Neuro-PID Control of Speed and Torque of Electric Vehicle

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***Abstract*—In this paper we consider the neuro-control method and its application to control problems of an electric vehicle. The neuro-control methods adopted here are based on proportional-plus-integral-plus-derivative (PID) control, which has been adopted to solve process control or intelligent control problems. In Japan about eighty four per cent of the process industries have used the PID control. After deriving the self-tuning PID control scheme (neuro-PID) using the learning ability of the neural network, we will show the control results by using the speed and torque control of an electric vehicle.**

***Keywords*-neuro-PID; electric vehicle control; speed control; torque controlcomponent;**

I. Introduction

In applying conventional control theory to practical problems, we have to model the plant or system. The modeling is done by using a set of linear differential or difference equations, in which unknown parameters are included. But the range of applicability is not so wide to cover real control problems. In real world, the plant and its environment are too complex to describe them by such linear models. For example, in a robotic control system, it may have many sensors providing inputs that cannot necessarily be interpreted as state variables. Furthermore, the models of the system may be unknown and interact with unknown changing environment.

Therefore, it is necessary to adopt new methods of control. They may not be so rigorous mathematically so that it can work in a wide range of domains and under more dynamic and more realistic conditions. One of the powerful methods is neuro-control based on the neural networks since the neural networks have preferable properties to overcome the difficult problems stated above. Some of them are 1) learning by experience (training), i.e., human-like learning behavior, 2) generalization ability, i.e., mapping ability of similar inputs to similar outputs, 3) nonlinear mapping ability, 4) parallel distributed processing, allowing fast computation for large scale systems, 5) robustness for noise and environmental change, 6) self-organizing property, etc. These properties make neuro-control suitable for applications to real control problems.

In this paper, we will adopt the proportional-plus-integral-plus-derivative (PID) control and tune the PID gains based on neural networks, which will be called as neuro-PID control. After deriving the neuro-PID controller, we will show the real application to torque control and speed control problems of an electrical vehicle [1].

II. Historical Review of Neuro-Control

The first neuro-control was discussed by Widrow and Smith [2] who used ADALINE to stabilize and control the pole balancing act. Other early research on neuro-control could also found in Waltz and Fu [3], Michie and Chambers [4], and Barto et al. [5].

Neuro-control research has begun sharp increase around 1987 when the first IEEE Conference on Neural Networks has held in San Diego. These papers have demonstrated that neuro-control methods can be applied successfully to control unknown nonlinear systems while conventional control approaches based on linear dynamical system theory could not solve such control problems. Many neuro-control structures were also proposed. Typical neuro-control methods are 1) feedback error learning by Kawato et al. [6], 2) neuro-internal model control by Hunt and Sbarbaro [7], 3) neuro-predictive control by Willia et al. [8], 4) Forward and inverse modelling by Jordan et al. [9]), 5) generalized and specialized learning by Psaltis et al. [10], 6) Self-tuning neuro-control by Omatu [11]. More information on neuro-control could be obtained by the books by D.A. White and D.A. Sofge [12], W. T. Miller III et al. [13], S. Omatu et al. [14], P.M. Mills et al. [15], and N.W. NG [16].

III. Error Back-Propagation Algorithm

The error back-propagation (BP) algorithm has been well-known since it was proposed by Rumerhart et al. [17] in 1985. As a neuro- PID control being described in detail later is derived based on the similar method of BP algorithm, we will explain the derivation of the BP algorithm in compact way.

The form of a neural network described by Fig. 1 is called a layered neural network since they have more than three layers which are called input layer, hidden layer, and output layer. Outputs of neurons in the input layer are the input data which should be processed. We assume that numbers of neurons in the input, hidden, and output layers are I, J,

