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Artificial Neural Networks for Microstructure Analysis of Rolling Process

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Abstract: The object of this work is to be able to predict the changes, which occur in the microstructure of metal and alloys during thermomechanical process like rolling. At present reliable model exists for its determination. Optimization of such processes normally demands a combination of several experiments and expensive trials. The final microstructure is dependent on various parameters such as alloy composition of metal, working temperature, local compression rate etc. Determination of grain size of an image of microstructure is difficult to predict with traditional micro-mechanical models. Neural networks however, are ideally suited to such non-linear, multi-parameter problems. In the present work, an attempt has been made to investigate and develop suitable neural network architecture, implementing multi-layer error-backpropagation algorithm, which is appropriate for this metallurgical application. The project lies at the boundary of the practical industrial problems and academic information analysis theory.

Key Words: Neural Networks, Backpropagation Algorithm, Microstructure Analysis, Rolling Process

Introduction

The ability to model the thermo-mechanical processing of materials is an increasingly important requirement in many areas of engineering. This is particularly true in high tech industry where expensive materials are used having high processing cost. Thus the models are demanded that can reliably predict the microstructure of rolled materials. The problem in the modeling of materials rolling can be broadly stated as follows:

Given a certain material, which undergoes a specified rolling process, what are the final properties of this material? Typically final properties in which we are interested are the micro-structural properties such as the mean grain size. Relevant rolling process control variables are local compression ratio and temperature.

A trial and error approach to solve this problem has often been taken in material industry, with many different rolling conditions attempted to achieve a given final product. The obvious drawbacks of this approach are large time and financial costs. Another method is to develop a parameterized, physically motivated model, and to solve for the parameters using empirical data.

However the limitation with this approach is that in terms of physical theory the microstructure evolution depends upon several intermediate microscopic variables, which have to be measured in order to apply the model. Some of these variables, such as dislocation density, are difficult and time-consuming to measure, making it impractical to apply such an approach to large-scale industrial process.

An approach to the prediction of rolled microstructures is therefore to develop an empirical model in which we define a parameterized, non-linear relationship between the micro structural variables of interest and those easily measured process variables (Coryn *et al.*, 1998; Coryn *et al.*, 1997). Such a model could be implemented, for example, as a neural network with the hidden nodes essentially playing a role analogous to the intermediate microscopic variables. For the given problem we employ the Back Error Propagation Neural Network model with momentum term (Albert Nigrin, 1993; James, 1994). This model can be seen as generalization of feed-forward neural networks with very powerful interpolation capabilities. This architecture is very general and likely to be capable of modeling a wide class of static systems and processes. Results are presented which demonstrate the excellent generalization capabilities of this model.

Thermo-Mechanical Process: The thermo-mechanical process in which we are interested is rolling of Aluminum-Nickle alloy, a low weight and high strength material that is a replacement of conventional materials in almost all the relevant fields.

Rolling: Generally speaking all the engineering metals and alloys are casted into ingots and further processed by hot rolling into blooms, slabs and billets. These are known as semi finished products because they are subsequently rolled into products such as plate, sheet, tube, rod, bar and structural shapes. A rolling mill consists of one or several stands. The rolling mill used in this work, contains the roll bearings and sustains the roll separating force imposed on the bearings. The rolls are driven by an electric motor via a mechanical gearbox. The rolling mill stands with two rolls (two-high mills) that roll the material in one directionally (pull over). A certain amount of tension is maintained between the rolls in order to control the process and to prevent the material from coiling up between the stands.

The process can be carried out hot, warm or cold, depending on the application and the material involved. Many industrial investigators prefer to divide rolling into cold and hot rolling processes. However, from a fundamental point of view, it is more appropriate to classify rolling processes on the bases of the complexity of metal flow during the process and the geometry of the rolled product (Metals Hand Book; Furu *et al.*, 1996).

