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Speed Control of DC Motor Based on Neural Net and Fuzzy Logic

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Abstract:

This paper presented the speed control of DC motor based on neural net and fuzzy logic. To bypass the difficulties caused by system constraints and modelling uncertainties of the speed control of DC motor a neural network approach for on-line speed control of DC motor is designed. In comparison to several existing neural control schemes, the proposed direct neural controller is characterized by the simplicity of its structure and its practical applicability for real time implementation.

I. Introduction:

For DC motor work on optimal control began as early as the early 1970s [1]. By studying the properties of acceleration and deceleration curves and by relating the control switching time explicity to the target point, in [1] it is derived braking predictor to approximate the phase plane switching curve. However, they did not present a close-loop control law nor did they demonstrate experimentally the effectiveness of their approach. In a method developed by Newman and Sourccar in [2] can handle current constraints effectively. The approach developed in [3] still has some implementation problems to be resolved.
To bypass the difficulties associated with current constraints and modelling uncertainties, this paper develops a neural network based control method.

II. Mathematical Modeling and Algorithm:

Mathematical Model:

The equations used for separately excited DC motor for armature current are as below:

$$I_a(S) = \frac{E(s) - K_b.W(s)}{L_a.S + R_a}$$

$(J_s+B)W(s) = K_T.I_a - T_D$

Where motor parameters are:

L_a Armature Inductance = 0.067H
J_m Inertia of the motor = 0.2407 kgm^2
K_b Back emf constant = 1.03 vs/r
B_m Coefficient of friction = 0.02 Nm/rad
R_a Armature resistance = 5 Ohms
K_t Tachogenerator Constant=0.0318 v sec/rad
K_T Torque Constant = 0.5 Nm/A
n Gear ratio = 10
J_L Load inertia = 0.4 kgm^2
B_L Load friction = 0.8 Nm/rad
T_D Disturbance torque

Hence overall transfer function of the system is:

$$\frac{W(s)}{E(s)} = \frac{K_T K_t - T_D(L_a S + R_a)}{(J_S + B)(L_a S + R_a) + K_b K_T}$$

The linear differrence equation can be given as:
$Y_p(K+2) = 1.476\ Y_p(K+1) - 0.476\ Y_p(K) + 0.007\ U(K+1)$
The linear Simplified model of DC motor is considered. The simulation task is to find a controller which can regulate the speed of DC motor to some desired speed.
The speed error are as below:

$e_k = Y_p(K)T - Y_p(K)$: From - 3000 rpm to + 3000 rpm
$\dot{e}_k = Y_p(K-1)T - Y_p(K)$: From –150 $rpms^{-1}$ to +150 $rpms^{-1}$

Initial conditions are :
$Y_p(1) = 719$ rpm $Y_p(2) = 745$ rpm
$Y_p(3) = 772$ rpm $U(2) = 108$ v , $U(3) = 113$ v
All the above intial conditions are founds through simulation results [4].

III. Use of fuzzy logic:

In order to improve the performance of the direct neural controller, a series of interim target [5] have been used instead of final target. Selecting an interim target Y_k^t rather than a static target Y_k^T (i.e. the desired plant out put) is more reasonable for network training, because there is no sense in setting a target which the neural controller is unable to achieve within one operation interval. The underlying idea is to "Slice" the final big target into several small reachable interim targets which are generated from a set of fuzzy rules given in table 1.
Unlike fuzzy logic controller table 1 does not present a control strategy. Instead, it provides a reachable training target for the neural controller so that the fluctuation and saturation problems referred to earlier can be effectively tackled. The basis idea behind the neural network approach is to capture the system input-output relation and then to generate on appropriate control signal to drive the plant to an identified interim target.
Because the control signal is obtained by processing e_k and $\dot{e}_k$ using the fuzzy table and then by training the neural network, the high frequency control signals are significantly reduced in number in a noisy environment. The positive outcome from this is that the neural controller can filter out the influence of most of the measurement noise during the control process.

