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Neural Network Multiobjective Optimization of Hot Forging

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Abstract

Hot Forging optimization depends on several factors, known with uncertainty: die pre-heating, geometry, tempering, workpiece temperature and shape, lubricant. There are also several objectives: quality, energy consumption and tool life.
Global optimization methods require a numerous process evaluations to reach the optimum. While tests can be simulated by Finite Element Method (FEM), most of them were substituted by a Neural Network model. Neural Network training is less sensitive to problem dimension than standard Design of Experiments. The approach is assessed against the traditional Finite Element Optimization by exploiting a case study of a steel disc.

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Keywords: Finite Elelements Method; Neural Network; Design of Experiments; Nonlinear Optimization

1. Introduction

Die design and optimization of process parameters in hot metal forging are usually performed by applying empirical design rules based on enterprise's experience and by making tests on prototypes. There are several reasons behind the lack of a formal and structured design method in forging. They can be summarized in the difficulty to cope with the large number of production control parameters, the difficulty in building reliable models of highly nonlinear phenomena and the large process variability. Due to the increasing cost of tools and to the demand for defect free production parts, the traditional trial and error design process should anyway be replaced by a virtual prototyping approach, based on the simulation of a part or of the whole forging process and consequent heating treatment.

Due to the large number of factors influencing the process, it is necessary to use methods of global optimization, like genetic algorithms, particle swarm, etc. They require many tests to assure the global optimum. Test time can be shortened by recurring to the simulation with Finite Element Method (FEM). Even so, a considerable computational time is required to execute a full thermal-mechanical 3D simulation. FEM simulations can be executed only few times and the remaining testing points should be substituted by a numerical model of the response function. Among these numerical models, the polynomial regression, used in statistical Design of Experiment (DOE) or the Kriging approach have some limitations, described in the paper. Therefore, a Neural Network (NN) has been used and natural process variability was accounted for. Even NN demands for a large number of tests but, as the variables increase, the test number increases with a slower rate with respect to DOE. Furthermore, it is possible to train the NN using a set of values not covering systematically the space of solutions.

In present study, FEM simulations were executed in selected points. They were repeated with different values of disturbance factors. NN was trained, validated by additional set of tests data and eventually used to create a complete response surface to feed the optimization procedure.

Solution is checked against FEM and the procedure is repeated iteratively until convergence. Due to process

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variability attention was given to obtain a robust optimal solution by considering in the cost function all the desired outputs and by giving preference to a stable solution.

The method was developed having as a target the applicability in the context of industrial process design, so paying attention to easy implementation and to computational time requirements. NN allow to replicate the expert reasoning based on the experience. A case study of a steel disc has been used to present the method and to test the actual ease of use.

2. Issues in process design

The process parameters involved in hot forging and their role have been subject of investigation by [1] and [2]. They can be clustered under the following main groups [3]:

- Product geometry
- Product material
- Tooling
- Machine
- Process
- Tool-workpiece interface effects

Every group is composed by several parameters, each of them needing thorough investigation to understand its effect on the different quality and performance indicators and to define the guidelines for their optimal setting. As an example, flash allowance has important and conflictive effects on both the die filling and the die life [4]. Several models have been proposed to design the flash land. [5] compared 6 models, used them to design the flash land and verified the results by FEM simulation. They chose one model focusing on the minimization of die wear, but they recognized that, considering all of the outputs, there was not a clear winner. In table 1 the most significant parameters are listed, concerning the process and the tool-workpiece interface.

It is easy to understand the level of complexity when the parameters are considered all together. An additional difficulty is due to the difficulty in controlling all of the referred parameters. Workpiece and die temperature are defined at design stage but could change, due to the waiting time before forging and to the variability in the heating procedure.

Table 1. Selection of significant process parameters

Group	Parameter	Metric	Controlled?
Process	Workpiece's initial temperature	°C	Design
	Die temperature	°C	Design
	Time in air	s	Disturbance
	Time in open die	s	Disturbance
	Forging sequence	-	Design
	Die-part centering	mm	Disturbance
	Kinematics	-	Process
Interface	Friction coefficient	-	Design
	Heat conduction	°C	Design
	Lubrication properties	mm	Design

The amount of time spent on the die before the blow is widely variable and should be considered more a disturbance than an input parameter for the process.

