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ABSTRACT: Robust processes and robust engineering are enjoying increasing interest throughout industry. Robust engineering is taking into account variation that can occur during manufacturing processes when we analyse or optimise them. Corus is interested in robust engineering, being a supplier of steel not just for its own processes but also for supporting customers. Robust engineering, if properly applied to e.g. the stamping process, ensures that the customer’s forming process is stable and insensitive to material and process variations, thus reducing scrap rates. To analyse a stamping process for robustness input in terms of variation in process and material properties is needed. As a material supplier we focus on the variation in material properties. This paper deals with the effect of the material models used in simulation on the prediction of process variation as well as scrap rate. The effect of models on the variation itself is small, however, the effect on the mean (and thus on e.g. scrap rate) is significant. Some examples of the capabilities of commercial software are also added.

KEYWORDS: Forming, Simulation, robustness, variation

1 INTRODUCTION

Available stamping simulation software for stochastic analysis often assumes independently varying properties which is incorrect. Also, input material properties depend on the material model used and consequently so does the resulting variation.

Earlier, we have shown that the interdependency of material parameters does matter [1]. Corus has looked at material modelling for sheet metal forming for decades and has come up with advanced material models such as Corus-Vegter and Vegter-Lite [2][3]. Based on [1] we looked at the influence of the hardening model [4] and the yield locus model [5]. In both cases a reduction in the variation of results was expected but not found. It was concluded in both [4] and [5] that the choice of model is not important for variation analysis since it influences the mean much more than the variation.

Here, the results are revisited and we will argue that the implications for stamping e.g. in predicting a scrap rate are nonetheless huge, see section 3 and 4 respectively. The research mentioned above used DoE and RSM (see section 2) on finite element simulations [6]. While efficient and powerful it is somewhat limited in that only single parameter results can be easily used. Often a process design engineer wants to look at a range of results. Hence, in this paper we will also show some results obtained from commercial codes Autoform™ and PAM-STAMP™ and discuss their merits in section 5.

2 NUMERICAL MODEL

2.1 Stochastic recipe

In this section the strategy of stochastic modelling as chosen by Corus is outlined. For a non-linear Finite Element Analysis (FEA) to produce a statistically significant result it needs to be repeated many times. Since non-linear FEA is very expensive in terms of CPU, we chose to build a meta-model using Response Surface Methodology (RSM) on a few FEA results and apply the stochastic analysis to this meta-model instead.

In order to build a solid meta-model, the Design of Experiments (DoE) technique was used to determine the sets of parameters (sampling points) on which a full non-linear FEA was to be performed. In order for the meta-model to be as representative as possible for the real process we want the DoE to have sampling points that represent possible parameter sets within the variation occurring in the material. The physical parameters are partly mutually dependent and so physical parameter space is not a good choice for the DoE, see Figure 1.

Figure 1: DoE sampling in physical parameter space
Two interdependent parameters are shown in Figure 1, with their distributions plotted on the axes and the cloud representing the real variation found in the material. While the two solid symbols are sensible DoE points, the two open symbols are highly unrealistic DoE points. So the DoE was not based on physical parameters but on a set of parameters derived from the physical parameters by Principal Component Analysis (PCA). Principal components (PC’s) are independent and setting up the DoE in principal component space, see Figure 2., ensures it to be orthogonal in a statistical sense. Except for a choice of space in which the points have to be selected the spacing also needs to be set since it can influence the RSM and hence the result of the analysis. It is our view that between 2σ and 3σ is optimum. Closer than 2σ and the model will not be accurate in the tails of the distributions, and wider apart than 3σ the model will be based on results unlikely to occur in practice.

![Figure 2: DoE sampling in principal component space](image)

Additionally, after the FEA is run on the DoE points and the RSM is constructed, the PCA is used to randomly and independently sample each principal component to construct a distribution of the process output, see Figure 3. This is known as the Monte Carlo (MC) method. The meta-model is basically a very simple model and 10,000 samples are processed in a few seconds.