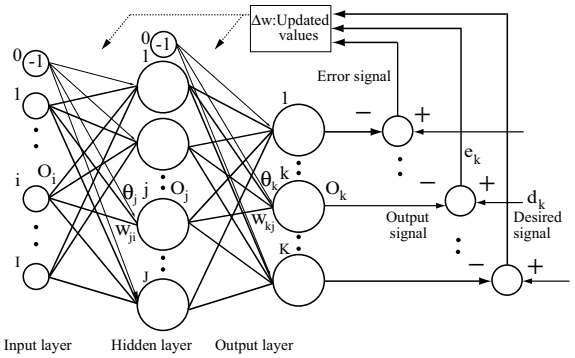


Figure 1. Structure of a layered neural network

and K, respectively. In Fig. 1, large circles denote neurons and each neuron, for example, neuron j can be described by the following nonlinear input-output relation:

$$O_j = f(\text{net}_j), \quad (1)$$

$$\text{net}_j = \sum_{i=1}^{I} w_{ji} O_i - \theta_j, \quad (2)$$

$$f(x) = \frac{1}{1+\exp(-x)} = sigmoid(x). \quad (3)$$

where O_j denotes the output of neuron j, w_{ji} denotes the connection weight from a neuron i to a neuron j, θ_j is a threshold value of neuron j.

Note that the output of a neuron is limited within 0 to 1 since $f(x) \in [0,1]$. If we assume that $O_0 = -1$ and $w_{j0} = \theta_j$, then we can rewrite net_j as follows:

$$\text{net}_j = \sum_{i=0}^{I} w_{ji} O_i. \quad (4)$$

From now on, we assume that threshold θ_j has been included in the weighting function and use the expression Eq.(4) instead of Eq.(2).

When the input data $\{O_i, i = 0, 1, \ldots, I\}$, connection weights w_{ji} from a neuron i in the input layer to a neuron j in the hidden layer where $\{j = 1, 2, \ldots, J, i = 0, 1, \ldots, I\}$, and connection weights w_{kj} from a neuron j in the hidden layer to a neuron k in the output layer where $\{k = 1, 2, \ldots, K, j = 0, 1, \ldots, J\}$, we can get the output values of the neural network by the following equation:

$$O_k = f(\text{net}_k),$$

$$\text{net}_k = \sum_{j=0}^{J} w_{kj} O_j.$$

Then we will compare the output $\{O_k\}$ with the desired value $\{d_k\}$ for each $k, k = 1, 2, \ldots, K$ and if there are large discrepances, we will correct the weighting functions, w_{ji} and w_{kj} such that the following error function E will be decreased.

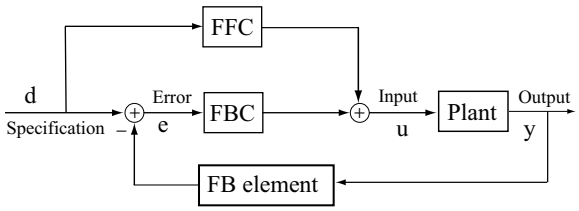


Figure 2. General structure of control system

$$E = \frac{1}{2} \sum_{k=1}^{K} e_k^2, \qquad e_k = d_k - O_k.$$

Using the gradient search, the minimizing cost of E is given by the following relation(the error back-propagation algorithm):

$$\Delta w_{kj} = w_{kj}(\text{new}) - w_{kj}(\text{old}) = \eta \delta_k O_j$$

$$\delta_k = e_k O_k (1 - O_k).$$

$$\Delta w_{ji} = w_{ji}(\text{new}) - w_{ji}(\text{old}) = \eta \delta_j O_i$$

$$\delta_j = \sum_{k=1}^{K} \delta_k w_{kj} O_j (1 - O_j)$$

$$k = 1, 2, \ldots, K, \quad j = 0, 1, \ldots, N.$$

Since the output O_k is limited within [0,1], we should modify the form when we need the value of (-∞, ∞), for example, $f(x) = x$, $f(x) = A(\frac{1}{2} - sigmoid(x))$, etc. Furthermore, to speed up the convergence of the gradient algorithm, we use an additional term as follows:

$$\Delta w_{kj}(\text{new}) = \eta \delta_k O_j + \alpha \Delta w_{kj}(\text{old}) \quad (5)$$
$$j = 0, 1, \ldots, N, \quad k = 1, 2, \ldots, K$$

$$\Delta w_{ji}(\text{new}) = \eta \delta_j O_i + \alpha \Delta w_{ji}(\text{old}) \quad (6)$$
$$i = 0, 1, \ldots, M, \quad j = 1, 2, \ldots, N$$

where the first term and second terms of (5) and (6) are called the learning term and the momentum terms, respectively and η and α are called learning rate and momentum rate, respectively.