Therefore, the standard procedure adopted in the majority of companies is to empirically repeat proven functioning sets of parameters, making changes only on the process variables taken one by one. Recently, some authors propose to use the possibility of executing FEM simulations to look for optimal values of process variables, as in [6] or in [7]. In [8], FEM is used to concurrently optimize both process and product, obviously on a reduced number of variables. The optimization procedure is deeply related to the objective of the optimization. Some study researches the minimization of the plastic deformation energy, others the under-filling of the die, the die wear, the folding defects and so on.

The complexity of global multi-objective optimization of every factor in the process is so high that several authors prefer to develop empirical expert systems to assist in the design phase [9] and [10]. These systems are coded with the support of a campaign of experiments. Thus, the complexity of the problem is so high that presented case study are referring only to 2D axisymmetric process.

Eventually, some researchers [11], [12] proposed to use a Sequential Approximate Optimization algorithm (SAO) to optimize forging process, using the time-consuming FEM simulation only to fit a metamodel of the process, by Polynolmial regression or Kriging interpolation. The metamodel is used by the optimization algorithm that is evaluated by simulating the optimum with FEM.

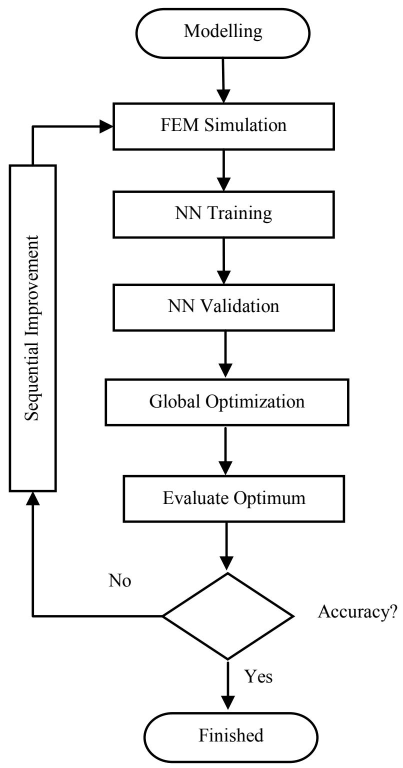


Fig. 1. Sequential Approximate Optimization Algorithm using NN

3. The NN optimization procedure

In the present study, a version of the SAO algorithm is implemented where the metamodel is changed with a NN. The NN is trained on examples obtained executing a set of FEM simulations that are selected using the DOE methodology. The implementation of the SAO algorithm, used in present study, is presented in Fig.1.

The reason for choosing NN instead of a metamodel is the following. Metamodel shape is constrained by the need of being able to fit it with polynomial regression or kriging. It means that, in order to obtain fair results, the function should be linear or quadratic, possibly without interactions among the variables.

The NN, conversely can be trained with whatsoever number of input factors (design parameters and disturbances as well) without imposing constraints on the shape of the response surface (the metamodel). Furthermore, it is possible to train the NN with input distributed in a non-regular way. After the first iteration of the algorithm it is therefore possible to refine the NN just in the area near the optimum, without the constraints posed by DOE construction.

3.1 Neural network design

The capability of the NN model to generalize regarding unknown data depends on several factors such as appropriate selection of input–output parameters of the system, distribution of the input–output dataset, and format of the input–output dataset presentation to the NN.

Accordingly, four steps were followed in the development of the NN model: (i) input–output dataset collection, (ii) input–output dataset pre-processing, (iii) NN design and training, and (iv) NN performance evaluation.

The optimal NN architecture was determined after several simulation trials. Diverse configurations of NNs were trained to identify the best arrangement for the prediction of flank wear. The parameters that were changed among the different configurations are the following:

- number of nodes in the hidden layers;
- number of hidden layers;
- activation function of the node neurons.

In particular, to predict the T_{eq} 3, three diverse NN configurations were constructed and tested: NN5, NN8 and NN15 with 5, 8 and 15 nodes in the hidden layer, respectively. While, to predict the wear_t value, two different NN configurations were constructed and tested: NN3 and NN5 with 3 and 5 nodes in the hidden layer, respectively

In all tested NN configurations, the input layer had three nodes to receive the feature vector (Tp, Td and f) while the output layer had only one node to predict the T_{eq} or wear_t,.

The number of hidden layers was set equal to one and the number of hidden nodes was chosen according to a ''cascade learning'' procedure [14]: hidden units are added one at a time until an acceptable training speed is achieved. The hidden nodes were initially set equal to four and further nodes were added incrementally. The addition of hidden nodes continued until there was no significant progress in the NN performance.

