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A SENSITIVITY ANALYSIS ON ARTIFICIAL NEURAL NETWORKS FRACTURE PREDICTIONS IN SHEET METAL FORMING OPERATIONS

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Abstract

In the last years the investigation of formability limits in sheet metal forming operations was one of the topic in the academic and industrial research due to the wide interest on fracture prevention in such processes. Many approaches were proposed mainly based on the development of fracture criteria or on the utilisation of Forming Limit Curves (FLCs). Actually, such approaches are not effective enough, in particular, when complex deformation path are concerned, namely when multi-step processes are taken into account. The authors have recently proposed a different approach to fracture prediction based on the utilisation of artificial intelligence tools. Such approach is based on the idea that a properly designed and trained artificial neural network is able to predict fracture occurrence for different deformation conditions i.e. for different processes. The early results of the application of such approach were very satisfactory but the robustness of the prediction has to be demonstrated. In this paper, the authors present the results of a sensitivity analysis performed on the neural network fracture predictions in order to assess the robustness of such predictive tool.

Key words: sheet metal forming, ductile fracture, neural networks

1. INTRODUCTION

In the last years, the investigation of formability limits in sheet metal forming operations was one of the topic in the academic and industrial research due to the wide interest on fracture prevention in such processes. The main topic in this field is the availability of an effective fracture prediction tool: fracture criteria, damage mechanics approaches and Forming Limit Diagrams are probably the most relevant tools investigated by many researches.

Fracture criteria were traditionally based on different formulations and some researchers aimed to prove the effectiveness of each approach for specific process mechanics (Cockcroft and Latham, 1968; Brozzo et al., 1972; McClintock, 1968), Gurson, 1977; Oyane, 1972). More recently, some authors proposed studies aimed to validate the applicability of different fracture criteria in sheet metal forming processes (Takuda et al., 1995; Takuda et al., 1996; Takuda et al., 1999; Yoshida et al., 2005).

Also damage mechanics approaches have been investigated by Chow and Jie (2004), Tang et al. (1999) and Teixeira et al. (2006).

Nevertheless, Forming Limit Diagrams (FLDs) remain the most investigated tool for fracture prediction in sheet metal forming. In this way, Yao and Cao (2002) proposed a study on anisotropic yield functions utilisation to predict forming limit curves. Han and Kim (2003) took into account forming limit curves at neck and forming limit curve at fracture,

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while Ozturk and Lee (2004) analysed forming limits using ductile fracture criteria.

The most recent investigations on FLCs concern their capability to foresee fracture for processes characterised by non linear loading paths. In particular, some researches emphasised the importance of taking into account a stress based formulation of FLCs (Stoughton and Zhu, 2004; Smith et al., 2003). On the other hand, some researchers investigated the influence of predeformations on formability in order to understand the fracture predicition capability of FLCs for non linear strain paths (Merklein and Beccari, 2005; Merklein and Geiger, 2003).

In this paper, the authors present a sensitivity analysis on the results of a research project focused on the utilisation of artificial neural networks (ANNs) to foresee fracture in sheet metal forming operations. The utilised ANNs are properly designed and trained by utilizing stress and strain paths data derived by a experimental/numerical campaign carried out on some sheet metal forming operations (Di Lorenzo et al., 2006; Di Lorenzo et al., 2007). The main advantage offered by such approach is that it could be utilized for a wide range of processes, also for the ones for which the FLDs are not effective.

In particular, the results obtained with the above addressed approach are deeply analysed and a sensitivity analysis is performed aimed to demonstrate the robustness of the fracture prediction based on ANN tool in sheet metal forming operations even characterised by non linear strain paths. In the following sections, the ANN based approach is presented together with the experimental and numerical campaign, and the results of the sensitivity analysis are discussed.