IV. Feedback Control System Algorithm

We will consider the neuro-control scheme. The general control system can be described in Fig. 2 where FFC and FFB stand for feed-forward controller and feedback controller, respectively and FB is feedback. The aim of the controller is to find the suitable plant input u in order to follow the plant output y to the plant specification by adjusting the FFB and FFD.

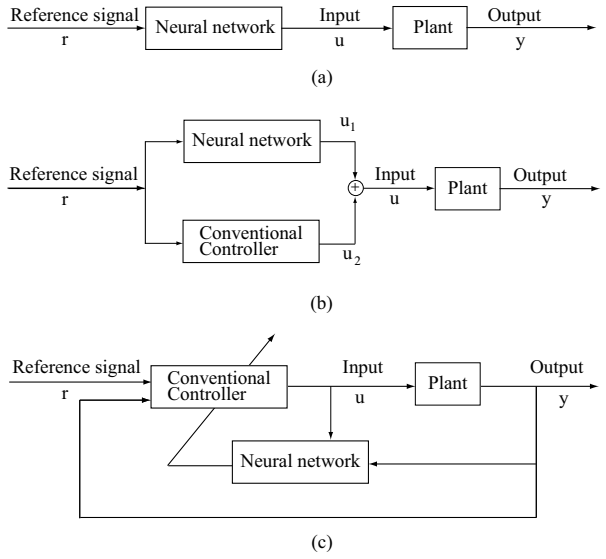


Figure 3. Three types of neuro-control system

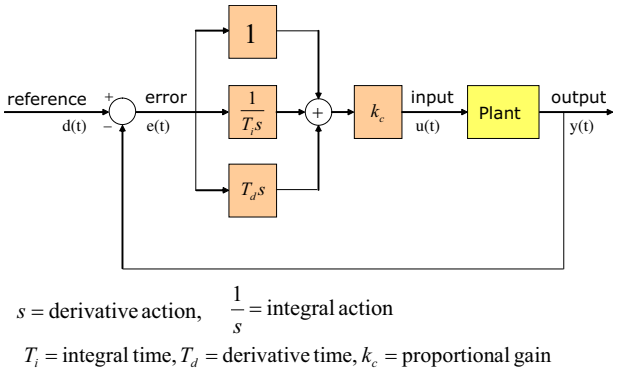


Figure 4. PID control system

The neuro-control is to determine the control input by using neural networks. Three types of neuro-controllers were proposed [14], [18]. They are 1) series type, 2) parallel type, and 3) self-tuning type as shown in Fig. 3.

Among them, we consider the third type. As a conventional controller we adopt the PID controller as shown in Fig. 4 and find the PID gains by using the BP algorithms.

A. Series Type Neuro-Control

This is to use the neural network directly such that the plant output will approach to reference signals as much as possible. The basic configuration is shown in Fig. 5 where (a) is the original structure, (b) is the series neuro-controller with an emulator, and (c) is the inverse dynamical structure. More detail algorithms have been explained in [19], [20], [21].

This approach is direct application of the layered neural network to find the control input and it is powerful for process control without so many fluctuations. But we need

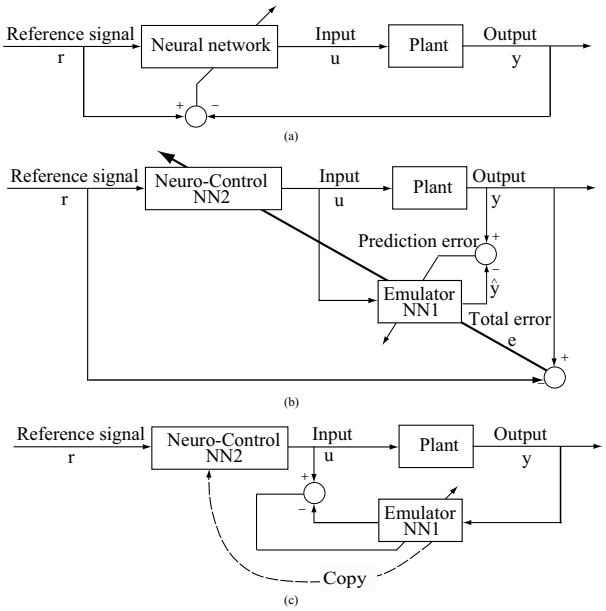


Figure 5. Series type neuro-control structure.

the emulator of the plant and it takes much time to find a stable parameter set of the neural network.

