Development of an Artificial Neural Network Constitutive Model for Aluminum 7075 Alloy

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Abstract

Development of an accurate neuronal material model for aluminum alloys would facilitate better process control and parameter optimization in the aircraft industry. This research primarily attempts to design a connectionist constitutive model for aluminum 7075 alloy using multi-layer perceptrons. The backpropagation algorithm is used to train the designed network whose performance is then validated using experimental data from a test set.

Keywords
Artificial Neural Networks (ANNs), Constitutive Modeling, Intelligent Systems, Connectionist Material Model

1. Introduction
Constitutive equations are mathematical relationships that describe the macroscopic response of a material to applied stress under different combinations of strain (e), strain rate ($\dot{e}$), and temperature (T). It is usually of the form, $s = f(e, \dot{e}, T)$, where s = flow stress. It is impossible to build a single set of equations to accurately approximate the behavior of any metal. However we strive to formulate equations to predict material behavior under a subset of conditions. The material behavior is thereby described; to be used in analysis, design of processes and possibly in the development of the materials themselves. Hence constitutive equations are the mathematical idealization of material behavior under a set of given conditions.

The typical approach to the development of constitutive models is parametric. The major drawback of parametric modeling is the assumption of the model form, which relies heavily on the modeler's expertise. As a consequence the form taken by the final model may be too specific to generalize beyond new unseen data or too inaccurate to be of use. System design using Artificial Neural Networks (ANNs) is a non-parametric modeling technique. The neural network modeling technique can suffer from the same problems, being too specific or too inaccurate, but relies less on the modeler's expertise. Therefore they are more often better predictors. This paper reports preliminary results of a neural network constitutive model of aluminum 7075 alloy. This research is a part of a larger body of work that attempts to model high speed machining processes for the aircraft manufacturing industry.

2. ANN Constitutive Models and Mathematical Relationships
Mathematical constitutive models are rigid and may compute erroneous variable magnitudes during parameter range shifts. Neural networks have contemporarily been used as alternatives to mathematical constitutive modeling. ANN approaches have essentially been justified owing to the capabilities of neuron models to learn the non-linear relationships between input and output parameters in the system. This feature of the ANN approach is in essence of the complexity involved in quantifying the behavior of metals under varying external conditions. According to Gaboussi et al [5], the inherent properties of ANNs in constitutive modeling as an alternative to classical rheological modeling are; ability of adaptation, distributed memory, ability of generalization and a strongly parallel structure. These properties significantly avoid sensitivity to noise and facilitate fast data processing. Fast data processing is essential for its use in finite element analysis.

2.1 Parametric approach to constitutive modeling
The primary difficulty is to address nonlinear phenomena like elastoplasticity with cold work and viscoplasticity in the material whose response is to be modeled. Various approaches have been researched in the past. A parametric identification method as a starting procedure is described in Pernot and Lamarque [2]. The parameters are identified from experimental time series that approximate displacement, strain and stress magnitudes for different quasi-static loading conditions. In conformance to the specified relationships between stress states and the strain field, the

parameters that affect the model can be computed. Subsequently intrinsic formulations are investigated from experimental data. The output from the model is compared with the experimental results marked apriori as the test set. Thus the model performance is validated. Several iterations are required until the output converges to an acceptable degree of agreement with the test set. The rheological framework of modeling constitutive equations incorporates parametric identification and computation of intrinsic variables [1,4,6].

2.2 Non-parametric approach to constitutive modeling

As stated above, the ANN approach is classified as a non-parametric technique [3]. The convenience of the ANN approach is that the understanding of complex nonlinear responses of the material is not necessary. The objective is to design a connectionist model using data available as fitting parameters thereof. A rudimentary network is first designed using experimental data. The identification of internal parameters of the network is then processed during the training phase. The training of the network is an iterative process wherein the objective of the learning phase is to get the designed network to simulate actual outputs of the physical system in correspondence to the inputs presented. The training method or the network design is accordingly modified to obtain a close agreement between network predicted and experimentally procured test magnitudes. The ANN methodology involves the computation of weights in accordance to the backpropagation training in the learning phase. The advantages of the neural approach to constitutive modeling [2] can be summarized as,

- It allows to avoid apriori assumptions about the type of constitutive laws
- It can solve the problem of constitutive law inversion
- It can be used to control "rheological behavior" of an in-situ material
- It can directly use experimental results in order to build a model
- The training phase can be extended to improve the model

Neural based constitutive laws may be implicit or explicit depending on their mathematical description. Furukawa and Yagawa [3] formulated an implicit relation, wherein y is the implicit mapping in terms of the state space method, $\dot{x} = y(x,u)$, x and u being state variables and control inputs. State space forms in various applications have been learnt successfully by neural networks. This research would focus on the development of an implicit constitutive model for Aluminum 7075. The most important advantage of the implicit model is that it can be constructed from experimental input output data.