2. FRACTURE PREDICTION BY ANNS

The idea to predict fracture in sheet metal forming basing on the utilisation of an artificial neural network was driven by the aim to develop a fracture prediction tool which could be able to foresee fracture for different sheet metal forming process mechanics overcoming the drawbacks of other approaches typically utilised in this field. In fact, ductile fracture criteria are not “process insensitive” i.e. they often fail in predict fracture in operations whose mechanics is significantly different from the one characterising the processes utilised to calibrate the specific criterion. On the other hand, FLCs demonstrated their lack of effectiveness in predicting fracture for operations characterised by non linear strain paths.

In this way, a properly designed artificial neural network is able to predict fracture occurrence/absence basing on stress-strain histories and, for this reason, it offers the possibility to develop a process insensitive fracture prediction tool.

The development of such a tool was based on the following steps:

1. definition of a set of sheet metal forming operations characterised by different strain paths and different fracture mechanics;
2. development of an experimental campaign on the defined set of operations in order to observe fracture occurrence;
3. numerical simulations of the set of forming operations in order to reproduce the experimental evidences and to be able to extract stress/strain data;
4. building up of a knowledge base, consisting of stress/strain data associated to fracture occurrence and fracture absence in each analysed operation, which is the training set for the ANN;
5. training of the ANN through the training set;
6. design of a proper architecture of an ANN to obtain the best performance in fracture prediction;
7. testing of the ANN on sheet metal forming operations not included in the training set in order to evaluate its generalisation ability.

In other words, the basic idea is to experimentally analyse a set of sheet metal forming operations to detect fracture and then to reproduce them by numerical simulations with the aim to follow some stress and strain variables and extract their paths during each process until fracture. In this way, each stress/strain path can be associated to a variable indicating fracture occurrence or absence (namely a binary parameter which is equal to 1 if fracture occurs while is 0 if fracture is avoided). Thus, the training set for an ANN is built up and the ANN can be designed and then trained thanks to this training data. Finally the testing of the ANN can assess its predictive capability. In fact, the training set is built up in order to make the ANN able to distinguish stress/strain paths leading to fracture from the ones avoiding fracture. As a consequence, the ANN is able to predict fracture only classifying stress/strain conditions as fracture related or not. This is the crucial advantage of the approach since such capability does not depend on a particular process mechanics, but, on the contrary has a general applicability.

3. EXPERIMENTAL CAMPAIGN

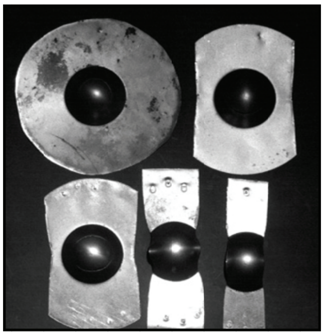
Different sheet metal forming operations were investigated, each one on ASTM A622M deep drawing steel specimen for which the following flow rule was experimentally determined:

$$\sigma = 665\varepsilon^{0,311} \tag{1}$$

A set of 19 different experimental tests was carried out on 0,5 [mm] thick sheets and each test was replicated in order to guarantee that the results were not affected by casual errors. Such tests were utilised to build up the training data, thus different operations were taken into account since a wide range of fracture mechanics had to be represented.

For instance, some dome tests were developed as well as deep drawing operations with different deep drawing ratios and tensile tests. Some examples of the experimental tests are reported in the following figures. Figure 1 shows the result of one of the dome tests in which fracture was obtained after 13,5 mm of the punch stroke (dome1) while figure 2 shows the results of a dome test with fracture height equal to 14,5 mm (dome2).

Table 1. *Details of some experiments*

	Process
	Balanced biaxial
	Dome test 1
	Dome test 2
	Dome test 3
Die diameter = 33 [mm] Punch diameter=26 [mm] Die radius= 0,75 [mm]	Dome test 4
 Punch diameter = 45 [mm] Clearance = 0,55 [mm] Dies and punch radius = 3 [mm] Blank diameter = 110 [mm]	Deep drawing test 2

Geometrical parameters fixed over some of the experiments are illustrated in Table 1 (an extreme pressure grease was utilised all over the experiments).

