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Early Shear Failure Prediction in Incremental Sheet Forming Process Using FEM and ANN

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Abstract. The application of incremental sheet forming process as a rapid forming technique is rising in variety of industries such as aerospace, automotive and biomechanical purposes. However, the sheet failure is a big challenge in this process which leads wasting lots of materials. Hence, this study tried to propose a method to predict the early sheet failure in this process using mathematical solution. For the feasibility of the study, design of experiment with the respond surface method is employed to extract a set of experiments data for the simulation. The significant forming parameters were recognized and their integration was used for prediction system. Then, the results were inserted to the artificial neural network as input parameters to predict a vast range of applicable parameters avoiding sheet failure in ISF. The value of accuracy R2 ~0.93 was obtained and the maximum sheet stretch in the depth of 25mm were recorded. The figures generate from the trend of interaction between effective parameters were provided for future studies.

1. Introduction

The majority of systems considered are often too complex to yield simple analytical solutions and thus, numerical methods are generally used [1]. In many of complex systems, there are generally too many parameters to consider. Besides, experimentation may take a considerable period of time and is often costly. On the other hand, computational modelling, when combined with limited experimental tests, can provide important insights, parametric screening analyses and optimisation, and design guidance for further experimentation. The Finite Element simulation of ISF process requires a long computational time due to the large model deformation and non-linear conditions (large displacements, friction contact, and plastic deformation of the material) in the technique. Using ABAQUS® (Dassault systemes Corporation) analysing tool, there are two main approaches that can be used to reduce this computational time; time scaling and mass scaling. Mass scaling method is almost the first potential candidate for reducing the computational time. However, it still keeps the kinetic energy of deforming material below 4%-10% of the system total energy [2].

Mathematically, the Finite Element Method (FEM) is a numerical method to find an estimated solution for Boundary Value Problems (BVP). FEM employs a variation of methods effect on the

process parameters to minimize an error function and generate a stable solution. One of the most prevalent aims for new manufacturing processes is to optimise these process parameters to achieve an applicable part with a high geometrical accuracy together with an increase in productivity and minimizing production expenses [3]. There are some parameters, as per Gatea et al. (2016), which have a significant effect on the modelling and simulation of the ISF process. These parameters are the forming temperature, forming angle, incremental depth and feed rate, all of which have a strong influence on the formability and sheet failure of the ISF method [4].
A clear example of using numerical investigation in the ISF method is toolpath optimisation, which is determined by FEM, by applying a response surface method (RSM). This technique was first presented by Azaouzi and Lebaal (2012) to enhance the thickness distribution of parts with asymmetric designs [5]. It was found from their study that after three repetitions, the optimal solution proposed an enlargement of around 7% of the sheet thickness distribution. Moreover, another study using the FEM for toolpath optimisation is that of Filice et al. (2013). In their study, to solve the issues related to inhomogeneous sheet thickness distribution in an aluminium alloy part as an example, a model for optimisation is created to optimise the toolpath design by applying a trajectory related to a decrement of ±10° in slope differential [6].

2. Method

Simulation of ISF contains of multiple steps such as creating CAD models, generating toolpaths for monitoring the tool navigation, building FEM which consists applying boundary conditions, rendering material properties and contacting parameters and finally solving the FEM model [7]. In this study, a 3D thermo-viscoplastic FE model was used for the numerical investigation of ISF to obtain the thermo-mechanical responses of the procedure on Aluminium alloy 6061. The numerical computation was completed using the commercial code of the ABAQUS/CAE® software.
To find the optimum parameters, the Design-Expert® (State-Ease Corporation) software was employed to design the experiments for a better interaction between the parameters as the input data and the STD value as the output factor. Hence, the parameters were inserted in the software environment and the RSM with central composite design technique was applied to create 30 sets of data.
Table 1 presents the range of input data for the software for creating the set of data in this study. Based on the literature, the minimum and maximum values for each parameter were selected and inserted into the software. In regard to some inapplicable values suggested by the software, for example, -0.1 mm for depth step (or DOC), the Alpha function was activated to bring in real values and reduce the negative values since all the applied variables should be more than zero in these numerical study.

