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# Nonlinear autoregressive network with exogenous inputs based contour error reduction in CNC machines

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ABSTRACT

A new approach for reducing the contour errors in two-dimensional CNC machines is presented in this study. In the approach proposed here, two pre-trained nonlinear autoregressive networks with exogenous inputs (NARX), one for each axis, are used to predict the output position of the machine in the next sampling instant. The contour error in the next instant is then estimated and, based on this, the required compensation terms to be added to the reference input positions to reduce the contour error are determined. In the proposed approach, the compensation terms can be updated through an iteration process which reduces the contour error each time. Simulation experiments applying this approach to linear, circular and parabolic contours show that, even without extensive training of the NARX models, the contour errors can be significantly reduced. Actual experiments conducted on a small two-axis CNC machine confirm the effectiveness of this approach in reducing contour errors for linear, circular, parabolic and a free-form "goggles" contours.



## 1. Introduction

CNC machine tools have been widely used in the manufacturing industry primarily to achieve high productivity and high accuracy in machined parts. Due to the increasing demand for higher accuracies, a key challenge for machine tool designers and control engineers is achieving accurately machined contours in complex parts. This requires the simultaneous and accurate control of the multiple axes of these CNC machines. There are two basic approaches in achieving accurate two-axis contouring control. One is the individual axis approach and the other is the coordinated axes approach.

In the individual axis approach, the primary focus is on achieving accurate axial position following for each of the two axes. No regard is given to, nor advantage taken of, the coordination between these axes. The basis of this approach is that if the following errors in both the axes are reduced, or eliminated, then the resulting contour errors will also be reduced, or eliminated.

Much work has been done to achieve high performance in position feedback systems and to reduce the position following errors. This is generally achieved either through the design of advanced position feedback controllers, or through modification of the position reference inputs through the addition of compensation terms [1–3].

In the coordinated axes approach, on the other hand, the primary focus is not on reducing the following errors of the individual axes. Although small following errors are always desirable, but on coordinating the motions of the axes so that the individual following errors cancel each other out to achieve accurate contours. Through simulation and actual experimentation, Poo et al. [4] and Xi et al. [5] showed that although axial following errors can lead to significant contour errors when the axial dynamics are not properly matched, even significant axial following errors can be made to cancel each other out to achieve perfect linear and circular contours when the axial dynamics are properly matched.

Instead of focussing on reducing axial following errors, Koren [6] proposed a cross-coupled controller (CCC) for biaxial control of the machine tool axes which aimed at directly reducing the contouring error primarily for linear contours. Subsequently, Koren and Lo [7] proposed a variable-gain cross-coupled controller as an attempt to overcome the low effectiveness of the CCC in dealing with non-linear contours and the non-zero steady-state errors.

Huo et al. [8] proposed a generalized Taylor series expansion error compensation (GTSEEC) method which can be applied to any free-form contour following without the need for *a priori* knowledge of the mathematical function describing this contour. In this model-based approach, a real-time contour error estimation algorithm based on piecewise straight lines defined by

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adjacent desired contour path reference points was used to generate compensation terms to ba added to the reference axial inputs. Through simulation, this approach was shown to be capable of canceling out the axial following errors to achieve perfect contour following despite any mismatch in the axial dynamics if perfect knowledge of the axial dynamics is known. For good performance, this approach requires a good knowledge of these dynamic models.

To overcome the parameter uncertainty problem, neural network techniques have been investigated. Neural networks are especially attractive for machining applications as they do not require a first principles model. Their ability to learn the input–output relationship of a process has enabled them to be classified as building blocks of intelligent control systems. But applying neural networks to contour error control was only studied in very few research papers.

Luo et al. [9] proposed a neural network approach to simultaneously control the average resultant cutting force and the contour error in multidimensional milling. The control system consisted of a neural force controller, a neural dynamic lag error controller and a feedforward input to compensate for static friction in the feed drives. To simplify the procedure for on-line learning, the neural force controller used an appropriate identification model to specify the feedrate. The neural dynamic lag error controller, on the other hand, was based on non-parametric process identification. Experimental results verifying the proposed methodology were presented for machining two-dimensional circular slots and a three-dimensional spherical surface. The proposed methodology was applicable to any contour.

A neural-network based cross-coupled control algorithm that integrates the cross-coupled control and neural network techniques together was presented in [10]. In this neural network based cross-coupled control system, fixed gain PID controller for each individual axis was replaced by a heuristic neural network learning controller, the conventional cross-coupled controller was substituted by an efficient neural network cross-coupled controller. Experimental results demonstrated that the performance of the neural network based cross-coupled control scheme is superior to the conventional cross-coupled control scheme.

