Neural Network-Based Control for the Fiber Placement Composite Manufacturing Process

P.F. Lichtenwalner

At McDonnell Douglas Aerospace (MDA), an artificial neural network-based control system has been developed and implemented to control laser heating for the fiber placement composite manufacturing process. This neurocontroller learns the inverse model of the process on-line to provide performance that improves with experience and exceeds that of conventional feedback control techniques. When untrained, the control system behaves as a proportional-integral (PI) controller. However, after learning from experience, the neural network feedforward control module provides control signals that greatly improve temperature tracking performance. Faster convergence to new temperature set points and reduced temperature deviation due to changing feed rate have been demonstrated on the machine. A cerebellar model articulation controller (CMAC) network is used for inverse modeling because of its rapid learning performance. This control system is implemented in an IBM-compatible 386 PC with an A/D board interface to the machine.

Keywords
Adoptive control, CMAC, neural network, neural control, on line learning, process control

1. Introduction

AUTOMATION is a key factor in achieving affordable composite manufacturing. As processes become automated, the need for high-performance process control becomes critical for maintaining quality while reducing cost. Fiber placement (Fig. 1) is being developed at McDonnell Douglas Aerospace (MDA) to achieve an automated composite structure fabrication process. In this process, successive plies of composite tow are placed on a tool and consolidated with heat and pressure to form the structure.

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A neural network-based control system has been developed and implemented to control the laser that heats the prepreg composite material to achieve a specified temperature profile. A focused infrared camera provides the temperature feedback to the control system. This neurocontroller learns the inverse model of the process on-line and provides performance that improves with experience and exceeds that of conventional feedback control methods. This system has demonstrated faster convergence to new temperature set points and reduced temperature deviation due to feed rate changes when compared to the originally installed PI controller.

2. Process Discussion

Fiber placement is a relatively new process that has evolved from two other automated composite fabrication processes: filament winding and tape laying. Similar to filament winding, fiber placement uses multiple tows of continuous composite material. In fiber placement, these pieces are generally pre-impregnated composites and are placed with high accuracy, similar to tape laying. Combining the features of tape laying and

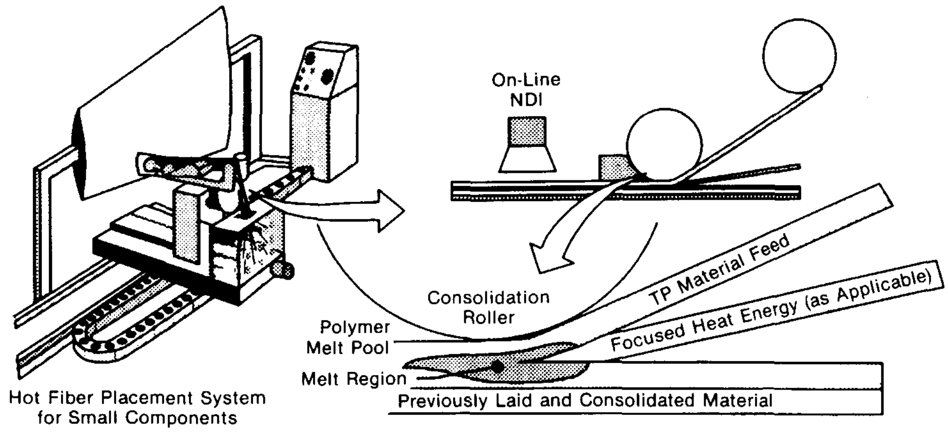

Fig. 1 Fiber placement composite manufacturing process.