IV. Neural Network and Fuzzy Logic Model:

The inputs to neural network contains six variables that is $Y_p(K-1)$, $\acute{Y}_p(K-1)$, $Y_p(K-2)$, $\acute{Y}_p(K-2)$, $U(K-1)$ and $U(K-2)$.
Where $\acute{Y}_p(K-1)$ and $\acute{Y}_p(K-2)$ are respectively the rate of change in the speed at (K-1) and (K-2) th instant. In practice it measures the difference between successsive speed values:
$\acute{Y}_{PK} = Y_{PK} - Y_{PK-1}$
At the beginning of each time interval k, the weights of the neural networks are initialised to small random values uniformly distributed between –0.05 to 0.05. The previously

measured speed, rate of change of speed and voltage applied to the DC motor at the time K-1 and K-2 are used for training. The input data set for network training consists of six variables, i.e. in this cass inputes are six and output is one.

IV.a Fuzzy Inference:

The measured error e, change in error $\dot{e}$ are numerical, so that e and $\dot{e}$ have to be fuzzified into fuzzy sets. The rules are inter preted as fuzzy sets charecterised by the membership function and the Back Propagation Neural Network (BPNN) is trained accordingly. Due to fuzziness interpolation or approximation, has been replaced in some degree by the generalisation property of the BPNN due to the distributiveness of the BPNN. After appropriate training, the BPNN was used as the controller in the system [6-8].

There are two state fuzzy variables and one control fuzzy variables. The first state fuzzy variable is the error e_k that is the differnce between measured and desired speed.

The second state fuzzy variable is $\dot{e}_k$ which measures the instantaneous rate of change of speed.

In practice it measures the difference between successive speed valuse.

$$\dot{e}_k = Y_{Pk-1} - Y_{PK}$$

IV.b Fuzzy Rules:

On the basis of table 1, the following fuzzy have been generated for the selection of interim target:

1. IF e_k = NB. AND $\dot{e}_k$ = NB
INTERIM TARGET (IT)
.OR. $\dot{e}_k$ = NM
OR. $\dot{e}_k$ = NS
.OR. e_k = NM. AND. $\dot{e}_k$ = NB
THEN IT = +B
. OR. $\dot{e}_k$ = NM
.OR. e_k = NS . AND. $\dot{e}_k$ = NB

Where:
NB: Negative Big
NM: Negative Medium
NS: Negative Small

Training has been done with learning rate of n = 0.70 and a momentum factor of α = 0.45 Different NB to PB values with tight and loose range have been tested. The simulation results presented include two different curves with different combination of the notation values, as shown in table 2, where values for e_k and $\dot{e}_k$ are given .

All graphs are drawn for the speed control of DC motor intially running at 772 rpm them consequently changing the speed from 500 rpm to –500 rpm and at the last from –500 rpm to 500 rpm. The graph 1.a shows output speed V_s. number of iterations for NN controlled DC motor and PID controlled Dc motor, and 1.b show the errors in output speed V_s. number of iterations.

Table 1: Fuzzy rules for selecting interm targets

$\dot{e}_k$ \ e_k	**NB**	**NM**	**NS**	**ZR**	**PS**	**PM**	**PB**
NB	+B	+B	+B	+M	+M	+S	ZR
NM	+B	+B	+M	+M	+S	ZR	-S
NS	+B	+M	+M	+S	ZR	-S	-M
ZR	+M	+M	+S	ZR	-S	-M	-M
PS	+M	+S	ZR	-S	-M	-M	-B
PM	+S	ZR	-S	-M	-M	-B	-B
PB	ZR	-S	-M	-M	-B	-B	-B

PB = Positive BIG, PM = Positive Medium
PS = Positive Small, ZR = ZERO, NB = Negative BIG, NM = Negative Medium, NS = Negative Small
There are 49 fuzzy rules are generated from table 1 and correlation minimum inference procedure is applied for picking off single fit value from the quantizing fuzzy-set values of the fuzzy variables.