![Figure 3: Response surface and result of a MC analysis](image)

As an aside: normal distributions have been used throughout this analysis. When measured data is subjected to a test of normality this does not hold. However, the deviation in terms of the parameter from a normal distribution is not too large. Yield stress e.g. does not deviate more than a couple of [MPa] from a normal distribution. For the sake of simplicity we therefore keep using normal distributions.

### 2.2 FE model

The stretching of a dome in the material was modelled in FE (PAM-STAMP) using for all parameters, such as friction, the usual Corus default. The main formability aspect of the dome height test is obviously the height of the dome. The dome height at failure is the punch displacement where the force is at maximum.

![Figure 5: Hardening curves for DX54D+Z](image)

### 3 HARDENING MODEL

For a number of years Corus has been using and promoting the Bergström-van Liempt hardening law (1) for details see [2][7]. This law is based on dislocation dynamics in a single-phase material.

\[
\sigma_f(\varepsilon) = \sigma_0 + \Delta\sigma_m \cdot \left[ \beta \cdot (\varepsilon + \varepsilon_0) + \left[ 1 - e^{-\frac{\Delta \varepsilon}{\Delta \varepsilon_0}} \right]^{n'} \right] \\
+ \sigma_0^* \cdot \left[ 1 + \frac{kT}{G_0} \ln \left( \frac{\dot{\varepsilon}}{\dot{\varepsilon}_0} \right) \right]^{m'}
\]

Equation (1) consists of a static strength term, a hardening term and a strain rate dependent term. Besides the parameters listed in Table 1 there are temperature (T), equivalent strain (\(\varepsilon\)) and Boltzmann’s constant k.

<table>
<thead>
<tr>
<th>Term</th>
<th>static</th>
<th>hardening</th>
<th>strain rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
<td>(\sigma_0)</td>
<td>(\Delta\sigma_m)</td>
<td>(\beta)</td>
</tr>
<tr>
<td>units</td>
<td>[Mpa]</td>
<td>[Mpa]</td>
<td></td>
</tr>
<tr>
<td>typical</td>
<td>100</td>
<td>100</td>
<td>0.25</td>
</tr>
</tbody>
</table>

In [4] the recipe of section 2.1 was used to analyse variation of a DX54D+Z. The differences between Swift and Bergström-van Liempt are mainly visible for higher strain; see Figure 5, because clearly both laws are fitted to the same tensile test data up to the point of necking.
Figure 6 shows the process variation resulting from material variation for both hardening models.

The standard deviation with Swift is 0.44, with Bergström-van Liempt 0.46. The difference is small and not important, given all the assumptions in the stochastic modelling. Incidentally, the difference between $2\sigma$ and $3\sigma$ sampling for the DoE is larger, but still insignificant. The mean however is very different.

4 YIELD LOCUS

This section deals with the yield locus, for which often Hill’48 is used, based solely on $r$-values. The variation in a yield surface based on more stress states as per Corus-Vegter model is probably different from Hill’48 and consequently so is the resulting variation in the process. The Corus-Vegter yield locus is by now well known [2][3]. Instead of relying on an a priori assumed shape, four different stress states are tested and a smooth interpolation is constructed. The measured stresses are normalised to uni-axial point in rolling direction (RD), to obtain a stress factor: $f$.

$$ f^{\text{direction}}_{\text{stress-state}} = \frac{\sigma^{\text{direction}}_{\text{stress-state}}}{\sigma^0_{\text{uni}}} \quad (2) $$

The stochastic input for Corus-Vegter, however, was based on assumptions since the testing is too costly to obtain a statistically meaningful population of data. We felt however (albeit based on limited experience) the variation in the biaxial point of the yield locus is overestimated when using the Hill’48 model. Since testing was too expensive we linked the biaxial point to the average of three direction tensile yield stresses (3).

$$ \bar{f}_{\text{uni}} = \frac{1}{4}(f^0_{\text{uni}} + 2 \cdot f^{45}_{\text{uni}} + f^{90}_{\text{uni}}) \quad (3) $$

$$ f_{\text{hi}} = \bar{f}_{\text{uni}} \cdot \frac{f^{\text{ref}}_{\text{hi}}}{\bar{f}^{\text{ref}}_{\text{uni}}} \quad (4) $$

There was one example for which the biaxial point was measured and this was used to set a reference $f^{\text{ref}}_{\text{hi}}$. To compare the variation of the Hill’48 model and the Corus-Vegter yield locus we plot histograms of the resulting dome height.