To set up the NN models, the NNet toolbox of the Matlab software package was used. In particular, the Levenberg–Marquardt backpropagation algorithm was adopted for its performance in terms of rapid network error convergence and good reliability.

For optimal NN architecture configuration, weights and thresholds were randomly initialized between -1 and +1. Learning coefficients were: learning rate between input and hidden layer: 0.3, learning rate between hidden and output layer: 0.15, momentum: 0.4. The learning rule was the Normal Cumulative Delta Rule and the transfer function applied to the nodes was the sigmoid function $f(x) = 1/(1 + e^x)$ [15].

The number of learning steps for a complete training was set at 2000 on the basis of the time to convergence. Epoch size, i.e. the number of training presentations between weight updates, was set at 100.

4. Case study: optimization of a extruded forged disk

The case study is a C22 disk obtained in two steps by extrusion forging. The first step is the blocking phase. After flash removal, it is followed by a finishing step. The maximum die wear is found in the blocking phase that therefore is subjected to optimization. In this test of the method, only the parameters of the process and of the interface were considered, together with the disturbances variables. Fig. 2 shows the initial and the forged part.

The original process is executed on a 6.3MN crank press, 250mm/s ram velocity, the workpiece temperature is 1200°C, the dry lubricant is graphite with water vapor for a friction factor of 0.4. Both dies are H13 - AISI steel with ion nitride surface treatment and are pre-heated to 200°C. The flash is 3mm thick.

The process has been chosen as a benchmark because the FEM simulation is in good agreement with the experiment. The coupled thermos-mechanical simulation is executed with the QForm3D software from Quantor.

The temperature in the workpiece and in the die changes consistently during forging. In Fig.3 it is possible to see that external temperature lowers to 800°C, while internal rises to 1278°C. Die temperature in Fig.4 rises to 662°C.

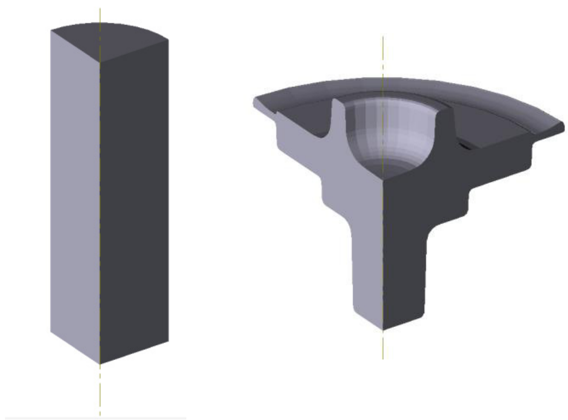


Fig. 2. The initial and forged workpiece.

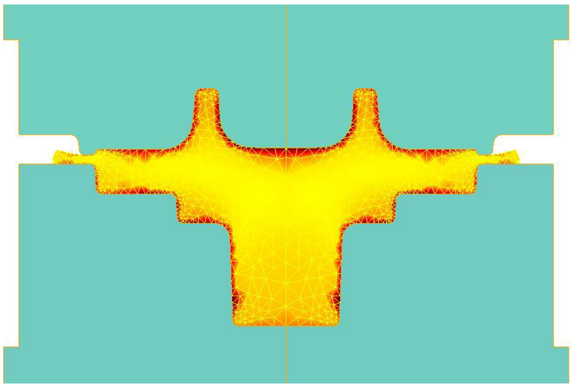


Fig. 3. The temperature on the workpiece at the end of the process (min 802°C, max 1278°C).

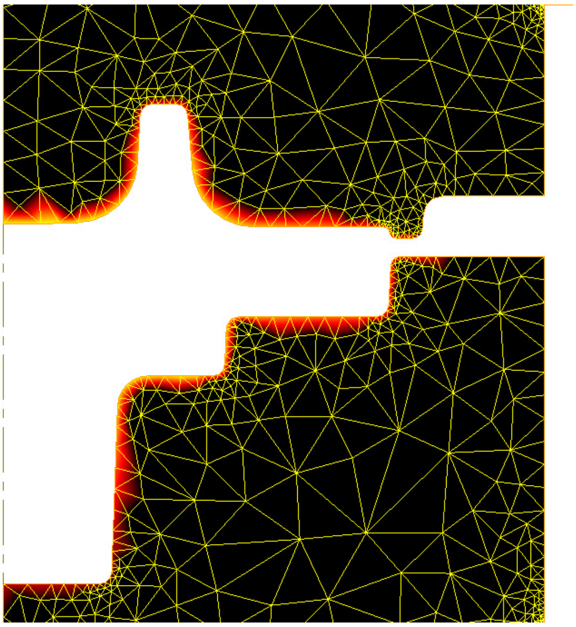


Fig. 4. The temperature on the die at the end of forging process (min 200°C, max 662°C).

