MICROSTRUCTURE DEVELOPMENT FOR EXTRUSION – NARMA_L2 CONTROL APPROACH

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ABSTRACT

In the present study an attempt was made to control the microstructure evolution during extrusion using the NARMA_L2 Control approach with Neural Networks. The final grain size after extrusion was considered as the optimal criterion and the grain size was expressed in terms of strain, strain rate and temperature. The steps involved in NARMA _L2 Control approach include process modelling, system identification and controller design. The trajectories of the independent variables to achieve the desired grain size were obtained and the strain values were further utilized to optimize the dimensions of the extrusion die profile to achieve the required grain size.

Keywords: microstructure control, extrusion, NARMA_L2 control

INTRODUCTION

Neural computing is one of the fastest growing areas of artificial intelligence. The reasons for this growth is that neural networks hold great promise for solving problems that have proven to be extremely difficult for standard digital computers. There are two key differences between neural computers and digital computers. First neural networks are inherently parallel machines and as a result they can solve problems much faster than a serial digital computers. Secondly and perhaps more importantly, many neural networks have the ability to learn [1]. Recently it has been proved that multi-layer feed forward neural networks offer interesting possibilities for modelling any non-linear process without a priori knowledge [2]. A Nonlinear Autoregressive – Moving Average (NARMA) is one that uses a model to evaluate how control strategies will affect the future behavior of the plant. With neural network as the model, NARMA_L2 Control can be used to control non-linear plants. The use of dynamic process models allows the user to systematically design a control system without resorting to adhoc tuning methods [3]. Therefore the application of neural network based NARMA_L2 control becomes very attractive.

OBJECTIVES OF THE PRESENT STUDY

The objectives of the present work include development of dynamic modelling for Hot extrusion of 0.3% carbon steel using Levenberg Marquardt algorithm, which is a modification of standard back propagation algorithm and to design a neural network based NARMA_L2 control for the above process. The micro structural variables such as strain, strain rate and temperature were optimized in the first stage. Based on the optimized parameters the die profile for extrusion were optimized in the second stage.

PROBLEM DESCRIPTION

The control of microstructure in metal working processes is needed for better quality. A new methodology for calculating optimal control parameters for hot deformation process for micro structural control is proposed. This approach is based on the Neural network control and involves developing neural network models from available material behavior and hot deformation process models. The control system design consists of two stages, analysis and optimization. In the analysis stage, using the empirical models for microstructure development and NARMA_L2 control optimum strain ($\varepsilon(t)$), strain-rate ($\dot{\varepsilon}(t)$), and temperature ($T(t)$) trajectories for processing were estimated. The available simulation models for ram velocity and extrusion profile were then used to calculate process control parameters such as ram velocity and die profile to achieve the strain, strain rate and temperature trajectories obtained earlier. The two-stage approach for micro structural control was applied to the hot extrusion of 0.3 % carbon steel based on the models used by Frazier et al [4].

Average recrystallized grain size

$$D = 22{,}600\varepsilon\dot{\varepsilon}^{-0.27} e^{-0.27(Q/RT)}$$

Activation energy and gas constant

Q = 267 KJ/Mol,
R = 8.314X10^{-3} KJ/ Mol.k.

Time derivative of temperature

$$\hat{T} = \frac{\eta}{pc_p}\sigma(\varepsilon,\dot{\varepsilon},T)\dot{\varepsilon}$$

σ -flow stress (kPa)
η = 0.98

OPTIMIZATION OF PROCESS PARAMETERS

The trajectory of strain, strain rate temperature are obtained in the first stage. Process parameter such as die geometry, ram velocity, billet temperature are obtained in second stage.

$$V_{ram} = \frac{L}{\int_0^t \varepsilon(t)dt}$$

where L = die length. ε (t) = strain trajectory, V_{ram}= ram velocity

The die shape can be described by the radius r and axial distance (die throat length) y, radius at entrance r_0,

where $r(t) = r_0 e^{-\varepsilon(t)/2}$

and $Y(t) = V_0{}^t{}_{ram} \int e^{\varepsilon(t)} dt$

The optimal die profile for achieving final grain sizes of 26 and 30 μm obtained using this approach.

