Neural network modelling and simulation of hot upsetting

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Modern metal forming often caters to rapidly changing product specifications determined by the continuously increasing productivity, flexibility and quality demands. Automatic selection of press tools and accessories heavily relies on the forging force estimation. There is a complex relationship between process parameters like die velocity, temperature of the billet, coefficient of friction at the interface of die and workpiece, tool geometry and forging forces. Models are needed to enable fast computation of the forging forces based on these factors. However, it is not easy to develop mathematical formulations for this purpose. Finite element methods (FEM) now offer reliable means of modelling metal forming processes. The main limitation of these methods is the requirement of lot of man-hours of code development time, and CPU time for simulation and computer resources. This is because a small change in one parameter requires a fresh simulation run to predict the forging force and combinatorial explosion takes over. Computational paradigms like the artificial neural networks (ANNs) offer an approach to this problem. In the present work, the applicability and relative effectiveness of the artificial neural networks based models for rapid estimation of the forging force by invoking the function approximation capabilities of these models have been investigated. Neural network models are developed that can predict forging force given the initial temperatures of billet and die, friction coefficient at die-billet interface and die velocity. The results obtained by these models correlate well with the finite element modelling results. This work has implications in the real time monitoring and control of the forming process and design of dies, computation of optimal parameters like punch velocity, billet and die temperatures.

Hot upset forging is a metal forming process for enlarging and reshaping some of the cross-section of a bar, tube or other product form of uniform section. The process is widely used for producing finished forgings ranging in complexity from simple bolts or flanged shafts to wrench sockets that require simultaneous upsetting and piercing. Hot upsetting is also occasionally used as a finishing operation following hammer or press forging, such as in making crankshafts. A wide variety of shapes can be forged in hot upsetting.

The traditional build and test methods of developing a complete manufacturing process in hot forging domain are heavily experience based, because the analytical approach to process design was inadequately developed. The advent of numerical methods such as general purpose finite element method (FEM) codes to handle large deformation plasticity has made accurate analysis possible. Many researchers have attempted the modelling of upsetting and thermoplastic analysis for plane strain and axis-symmetrical deformations. The generation of solution adaptive grids for FEM has received a great deal of interest. In simulation of hot forging by an updated Lagrangian approach, the remeshing problem becomes crucial to allow large deformations. The recent publications clearly demonstrate the advantage of using this approach to hot metal forming problems. FORGE2 is an FEM environment used to perform simulation of hot upsetting process on steel billets. A detailed presentation of capabilities of FORGE2 is given by Hans Raj et al. FORGE2 can be used to estimate the forging force for any given set of process parameters.

The finite element modelling techniques still have several limitations and are quite expensive to use in terms of required computer time and facilities. Because the potentially viable processing routes are numerous, many FEM process simulations are necessary to identify optimal processing methods. The problem of large design solution spaces is not restricted to the design of the deformation process, but also applies to the selection of correct combinations of processing temperatures, die profiles, friction conditions and strain rates etc. Though the finite element modelling is capable of giving detailed analysis of the problem at hand, the pre-processing and program execution consume a lot of time. A small change in a single process parameter requires a new simulation run to predict its effect on forging.
force. Therefore, a need is felt to develop a much more generalized model, which can predict the forging force for a wide variation in process parameters quickly without extensive numerical modelling and give assistance to a production engineer on factory floor in real time.

Recently, artificial neural networks (ANNs) are gaining wide popularity in the intelligent manufacturing field. ANN's are massively interconnected networks of simple elements and their hierarchical organizations. The ANN approach is an inductive approach driven by data. The data driven approach of the ANNs enables them to behave as model free estimators, i.e., they can capture and model complex input-output relationships even without the help of a mathematical model. Some attempts have been made to apply this technique as an opportunity to shorten the reaction time of the manufacturing systems, increase the product quality, make systems more reliable and enhance the system's intelligence by the learning capabilities of neural networks. Excellent surveys of these attempts are found in Monostori and Zhang and Huang. As per these surveys the most promising application fields of ANNs in manufacturing include learning of process models and monitoring and diagnostics.

In this paper, initial investigations are carried out using FEM with upsetting of ck-45 steel billet (whose height versus diameter ratio is 1/2) under varying friction conditions, temperatures and die velocities. These investigations provide valuable data for estimation of forging force required under various parameter conditions. An ANN is trained with the data obtained from FEM simulation. This uses Levenberg-Maquardt rule for learning. The ANN model is validated by comparing its predicted values of the forging force for untrained data with those of FEM. This generalization capability of the ANN model demonstrated the necessity to simulate the process for each selection of process parameters and can be used by the process engineer to determine the force required for any combination thus saving enormous time. The idea is being extended to other metal forming processes for the formation of a metal forming advisor to be used in factory environments.

