DEVELOPMENT OF AN INTELLIGENT CONTROLLER EMBEDDED INTELLIGENT ROBUST DESIGN USING FUZZY NEURAL NETWORK-BASED CONTROL

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Abstract

Recently, electric controllers that use the model-based control of modern control theory have had frequent failures and become a problem for industry. This is due to the fact that the control gain is fixed. To address this problem, we have developed the first intelligent controller incorporating intelligent robust design using next-generation fuzzy neural network-based control, which presents the only solution to the problem. This controller includes a new kind of intelligent robust gain compensator that adaptively adjusts gain to changes in target trajectory error for sufficient control against system parameter variations, sudden disturbance, and
target changes.

Keywords: fuzzy control, fuzzy-neural network, intelligent robust

1. Introduction

In general, system design for manipulators regards the controlled object as a single-degree-of-freedom system even in a multi-degree-of-freedom system, and an approximate equation is used to design the control system. A method that builds an independent control system for each joint axis is employed for numerous products. However, in most cases rigidity is weak and the nonlinear multi-input, multi-output system is subject to gravity and centrifugal force. In addition, conventional methods achieve precision, vibration suppression, and robustness by utilizing PID control, phase compensation control, optimal servo systems, disturbance observer-based systems, or $H\infty$ control systems. Sufficient control, however, currently cannot be obtained. On the other hand, related research both in Japan and abroad have achieved robust control systems using an observer when disturbance is pronounced, such as with centrifugal force, gravity, and coulomb friction, but they remain unsatisfactory. In industry, the impact of sudden disturbance cannot be coped with because gain is fixed, and failures have become an issue. Therefore, a next-generation intelligent robust control method is strongly desired. An embedded intelligent controller incorporates a new type of intelligent robust gain compensator (fuzzy neural-based control) that adaptively adjusts gain to variations in target trajectory error, and acquires sufficient target trajectory follow-up control capability against system parameter variations, disturbance, and target changes. To build a control system that allows robust, automatic gain adjustments, we built a control system that establishes variable feedback gain in response to positional error in space segmentalized with fuzzy partitioning. The control system is configured as a double-degree-of-freedom system and the feed-forward component is built using a neural network. Plant dynamics are learned through the parameters of displacement, velocity, and acceleration to obtain the inverse dynamics of the plant and linearize the system. In addition, the feedback component acts as a compensator that reduces nonlinear error by using a fuzzy neural network to achieve perfect tracking capability. These control systems are run in real-time processing (sampling time: 1msec).

2. Intelligent Robust Control Scheme

The proposed multi-variables robust fuzzy neural network (FNN) based control scheme consists of three elements: a) the feed forward compensation which has inverse dynamics of the PD controlled plant based on neural networks; and b) the nonlinear deviation compensator based on the fuzzy neural networks. The block diagram of the proposed control system is shown in Fig. 1. This control system is a two degree-of-freedom system, which permits us to design the tracking characteristic for the desired input and the closed loop characteristic for the disturbances separately. Its aim is the complete tracking for the desired input and the perfect removal of the effect of disturbances. Moreover, it decreases the modeling error and the tracking error generated by intermittent disturbances. This control system would do the groundwork for the robust-control system against the nonlinear characteristics such as friction, variations of load and system parameters, and unknown disturbances in mechatronic position servo system.Block diagram of F-N robust control shown in Fig. 2.

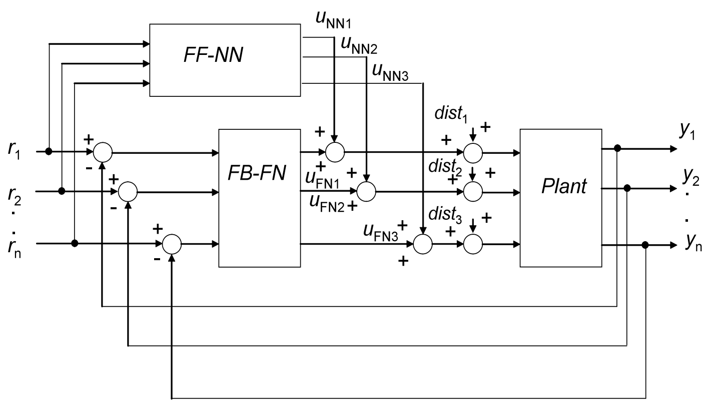


Fig. 1 Block diagram of Multi-Variables fuzzy neural network based control systems