The specific rolling process used in this work is "Uniform Reduction in Thickness with no Change in Width". The deformations in grains in longitudinal direction after the rolling process are shown in the Fig. 2(a to e), for comparison. The grain size is reduced in horizontal direction. After appropriate reduction rate in mechanical working and heat treatment a uniform and fine grain size can be obtained. A fine grain size is desirable to achieve the required properties for applications in relevant fields. In this study, however only rolling process was carried out and no heat treatment was involved. This work was only limited to grain size in rolling direction (longitudinal direction) up to certain reduction. The cast grains were not broken to smaller size at this reduction.

Neural Network for Microstructure Analysis: A neural network model is developed for microstructure analysis, which is an implementation of feedforward network. The development procedure and working capabilities of the model are also described here.
The architecture described is a particular type of feed-forward neural network known a multi-layer perceptron (Fig-1). As the name suggests, this architecture is a development of the perceptron, which was a very simple predecessor of neural networks consisting of a single layer of processing nodes (MacKay, D.J.C., 1995).
A computer software program for the proposed neural network model is simulated. The software is the implementation of the equations below,

$$z = \tanh(y) \tag{1}$$

where

$$y = \sum_i \omega_i x_i \tag{2}$$

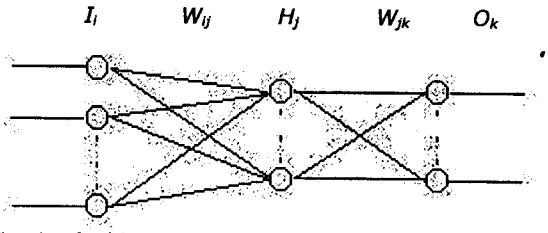


Fig. 1: Architecture of the Proposed Neural Network

Sum of the weighted outputs of neurons in previous layer is the input of the neurons in the next layer. Which is propagated through the network and finally output layer provides the estimated results.
User depending on his requirement provides the number of neurons in each layer. The user depending on complexity of the problem suggests the maximum number of the neurons.
Implementation of Training Algorithm: Training of the designed model is carried out using the error-back-propagation algorithm. The goal of proposed model is to minimize iteratively

$$E = \frac{1}{2}\sum_k (O_k - T_k)^2 \tag{3}$$

With respect to the network weights. In above equation O_k is the estimated output of k^{th} neuron where as T_k is the desired target value.
The network is trained iteratively, and the weights are perturbed towards their optimal values after each pass of the data or a subset of it. The cycle between weight updates is a single *iteration,* which I label *t*. Thus the general equation for weight updates between two layers, indexed by *i* and *j* is

$$\Delta\omega_{i,j}(t) = -\eta \frac{\partial E}{\partial \omega_{i,j}} \tag{4}$$

Where, $\omega_{i,j}$ is the weight connecting node *i* in previous layer to node *j* in the next, and η *is* a constant. The rate of convergence towards the minimum of *E* can be improved by addition of a *momentum* term. This term is simply the previous weight update, and forces the present weight update to continue in the general direction of a negative gradient, rather than respond only to individual updates of *w*, which may leave the function trapped in a local minimum. In this sense the term adds inertia to the gradient descent. Although the use of a momentum term is not the most efficient means of converging on the global minimum in the shortest possible training time, it nonetheless improves training times over pure gradient descent, but is quite robust and helps to avoid local minima in the error minimization surface (Rumclhart *et al.*, 1986). A faster approach is to search for minima along the *conjugate gradients*. But this method is even more prone to becoming stuck in local minima (Bishop, 1995).
When the momentum term is included, the update equations for the hidden-outputs and input-hidden weights become

$$\Delta\omega_{i,j}(t) = -\eta I_i g'(y_j)\sum_k (O_k - T_k) f'(x_k)\omega_{j,k} + \alpha\Delta\omega_{i,j}(t-1) \tag{5}$$

and

$$\Delta\omega_{i,j}(t) = -\eta H_j (O_k - T_k) f'(x_k) + \alpha\Delta\omega_{j,k}(t-1) \tag{6}$$