B. Parallel Type Neuro-Control

A parallel neuro-control architecture is shown in Fig. 3(b). For any conventional control scheme, we can use this type and the neural network works as the compensator of the adopted control scheme. If we take a feedback controller, this control becomes to the feedback error learning structure proposed by Kawato et al. [6].

Control engineers design an excellent controller at the laboratory or factory which is given by u_1 but when it is set at the real working place in an industrial factory, the control engineers must adjust the control input level such that it is suitable for real production under several environments. The adjustment is u_2 given by neuro-control in Fig. 3(b). This means that a well-trained cook at the restaurant could provide a delicious dinner for customers but on each table there are pepper and salt to be added to suit the taste of each individual dish. For detail algorithms see [14].

C. Self-Tuning Type Neuro-Control

The self-tuning neuro-control scheme is illustrated in Fig. 3(c) where a neural network is used to tune the parameters of a conventional control method like a human operator in the factory. The transfer function of PID controller is given by the following eauation.

$$G_c(s) = \frac{U(s)}{E(s)} = k_c\left[1 + \frac{1}{T_i s} + T_d s\right] \qquad (7)$$

where $U(s)$and $E(s)$ are input and error between the desired value and output. Here, k_c, T_i, and T_d are called as propor-

tional gain, integral time, and derivative time, respectively. In time domain, it can be written as follows:

$$u(t) = k_c \left[e(t) + \frac{1}{T_i} \int_{-\infty}^{t} e(\tau) \mathrm{d}\tau + T_d \frac{d}{dt} e(t) \right] \quad (8)$$

$$e(t) = d(t) - y(t) \quad (9)$$

Therefore, in the PID control it is essential to find a suitable PID gains. Many researchers have tried to determine them as precise as possible. The most famous method was proposed by Ziegler-Nichols and to determine them by the following relations(Ziegler-Nichols method).

$$k_c = \frac{1.2}{RL}, \qquad T_i = 2L, \qquad T_d = \frac{L}{2}$$

where R and L are maximum slope of the step response and the equivalent delay of the step response, respectively.

By rapid progress of computer, digital control has become common approach in control method and discrete PID control is also discussed. By discritizing Eq.(8) using trapezoidal rule for numerical integration, we obtain the following relation.

$$\begin{aligned} u(t) &= u(t-1) + K_p \big((e(t) - e(t-1) \big) + K_i e(t) \\ &+ K_d \big(e(t) - 2e(t-1) + e(t-2) \big) \end{aligned} \quad (10)$$

$$K_p = k_c - \frac{1}{2} K_i, \;\; K_i = k_c \frac{T}{T_i}, \;\; K_d = k_c \frac{T_d}{T}$$

As in the continuous-time case, Ziegler-Nichols method in the discrete-time case has become as follows:

$$\begin{aligned} K_p &= k_c - \frac{K_i}{2}, \\ K_i &= \frac{1.2}{RL} \frac{T}{2L} = \frac{0.6}{(\frac{L}{T})^2 (RT)} = \frac{0.6}{G_0 L_0^2}, \\ K_d &= k_c \frac{T_d}{T} = \frac{0.6}{G_0}, \\ G_0 &= \max_n \big(y(t) - y(t-1) \big), \qquad L_0 = \frac{L}{T} \end{aligned}$$

Ziegler-Nichols method is helpful to find the rough estimation of PID gains, it is not so good in any case. Therefore, in the process control the operators are adjusting these gains based on their experience and knowledge in trial and error as shown in Fig. 6.

We have developed a self-tuning PID controller. The control structure is shown in Fig. 7.

V. Derivation of Neuro-PID control

Using the learning ability of the neural networks, we will derive the neur-PID controller. Using (10), the output $y(t+1)$ of the plant is produced. Then the total error $E(t+1)$ is defined by

