the applicability of machine learning based metamodels to tackle the high computation time problem encountered during the material parameter tuning task in the context of clinching process simulation. It is shown that simple neural network metamodels are able to learn with high precision the relation between material parameters and joint geometry as predicted by FEM numerical simulations. They then are used to replace simulations inside the optimization loop.

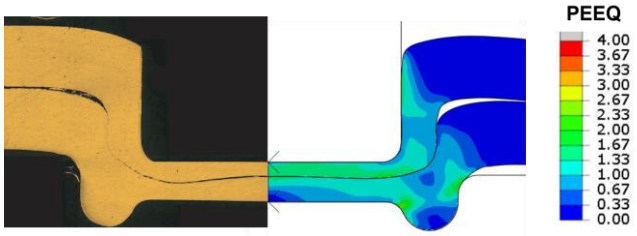

Fig. 12. Simulation results on the configuration C with optimized material parameters.

The obtained results are promising. The optimized material parameters help to reduce significantly the error between simulated results and experimental results, not only in the configurations where metamodels are constructed but also on a new simulation. This methodology shows its value in the cases where material parameters are not available or difficult to measure. On top of that, it may help to understand more about physical phenomena behind the numbers.

In order to increase the reliability of the determined material parameters, it is worth to conduct more experiments. The applicability of others machine learning algorithms can also be assessed.

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REFERENCES

[1] S. Gao, B. Lothar, “Mechanism of mechanical press”, Int J Mach Tools Manufact 34, 1994, pp 641–657.

[2] N. Nong, O. Keju, Y. Zu, Q. Zhiyuan, T. Changcheng, L. Feipeng, “Research on press joining technology for automotive metallic sheets”, J Mater Proc Techn, vol. 137, 2003, pp. 159-163.

[3] F. Lambiase, A. Di Ilio, “Optimization of the clinching tools by means of integrated FE modeling and artificial intelligence techniques”, Procedia CIRP, vol. 12, 2013, pp. 163-168.

[4] E. Roux, P.O. Bouchard, “Kriging metamodel global optimization of clinching joining processes accounting for ductile damage”, Journal of Materials Processing Technology, vol. 213, 2013, pp. 1038-1047.

[5] M. Eshtayeh, M. Hrairi, “Multi objective optimization of clinching joints quality using Grey-based Taguchi method”, Int J Adv Manuf Technol, vol. 87, 2016, pp. 233–249.