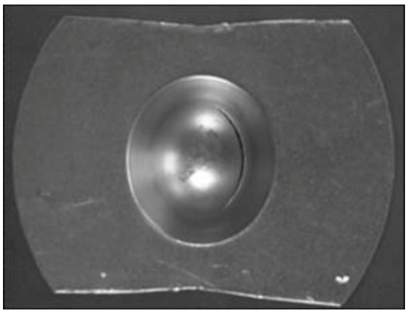


Fig. 1. *Fracture occurrence in dome1 test*

Fig. 2. *Fracture occurrence in dome2 test*

Moreover, figure 3 shows the results of a tensile test with an elongation to fracture of 20%. Figure 4 reports the fracture occurrence in one of the axisymmetrical deep drawing tests characterised by a cup height to fracture equal to 12,5 mm.

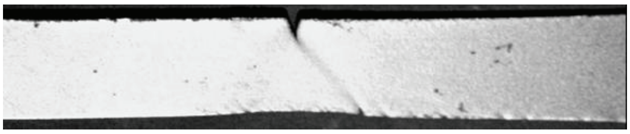


Fig. 3. *Fracture occurrence in tensile test*

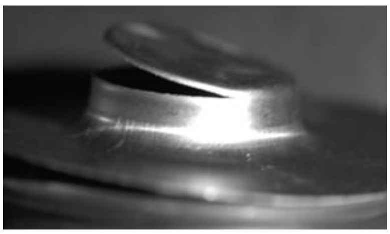


Fig. 4. *Fracture occurrence in one of the deep drawing tests*

It has to be underlined that also more complex deformation paths were included in the experimental campaign. In fact, some dome tests were applied on sheets previously pre-deformed: in particular two kind of pre-deformations (uniaxial and biaxial) were coupled with some different dome test deformation paths. For instance an uniaxial deformation on the sheet (5%elongation) followed by the dome test shown in figure 2 (dome2) was carried out among the experimental tests (see figure 5).

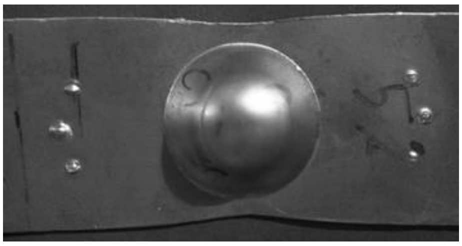


Fig. 5. Experimental result of the uniaxial predeformation (5% elongation) followed by dome2 test

As well biaxial pre-deformation followed by the dome test reported in figure 1 (dome1) was applied (see figure 6).

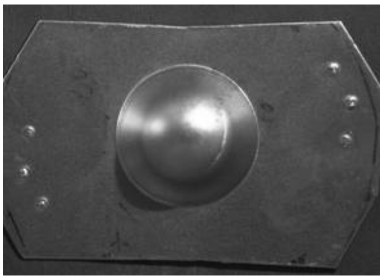


Fig. 6. Experimental result of the biaxial predeformation followed by dome1 test

Moreover, two different levels both of uniaxial and biaxial pre-deformations were utilised, namely 5% and 10% elongation for uniaxial pre-deformation and two different heights for biaxial pre-deformation (5mm and 8mm).

In this way, a wide range of fractures were investigated and the sheet region where fracture occurred was known for each operation. As well, the process stage corresponding to fracture occurrence was experimentally known.

4. DEFINITION OF THE TRAINING DATA

After the experimental tests, the numerical simulations of the same processes experimentally investigated were carried out. For each test, starting from experimental data available on fracture, it was possible to track (by numerical simulations) some critical regions of the sheets (where fracture occurs) in terms of stress and strain values. Moreover, since the proposed approach is based on the utilization of an ANN able to classify stress strain paths by distinguishing histories leading to fracture from paths which do not lead to fracture, a set of data related to no fracture conditions was collected: numerical simulations allowed to track also stress-strain paths related to such conditions. The collected data were associated to an output indicator of fracture occurrence (output variable = 1) or fracture absence (output variable = 0). In this way, the data set to be utilized for ANN training consists of some input variables expressing stress-strain histories and an output vector indicating fracture occurrence/absence. The numerical simulations of the investigated operations were performed by LS DYNA commercial code. Critical regions of the sheets (where fracture occurs) and safe regions (fracture absence) were tracked in terms of stress and strain values. In particular the following variables were numerically tracked:

- major strain (ε_{major});
- minor strain (ε_{minor});
- accumulated plastic strain (ε_{acc}) ;
- maximum principal stress ($\sigma_{max\ princ}$) ;
- mean stress (σ_{mean}).

The chosen variables paths were tracked along six different process steps in order to follow their evolution towards fracture or safe conditions. Some points were tracked until fracture while some others were followed partially, i.e. stopping the tracking before fracture occurrence. In this way, the training set contains the information related to "levels" of the input variables to be reached for fracture occurrence, in fact, histories related to safe regions were associated to fracture absence.

It has to be underlined, that the numerical simulations show a quite good matching with the experimental evidences as both deformed shape and thinning distribution are concerned. An example of such matching is shown in figure 7 which refers to a test characterised by a biaxial pre-deformation followed by dome2 test. Figure 8 shows the numerical-experimental comparison for a tensile test.

Figure 9 reports the numerical tracking of some of the input variables for dome1 test.

Fig. 7. Comparison of experimental test and numerical simulation for biaxial pre-deformation followed by dome2 test

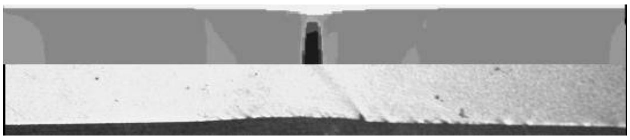


Fig. 8. Comparison of experimental test and numerical simulation for tensile test

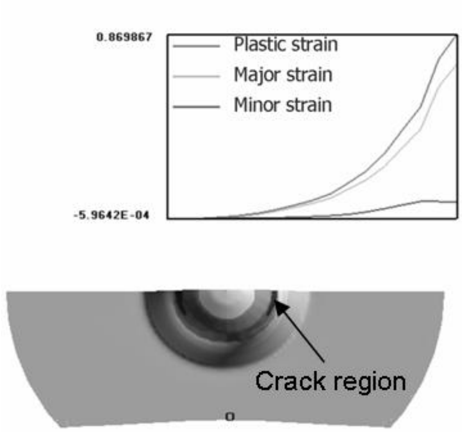


Fig. 9. Strains numerical tracking in simulation of dome1 test

The 5 stress and strain variables chosen for the numerical tracking, consisting of 6 steps, led to an input vector for the ANN consisting of 30 components (5 variables each one followed through 6 values along a given operation); thus the input layer of the network is composed of 30 neurons. The training data set consisted of about 200 data records (i.e. 200 vectors each one consisting of 30 components).

The design of the ANN was carried out, within a MATLAB environment, with the aim to determine the best performing architecture: in particular, a proper number of hidden layers and neurons had to be fixed in order to reach an effective prediction capability. For this reason, a proper set for ANN testing was collected in order to find out the network architecture providing the lowest prediction error over the testing data.

5. DEFINITION OF THE TESTING DATA AND ANN DESIGN

The neural network was tested on sheet forming operations not taken into account for its training. In particular, further experimental and numerical investigations were performed on two processes whose mechanics is rather different from the ones belonging to the training data. In particular, the test data set consisted of an uniaxial pre-deformation (5% elongation) followed by a deep drawing of rectangular box test (test1) and a stamping process (test2) of an S-shaped rail (see figure 10).