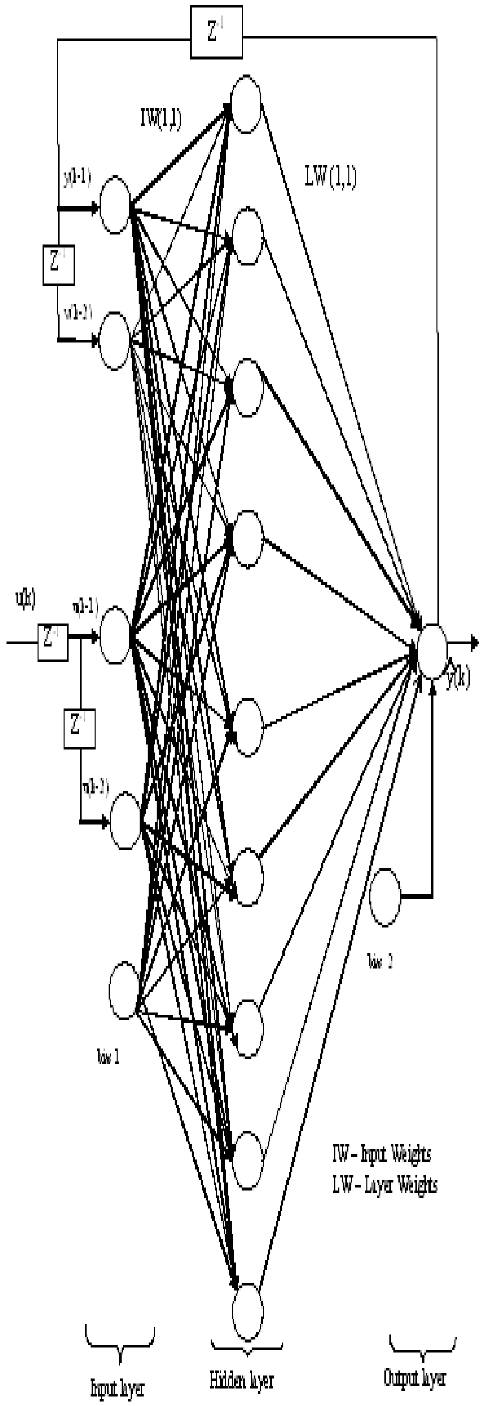

Fig.1 Neural Model

NEURAL MODEL

The architecture of neural network plant model is shown in Fig.1. The architecture of the neural network used for identification is 5-9-1, where two of the input nodes are used for the shifted feedback signal from the output of the network and one node is used as bias and the remaining nodes are used for shifted input signal.

SYSTEM IDENTIFICATION USING NEURAL NETWORKS

Neural networks have been applied very successfully in the identification and control of dynamic systems. The universal approximation capabilities of the multi layer networks make it popular choice for modeling non-linear systems and for implementing general-purpose non-linear controllers. In the system identification stage, a neural network model of the plant to be controlled is developed. In the control design stage, the neural network plant model is used to design the controller. The advantage of using artificial neural networks (ANN) to simulate the process is that after they are trained, they represent a quick and reliable way of predicting their performance. They can also be continuously updated. The whole training procedure uses 10,000 iterations. The corresponding model validation and testing data are shown in Fig.2 and Fig.3. The responses of the plant output and neural model output for the given input were found to almost same and hence the system identification is acceptable. The mean square during training of neural networks was found to be 5.705 X 10^{-10}, which proved that the network has been trained with sufficient data.