There is a consistent effect of thermal softening that reduces die life because of plastic deformation of the die [13]. The equivalent temperature, expressed as (T_{max} and T_{min} are the highest and lowest temperature in the same point on the die during the forging cycle):

$$T_{eq} = \frac{2T_{max} + T_{min}}{3} \tag{1}$$

is 508°C that gives an estimated die service life of about 20000 cycles (the amount of plastic deformation after which the die life is terminated is a matter of choice). At the same time the wear traction on the most stressed zone of the die, can be calculated from the Archard abrasive wear model as

$$W = \frac{k}{3h} \int_{tcycle} \mu p v_s dt \tag{2}$$

where W is the wear traction, k a wear coefficient, μ the friction coefficient, p the normal pressure on the die surface, v_s the sliding velocity, h the HrC hardness of the die. Assuming k as 1000, the wear traction is 0.94 that gives an estimated die service life of about 10400 cycles (again, the amount of acceptable wear before changing die is a matter of choice). Every action that increases the equivalent temperature worsens the die life due to plastic deformation, but improves the die life due to abrasive wear.

Fig. 5 shows the wear traction on the dies. Wear figures are concentrated in few zones. One of them is, as expected, the flash land. The others are in correspondence with curvature radii of the dies.

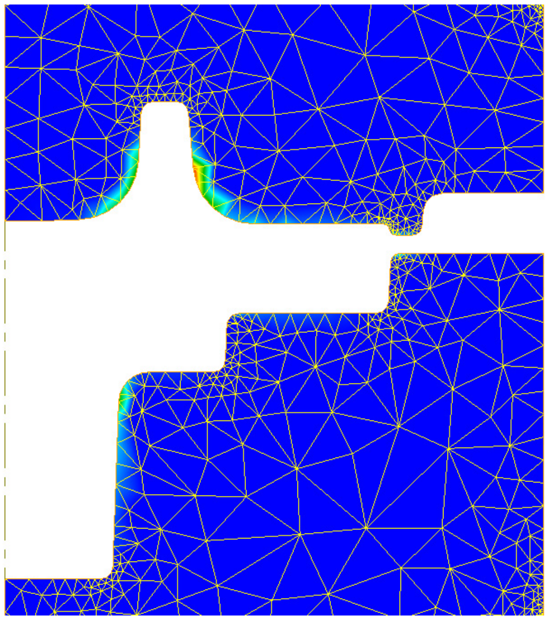


Fig. 5. The wear traction on the die at the end of forging process (min 0, max 0.94). The wear is concentrated in a few spots.

5. Analysis and results

The simulations used for the initial training of the NN have been executed following a 3^3 full factorial design with as factors: workpiece initial temperature, die temperature and lubricant type. The range of variation of the factors has been chosen very wide, to cover the largest experiment area. The 3 levels of the factors are reported in Table 2. Disturbances are considered by introducing random variations of the variables that are not under control.

Table 2. The values of process parameters used to build a full factorial design structure for NN training (3 factors on 3 levels)

Parameter	Level 1	Level 2	Level 3
Workpiece temperature	1050°C	1150°C	1250°C
Die temperature	20°C	200°C	400°C
Lubricant	glass	Graphite + water	Unlubricated

5.1. Neural network training and testing

During the training phase, input vectors were sequentially presented to the NN input layer, and the corresponding measured Teq or wear_t value was fed to the output layer (Table 3).

During the recall phase, the output of the NN was the predicted value of T_{eq}, T_{eqpp}, or wear_t, wear_tp, for each input vector.

By setting normalised error $En_{Teq} = (T_{eqp} - T_{eq})/T_{eq}$, and En_w = (wear_tp - wear_t)/wear_t, the NN output identification is correct if $En \in [-0.5, +0.5]$; otherwise, a misclassification case occurs. The ratio of correct classifications over the total number of input feature vectors yields the NN success rate. The normalised errors were calculated and plotted versus the number of NN input vectors (Figure 6) for the different NN models.