**Finite Element Modelling**

**Methodology**

A domain specific software FORGE2 is used to model the hot upsetting. The material is assumed to be homogeneous, isotropic and incompressible. The elastic strains in comparison to viscoplastic ones are considered to be negligible. The material behaviour is assumed to follow Norton Hoff law. The friction law between die and workpiece is similar to the constitutive law. Using the penalty approach to enforce approximate incompressibility the variational principle states that the velocity field solution of the problem minimizes the functional

$$
\phi(\mathbf{v}) = \left[ \frac{k}{m} + \frac{1}{3} \right] \int_{\Omega} \nabla \mathbf{v} \cdot \nabla \mathbf{v} \, d\Omega + \int_{\Gamma} f \cdot \mathbf{v} \, dS_f + \frac{\mathbf{f}}{2} \left[ \frac{K}{m} \right] \int_{\Omega} \mathbf{v} \, d\Omega
$$

Where \( k \) is the material consistency, \( \mathbf{v} \) is the strain rate tensor, \( \mathbf{\varepsilon} \) is the equivalent strain rate, \( \mathbf{\varepsilon}_m \) is the strain rate sensitivity, \( \Omega \) is the work piece domain, \( \mathbf{v} \) is the velocity field, \( S_f \) is the surface on which stress vector is prescribed, and \( r \) is the large positive constant (10³).

A fully automated remeshing procedure is incorporated into the analysis. Six nodded triangular elements are used to model the part. The remeshing procedure uses trigger values to decide the generation of a new mesh (for instance when any element of the existing mesh degenerates). Then a new boundary suitable to the problem at this increment of time is built. Internal nodes are added according to the prescribed level of refinement and triangulation is obtained through a Delaunay type algorithm. This new mesh is regularized and its topology improved. Middle points are added on the sides of the triangles to build 6 node elements. At the end state parameters of the previous mesh are interpolated on the new one.

**Simulations**

A number of FEM simulations are performed for hot upsetting of a ck-45 steel preform at temperatures varying from 350 to 1300 °C under different punch velocities (1 to 5 mm/s) and friction conditions (where \( \mu \), the friction co-efficient is 0.1 to 0.8) using the model described above. The dies are kept at 350 °C. The material parameters chosen are

- \( m = 0.02 \)
- \( n = 0.1 \)
- \( \alpha = 0.2 \) \( s^{n-1} \text{mm.mm.s}^{-1} \)

The geometry is axi-symmetric in nature so only one half of the section is simulated. The billet height is initially kept at 10 mm and the final height is 5 mm. The diameter of the billet is 20 mm. The forging force
Table 1—Forging load (Tonnes) required in hot upsetting for 50% deformation at different input conditions

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required for 50% reduction at different punch velocities, at temperatures varying from 350 to 1300 °C under varying friction conditions is obtained (Table 1). Results of radial stress contours with evolving mesh, equivalent strain contours, equivalent stress contours and the temperature contours at 50% deformation for a sample simulation are presented (Figs 1-6). In this simulation, the initial billet is kept at 1200 °C and upset between rigid dies is kept at 350 °C with a press velocity of 3 mm/s and a friction coefficient of 0.6. The variation of forging force with change in temperature (Fig. 7), the effect of friction co-efficient on forging force (Fig. 8) and the influence of variation in die velocity on forging force (Fig. 9) are plotted.

The radial compressive stress contours and equivalent stress contours indicate that radial stress is maximum at the axis of symmetry and equivalent stress is maximum at the corners indicating folding tendency of upset. The hydrostatic pressure contours also depict that the maximum hydrostatic pressure occurs at centre of the specimen along its axis of
Fig. 1—Radial stress contours (MPa) with auto-generated final mesh at 50% deformation.

Fig. 2—Equivalent strain contours at 50% deformation.

Fig. 3—Equivalent stress contours (MPa) at 50% deformation.
Fig. 4—Hydrostatic pressure contours (MPa) at 50% deformation

Fig. 5—Temperature contours (°C) at 50% deformation

Fig. 6—Principal stress contours (MPa) at 50% deformation
The temperature contours indicate that the maximum temperature is at the central region of the work piece away from the dies and free surface. It is minimum near the dies due to the heat losses occurring at the die interface. The results of this analysis also confirm that at high temperature the effect of heat conduction is largely more important than those related to heat generation due to conversion of plastic work. The temperature and equivalent strain contours are very significant in bulk forming as they can be used to predict the phase changes inside the billet. The processing maps indicate the problem regions in the billet as the defects may develop at unstable regions and hence, the need for corrective measures in choosing process parameters. Principal stress contours depict that maximum principal stress is compressive in nature as is expected in upsetting and occurs at the bulge.