Table 2: Different combination of the notation values

	Range	**NB**	**NM**	**NS**	**ZR**	**PS**	**PM**	**PB**
e_k (rpm)	Tight Loose	-180 -360	-120 -240	-60 -120	0 0	60 120	120 240	180 360
$\dot{e}_k$ (rpm/sec)	Tight Loose	-30 -60	-20 -40	-10 -20	0 0	10 20	20 40	30 60

V. Performance and Numerical Results:

The simulation test compared the performance of the neural and PID controllers under ideal conditions. It has been observed, the PID controller achieved smooth responses with an acceptable overshoot. Although the overshoot can be reduced further and smooth control was obtained by increasing the gain as shown in graph 1.a with hidden neurons equal to 3.

The different number of hidden units (3, 5 and 7) have been tested and it was found that a network with three hidden units gave good results. In case of 3 units errors settle down faster than other units as shown in graph 1.a , 2.a and 3.a respectively for 3, 5 and 7 units.The numbers of iteration vs. erros shown in graphs 1.b, 2.b and 3.b respectively.

VI. Conclusion:

This paper presents a neural network approach for speed regulation of DC motor. In order to overcome the fuzzy relation between the plant behaviour and the interim training targets is set up.

The merit of this strategy lies in the adaptive property it imparts to the controller to cope with complicated interactions between the DC motor running on line and changeable surroundings.
Results from simulation in the case of speed regulation of DC motor shows the feasibility of the proposed neural controller when compared to the conventional PID controller.

