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# ROBUST IDENTIFICATION OF AN AUGMENTED GURSON MODEL FOR ELASTO-PLASTIC POROUS MEDIA

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*Summary* In the paper we investigate robust identification approach to identify the material parameters in the augmented Gurson model for the elasto-plastic porous media. We consider the robust loss function given by Huber [3] and the loss function based on the $L_1$–norm. Our aim is to compare the results with our earlier standard least squares estimates.

## PROBLEM FORMULATION

Our identification problem arises in modelling of the processes of nucleation and growth of voids in the elastic-plastic media. We consider the uniaxial test in the room temperature. At the neck there exists a complex state of stress and maximum deformations. Identification is carried out on the basis of Fisher's data [2] measured on the steel cylindrical specimens subjected to the uniaxial tension. We assumed that the effects of nucleation and growth of microvoids are summing up and we combined in one model, two models formulated separately for each of those two effects. Usually in literature material function g appearing in the model part responsible for the growth of microvoids is taken to be constant equal to 1 (no interaction of existing or nucleated new microvoids on the growth process is included). In our work we have assumed various shapes of g. Among others we have also studied the case with constant although unknown g function.

## $L_1$–NORM MINIMIZATION

The $L_1$–norm minimization is an alternative approach to the standard least squares. In that case instead of the sum of the second powers of deviations we minimize

$$F_1(\Theta) = \sum_{i=1}^{M} |r_i(\Theta)|$$

with respect to the unknown parameters $\Theta$. $r_i(\Theta)$ is the difference between the measured output and the output of the model for the particular values of the parameters $\Theta$. The $L_1$–norm minimization decreases the influence of the large deviations compared to the least squares approach.

## ROBUST IDENTIFICATION

Robust identification method (see Huber [3] or Seber and Wild [8]) is similar to the least squares. However, deviations larger then a given threshold value are rejected. Robust identification assumes minimization of the sum of the selected weighted differences between the measured and calculated from the model output values, i.e. we minimize loss function of the form

$$F_2(\Theta) = \sum_{i=1}^{M} \rho\left(\frac{r_i(\Theta)}{\chi}\right)$$

where

$$\rho(t) = \begin{cases} t^2, & |t| \le A, \\ 2A|t| - A^2, & |t| \ge A. \end{cases}$$

and $\chi$ is some measure of dispersion approximated by

$$\chi^a \approx \frac{1}{M}\sum_{i=1}^{M} |r_i(\Theta^a)|.$$

where $\Theta^a$ is an approximation to the estimate $\Theta$.

The advantage of using a robust method which automatically rejects extreme observations is that it does not require a subjective decision on the part of the experimenter.

In the paper we investigate robust identification approach to identify the material parameters in the augmented Gurson model for the elasto-plastic porous media. The model describes processes of nucleation and growth of voids in the porous body subjected to inelastic deformation.

The identification problem is solved as in our earlier papers Nowak and Stachurski [5], [6] and [7] by means of the global optimization method of Boender at al. [1]. In the current version of our solver we permit the use of the Hooke-Jeeves [4] (see also Stachurski and Wierzbicki [9]) direct search method as the local minimizer that does not involve any derivatives. Our aim is to repeat identification of the material functions parameters using the robust identification and compare the results with our earlier standard least squares estimates.

## CONCLUSIONS

Our earlier numerical experiments using the least squares method suggest that the nucleation of new voids can be modelled using the normal distribution material function. This choice was among the best in all cases tested by us. We have observed equally good results for the shifted hyperbolic tangent function. We have recommend the use of the normal distribution function because it is easier to interpret its parameters in mechanical terms. In view of our results we have found reasonable to use the porosity model with a constant value of the growth material function $g$, although with the constant not equal to $1$. For the ductile steel this constant is probably near $0.86$. It was somewhat unexpected by us and contrary to the common practice. We intend to verify those corollaries using other deviations measures. We expect that the results would be similar.

## References


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