3. Material constitutive model for aluminum

Aluminum 7075 is among the most extensively used alloys for aircraft fuselage structures owing to its high strength-to-density ratio. According to a generic observation, it is not realistic to express flow stress as a single function of strain, strain rate and temperature that is applicable for all possible combinations of these parameters [11]. In conventional constitutive theories, a mathematical model is constructed, primarily to represent the behavior of the material at moderate ranges of temperature and strain rate. There also exists a class of constitutive relations that model material flow properties and are pertinent to the microstructure of the metal subjected to external variables. Work on metals has been documented from the viscoplastic perspective and extensive models have also been designed for non-metals [10]. However, a robust model for aluminum and its alloys does not exist for high strain rates and high ranges of temperature. The complexity of material responses for different segments of the parameter range could not be incorporated by a static mathematical model. Thus the mathematical approach would require defining multiple equations for different range domains. From the perspective of industrial processes involving Aluminum 7075, a robust dynamic system that would predict the alloy behavior for the designated parameters over any given process range is required.

4. Experimental data and parameter sensitivity

Experimental data of the dynamic impact properties of aluminum 7075 alloy were obtained using a Split Compression Hopkinson Bar (SHPB). This method has been extensively used to procure material property data under high strain rate magnitudes [7].

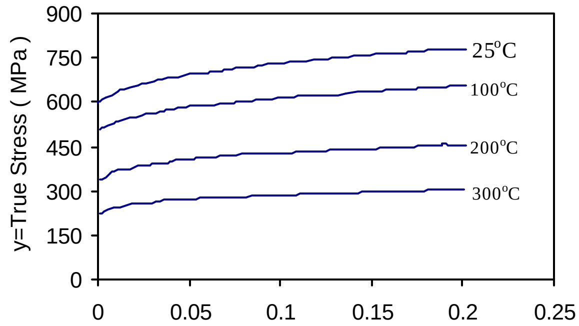

Figure 1(strain rate 1300/s) x=True Strain

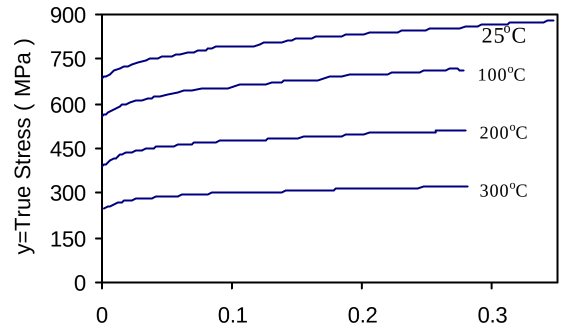

Figure 2 (strain rate=2400/s) x=True Strain

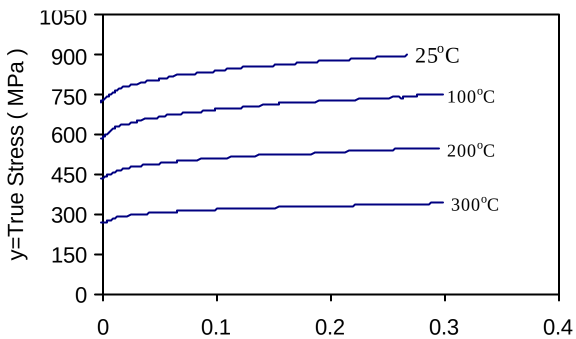

Figure 3 (strain rate = 3100/s) x=True Strain

The experimental results were documented in a previous study [8] as parameter responses for three different strain rate sets, $\dot{\varepsilon}$=1300s^{-1}, 2400 s^{-1} and 3100 s^{-1}. The alloy behavior at each of the strain rate magnitudes are represented by figures 1, 2 and 3. The stress strain curves are tabulated at four temperatures for each strain rate response s et, T_1 = 300 °C, T_2 = 200 °C, T_3 = 100 °C and T_4 = 25 °C, represented in that order by the curves starting at the bottom of each graph upwards. Flow stress (true stress), represented on the y-axes of each of the 3 graphs is a function of temperature (T), true strain (ε) and strain rate ($\dot{\varepsilon}$). After initial yielding, the flow stress exhibits a steady increase with increase in true strain. This increase is accompanied with different strain hardening rates in the continuum, a variable that has not been included in the preliminary study. According to the sensitivity analysis, the effect of temperature on the flow stress is more pronounced than that of the strain rate. This is further substantiated by an appreciable decrease in flow stress with a corresponding increase in temperature for a constant strain rate. Also, the temperature sensitivity is independent of the strain rate. Previous studies have also documented the evolution of the microstructure during deformation of the material specimen [9, 12], as a consequence of external loading.

Various systems simulation processes have also been used to study aluminum alloy responses at different loading parameters. The designed neural network model in this research would be trained to predict the output based on the experimental data discussed in this section.

5. Network Architecture

The ANN model developed may be classified as a knowledge based constitutive relationship system. This model would approximate the material behavior in a radically different way; moreover it will not be confined to the boundaries of a computed mathematical model. The ANN model thereby designed would approximate the alloy response over the entire continuum for the designated parameters.