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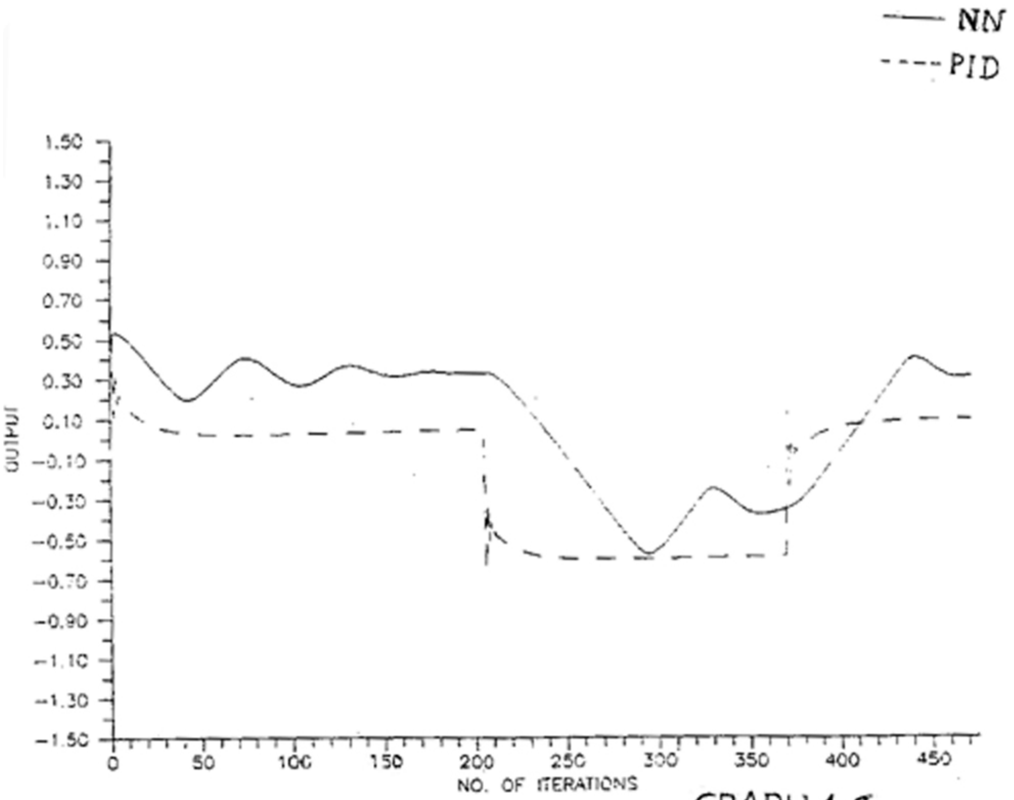