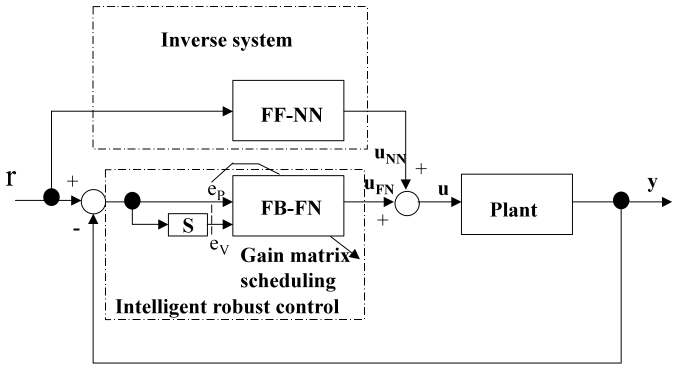


Fig. 2 Block diagram of FN robust control

2.1 Feedforward Compensation Based on Neural Networks

By ignoring nonlinear characteristics, the plant can be liberalized as follow:

$$J\frac{d^2y(t)}{dt^2} = -k_v\frac{dy(t)}{dt} - k_p y(t) + k_p u(t) \qquad (1)$$

Where $u(t)$ is the input, $y(t)$ is the output of the position, k_p and k_v are the position and velocity
feedback gains respectively. The inverse dynamics of the plant is represented by

$$u(t) = r(t) + \frac{k_v}{k_p}\frac{dr(t)}{dt} + \frac{J}{k_p}\frac{d^2r(t)}{dt^2} \qquad (2)$$

Where $r(t)$ is the desired position. This model expresses the basic characteristics of a positioning servo system. But the actual model has differences in the values of the inertial moment, and has the nonlinear element that cannot be represented by the second order model. It is evident that the inverse dynamics given by (2) include the modeling error. However, a learning of inverse dynamics of actual servo system is executed through the neural networks (NN)shown in Fig. 3. The neural networks consist of 3 layers, 3 inputs, 4 intermediate units, and 1 output. The learning is done by the back propagation method using the positions of input and output and their time derivatives. After the learning, it is expected that the responsibility of the system rises through feed forward (FF)input of this network.

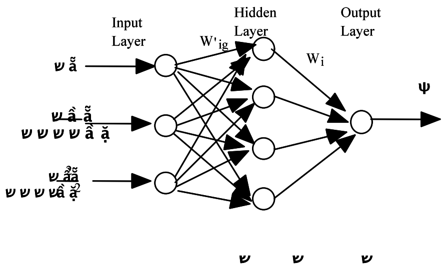


Fig. 3 Feed forward neural network compensator

2.2 Robust on Fuzzy Neural Networks

The deviation between the desired position and the output position is caused by the modeling error and unknown disturbances. The nonlinear deviation compensator based on the fuzzy neural networks reduces the deviation adaptively. A scheme of the
fuzzy neural network is shown in Fig. 4(1). This fuzzy neural network is 2 inputs, 1 output and 4 layers; A is input layer; B and C are middle layers; and D is output layer. Each element of B layer generates an output of a membership function formed by a gauss function as shown in Fig. 4(2), and this part is called a premise. C layer outputs an adaptation that is reasoned based on the fuzzy rule, and this part is called a consequent. According to the structure of the neural networks with the fuzzy rule, this is called fuzzy neural networks. The fuzzy neural networks can be applied learning by the back propagation (BP) method and be related to the fuzzy reasoning rule by the devisal of the connection of the layered neural network.
This system is composed of an F-NN which has 2 inputs, 1 output, and 4 layers. The input has a position error e_p and a velocity error e_v. The input is the direct input of the plant. The fuzzy part divides (division into 9) the input space, and then generates adaptation:

$$\mu_i = A_{i_1}(e_p)A_{i_2}(e_v) \quad i=1, 2,...,9, i_1, i_2=1,2,3 \tag{3}$$

Adaptation is normalized as follows:

$$\overline{\mu}_i = \frac{\mu_i}{\sum_k \mu_k} \tag{4}$$

The fuzzy rule for No.1 is as follows:

$$R^i\text{: IF } e_p \text{ is } A_{i_1} \text{ and } e_v \text{ is } A_{i_2} \text{ THEN } y=f_i(e_p e_v) \tag{5}$$