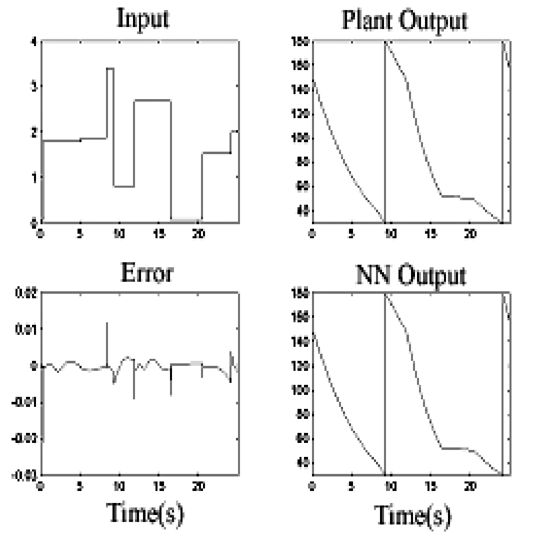

Fig.2 Validation of the Identified Neural Model

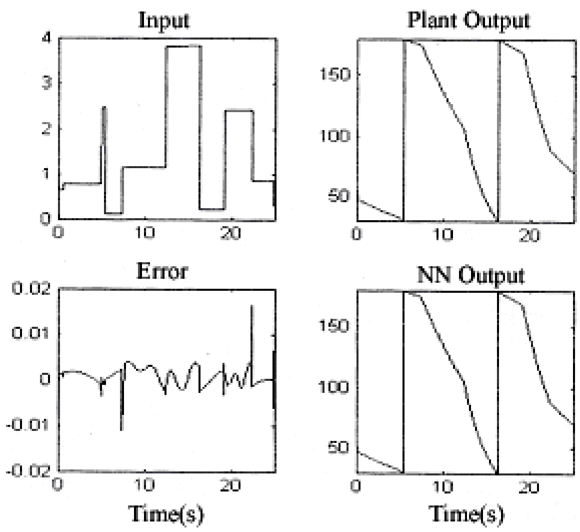

Fig.3 Testing of identified Neural Model

NARMA-L2 CONTROL

NARMA-L2 is one of the neural network architecture that have been implemented in the MATLAB for prediction and control. NARMA-L2 controller design is performed by two stages.
1. System identification and 2. Control design.

In the system identification stage, the neural network model of the plant which is to be controlled is designed. For controller design, the plant model which is identified is used.

The neurocontroller designed is referred by two different names. (i) NARMA-L2 control and (ii) Feedback Linearization control. When the plant model is in companion form, then it is said to be NARMA-L2 control and when the plant model can be approximated by companion form is feedback linearization control. The central idea of this controller is to transform nonlinear system dynamics into linear dynamics by cancelling the nonlinearities. In NARMA-L2 control, the controller design is simply the rearrangement of plant model, which is trained offline in batch form. It requires the least computation than model predictive and model reference controllers. If neural network is used as a controller, the parameters of NARMA-L2 have to be adjusted to achieve on line control. Only approximated methods are used in practice for controlling a plant represented by a NARMA-L2 control which reduces computational complexity. The desired input can be computed algebraically from the identification model and hence a separate controller neural network is not needed in NARMA-L2 controller. The model outputs are very close to the actual plant output in NARMA-L2 which implies that the identification error is marginally less. In adaptive control problems where the plant parameters are assumed to be unknown, NARMA-L2 makes the estimation procedure straight forward [3].

CONTROLLER DESIGN

In NARMA-L2 controller, design is simply the rearrangement of plant model. Approximated NARMA-L2 model is

$$y(k+d) = f[y(k), ...y(k-n+1),u(k-1),..u(k-m+1)] + g[y(k), y(k-1), \ldots y(k-n+1), u(k-1),\ldots u(k-m+1)]\, u(k)$$

When y(k+d) = yr (k+d),
then the next control input

$$u(k) = \frac{yr(k+d)-f[y(k),\ldots y(k-n+1),u(k-1)\ldots u(k-n+1)]}{g[y(k),y(k-1),\ldots y(k-n+1),u(k-1)\ldots u(k-n+1)]}$$

Direct use of this equation can cause realization problems, because of control input u(k) determination is based on the output at the same time y(k), where d>2. The block diagram of NARMA – L2 controller is shown in Fig.4.

The output error is used to adjust the neural network through a dynamic procedure. This approach combines the advantages of adaptive control and neural networks and is considered as a basic form to design a neurocontroller.