Where $\omega_{j,k}$ and $\omega_{i,j}$ are the hidden-output and input-hidden weights respectively. The constants η and α determine the relative contribution of the update momentum terms as well as the overall magnitude of the weight updates. The functions $f(x_k)$ and $g(y_j)$ be are the non-linear transfer functions of the output layer and hidden layer, so that the network outputs, O_k, are given by

$$O_k = f(x_k) \tag{7}$$

where,

$$x_k = \sum_j \omega_{j,k} H_j \tag{8}$$

and

$$H_j = g(y_j) \tag{9}$$

where

$$y_j = \sum_i \omega_{i,j} I_i \tag{10}$$

Equations (5) and (6) have not assumed any specific functional form for the transfer functions $f(x_k)$ and $g(y_j)$. The derivation is carried out with a sigmoid transfer function, which has the form

$$F(x) = \frac{1}{1+e^{-\lambda x}} \tag{11}$$

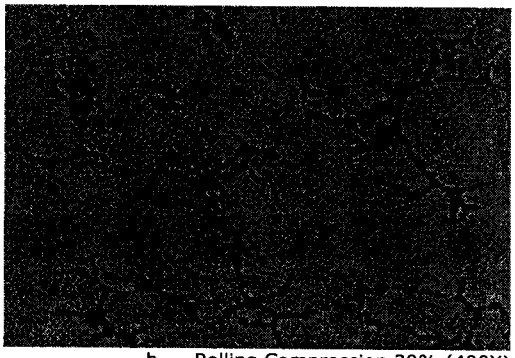
Its use in neural networks was actually inspired by its similarity to the neuron transfer function. Its implementation can also be justified on the grounds that it gives a convenient mapping of an unbounded input to a bounded output. In this function λ dictates how sharply the function rises to its peak value. Although, sigmoid function is used for both *f* and *g*, but constants are still different ($\lambda_f \neq \lambda_g$). Another feature of the sigmoid function, which encourages its use, is that it has simple derivatives.
Hence the weight changes for iteration *t* becomes

$$\Delta\omega_{j,k}(t) = -\eta\lambda_f H_j (O_k - T_k) O_k (I - O) + \alpha\Delta\omega_{j,k}(t-I) \tag{12}$$

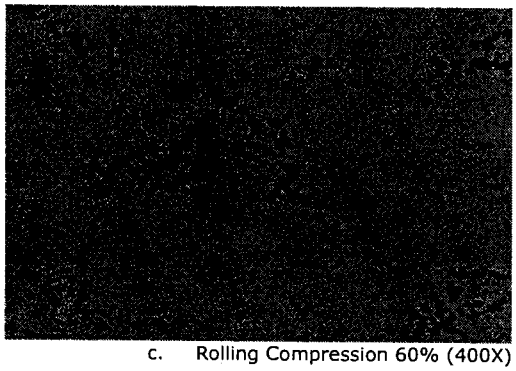
and

$$\Delta\omega_{i,j}(t) = -\eta\lambda_f\lambda_g I_i H_j (I - H_j)\left[\sum_k (O_k - T_k) O_k (I - O_k)\omega_{j,k}\right] + \alpha\Delta\omega_{i,j}(t-I) \tag{13}$$

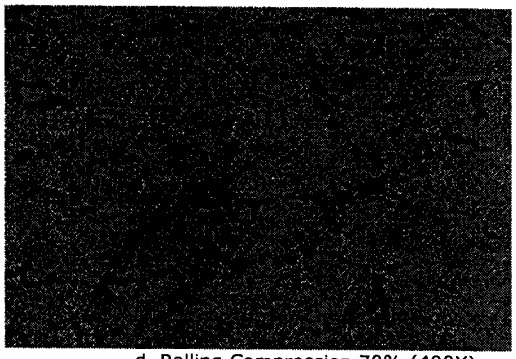
a. Casted Material (500X)



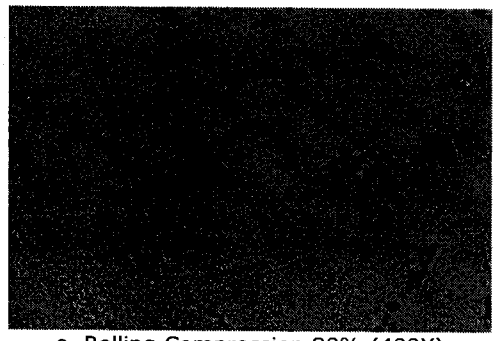
b. Rolling Compression 30% (400X)



c. Rolling Compression 60% (400X)