And the reasoning is given by:

$$u_{FN} = \sum_{i=1}^{9} \overline{\mu}_i f_i(e_p, e_v) \qquad (6)$$

f_i is assumed as:

$$f_i = k_{iI} \int e_p dt + k_{ip} e_p + k_{iv} e_v \qquad (7)$$

But f_i is a gain, as shown in Table 2:

Both e_p and e_v are small: PID control

e_p is not small, e_p is different from e_v: P control

(When | e_p | is big, the speed feedback which makes the value of $k_{ip}e_p$ small is removed) For the left cases, this Neural Network learns gain in the following Neural Network in order to generate PD control.

By this composition, additional control rule can be constructed. In addition, this control rule is adapted to error. Neural Network learns the control gain.

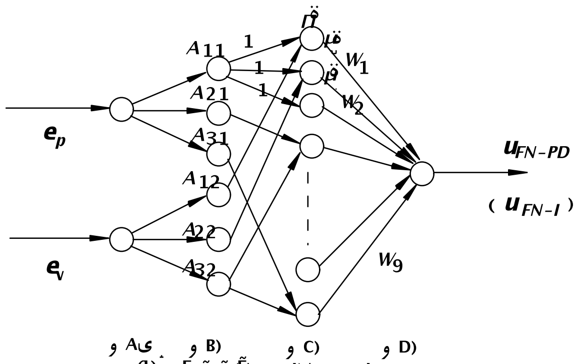
The learning is performed under the condition that the square of the position error becomes the smallest. And then,

$$E_p = \frac{1}{2} e_p^{\ 2} \qquad (8)$$

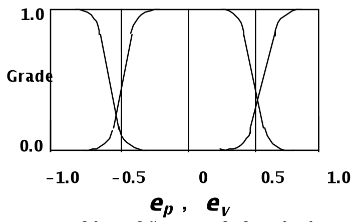
$$k_{ij} = w_{ij}^{\ 2} \qquad (9)$$

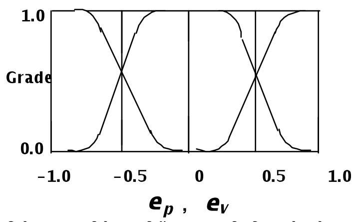
And then, $k_{ij} = w_{ij}^{\ 2}$ is settled in order to get the following expression:

$$k_{ij} \geq 0 (j = I, p, v)$$

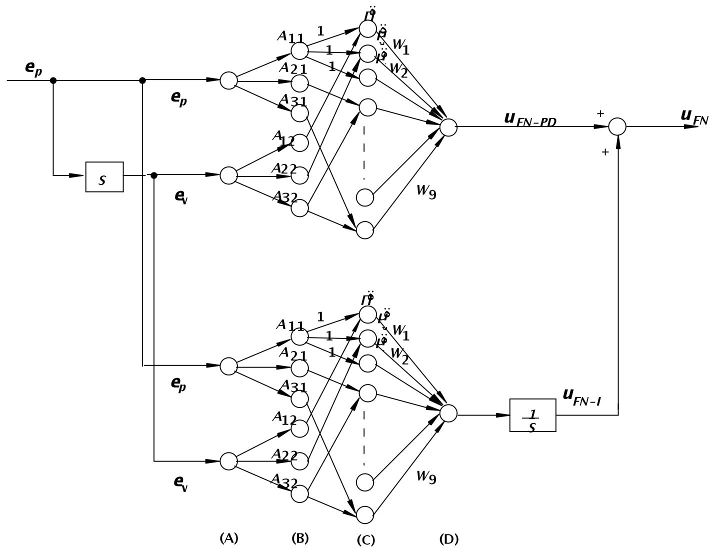


(1) NeuralNetwork





(2) (3) (FN-PD)