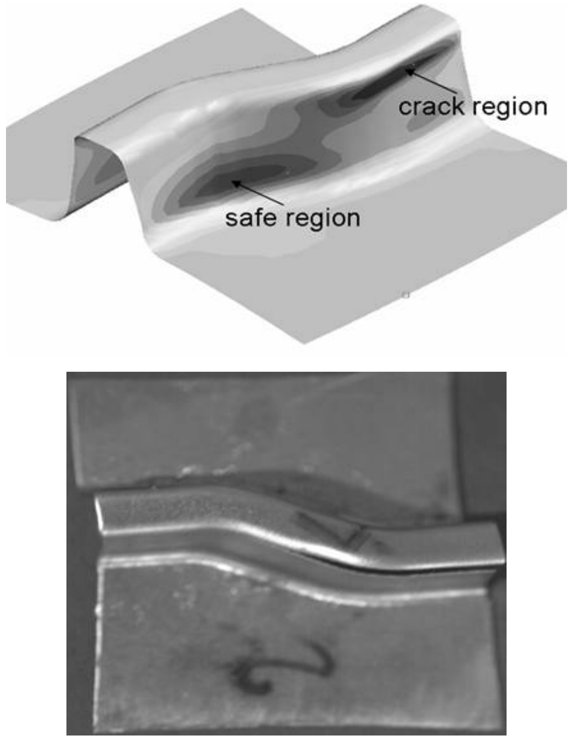


Fig. 10. The numerical thinning distribution and experimental result on test2

Test2 is a complex stamping operation in which safe regions are characterised by heavy thinning even if no fracture occurs. Such conditions may generate an incorrect classification by the ANN; nevertheless, the results provided by the network were very effective. The ANN testing data set consisted of 30 data records obtained from the two test operations. The stress and strain variables were tracked both from crack regions and safe ones. It has to be underlined that some of the safe points also take into account tracking of points related to fracture whose histories were followed partially. In other words, for each process some safe points were also tracked by stopping the tracking process before the process step in which fracture occurs.

Starting form the testing data, the ANN architecture was designed by trying different network configurations (i.e. networks with 2, 3, 4 and 5 hidden layers and different numbers of neurons for each layer). The best performance, in terms of predictions mean error, was obtained by a 4 hidden layer network with a total number of 12 hidden neurons (see figure 11) . Such ANN proved its ability to generalize the knowledge acquired during the training and to infer a right fracture prediction.

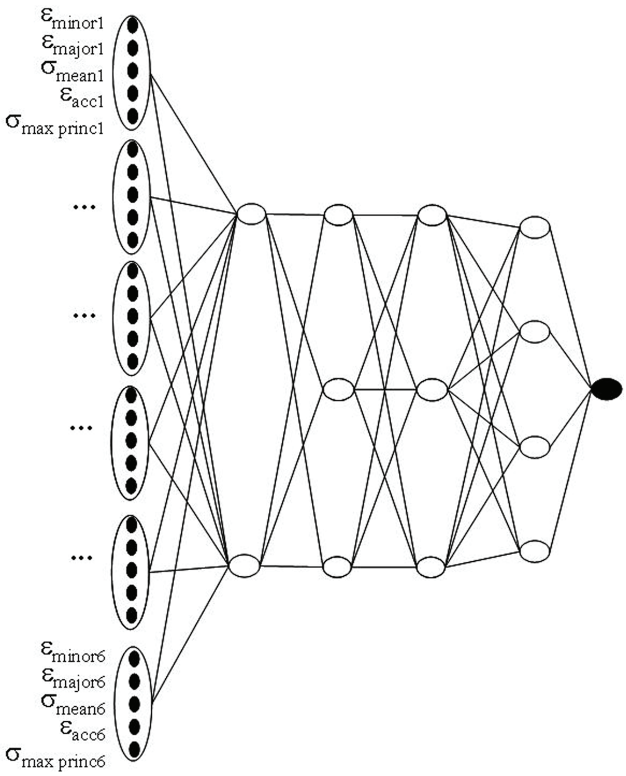


Fig. 11. The ANN architecture

6. RESULTS AND SENSITIVITY ANALYSIS

As mentioned above, the designed ANN was able to distinguish the fracture stress-strain conditions for the operations whose fracture mechanics was not included in the training data and also to identify the absence of fracture.