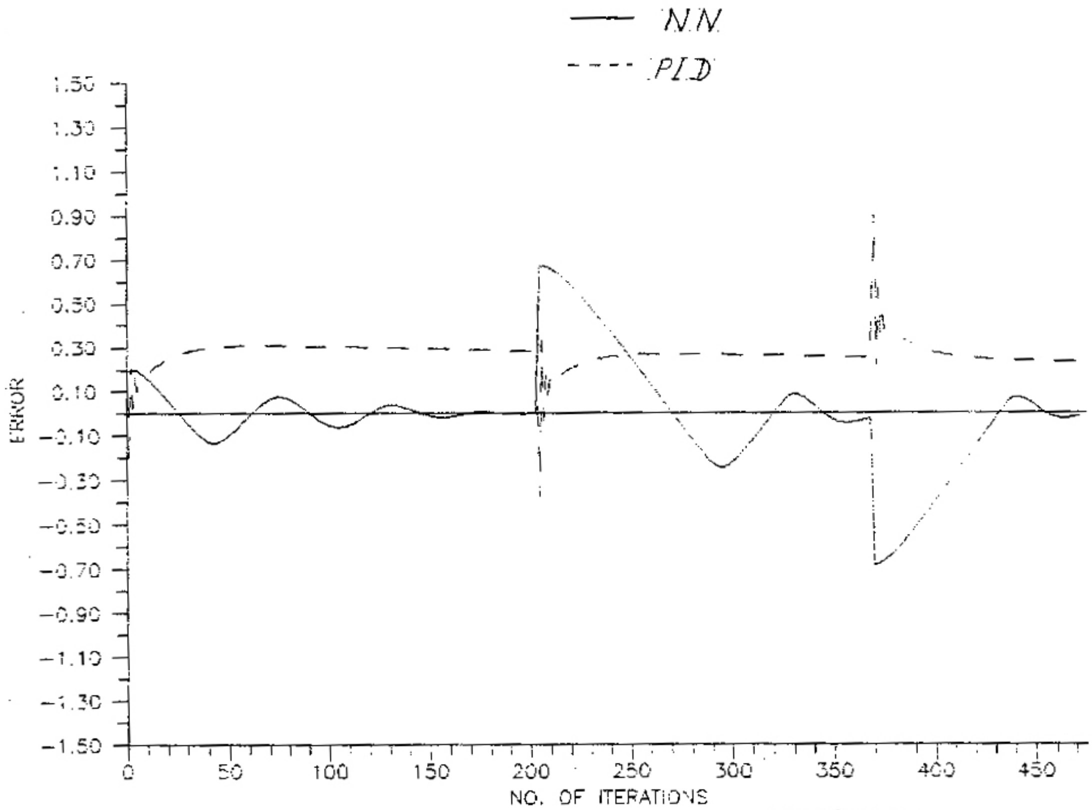
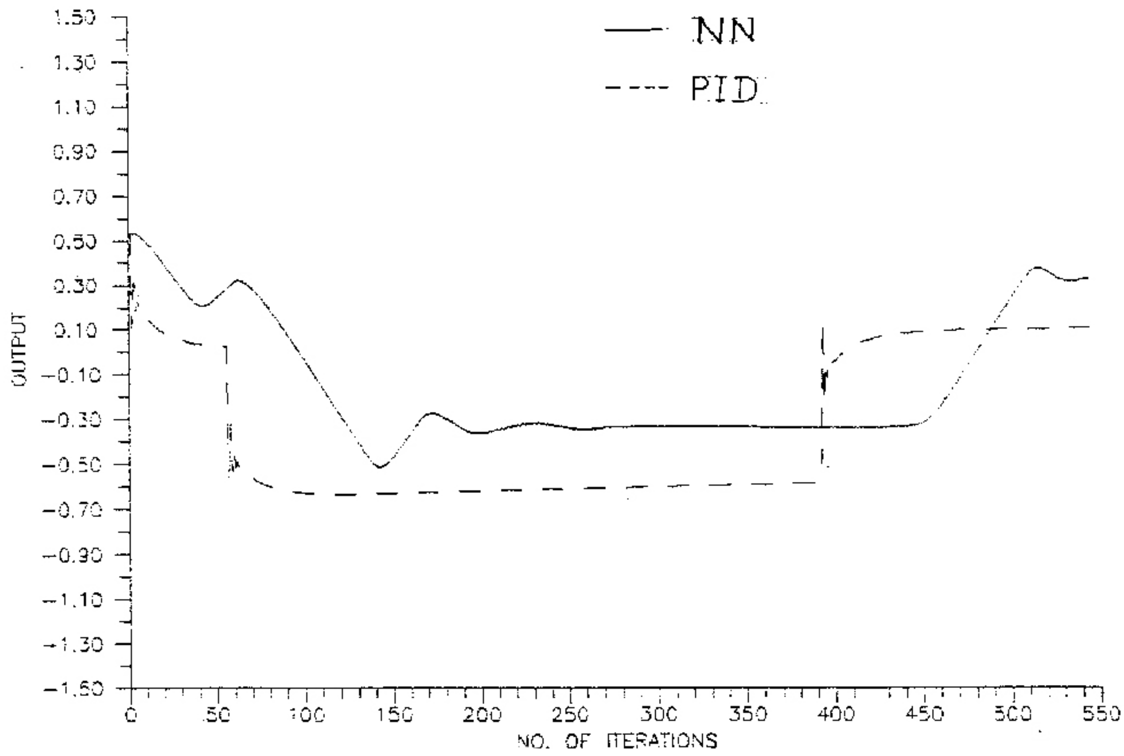