(4) Architecture of the fuzzy-neural network

Fig. 4 Fuzzy-neural network nonlinear deviation compensator

And the renewal quantity is calculated as follows:

$$\Delta w_{ij} = -\eta \frac{\partial E_p}{\partial w_{ij}} \tag{10}$$

$$= -\eta \frac{\partial E_p}{\partial e_p} \frac{\partial e_p}{\partial u_{FN}} \frac{\partial u_{FN}}{\partial f_i} \frac{\partial f_i}{\partial k_{ij}} \frac{\partial k_{ij}}{\partial w_{ij}}$$

$$= -\eta \, e_p \frac{1}{\sum_{l=1}^{9} \overline{\mu}_l w_{lj}^{\,2}} \, \overline{\mu}_i \, e_j \, 2w_{ij}$$

$$= -\frac{2\eta \, \overline{\mu}_i e_p \, e_j w_{ij}}{\sum_{l=1}^{9} \overline{\mu}_l w_{lj}^{\,2}} \quad j=I,p,v$$

Where w_i is a connection weight. The connection weights are learned by the BP method, in which initial values are set zero. The teaching data in the learning are the input and output of a PD controller, which is the same block diagram given by Fig. 4(4) on condition that the nonlinear deviation compensator is changed to the PD compensator. The proportional and differential gains are adjusted such that the output position follows the desired feasibly.

Fig. 5 FN-GS gain controller C(s) is calculated as follows:

$$C(s) = \sum_{i=1}^{9} C_i(s) = \sum_{i=1}^{9} \mu_i (K_{ip} + K_{iv} S + K_{iI} \frac{1}{S}) \tag{11}$$

For this reason, in the multidimensional case, the inverse dynamic model portion of the control law is called a linearizing and decoupling control law. Basic scheme, partitioning the control law into a inverse dynamic model portion and a servo portion.

$$F=\alpha F'+\beta \tag{12}$$

Where, for a system of n degrees of freedom, F, F', and β are n x 1 vectors and α is an n x n matrix.

αF': a servo portion (FB-FN)

α: decouple the n equations of motion n x n matrix

β: a inverse dynamic model portion (FF-NN)

$$F' = k_i \int E dt + k_v \dot{E} + k_p E + \ddot{\theta}_d \tag{13}$$

$$c(s) = \sum_{i=1}^{9} c_i(s) = \sum_{i=1}^{9} \mu_i (k_{ip} + k_{iv} s + k_{il} \frac{1}{s}) \tag{14}$$

It is possible to adaptive gain that will critically damp the response to disturbances for all configurations.

After learning, the adaptation plays a role as the dynamic compensator, and the output adapted to position and velocity errors is obtained. This means that a compensation output is suitable to errors is computed. Hence, it is expected that proposed fuzzy neural network based control system is robust for the disturbances and the parameter variations.

Table 1 Control rules

		e_v		
		Positive big	Small	Negative big
e_p	Positive big	P	PD	P
	Small	PD	PID	PD
	Negative big	P	PD	P

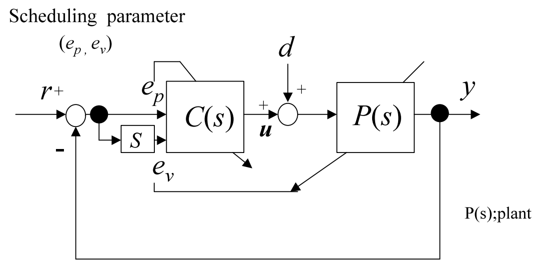


Fig. 5 Block diagram of F-N controller

3. Implementation of the intelligent controller

3.1 System configuration

The system configuration that implements the intelligent robust function for the embedded computer is as follows. It is shown in Fig. 6.

1) System development tool
2) Embedded computer
3) DC motor-driven table shifter

3.2 Main specifications for each component

1) System development tool
   MATLUB/SIMULINK/Real-Time-Workshop
2) Embedded computer
   RT Linux OS
3) DC motor-driven table shifter
   a) DC Motor: DC12V, 160mA, 4400rpm