$$E(t+1) = \frac{1}{2} e(t+1)^2 \quad (11)$$

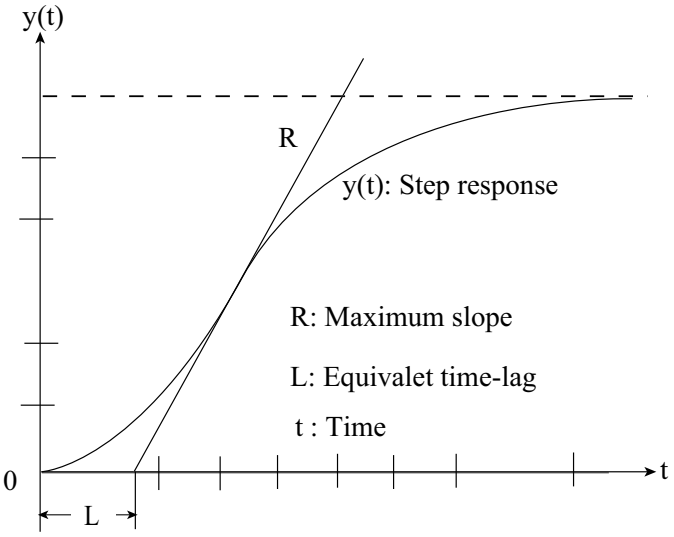


Figure 6. Ziegler-Nichols method

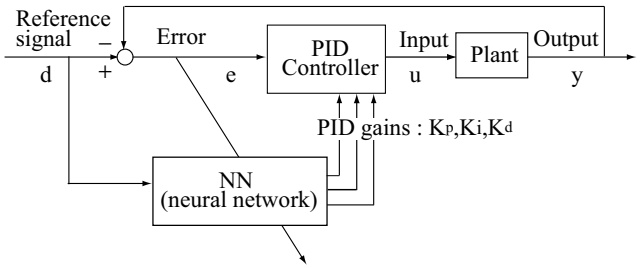


Figure 7. Self-tuning PID control system

where

$$e(t+1) = d(t+1) - y(t+1).$$

Let us consider the three layered neural network as shown in Fig. 8 where we assume that the output function is $f(x) = x$ in the output layer to extend the range of the PID gains over [0,1]. Using the three output neurons of the neural network, we denote the PID gains by

$$K_p = O_k(1), \qquad K_i = O_k(2), \qquad K_d = O_k(3) \quad (12)$$

$$O_k(m) = \mathrm{net}_k(m) = \sum_{j=0}^{N} w_{kj} O_j, \qquad m = 1, 2, 3 \quad (13)$$

$$O_k(m) = \mathrm{net}_k(m) = \sum_{j=0}^{N} w_{kj} O_j, \qquad m = 1, 2, 3 \quad (14)$$

where O_k shows the output of the neuron in the output layer.

By the similar way to the derivation of the BP algorithm,

we define the incremental values of w_{kj}, w_{ji} as

$$\Delta w_{kj}(t+1) = w_{kj}(t+1) - w_{kj}(t) = -\eta \frac{\partial E(t+1)}{\partial w_{kj}}\bigg|_{w_{kj}=w_{kj}(t)} + \alpha \Delta w_{kj}(t) \tag{15}$$

where $k = 1, 2, 3, \quad j = 0, 1, \ldots, N$.

$$\Delta w_{kj}(t+1) = w_{kj}(t+1) - w_{kj}(t) = -\eta \frac{\partial E(t+1)}{\partial w_{kj}}\bigg|_{w_{kj}=w_{kj}(t)} + \alpha \Delta w_{kj}(t) \tag{16}$$

where $j = 1, 2, \ldots, N, \quad i = 0, 1, \ldots, M, \quad .$

Let define δ_k as follows:

$$\delta_k = -\frac{\partial E(t+1)}{\partial \text{net}_k} \tag{17}$$

Then we have

$$-\frac{\partial E(t+1)}{\partial w_{kj}} = -\frac{\partial E(t+1)}{\partial \text{net}_k}\frac{\partial \text{net}_k}{w_{kj}} = \delta_k O_j. \tag{18}$$

By using the chain rule of the derivative, we have

$$\delta_k = -\frac{\partial E(t+1)}{\partial y(t+1)}\frac{\partial y(t+1)}{\partial u(t)}\frac{\partial u(t)}{\partial O_k}\frac{\partial O_k}{\partial \text{net}_k}. \tag{19}$$

Taking into account of the definition of $E(t+1)$ and $e(t+1)$ and the assumption of $f(x) = x$ and using (10) and $K_p = O_1, \ K_i = O_2, \ K_d = O_3$, we obtain

$$\frac{\partial u(t)}{\partial O_k} = \begin{cases} e(t) - e(t-1) & (k=1) \\ e(t) & (k=2) \\ e(t) - 2e(t-1) + e(t-2) & (k=3) \end{cases} \tag{20}$$