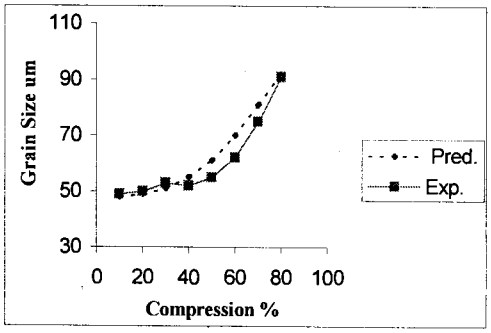


d. Rolling Compression 70% (400X)

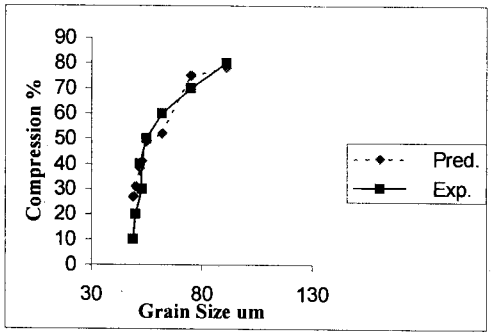


e. Rolling Compression 80% (400X)

Fig. 2: Micro-graphs of Different Samples



(a)



(b)

Fig. 3: (a) Presents the Comparison of Experimental and Predicted Values. (b) Presents Inverse Prediction for the parameters from Grain Size

Which are the final weights update equations implemented in simulation. The gradient descent method used above locates the steepest negative gradient and searches along it in steps for a minimum.

Predictions for Grain Sizes: The Rolling process model was trained using a set of 24 data pairs with reduction ratio from 10% to 80% at different temperatures from 380 to 490°C. Once trained the model was used to produce predictions of grain sizes for a range of the input variables.

A plot is drawn for comparison of the experimental results with predicted ones is shown in the Fig.3(a). The temperature is kept constant for true comparison. An excellent agreement in both, the experimental results and predicted ones is obvious from the plot. The average error between predicted and experimental values is 3%, which is much less then the noise in experimental measurement of grain size.

Prediction for Reduction Ratio (inverse problem): The ultimate objective of the modeling for rolling is the inverse problem: Given a set of desired final properties for a material, what is the temperature and rolling reduction, which will realize these properties? In this case there may be one-to-many mapping between the desired properties and necessary rolling process.

This problem is tackled in such a way that user will have to give his desired properties at the input of the network. User will have to fix some of his parameters, depending on the apparatus available to him. The modeling will predict the remaining parameters. For example, as in our experimental data, if user wants a prediction about reduction percentage for a specific grain size, he will have to choose a specific temperature for the rolling. The grain size and temperature will be given at the input of the model, which will predict the reduction percentage as output.

The model, which was used to predict the grain size, was applied for inverse problem also. Fig. 3(b) presents the comparison of experimental and predicted values. Temperature is kept constant i.e., 450 °C. Again the predictions are excellent and well with in error tolerance.

Conclusion

The predictions of models are very close to the experimental values for the microstructure analysis. Having such model, one needs not to perform the analysis experimentally. Results demonstrate the usefulness of this model for predicting interpolated values. Model is very feasible for the industry where frequent microstructure analyses are carried out.

Another interesting and much useful application of the same model is carried out in predicting the thermo-mechanical process, to achieve the desired properties of material.

Future Enhancement: The lightweight and high strength materials are emerging as a replacement of the conventional heavy materials in all the industries especially in automobiles, buildings, aerospace etc. Aluminum alloys are at the top of the list, for these replacements.

Models for such alloys are therefore needed which can predict other more complicated relevant features such as hardness, toughness, shear strength, wear and tear, etc. There should be a generalized model for the whole range of such alloys, which could be used (with little adjustments), to determine their properties for the processes, which are applied frequently in material industry. The model should also be able to propose an alloy and specific process to be employed on it to get the desired properties.

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