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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.

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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

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