Figure 12 shows the network predictions compared with the expected output in the testing phase. As it can be observed, only 2 points are incorrectly predicted; the mean prediction error of such network was about 0,07.

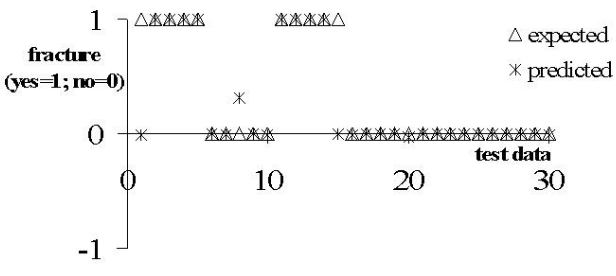


Fig. 12. The ANN prediction performance

The errors detected in the ANN predictions can be related to the necessity of a sensitivity analysis to be performed on the input variables in order to better understand the influence of each variable history.

For this reason, in order to improve the effectiveness of the predictive tool, a sensitivity analysis was performed with the aim to understand which stress and strain variables significantly influence the network predictive capability.

In particular, the possibility to achieve prediction performance similar to the ones obtained with the ANN illustrated in figure 11 but utilising less "information" (i.e. training a network with less input variables) was investigated.

Thus, the first step was to identify which variables among the ones utilised above gave the lowest contribution to the fracture prediction performance of the network.

Table 2 summarises the cases investigated in the sensitivity analysis in terms of input variables considered for the training and testing data set. Table 2 also reports the prediction errors of each network (cases are sorted by decreasing mean prediction error).

Moreover, table 1 shows the number of hidden layers included in the best performing network for each case; in fact, a design procedure of the network was carried out for each case in order to determine the best network architecture as illustrated in section 4.

Table 2. *Different ANN configurations for sensitivity analisys*

	Input training/testing variables	Mean prediction error	Best performing ANN architecture
A	ε_{minor} ε_{major} $\sigma_{max\ princ}$ σ_{mean}	0,2	3 hidden layers
B	$\sigma_{max\ princ}$ σ_{mean}	0,17	5 hidden layers
C	ε_{minor} ε_{major}	0,15	5 hidden layers
D	ε_{minor} ε_{major} σ_{mean}	0,09	3 hidden layers
E	ε_{minor} ε_{major} $\sigma_{max\ princ}$ ε_{acc}	0,05	3 hidden layers
F	ε_{minor} ε_{major} $\sigma_{max\ princ}$	0,032	4 hidden layers

The data utilised for the sensitivity analysis cases were the same utilised for training and testing of the ANN in figure 11, but, of course, they were partially utilised i.e. only the chosen input variables were taken into account.

The sensitivity procedure was driven by the following considerations: first of all, the performance of a network trained with only major and minor strains data was taken into account (case C in table2), in order to have the same level of information contained in a forming limit diagram. As well, the effect of considering only stress data was analysed (case B).

Both these cases led to not satisfactory results in terms of prediction error. Moreover, the utilisation of minor and major strains data together with stress data led to worse prediction performance (case A).

In this way, the idea was to evidence if one of the stress variable could have a negative effect on prediction performance of the network; for this reason both case D and case F were analysed leading to the conclusion that mean stress data do not contribute to correct fracture prediction while maximum principal stress has a great role in good prediction performances.

Another case was considered (case E) in which, beside minor and major strains data and maximum principal stress data, also the accumulated plastic strain data were utilised. Such case did not lead to any improvement of the predictive capability of the network with respect to case F, which definitely led to the best results.

As it can be observed in both case E and F the mean prediction error, obtained with the best network architecture, is lower than the one obtained with the network which utilised all the stress and strain data; in fact as mentioned above that network provided a mean prediction error of 0,07 while the networks obtained in case E and F led to errors equal to 0,05 and 0,032 respectively.