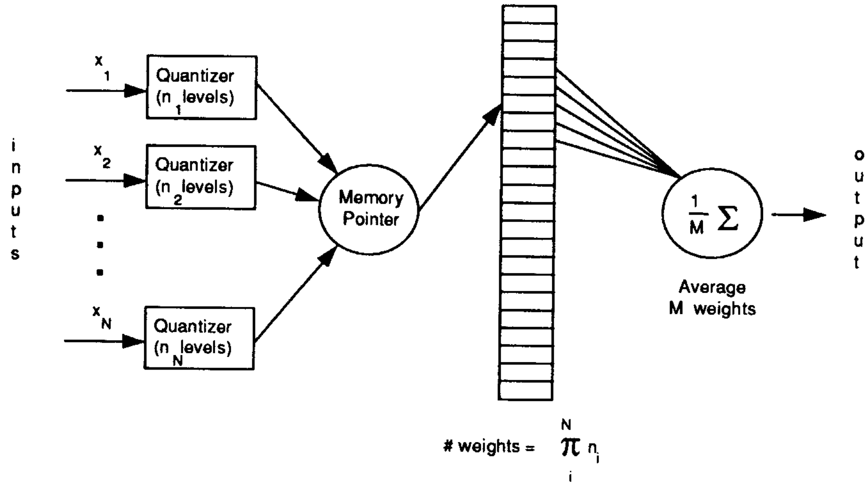

Fig. 2 Simplified schematic of CMAC neural network.

filament winding yields a process that can produce shapes that are too complex for either filament winding or tape laying alone.

When thermoplastic prepreg is used, fiber placement provides the ability to consolidate the composite material immediately upon laying it on the part form. This procedure, known as *in situ* consolidation, allows large composite structures to be manufactured without using an autoclave, thus lowering processing costs significantly. In the fiber placement process, a laydown head containing the heat and pressure sources moves along the part surface adding the prepreg tow. Temperature and pressure at the nip point are key process variables to be controlled to ensure successful *in situ* consolidation.

3. Control System Components

The neural network temperature control system is made up of the following components: (1) a laser heat source, (2) an infrared (IR) temperature sensor, (3) a tachometer for feed rate measurement, (4) an IBM-compatible 386 PC, and (5) a data acquisition plug-in board for A/D and D/A conversion.

The control algorithms are implemented in the C programming language with a Windows graphical user interface, allowing user friendly control of process variable set points. Real-time plots of process temperature, feed rate, and control voltage are provided to the user and also automatically logged to disk for post-process analysis. The control system iterates at a rate of 10 Hz. The following sections explain the theory, operation, and performance results of the neural network-based control system implemented in the PC.

4. CMAC Neural Network

Artificial neural networks[1] are biologically inspired computer architectures composed of many simple, highly interconnected processing elements. These processors execute in parallel and exchange information much like the neurons and synapses within the brain. The strength between connections, or weights, are analogous to the different synaptic efficiencies between neurons in the brain. The functionality of a neural network is determined by the values of the weights, which are adjusted during the training of the network. The ability of neural networks to form mappings of, or "learn," complex nonlinear functions makes them useful for adaptive control applications.

In adaptive control situations, neural networks with rapid on-line learning characteristics are required. For this reason, a modified version of the Cerebellar Model Articulation Controller (CMAC) network developed by Albus[2] and extended by Miller et al.[3] was used. The CMAC is a memory-based learning system that can be thought of as a dynamically adjustable look-up table (Fig. 2). The input vector to the network points to an address in memory where a localized group of values, or weights, is averaged to produce the network output. The size of the localized group of weights specifies the amount of generalization obtained. For a two-dimensional input vector, the generalization region is a square of memory, $2c + 1$ units wide, centered at the position selected by the input vector. The output value is computed by the equation:

$$y(k) = \sum_{i=-c}^{c} \sum_{j=-c}^{c} m_{ij}(k) / (2c+1)^2 \qquad [1]$$

where $m_{ij}(k)$ is the value of memory unit (i,j) for time k, and i and j range from $-c$ to c. During learning, the network weights are adjusted according to the first order learning law:

$$m_{ij}(k+1) = m_{ij}(k) + \beta * [\text{target}(k) - y(k)] \qquad [2]$$

where β is the learning rate. The localized weight adjustment of the CMAC produces the fast learning properties, which cannot