If we define the system Jacobian as

$$\text{Jac}(t) = \frac{\partial y(t+1)}{\partial u(t)}, \tag{21}$$

we have

$$\delta_k = e(t+1)\text{Jac}(t+1)\frac{\partial u(t)}{\partial O_k}, \qquad k = 1, 2, 3. \tag{22}$$

Therefore, we obtain the following relation.

$$\Delta w_{kj}(t+1) = w_{kj}(t+1) - w_{kj}(t) = \eta \delta_k O_j. \tag{23}$$

Similarly, we obtain the folowing relation.

$$\Delta w_{ji}(n+1) = \eta \delta_j O_i \tag{24}$$

$$\delta_j = \sum_{i=1}^{K} \delta_k w_{kj} O_j (1 - O_j). \tag{25}$$

From the above relation, we can adjust the PID gains step by step such that the minimum $E(t+1)$ could be achieved.

In order to caluculate the system Jacobian given by (21), we will propose the following approach by using the

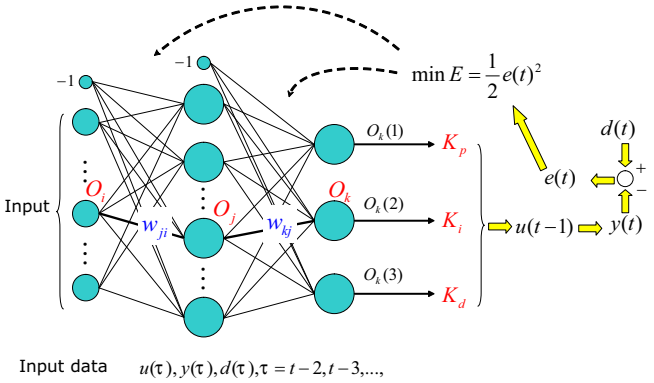


Figure 8. Neuro-PID structure

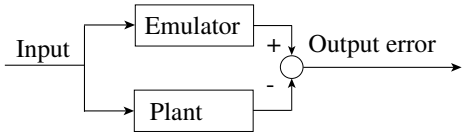


Figure 9. Emulator structure.

emulator. The emulator is constructed such that the output will become like the plant output for any input data as shown in Fig. 9.

The emulator can be designed by using a layred neural network as shown in Fig. 10. Using the neuro-emulator, we can approximate the system Jacobian. If the error of the neural network becomes small enough, the system Jacobian is given by the following equation:

$$\text{Jac}(t+1) \approx \sum_{j=1}^{N} W_{kj} O_j (1 - O_j) W_{j1}. \tag{26}$$

Here, W_{j1} denotes the connection weight from the input $u(n)$ to the neuron j.

VI. Application to Electric Vehicle Control

Due to environmental problems the automobile industry is currently venturing into producing electric vehicles. At the Shikoku Electric Power Company, Japan, a new type of electric car which is called PIVOT has been developed in 1993. The specification is shown in Table I and the overview and specific characteristics are illustrated in Figs. 11 and 12.

This PIVOT has equipped four wheels and each wheel has been made with in-wheel motor. Therefore, the wheels

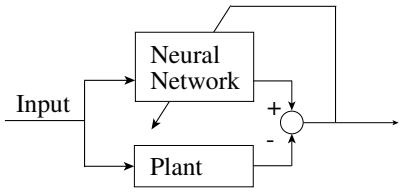


Figure 10. Neuro-emulator structure.

can be steered more than 90 degrees opposed to the body. This newly developed function accounts for universal drive performance such as lateral drive and rotation at a point. Another advantage is high-accuracy residual battery capacity indicator based on neural networks. A small and high accurate indicator has been developed. The residual battery capacity is calculated by a computer using voltage and current while driving.

The third one is an automatic battery exchange system. By the development of an automatic battery exchange system, the battery, having little residual capacity, is removed and a charged battery is installed within approximately five minutes, making refueling as easy as a gasoline-engine vehicle.

The fourth one is an energy-saving technology. Development of a regenerative braking system to convert kinetic energy to electrical energy and charge the battery during deceleration. Adoption of a lightweight frame/body and low air resistance body configuration and development of a lightweight heat-pump type air conditioning system are also equipped.