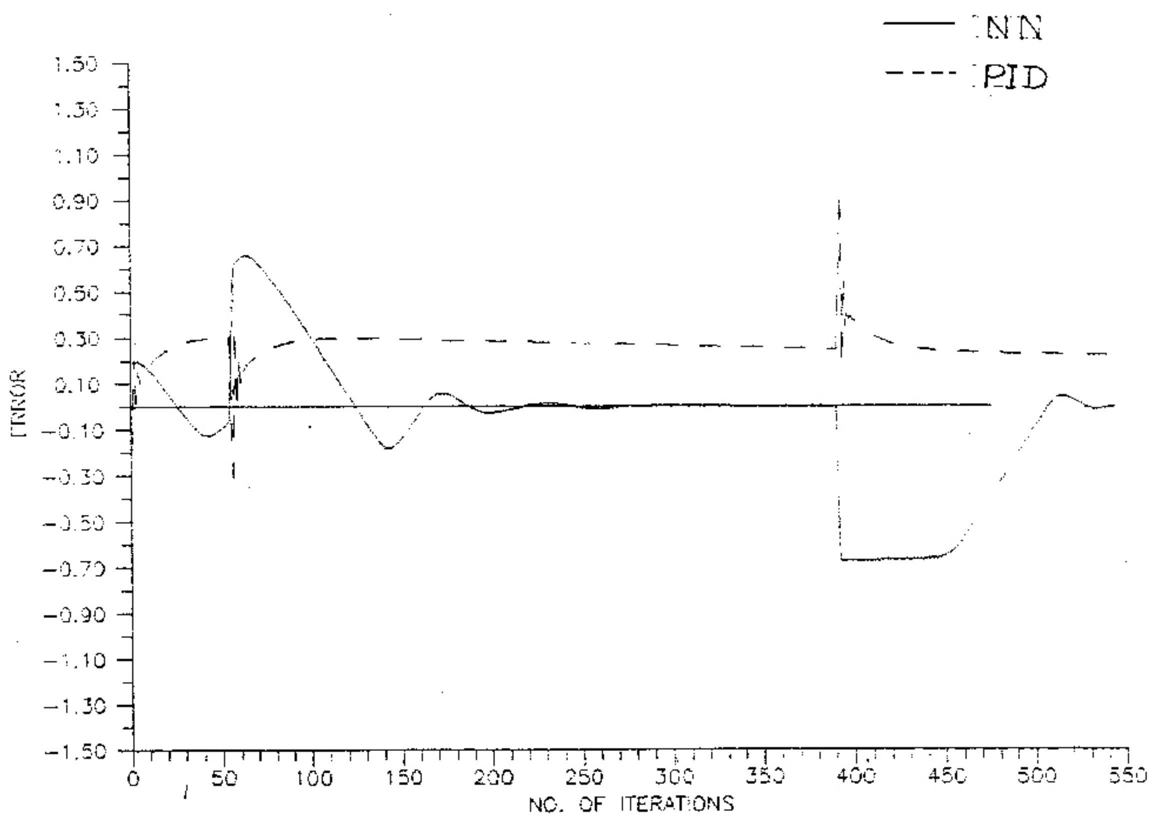
GRAPH 1·a



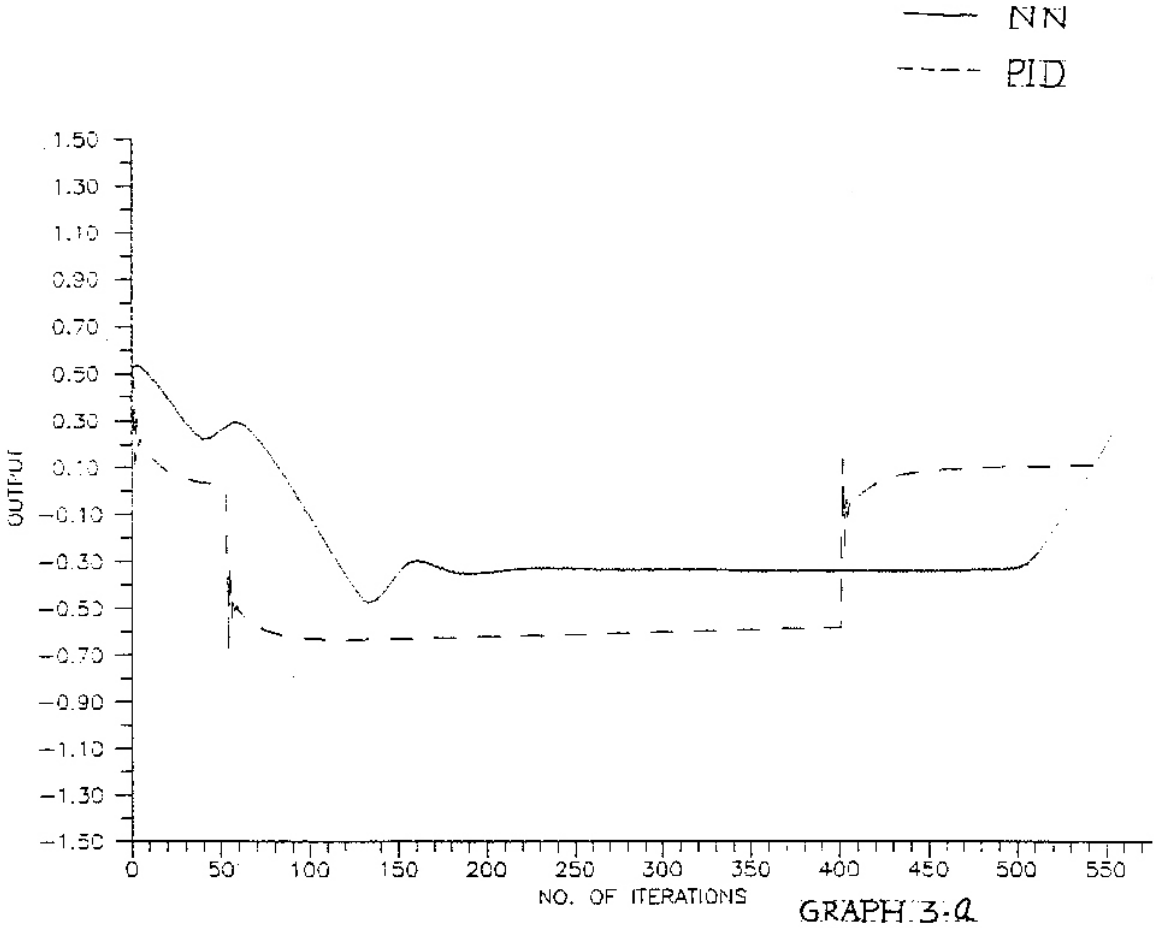