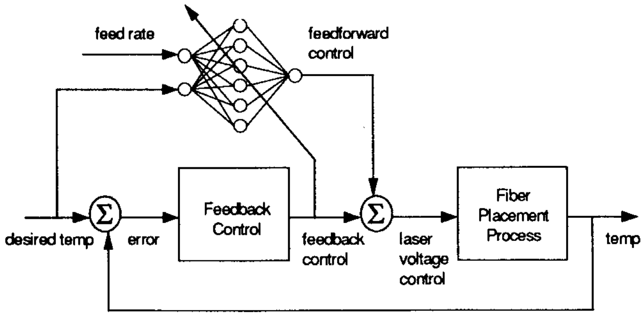

Fig. 3 Inverse model neurocontroller for fiber placement.

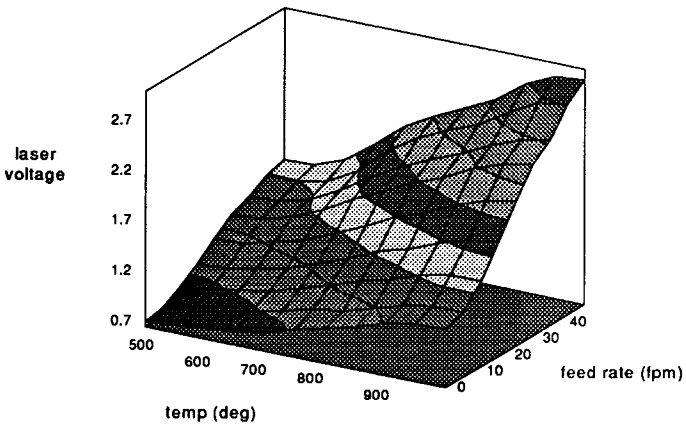

Fig. 4 Inverse model learned by CMAC network.

be obtained with more common neural networks such as the multilayer perceptron with backpropagation training.

5. Inverse Model Neurocontrol Architecture

A CMAC network has been used to develop an inverse model neurocontroller for the fiber placement composite manufacturing process (Fig. 3). Neurocontrol architectures using CMAC networks reported in literature[3,4] vary significantly in what the inputs to the network are, what the training signal is, and how the output is used in the overall control scheme. The proper architecture really depends on the characteristics of the particular application. Because the time constant of temperature dynamics in the fiber placement process is quite small (1 to 2 s), the CMAC network was used as a steady-state inverse model of the process. The network acts as a feedforward controller that computes control voltage as a function of desired temperature and measured feed rate. This voltage is then added to the control signal of a proportional feedback controller. The term steady state indicates that the network is not modeling the temperature dynamics of the process, which would require current and past temperature states to be input to the network. The network output is simply a function of the target temperature and actual feed rate. Although this inhibits the network to compensate for the process time lag, it reduces the chance of instability.

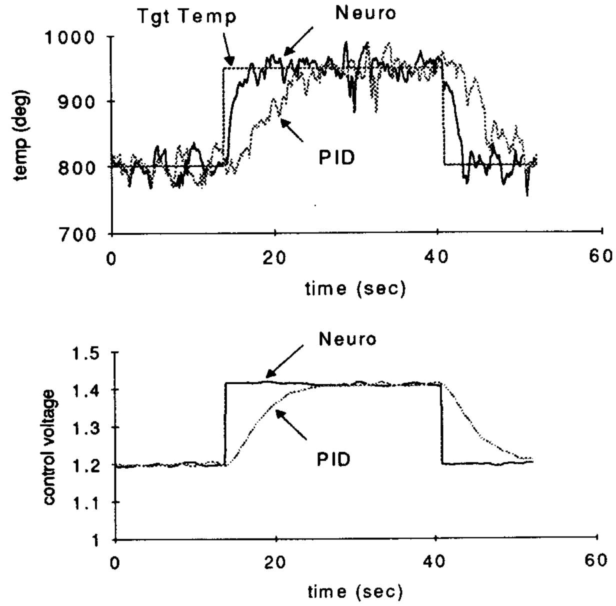

Fig. 5 Neurocontrol versus PID control for set point change.