The response characteristics in the form of true stress output magnitudes corresponding to various sets of temperature (T), true strain (ε) and strain rate ($\dot{\varepsilon}$) inputs, are learned by the neural network as representative functions to be incorporated into the proposed neuron constitutive model. The global training method used is in the form of an estimation of a function mapping ($R^m \Rightarrow R^n$) from samples of the function made available through experimental data discussed in section 4. The characteristics of this function to be approximated vary throughout the input space.

The network design objective is therefore characterized as a function approximation state space modeled using a multi-linear perceptron system with 3 input nodes each for temperature (T), true strain (ε) and strain rate ($\dot{\varepsilon}$) in the input layer and one node corresponding to the magnitude of true stress (σ) in the output layer. The number of hidden layers is experimentally determined. Among the designed networks tested, a four-layer network topology with 10 neurons in each of the two hidden layers (3-10-10-1 network) exhibited the best performance.

5.1 The ANN training algorithm

Algorithms like Classification And Regression Trees (CART), Multivariate Adaptive Regression Splines (MARS), ID3, and the Hierarchical Mixtures of Experts (HME), are local approximation models [14], where the input space is divided, at training time, into a hierarchy of regions where simple surfaces are fit to the local data [13].

The training method used to design the neuron constitutive model in this research is the backpropagation algorithm. This supervised training algorithm incorporates an application of the chain rule for ordered partial derivatives to calculate the sensitivity that a cost function has with respect to the internal states and weights of a network. The training error is backward-passed to each internal node within the network, which is then used to calculate weight gradients for that node. Learning therefore progresses by alternately propagating forward the activations and propagating backward the instantaneous errors.

Root Mean Square Error (RMSE) is selected as the success quantifying metric for the backpropogation training of the designed ANN constitutive model. The goal was to minimize RMSE over the entire range of the network output. The backpropogation algorithm is used to train the network to approximate the alloy response data iteratively minimizing the root mean square error of the computed output magnitudes.

The training set consisted of 562 input-output data pairs procured from experimental results discussed in section 4. Training was stopped after the RMSE appeared to stabilize over several iterations. The final network was selected by on the basis of the lowest RMSE on a separate validation or test set of data.

The validation set consisted of experimental data points over the same range as the training set. The validation set had 209 input-output data pairs, which do not have occurrences in the training set.

6. Preliminary results and network performance

The performance of the networks was evaluated based on the output generated for stress (s , MPa) versus the experimental data on the validation set, which is shown in figures 5, 6 and 7. Each of the figures are plots of true stress against true strain and is presented in the same format as the input data in section 4.

The four result curves in each figure correspond to temperatures 300, 200, 100 and 25 ^{o}C. The curves attest that the neural operator has accurately reproduced the nature of the curve and the ANN model has acquired the capability to approximate the decrease in true stress with a corresponding decrease in temperature.

The identification of the correlation between the parameters by the designed network is significant, as it would facilitate accurate network prediction of output magnitudes given any unlearnt data point outside the continuum of the training set.