Back Propagation Neural Networks

The back propagation neural network is a multiple layer network with an input layer, output layer and some hidden layers between input and output layers. Its learning procedure is based on gradient search with least sum squared optimality criterion. Calculation of the gradient is done by partial derivative of sum squared error with respect to weights. After the initial weights have been randomly specified and the input has been presented to the neural network, each neuron currently outputs from all neurons in the preceding layer. The sums and activation (output) values for each neuron in each layer are propagated forward through to entire network to compute an actual output and error of each neuron in the output layer. The error for each neuron is computed as the difference between actual output and its corresponding target output, and then the partial derivative of sum-squared errors of all the neurons in the output layer is propagated back through the entire network and the weights are updated. In course of the back propagation learning, a gradient search procedure is used to find connection weights of the network, but it tends to trap itself into the local minima. The local minima may be avoided by adjusting value of the momentum. This algorithm can be expressed succinctly in the form of a pseudocode.
Pick a rate parameter $R$.
Until performance is satisfactory
For each sample input
Compute the resulting output
Compute $\beta$ for nodes in the output layer using
\[ \beta = D - O \]  
where $D_j$ represents the desired output and $O_j$ represents the actual output of the neuron
Compute $\beta$ for all other nodes using
\[ \beta = \sum W_{ij} O_j (1 - O_j) \beta_i \]  
Compute weight changes for all weights using
\[ \Delta w_{ij} = r O_j O_i (1 - O_i) \beta_j \]  
Add up the weight changes for all sample inputs and change the weights.

Levenberg-Marquardt Approximation

This algorithm uses Levenberg-Marquardt learning rule, which uses an approximation of the Newton's method to get better performance. This technique is relatively faster but requires more memory. The Levenberg-Marquardt (LM) approximation update rule is:
\[ \Delta W = (J' J + \mu I)^{-1} J' e \]  
which is used for updating weights of the network instead of conventional back propagation update rule. Where $J$ is the Jacobian matrix of derivatives of each error to each weight, is a scalar and $e$ is an error vector. If the scalar is very large, the above expression approximates the Gradient Descent method while if it is small the above expression becomes the Gauss-Newton method. The Gauss-Newton method is faster and more accurate near an error minima. Hence, the aim is to shift towards the Gauss-Newton as quickly as possible. Thus, $\mu$ is decreased after each successful step and increased only when step increases the error. Due to this advantage the LM rule was used in the network designed.

Neural network model of upsetting

The simulation data obtained with the finite element model, Table 1, is used to train the feed forward back propagation network (Fig. 10) with LM rule described above. A three layer network is developed with three inputs, i.e., temperature of billet, co-efficient of friction, velocity of die and one output, i.e., forging load. The network predictions...
have demonstrated the advantage of such network in real time. The validation is done by submitting raw, untrained data to the network, evaluating the forging force and comparing the same with values obtained from finite element model (Table 2). The close comparison of values of forging force obtained using the neural network clearly enumerates the accuracy of the model.

Conclusions
A finite element model is developed under FORGE2 environment for hot upsetting. A comprehensive database is developed by simulating the FE model up to 50% deformation of ck-45 steel specimen under varying temperature, friction and die velocity conditions. A neural network model is developed and trained with LM rule using the data thus obtained. The neural network models developed in this work could effectively estimate the forging forces based on temperature of the billet, friction conditions, die velocity for upsetting ck-45 steel specimen in a forming press. It is validated by comparing the values of forging force obtained for untrained process variables with those of finite element model simulations.

ANN models have emerged as a new alternative method for estimating forging forces in an intelligent manufacturing environment. These techniques easily capture the intricate relationships between various process parameters and can be easily integrated into existing manufacturing environment. These techniques open new avenues of parameter estimation, function approximation, optimization and on-line control of complex manufacturing systems.

A brief review of the material modelling used for hot upsetting along with mathematical formulation used in the software was presented and its applicability to industry is depicted by an example of hot upsetting of a ck-45 preform with varying temperatures, friction conditions and die speeds. The example illustrated the advantage of Neural Network Simulation for producing parts with complex boundary conditions. The advantage of using Neural Networks for process modelling in real time is realized.

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Partial support for this research from the Department of Science and Technology under grant number III.5 (91)/96-ET (PRU) is gratefully acknowledged. The first author was introduced to FORGE2 environment and Finite Element Modelling of Metal forming by Prof. J.L. Chenot and Dr. L. Fournier at CEMEF Laboratory, France.

References