Comparing the distribution of both low curves in Figure 7 the spread in the result differs very little between the Hill’48 model and the Corus-Vegter model, but the absolute value does. The average dome height decreases from 39.2 [mm] to 31.2 [mm] when using the Corus-Vegter model instead of the Hill’48 model, whereas standard deviation is 1.00 and 1.10 respectively. So both the hardening model ([4] and section 3) and the yield locus model do not influence the variation of the dome height much. Finally, the yield locus (Hill’48) was fixed for the entire DoE, only the hardening behaviour was varied. The result is the high curve in Figure 7. Now the standard deviation is decreased to 0.25. This means, that the majority of the variation is due to the yield locus, not to the hardening behaviour.

5 COMMERCIAL SOFTWARE

A manufacturing engineer will only be interested in the scrap rate if the determination of such a result is thoroughly validated. Until then they will rather look at trends: which parameter is the most influential where? And look for optimisation of the safety of the process. An industrial part was simulated with both Autoform-Sigma and the optimizer of PAM-STAMP with this industrial perspective.

5.1 Autoform-Sigma

Autoform-Sigma has an advanced GUI to enable interpretation of all the statistical results which is otherwise extremely tedious. The down side of this code is that parameters can only be fully coupled or uncoupled. Hence the PCA cannot be applied, and this will affect final accuracy.

For trend analysis, however, it is unsurpassed. The software can visualise (on the part) for each result variable which parameter is the dominant influence, upper left Figure 8. For a pre-defined zone it can generate a Pareto-plot, lower left Figure 8, so the...
engineer can judge if and which other parameters are important. And it can show the relation between result variable and parameter, right Figure 8.

Figure 8: Autoform-Sigma GUI

5.2 PAM-OPT

A version of PAM-OPT was made available to us. Although less advanced in terms of GUI for stochastic analysis, the PAM-STAMP software can nevertheless be put to good use as well. For stochastic analysis Autoform-Sigma and PAM-OPT gave similar results. Since the visualisation of variation results is left to the user (e.g. in Excel) they are not shown here. The PAM optimizer was also run to establish if the process could be improved in terms of distance to FLC (safety). Blank size and position were the design variables [8].

Figure 9: Safety before and after optimisation

The colour-scale in Figure 9 is kept the same before and after and the improvement is clear. However, wrinkling prediction and automatic observation of that wrinkling by the optimizer is mandatory to obtain good results [8].

6 CONCLUSIONS

In [4] and [5] it was concluded that the difference in variation in the result for advanced models vs. standard models is so small as to be deemed insignificant. However, should one want to use the simulations quantitatively and determine a single sided tail-end probability (like e.g. scrap rate) the models used for hardening and yield loci will have a dominant influence. Both the hardening model and the yield locus treatment showed a significant shift in average which of course influences the tail end of the probability enormously.

If one looks at variation as a trend analysis (i.e. qualitatively) the choice of hardening and yield locus model does not seem to be crucially important. All this with the proviso that the yield locus modelling was rather contrived thus limiting the validity of the conclusions. Future research will concentrate on making the yield locus variation more physical. In the mean time commercial software can already be used for trend analysis in processes as well as optimisation, as long as quantitatively accurate scrap-rate predictions etc. are not required. Both PAM-OPT and Autoform-Sigma gave similar results.

ACKNOWLEDGEMENT

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REFERENCES


[6] M.H.A. Bonte, Optimisation Strategies for Metal Forming Processes, PhD thesis University of Twente, 29 June 2007, Enschede, the Netherlands