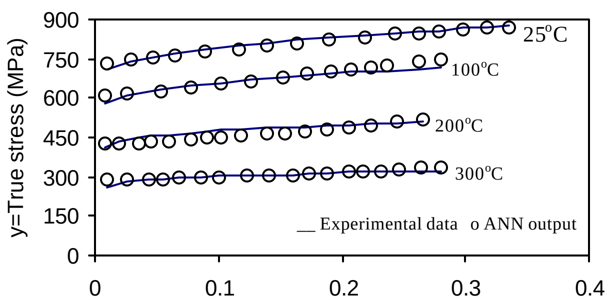

Figure 6 (strain rate 2400/s) x=True strain

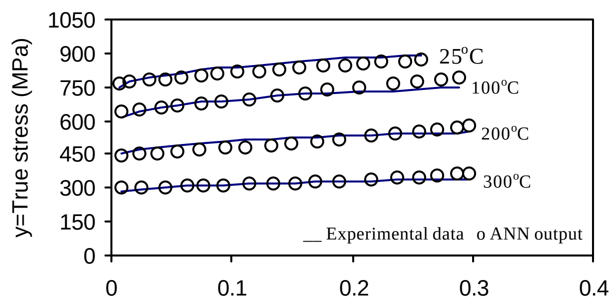

Figure 7 (strain rate 3100/s) x=True strain

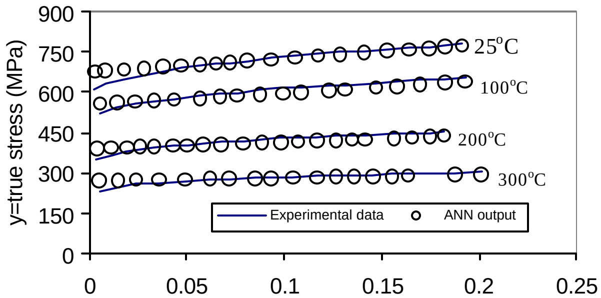

Figure 5 (Strain rate = 1300/s) x=True strain

Figure 8 represents the actual error of the output points generated by the ANN model corresponding to the experimental test data presented to the network during the validation phase.

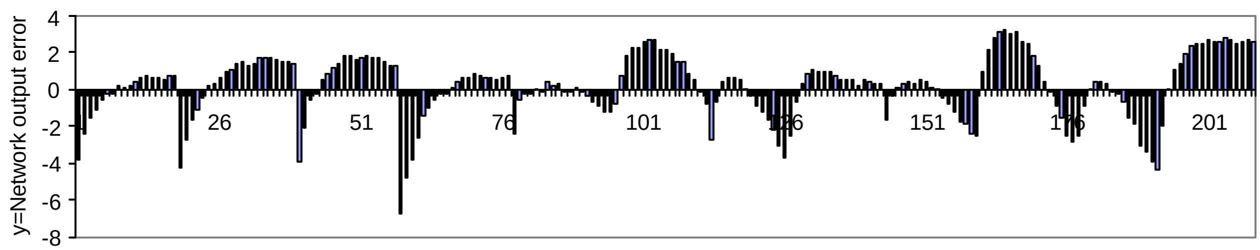

Figure 8 x=Serial number of experimental data point

The initial points show that there was a slight incoherence, which may be attributed to partial data assimilation. However, the error stabilizes and most data points are approximated to a perceptible degree of accuracy. The error magnitudes are represented for all the 209 data points in the test set, maximum error being 6.72 MPa and the minimum error being 0.0 MPa.

7. Concluding Remarks

This paper presents the preliminary results of current research in the development of a neuro-mimetic material model. The credibility of artificial neural networks in approximating material response presented as parametric trajectories has been established. Previous studies have documented ANN identification capabilities of non-linear dynamical systems [10]. Many aviation materials are processed without information about their mechanical behavior. Thus a tool that would accurately predict material behavior subject to machining parameters would facilitate greater process control in machining aviation alloys. A connectionist model may therefore be designed for any industrial material, based on experimental data and mathematical constitutive laws available. The ANN model would therefore be an evolutionary tool in the field of material constitutive modeling.

8. Anticipated results of ongoing research

Presently, a training procedure using smaller training sets over larger epochs is being explored. The research is also investigating another approach wherein multiple networks approximate the behavior of the alloy in a discretized input parameter domain, one network for each parameter range. The validity of the ANN predicted results outside the range of the training set are being experimentally verified. The results from the final connectionist model would be more accurate than corresponding mathematical and finite element models for the system.

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