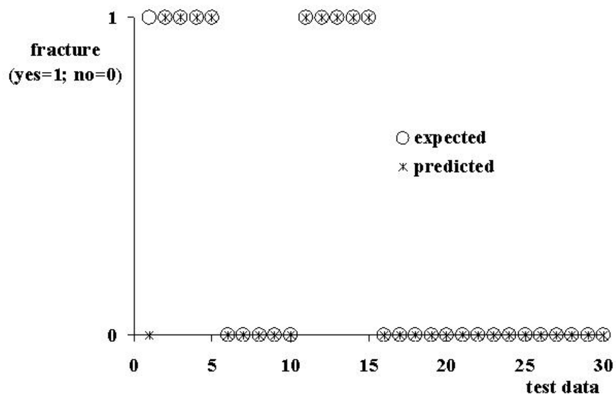


Fig. 13. The ANN prediction performance in case F

Figure 13 shows the predictions of the network built up in case F over the testing data. As it can be observed, such network (characterised by 4 hidden layers and 15 neurons) proved a great effectiveness in identify fracture occurrence and also guarantees the possibility to monitor a lower number of stress and strain data, thus reducing the computational effort necessary to collect data to implement a fracture prediction tool based on artificial neural networks.

7. CONCLUSIONS

In the paper, the design of an ANN aimed to predict fracture occurrence for ASTM A622M deep drawing steel in different sheet forming operations is presented. The testing performances of the network prove the suitability of the proposed technique in dealing with fracture predictions and its effectiveness in sheet forming processes design. Moreover, the proposed prediction tool is able to foresee fracture for a wide range of processes generally characterised by quite different fracture mechanics even, for instance, by non linear strain paths. Such aspect is very relevant since for instance a fracture criteria based approach is generally "process dependent" i.e. a fracture criterion has to be calibrated on given process conditions. On the contrary, the proposed approach seems to be "process insensitive".

Finally, a sort of sensitivity analysis was performed at the varying of the input variables to be monitored in order to predict fracture through the ANN. The results of such analysis led to the conclusion that also by considering major and minor strain data together with maximum principal stress data, a better performance in fracture prediction can be achieved.

The proposed approach has to be considered a step of a wide research project on fracture prediction in sheet metal forming which is still in progress. The results obtained in this applications seem very effective in terms of knowledge about fracture mechanics in sheet metal forming and makes the ANN based approach to fracture prediction more efficient and useful.

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ANALIZA WRAŻLIWOŚCI MODELU OPARTEGO O SZTUCZNĄ SIEĆ NEURONOWĄ PRZEWIDUJĄCEGO PĘKANIE W PROCESIE TŁOCZENIA BLACH

Streszczenie

Ze względu na duże zainteresowanie w zapobieganiu powstawania pęknięć w tłoczonych blachach, analiza odkształcalności granicznej w procesach tłoczenia była w ostatnich latach przedmiotem badań w licznych ośrodkach akademickich i przemysłowych. Zaproponowano wiele rozwiązań opartych na kryteriach pękania oraz na wykresach odkształcalności granicznej. Rozwiązania te nie są obecnie wystarczająco skuteczne, szczególnie w przypadku analizowania złożonych dróg odkształcenia, na przykład w procesach wielostopniowych. Autorzy zaproponowali ostatnio odmienne podejście do przewidywania pękania blachy, oparte na sztucznej sieci neuronowej. Ideą tego podejścia jest założenie, że prawidłowo zaprojektowana i nauczona sieć neuronowa jest w stanie prawidłowo przewidywać pojawienie się pęknięcia w różnych warunkach odkształcenia, na przykład w różnych procesach. Wstępne wyniki tej analizy były obiecujące, ale dla potwierdzenia skuteczności metody należy przeprowadzić analizę wrażliwości modelu na zmiany warunków procesu. W niniejszym artykule zaprezentowano wyniki takiej analizy uzyskane dla sztucznej sieci neuronowej przewidującej pękanie blach i na tej podstawie oceniono niezawodność tego modelu.

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