Table 1. RSM input variable range

Parameter	Unit	Range of values
Feed Rate	mm/min	10-200
Spindle Speed	rpm	50-200
Depth Step	mm	0.1-0.7
Width Step	mm	1-4

The toolpath generation is not a required step in simulation. Nevertheless, to simulate the ISF process, it is employed to move the tool along a predefined toolpath. For not complicated cases, toolpath coordinates are estimated using a Microsoft Excel® spreadsheet program, whereas in Pohlak et al. (2004), a Computer Automated Manufacturing (CAM) system was applied, as toolpath becomes much more complex in non-linear conditions [8].
The explicit method was applied due to the stable alteration of the contact boundary conditions and also small time steps in simulations. It should be noted that the explicit schema by increasing artificially the mass density will reduce the computational time of the numerical simulation.
In ISF process, a very small ratio between the thickness and other dimensions of the sheet call for the use of shell elements in FEM simulation. Therefore, to build up the model in this research work, shell elements were implemented. The tool is generally considered a rigid body, but the sheet is modelled as

an elastic-plastic material. Constraint conditions were determined by carrying out a preliminary static analysis based on a 3D model that includes the entire workbench [9]. This analysis proved the acceptability of constraining five degrees of freedom at the sheet border, leaving free the rotation about the axis parallel to the border only. The sheet was meshed with shell finite element with dimensions of 2×2 mm (in rectangular shape) allowing for reducing the integration. The final principal set up is provided at Figure 1.

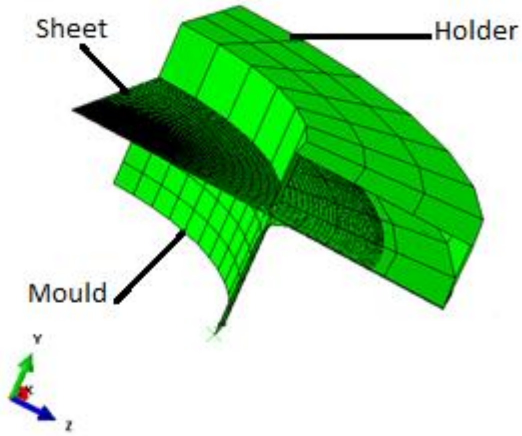

Figure 1. ISF process principle set up

The Johnson-Cook (J-C) constitutive model parameters of both sheet materials were considered for the numerical simulation of the material deformation in the ISF procedure. Therefore, the J-C flow stress was offered as the used material model for the sheet part. The parameter considered in simple forms of stress empirical relations with strain, strain rate, and temperature as per equation (1):

$$\sigma_y = [A + B(\varepsilon_P)^n]\left[1 + C\left[\frac{\dot{\varepsilon}_P}{\dot{\varepsilon}_0}\right]\right]\left[1 - \left[\frac{T - T_{room}}{T_{melt} - T_{room}}\right]^m\right] \quad (1)$$

Where A = 48 MPa which is the yield stress, B = 276 MPa (strain factor), C is the strain rate factor equal 0.015, T is (effective temperature), T_{melt} = 582°C (melting point), T_{room} = 20°C (ambient temperature), n = 0.042 (strain exponent) and m = 0.85 (temperature exponent). A, B, C, n, T_{melt}, T_{room} and m are material constants for the J-C strain rate dependent yield stress for Aluminium. The identified J-C constitutive model parameters that are relative to the applied material in this study are mentioned in Table 2.

Table 2. Material constants for the J-C constitutive model (aluminium)

A (MPa)	B (MPa)	C	n	m
48	276	0.08	0.042	0.85

The analytical tool will process all the points based on the STD (the units for STD would be logarithmic strain (LE) since the strain as the summation of numerous small differential segments is taken and thus it will express the final strain).
To check the accuracy of the calculated geometry, the highest normal distance d_{max} and the average normal distance d_{av} between the FE results and the experimental data were considered. The prediction of sheet thickness distribution was analysed using the highest deviation $d_{th,max}$ between the FEA and the experimental data.

To increase the accuracy of the model for prediction, in this study, back-propagation-type neural networks with 4 variables as inputs, an output, and a hidden layer were applied which in most cases, one hidden layer is satisfactory (Saljooghi and Hezarkhani, 2014; Van der Baan and Jutten, 2000) [10, 11]. The power of the network is increased through the increment of hidden layers or the number of neurons in the hidden layer. Hence, the error on the training data set will converge to a small value, however, when a new data is introduced, the error will be great. A complex network tends to memorize the data but it does not adapt to new data set. Therefore, a three-layer Artificial Neural Network (ANN) with a tangent sigmoid transfer function (tansig) at hidden layer and a linear transfer function (purelin) at output layer was implemented. To optimize ANN, 1 - 23 neurons in the hidden layer were trained at least five times using altered sets (which were randomly generated) of initial weights to find the lowest mean squared error. The data had been distributed randomly into three different groups (70% for training, 15% for the testing set, and 15% for cross validation). Overtraining was prevented by the validation data set, as the training continues; it lowers the training error function and the result of applying a validation set will improve. However, the likelihood of performance improvement on the validation data set with further iterations is not achievable. At this point, training should be stopped.