b) Rotary Encoder: 8-pulse output/rotation

c) Motor Driver: TA7281P

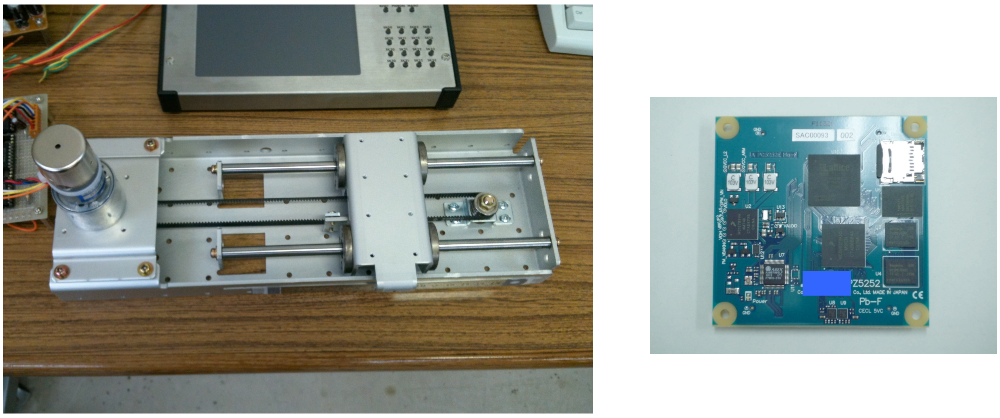


Fig. 6 External view of the developed intelligent controller system

4. Experiment

4.1 Experiment Method

An FNN control system was built using MATLAB/Simulink. The controlled object was the moveable table shifted by the DC motor drive. Position was controlled using the built control system. The command signal used a 30(s)-cycle sine wave of amplitude 5, and the motor was controlled with a sampling time of 1msec.

In addition, for purposes of comparison 3 control systems were run with and without disturbance, and a performance comparison was conducted. Disturbance was reproduced in the model, and after being run for 10sec., a manipulated variable of +5 was added.

1) PID control

Fig. 7 shows a model diagram of PID control. PID parameters for motor control were a proportional gain of P=12, integral gain of I=0, and a differential gain of D=0.

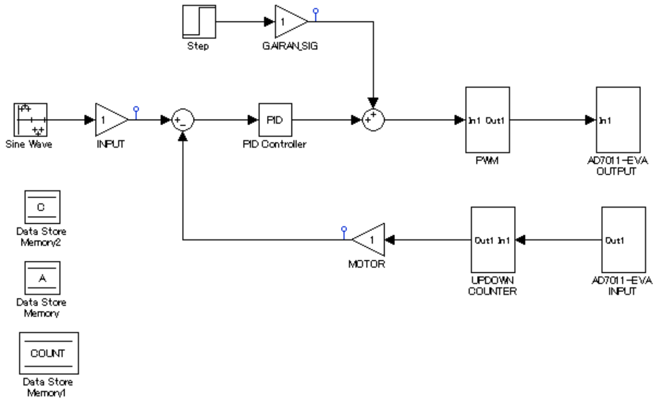


Fig. 7 Model diagram of PID control

2) NN-PID control

Fig. 8 shows a model diagram of NN-PID control. NN learning is carried out based on PID control data. Command signal displacement, velocity, and acceleration are input and the PID manipulated variable is learned as the instruction signal using the BP method. The NN obtained this way is fed forward to the PID manipulated variable. PID parameters are identical to PID control.

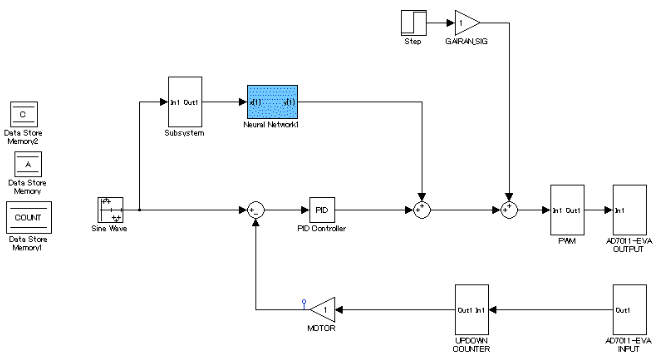


Fig. 8 Model diagram of NN-PID control

3) FNN control

Fig. 9 shows a model diagram of FNN control. FNN learning is based on PID control data. Displacement error and velocity error are input and the PID manipulated variable is learned as the instruction signal using a combination of the BP method and the least-square method.