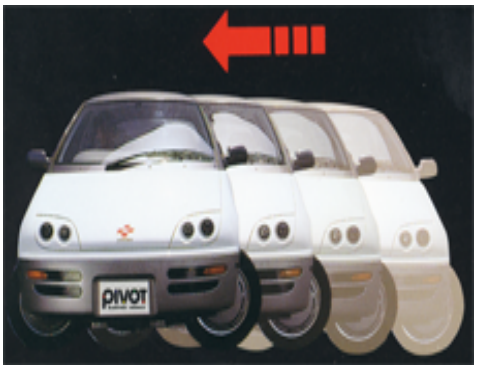
Table I
SPECIFICATION OF PIVOT.

Specification	Performance
length	4,126 mm
width	1,671 mm
height	1,603 mm
dry weight	2,200 Kg
passengers	4 persons
maximum speed	100 Km/h
range	200 Km(at a constant cruising spped of 40km/h
acceleration	Approximate 20 secs. from 0 m to 400 m
grand climb ability	30%
battery type	lead battery
equipment	power steering, heat-pump type sir conditioning

In 1993 when PIVOT was completed in Japan, there was no permission to drive any electric vehicle on the road in law and it is difficult to do the real driving experiment under various load change or load conditions, we have made experimental simulator as shown in Fig. 13. This can be written in Fig. 14 where DDC is direct digital controller which has been equipped with PID controllers, ACM is an alternative current motor which produces torque of OIVOT, DC is a direct current motor which produces any load with various specifications, T is a torque meter, and UFAS denoted a universal factory automation system.

For training the neural networks for various loads and various speeds, we have obtained the input and output data using the physical simulator illustrated in Fig. 13. As mentioned above, this simulator can be modeled as shown in Fig. 14 where DCM produces any kinds of loads and ACM outputs the corresponding control inputs by an AC motor. From our many experiences, we have used the neuro-control structure as shown in Fig. 15 where NNC means neuro-controller to adjust the PID gains and NNM was used to

Figure 11. PIVOT system and its driving mechanism.



Lateral drive

Rotation at a point

Figure 12. Feature of PIVOT system.

Figure 13. Experimental simulator.

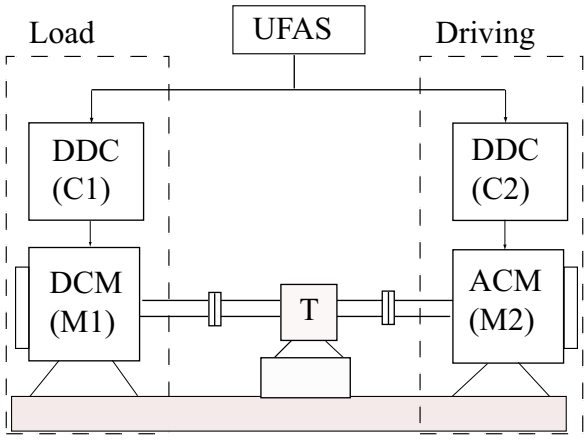


Figure 14. Experimental simulator model.

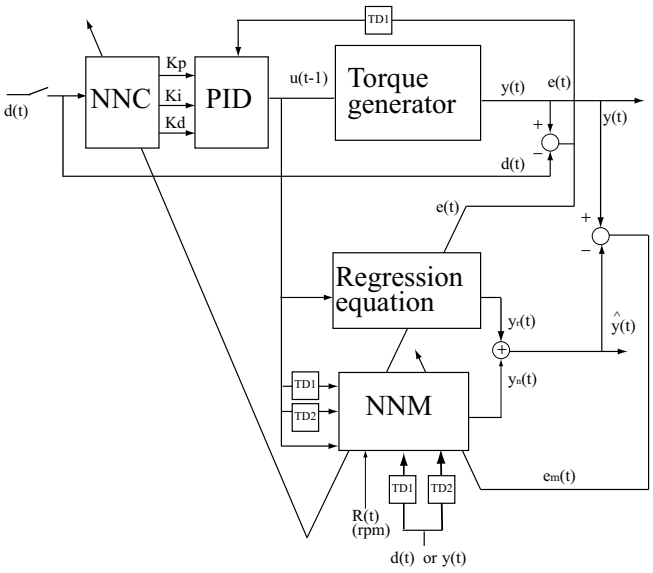


Figure 15. Experimental simulator where TD1 and Td2 are time-delay elements with one and two steps delays, respectively.

model the system emulator which is necessary to find the PID gains in NNC. Here, we use the parallel type emulator with regression model in order to speed up the modeling convergence and also used rotation number of motors. The notation $y\hat{(}t)$ means the estimated value of $y(t)$, $y_r(t)$ and $y_n(t)$ are estimated value of $y(t)$ by regression method and neural networks, respectively, $e(t) = d(t) - y(t)$, and $e_m(t) = y(t) - \hat{y}(t)$.