The training signal for the network is the output of the proportional feedback controller. For a fixed temperature set point and feed rate, a fixed region of weights in the network is updated according to Eq 2, which performs an integration of temperature error. Hence, the network output during learning behaves as an integral controller. This is desirable because adequate control performance will be obtained even when the network is untrained. As the network learns, its feedforward output becomes a significant contribution to the overall control command and performance improves.

6. Results

After experiencing several temperature set points and feed rates, the network learns to become a steady-state inverse model of the process (Fig. 4). When used as a feedforward controller, the trained network provides faster convergence to new temperature set points (Fig. 5) and reduced temperature deviation when feed rate is changing (Fig. 6), in comparison to conventional PI feedback control. The advantage of neurocontrol over conventional feedforward control is twofold. The feedforward control function is learned automatically on-line, and both linear and nonlinear control laws can be modeled accurately.

On-line learning is achieved quite rapidly with this system, as illustrated in Fig. 7 and 8. In Fig. 7, after only four temperature set point changes, an untrained network learns to significantly improve convergence to new temperature commands. Feed rate compensation learning is shown in Fig. 8. Again, starting with an untrained network, initial feed rate changes produce significant overheating and underheating. However, after six changes in feed rate, the network learns to adjust laser power accordingly and hold temperature close to the target set

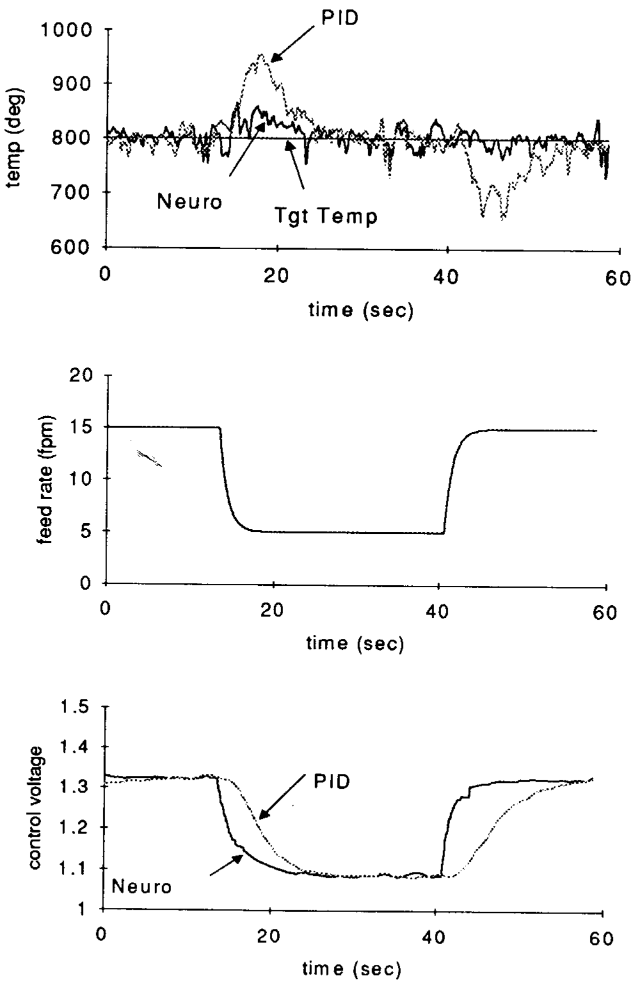

Fig. 6 Neurocontrol versus PID control for feed rate change.