3. Results and discussion

The forming cycles from the corner to centre continued until the Ultimate Tensile Stress (UTS) appeared similar to Moayedfar et al. (2013) [7]. In this stage, as illustrated in Figure 2, the maximum STD for a particular set of experiment is accrued up to LE 8.452e^{-01}, which showed a respectable agreement with achievements of Azaouzi et al. (2012) i.e. LE 8.227e^{-01} [5].

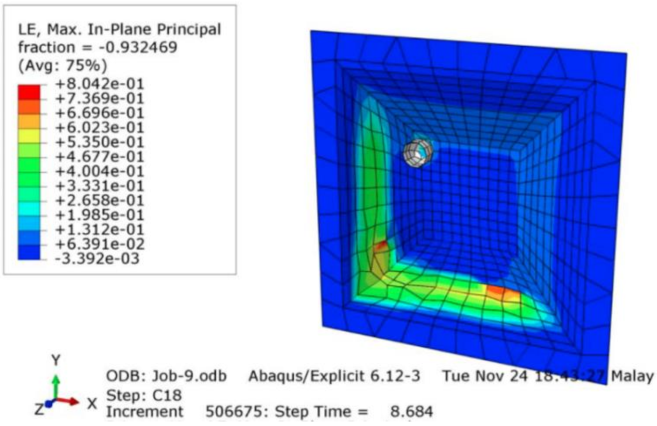

Figure 2. Maximum sheet thickness distribution

The large material deformation in ISF results in a several element entanglement and distortion. These may lead to reduce the size of stable time increment and also the accuracy of simulated results. Consequently, it is recommended to apply the adaptive meshing tool in the simulation of ISF process to enhance the meshing quality via a practical CPU cost for avoiding the elements distortion.

The result of the STD is inserted to the DE® to figure out the interaction between effective parameters with respect to the RSM. The influence of four parameters such as feed rate, spindle speed, depth of cut (depth of penetration in ISF), and width step versus the sheet stretching was examined via the statistical software. The behaviour of these four parameters versus sheet stretching during the simulation, where the (A) is the diagram of variation for feed rate, (B) spindle speed, (C) depth of cut, and (D) step width provided us a formula to predict the possible values of STD (Equation 2) which is not in presented 30 experiments.

$$STD = 0.42 + 0.081 * A + 0.032 * B + 0.020 * C + 0.072 * D + 0.091 * A2 + 0.056 * B2 + 0.044 * C2 + 0.066 * D2 - 0.012 * A * B + 4.919E\text{-}003 * A * C - 0.033 * A * D + 0.013 * B * C + 4.069E\text{-}003 * B * D - 4.244E\text{-}003 * C * D \quad (2)$$

The feed rate is the most influential parameter in this study. Moreover, step width also showed a considerable effect on the amount of STD in this analysis, while the spindle speed and depth of

penetration played a less important role in the forming process. High values of feed rate increased the friction and vibration of the process, which are the two major defects of ISF. In addition, a width step of more than 20% of the tool diameter increased the risk of sheet failure due to the huge pressure on the contact surface of the workpiece, which changes the process from stretching to chipping.
Respond values obtained from the RSM then, exported to the prediction software and the realizations were recorded. The result of ANN showed that the highest value obtained when R^2 was 0.931 (Figure 3) and the lowest value achieved in Means Square Error (MSE) that was 0.0073, with the application of 10 hidden neurons.

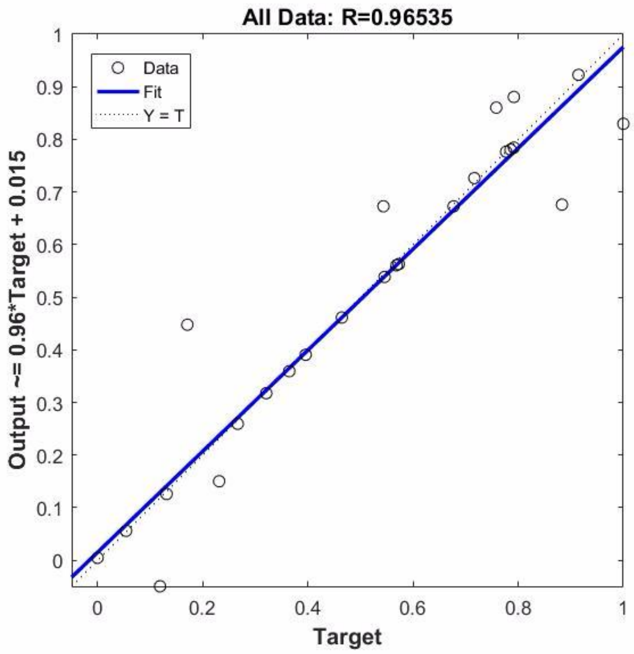

Figure 3. The predicted data *vs* the simulation data

The validation vectors are applied to stop the training early when the performance of network on the validation vectors remains the same or fails to enhance for the highest fail epochs in one row. Test vectors are applied as an additional check which shows the network is generalizing well, however, this test does not have any effect on the training. In order to prevent over training, a validation was performed. For this purpose, after eight times failing in finding the best network training was stopped (Figure 4).