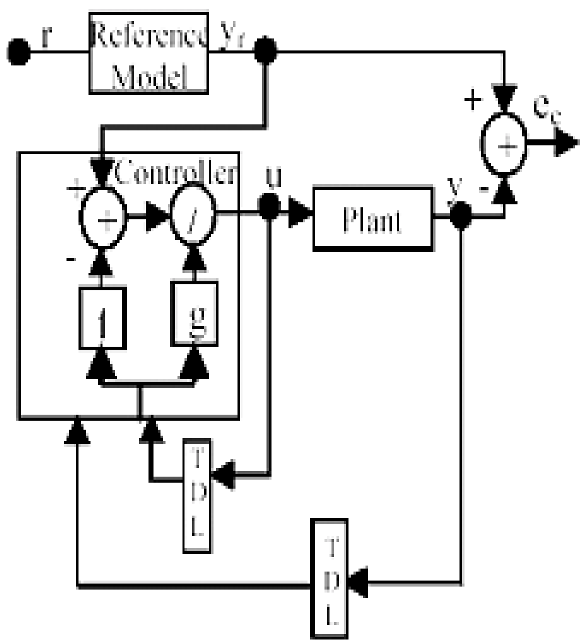

Fig.4 Block diagram of NARMA_L2 Control

OPTIMIZING THE MICRO STRUCTURAL TRAJECTORIES AND EXTRUSION PROFILE

The optimality criterion was chosen so as to attain a maximum strain of 2 while the recrystallized grain size was kept at a desired value of 26µm the average grain size of raw stock prior to extrusion was 180 µm starting at initial temperature of 1273K [4]. The results of additional optimization run to achieve grain size of 30µm is also presented. Since the extrusion profile (radius and throat length) is a function of velocity of ram and strain, the corresponding trajectories can be used for optimizing the extrusion profiles. The trajectories for the process parameters and extrusion profile were obtained for 26 and 30µm (fig. 5 & 6). The simulation time was found to decrease with increase in grain size and the radius of die at the exit was found to increase with the grain size(fig. 7 & 8).

CONCLUSIONS

1. NARMA_L2 control can be used for micro structural development in material processing.

2. The strain , strain rate and temperature trajectories can be optimized to achieve the required grain size

3. The strain and velocity trajectories can be used to optimize the extrusion profile to achieve the required grain size.

4. The simulated results can be validated through experiments.

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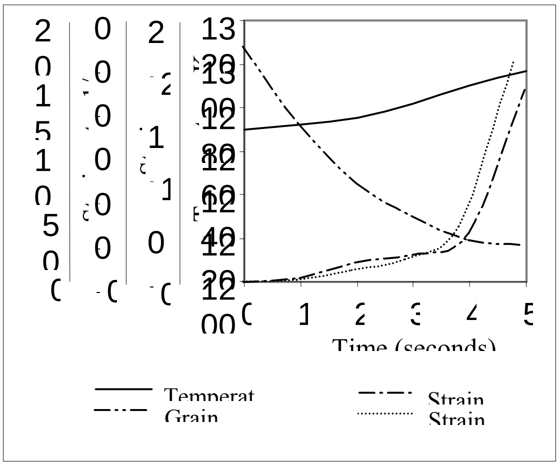

Fig.5 Optimal Trajectories for Gain Size = 26µm

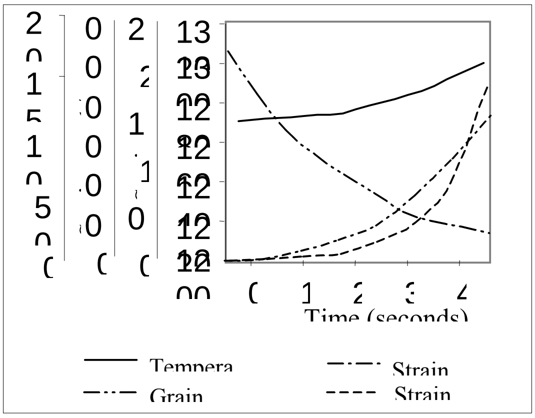

Fig.6 Optimal Trajectories for Grain Size = 30µm

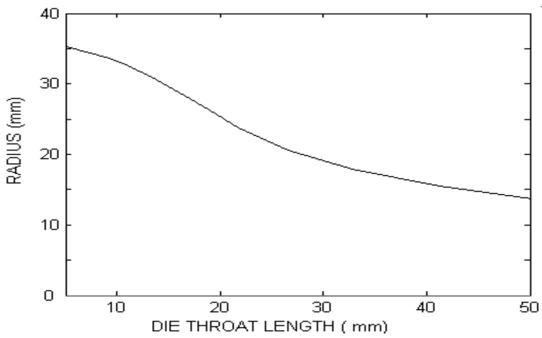

Fig.7 Optimal die profile Grain size = 26µm

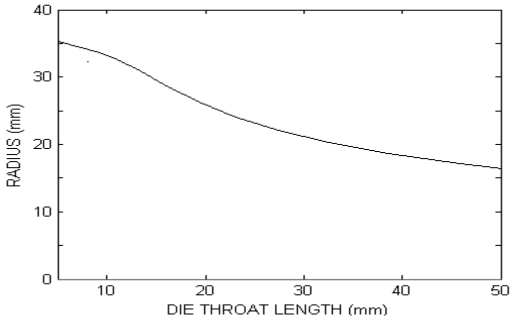

Fig.8 Optimal die profile Grain size = 30µm