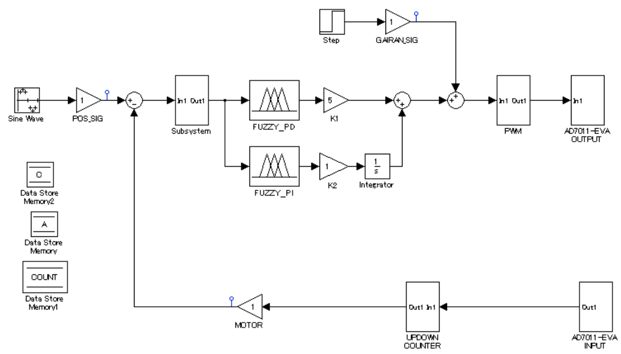


Fig. 9 Model diagram of FNN control

4.2 Experiment Results

1) Experiment results without disturbance

Fig. 10, Fig. 11, and Fig. 12 show a graph of experiment results for PID control, NN-PID control, and FNN control. The graph reveals that PID control had a time delay in response to the command signal, which appears as an error. NN-PID and FNN control accurately followed the command signal and had an error of nearly 0.

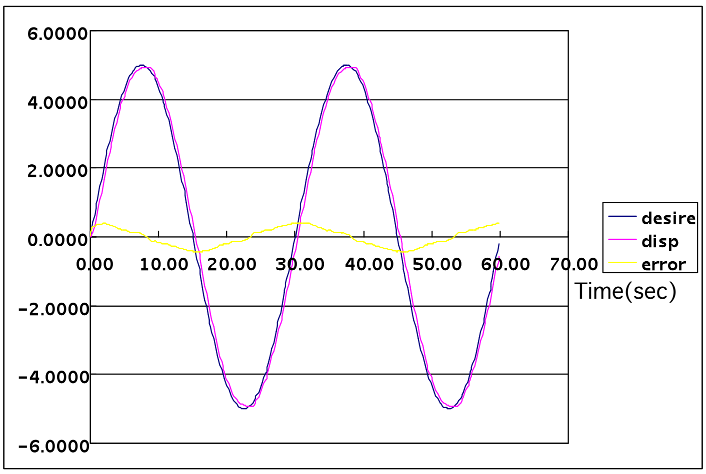


Fig. 10 Experiment results for PID control

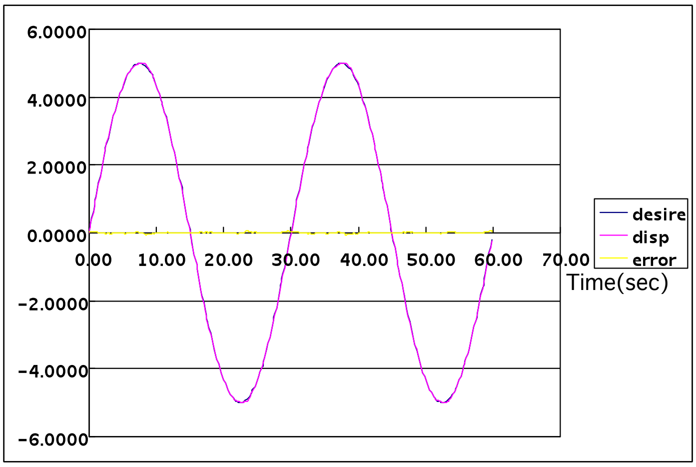


Fig. 11 Experiment results for NN-PID control

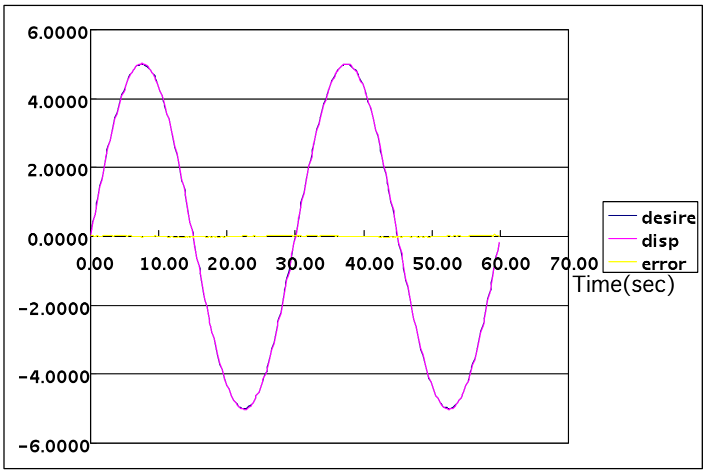


Fig. 12 Experiment results for FNN control

2) Experiment results with disturbance

Fig. 13, Fig. 14, and Fig. 15 show a graph of experiment results for PID control, NN-PID control, and FNN control. The graph reveals that for PID control, error shifted in a negative direction after disturbance. In NN-PID control, error appears as a steady-state deviation after disturbance. In FNN control, there was almost no change even after disturbance, resulting in error close to 0.