Crispin [11] developed an approach for improving the contouring performance of a computer controlled $x$–$y$ table by using a neural network to interpolate between measured optimal cross-coupling gain values. Experimental results showed that for a circular trajectory contour error was reduced as compared to the conventional uncoupled control of the two axes.

In this paper, a *nonlinear autoregressive network with exogenous inputs* (NARX) based contour error reduction (NCER) method is presented which can be used for any free-form contour without the need for *a priori* knowledge of the mathematical function describing the contour. The contour error estimation method used is the same as that used in [8] and, using the quantities obtained from this, the compensation values are computed. Experiments conducted using this approach on a small CNC machine with linear, circular, parabolic and goggles contours show the effectiveness of NCER in reducing contour errors, generally by three to four times.

The remainder of the paper is organized as follows: Section 2 introduces the basic structures of NARX model, the contour error estimation method used here and how to generate the compensation values for both $X$- and $Y$-axes. Section 3 presents the results of simulation experiment using the proposed error compensation strategy. In Section 4, experimental implementation of NCER on a bi-axial CNC machine is presented and the results obtained discussed. Finally, the conclusion follows in Section 5.

## 2. NARX neural network based contour error control

### 2.1. Brief introduction to NARX

Artificial neural networks (ANN) have been successfully used as a tool for time series prediction and modeling in a variety of application domains. In particular, when the time series is noisy and the underlying dynamical system is nonlinear and not easily approached through analytical means, ANN models frequently outperform standard techniques. In such cases, the ability of the ANN to learn from actual experimental data and to construct complex non-linear relationships from these seems to explain their better prediction performance.

The nonlinear autoregressive network with exogenous inputs (NARX) is an important class of discrete-time nonlinear systems. Not only are NARX neural networks computationally powerful in theory, but they have several advantages in practice. For example, it has been reported that gradient-descent learning can be more effective in NARX networks than in other recurrent architectures with "hidden states" [12]. In the NARX model, the predicted value of the output at the $(k+1)$th instance, $\hat{w}(k+1)$, is given mathematically by

$$\hat{w}(k+1) = F(\hat{w}(k), \ldots, \hat{w}(k-q+1), u(k), \ldots, u(k-q+1)) \tag{1}$$

where $F$ is a nonlinear function of its arguments, $\{u\}$ is the input sequence and $\{\hat{w}\}$ is the predicted output sequence. Fig. 1 shows the topology of a NARX network with tapped-delay-lines (TDL) implementing Eq. (1) [13].

There are two architectures that can be used for a NARX network. They are the parallel (P) and the series–parallel (SP) architectures. Fig. 1 represents the P architecture. In Eq. (1), previous predicted outputs from the NARX are used as part of the inputs to predict the output at the next instance. Higher prediction accuracies can be obtained if these are replaced by the actual values of outputs from the system. In this case, Eq. (1) will

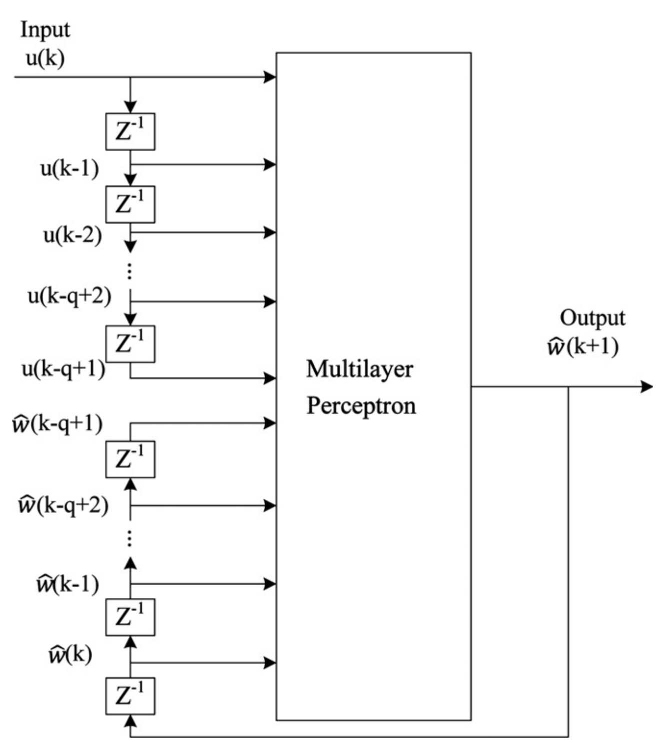


**Fig. 1.** A NARX network.