GRAPH 1.b



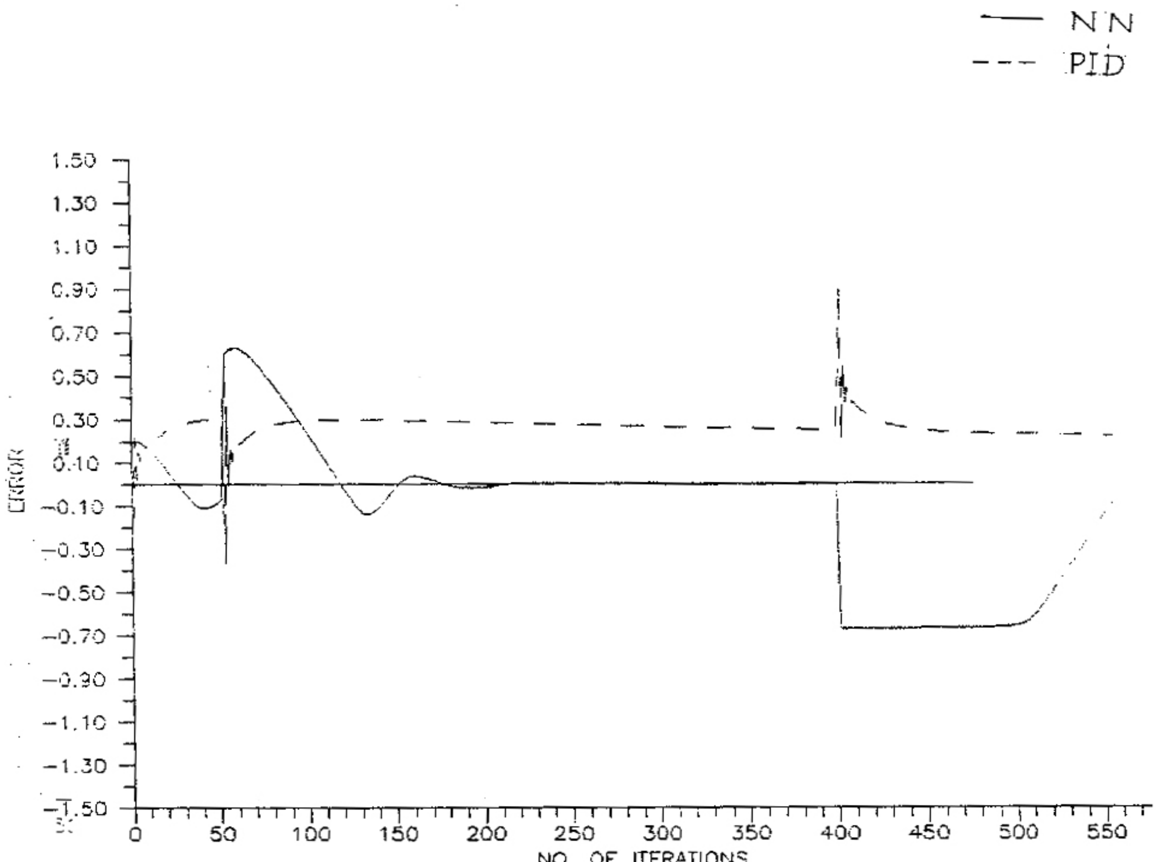
GRAPH 2.a



GRAPH 2.b



GRAPH 3-a



GRAPH 3-b