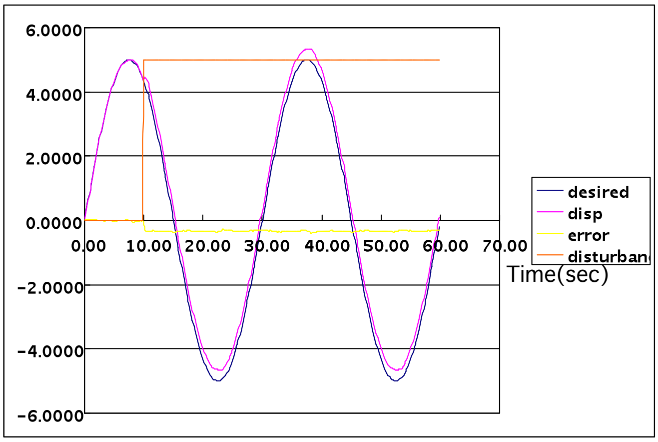


Fig. 13 Experiment results for PID control (with disturbance)

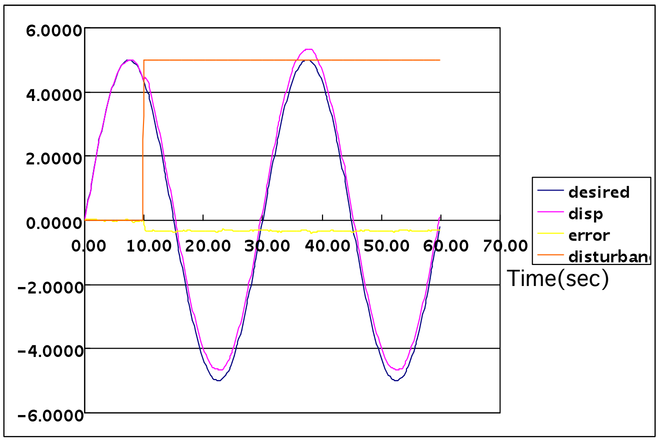


Fig. 14 Experiment results for NN-PID control (with disturbance)

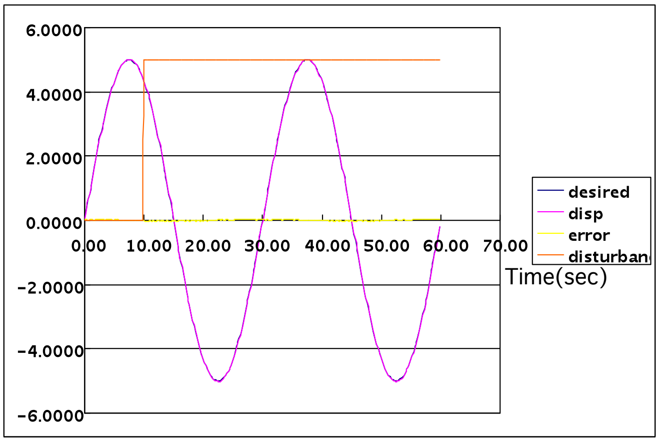


Fig. 15 Experiment results for FNN control (with disturbance)

5. Results

PID control had a time delay even in the position control of a single-degree-of-freedom system and some errors were seen, but the time delay was eliminated using NN feed-forward compensation. Therefore, it is believed that NN can respond to nonlinear factors of the controlled object. However, because error appears as a steady-state deviation when a disturbance occurs, NN lacks robustness and is insufficient.

FNN control followed command signals both in the absence and presence of disturbance, therefore it is believed that it adaptively adjusts to control gain. Thus, FNN control is a control method with robustness and is effective for disturbance and nonlinear factors in control instruments.

As shown above, we have developed an intelligent controller incorporating a next-generation intelligent robust design using fuzzy neural network-based control, the only solution to the failure of electric controllers that use the model-based controllers of modern control theory, which have become problematic in industry.

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