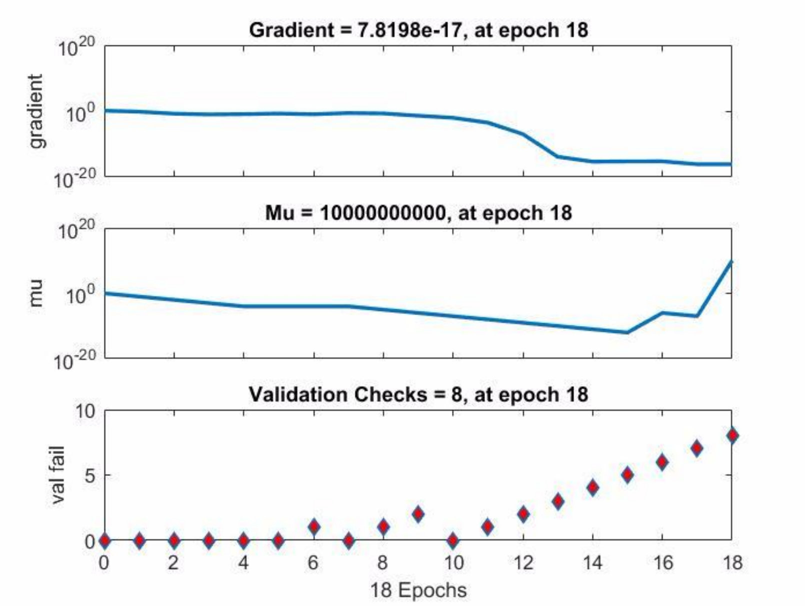

Figure 4. Normalized STD from ANN

Overfitting issue sometimes occur when a very low MSE is obtained, then, it will be a cause of confusion with a high accuracy. The final MSE created is due to the isolated test data that is random 15% of the samples. When the generalization is very poor, a low MSE may be possible tough. The validation MSE curve and follows the test MSE curve showing enhanced generalization (Figure 5).

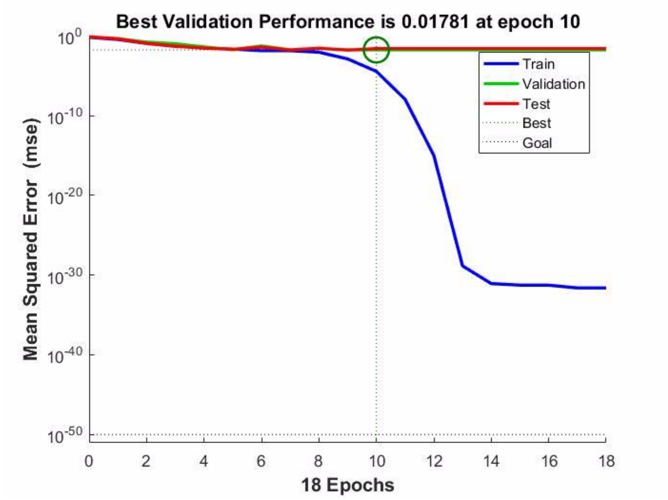

Figure 5. MSE *vs* the number of epochs

The results of this study illuminated that the ANN predicted model for the sheet thickness distribution based on the RSM analysing having a good correlation with the numerical simulation input data when the MSE = 0.0011

4. Conclusion

Last but not least, the Design of Experiment method was applied for 30 tests using numerical modelling together with a proper experimental study that would lead to the lowest and the highest STD when the maximum sheet stretch considered 25mm (in Z direction) in ISF for AISI 316. The significant parameters of feed rate, spindle speed, depth step, and width step are demonstrated and interactions between these effective factors are formulated for future studies. This formula is exclusive to this study but can also be applied in a variety of ISF procedures on AISI 316 material. With respect to the results of the design analytical software, a good agreement was achieved between the available numerical simulation and the literature. However, the number of parameters, which was used in this work, was more than the current studies in which used an explicit technique similar to this study. The respond of each set of parameters inserted as an input data to ANN for predicting a wide range of values for these four effective parameters with the R^2 equal 0.931. The results of this study will help other researchers to find the amount of sheet thickness distribution to predict the sheet failure in manufacturing process.

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