The evolution of forming process models – from process simulation to model-based control

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Abstract. The development of forming processes hinges on the availability of models. Analytical models are only useful for very simple processes and geometries. Since the early eighties, industrial forming simulations have been developed based on the finite element method. For many processes the models reached sufficient predictive accuracy to be used by default in tool design. Subsequently, the application of these models in process optimization is discussed. It is shown that robustness must be included in the models when used for optimization. A new step in this sequence is the integration of process models in ‘model based control’ of forming processes. For this application reduced order models are essential.

1 Introduction

Forming processes show highly nonlinear relations between forces and displacements due to 1. nonlinear material behaviour 2. large deformations and rotations and 3. contact between tools and workpiece. Before the advancement of computer technology, forming process analyses were limited to very simple geometries and material models. Slip line theory and upper bound methods were used to model 2D and primarily plane strain situations of upsetting, rolling, ironing, machining and other processes [1]. One typical example is the application to extrusion through conical dies by Chenot et al. [2]. In the 1970s, commercial nonlinear finite element codes became available, the first one being Marc (now MSC Marc) in 1971. Limited computer resources, however, postponed widespread application in forming simulations until the 1980s. At the first Numiform conference in Swansea in 1982 [3] papers were presented by participants from industry, software companies and academia. At that time finite element models were typically 2D plane strain or axisymmetric with about 100 elements. An early example is the 2D FEM simulation of molten polymer flows [4].

2 Bulk forming simulations

Early simulations often considered plane strain or axisymmetric bulk forming processes. Numerical issues like volume-locking and objectivity were solved. Thermo-mechanical coupling was introduced in fully implicit or staggered algorithms.

Typical for bulk forming simulations is that the large deformations induce significant mesh distortions, requiring regular remeshing operations. For quasi-steady state processes like extrusion and rolling, the process zone where plastic deformation takes place is often small compared to the complete work piece. For both problems, the arbitrary Lagrangian Eulerian method was developed e.g. by Huétink [5].

3 Sheet metal forming simulations

Anisotropic material modelling is especially important for sheet metal forming because predicted earing and thickness distributions are highly dependent on the applied yield function. In 1948, Hill postulated a quadratic function that can easily be used for 2D plane stress conditions, using 3 independent parameters. In industry, the Hill ‘48 model is still frequently used and for mild steel it is often also quite appropriate.

A whole series of non-quadratic yield functions were developed which were originally focused on the description of the behaviour of aluminium. But for advanced high strength steels, the non-quadratic models are also improving the predictive performance. By using shell elements and appropriate material models, efficient and accurate simulations are feasible and are now routinely used in automotive industry.

4 Numerical optimization

With the availability of sufficiently accurate numerical models, process optimization can be performed virtually. Standard optimization algorithms commonly require a lot of function evaluations and sometimes also need function derivatives. This direct approach would be very time consuming if every function evaluation requires a full nonlinear FEM simulation. Therefore, numerical

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optimization of forming processes is usually performed in two steps. First, an easy-to-evaluate meta-model is made based on a limited number of FEM simulations and subsequently, the optimization algorithm uses the meta-model. Meta-models can be relatively simple polynomial functions (classical Response Surface Modelling) or more advanced interpolating functions like Radial Basis Functions or Kriging. In Twente, the sequential improvement strategy of meta-models was investigated by Bonte et al. and at CEMEF, the meta-model assisted evolutionary strategy was developed for optimization of forging processes by Fourment et al. A comparison is given in [6].

5 Robust Optimization

A drawback of using the optimized process settings in practice is that the optimum that is found, is very often at one or more of the defined (active) process constraints. If the constraints represent specification limits, unavoidable material and process scatter will result in a large amount of products that are out-of-specification. For this reason, optimization problems should always include robustness requirements from the start on. This approach fits very well to the application of Statistical Process Control in real production processes. Robust optimization problems are defined in terms of stochastic parameters like the mean and standard deviation of input and output parameters. In this way it is possible to optimize virtually to a required process capability [7]. E.g. the cost can be minimized under the constraint that for a particular geometrical requirement, the mean plus 3 times the standard deviation is below the upper specification limit, to derive a 3σ process robustness.

6 Model based process control

Given the specification limits of a product and the variation in material and process parameters, robust optimization may fail to find a process setting that leads to a sufficiently robust process. In that case, the process settings must be adapted, based on the actual process conditions and material that is currently being processed. Apart from mean and standard deviation also the product-to-product correlation must be considered. Slowly varying process and material parameters can be controlled by a feedback controller, but for fast variations feed forward control is needed. In a multi-stage forming process, measurements in the early stages of the process (e.g. process forces) are affected by the variations of process and material parameters. Given the availability of highly accurate process models, the effect of these variations on the final properties of the product can be predicted based on the measurements from the early stages of the process. This prediction can be used to create a feed forward control loop for the final stages of the process, eliminating at least a part of the variation in product properties [8, 9]. The process models are used to estimate the variations of many different process and material parameters based on small product-to-product variations in the process measurements. Therefore, highly accurate process models are required for feed forward control in forming processes.

Model based control of a multi-stage forming process requires that the model reacts very fast. In a large EU project (MEGaFiT) [10], a multi-stage forming process demonstrator was developed with a production rate of 100 strokes per minute. This means that after measurements at one stage, only a few tenths of a second are available to evaluate the data and adapt the process settings of the next forming stage. FEM calculations are too slow to be applicable for real-time control of production processes. Therefore, easy to evaluate process models based on prior measured data or reduced order models based on off-line FEM calculations are used for feed forward control. These models require a high level of accuracy and short evaluation times, to be able to interpret complex non-linear interactions between process, material and control parameters in a real-time production environment.

References

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