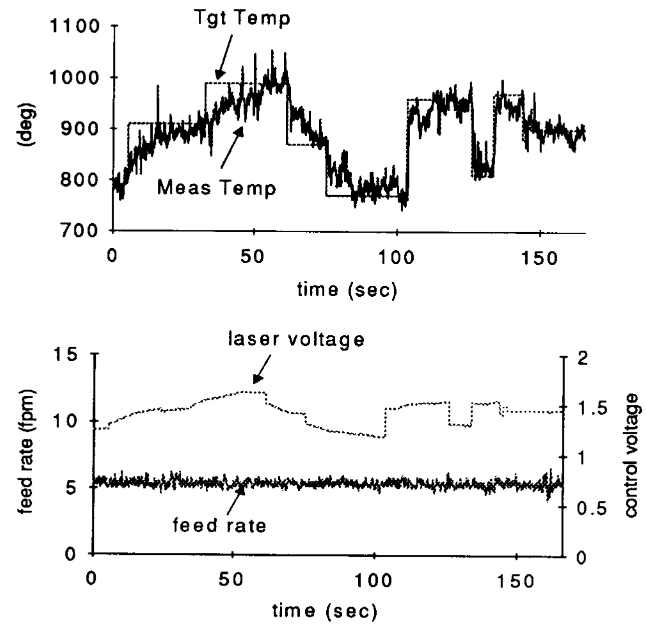

Fig. 7 Neurocontrol system temperature command learning.

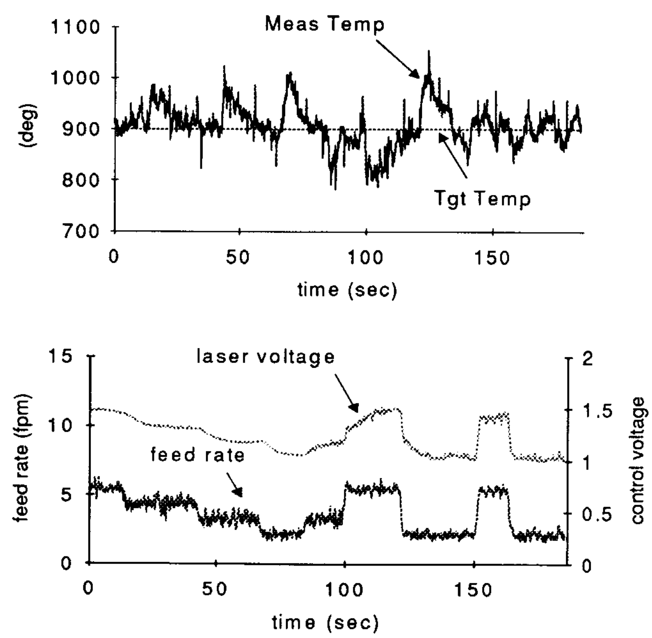

Fig. 8 Neurocontrol system feed rate learning.

point for the last increase and decrease in feed rate. With improved control performance, complex contoured structures can be fabricated at higher rates while maintaining high-quality consolidation.

7. Conclusions

An artificial neural network-based control system has been developed and implemented for the fiber placement composite manufacturing process. This neurocontroller uses a CMAC network for rapid on-line learning of the inverse process model. When the network receives an input that it has not experienced before, the neurocontroller behaves like a PI controller. However, after learning from experience, performance improves and significantly exceeds that of conventional methods. This system is implemented in an IBM-compatible 386 PC with an A/D interface to the machine.

Current development is underway to incorporate methods of learning and compensating for the dynamics of the process. This is required for achieving fast responses for processes with large time lags and for improving learning under constantly changing conditions. The neural network will also be expanded to use additional inputs such as lay-up geometry to provide on-line learning of other critical parameters that affect required laser power. Work is also being performed to extend the neurocontrol techniques developed for process control to active vibration control applications. Neural networks with one-pass learning capabilities such as the General Regression Neural Network[5] and the Radial Basis Function network with successive f-projection learning[6] are being evaluated in addition to the CMAC for fast on-line learning of dynamic systems.

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