Table 3. NN input and output vectors

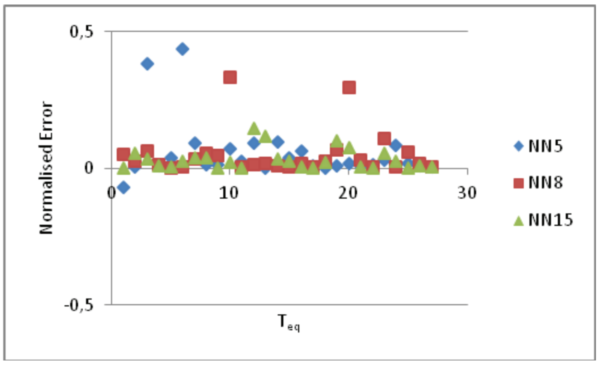
NN Input			NN output 1	NN output 2
Tp	Td	f	Teq	wear_t
1050	20	0,15	319	0,001200
1150	20	0,15	345	0,000919
1250	20	0,15	369	0,000728
1050	200	0,15	406	0,001260
1150	200	0,15	427	0,000956
1250	200	0,15	448	0,000722
1050	400	0,15	546	0,001180
1150	400	0,15	566	0,000968
1250	400	0,15	586	0,000743
1050	20	0,4	381	0,001500
1150	20	0,4	411	0,001175
1250	20	0,4	441	0,000948
1050	200	0,4	456	0,001660
1150	200	0,4	482	0,001480
1250	200	0,4	508	0,000940
1050	400	0,4	584	0,001700
1150	400	0,4	609	0,001180
1250	400	0,4	634	0,000931
1050	20	0,8	433	0,002189
1150	20	0,8	467	0,001770
1250	20	0,8	495	0,001353
1050	200	0,8	502	0,002590
1150	200	0,8	526	0,001928
1250	200	0,8	556	0,001460
1050	400	0,8	615	0,002540
1150	400	0,8	651	0,001900
1250	400	0,8	673	0,001390

The trained NN was fed to a global optimization method for mixed-Integer non-smooth problems. The chosen method is the genetic algorithm. The problem admits multiple local solutions and is always multi-objective. The problem has to be considered as mixed-integer because the friction coefficient in this case study, but also other parameters in a more complete optimization can assume a limited, integer, number of values.

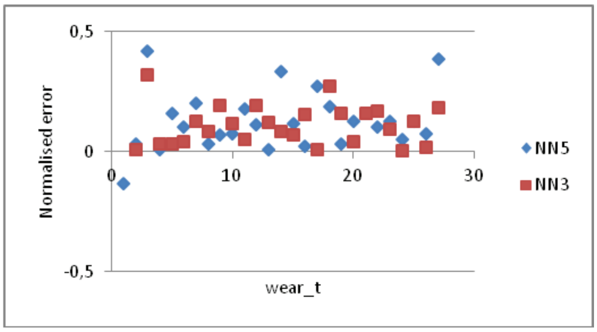
Table 4 shows the comparison of the results through optimization and the corresponding results obtained by FEM used as an evaluation tool. As the residuals are below the given accuracy threshold, the sequential optimization stopped. It is worth noting that sequential optimization requires a very short number of iterations. Unfortunately, the method cannot guarantee either the convergence or the convergence to an optimal solution. However, this limit is already present in the genetic optimization algorithm.

Table 4. Evaluation of the optimal solutions by comparing the NN based optimization of equivalent temperature and wear traction with the FEM simulation using the same input data.

Output	Optimized value / FEM	Workpiece temperature	Die temperature	Lubricant
Teq	318 / 319°C	1050°C	20°C	Glass
W	0.62 / 0.73	1250°C	20°C	Glass



(a)



(b)

Fig. 6: NN normalised error for the diverse NN configurations related to (a) Teq and (b) wear_t.

6. Conclusions and further developments

In the paper, a version of Sequential Approximate Optimization algorithm is implemented where the metamodel to be optimized is substituted by NN. The use of NN allows to find the optimal solution to multi-objective multi-factor forging design problem without executing too many computing intensive FEM simulations. With NN, the constraints on metamodel shape have been relaxed.

The application of the algorithm to a standard case study has made it possible to highlight the potentials of the approach but also the drawbacks: multi-objective model leads to as many NN as the objectives, but different NN can have different levels of fitting to the studied system, thus leading to uneven distances from the optimum.

Further developments of the research will be the training of the net using a large dataset obtained by 2D simplified (and faster) simulations of 3D complex parts to greatly increase the size of the training set and to further replicate the actual reasoning process of the factory expert: abstraction of design rules from the experience on simple problems.

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