Figs. 16 and 17 are simulation results for conventional PID control case and proposed neuro-PID case. Fig. 18 is the PID gains for various initial values of PID gains. From these results we can see that the proposed neuro-PID torque control is better that the conventional PID controller based on the Ziegler-Nichols method. Furthermore, even if we start any initial values of PID gains, the excellent control results

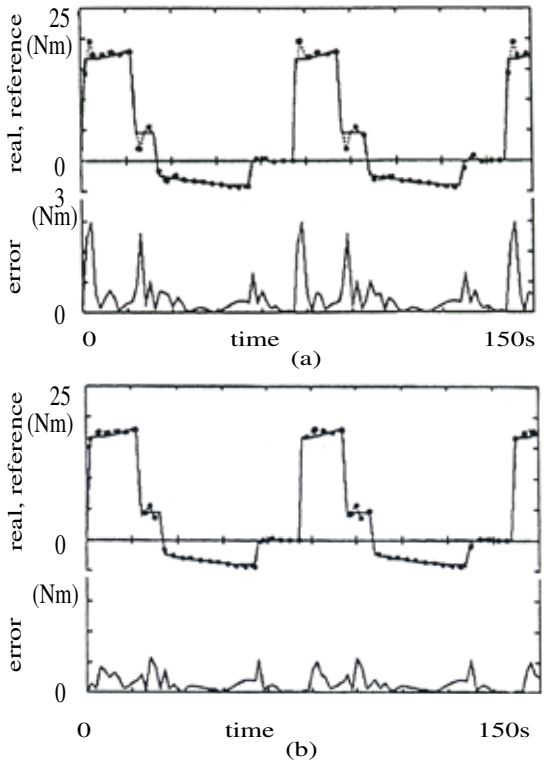


Figure 16. Conventional control results.

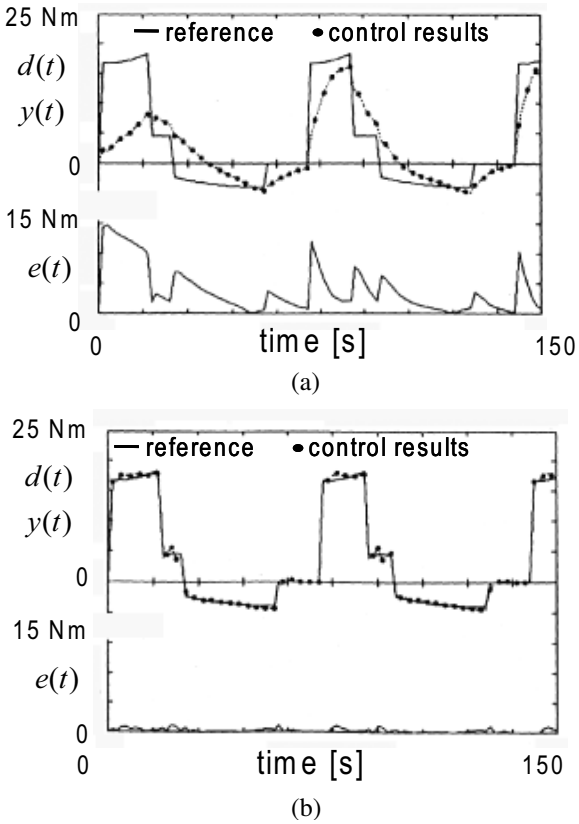


Figure 17. Torque control results by neuro-PID control

could be achieved compared with the values recommended by the company made of the physical simulator.

Figs. 19 and 20 are simulation results for speed control results in case of four modes and eleven mode speed control problems on-load. From these results we can see that the control results in the final stages are almost perfect even for any mode even if control results in the initial stage are not good. In these simulations, learning parameters are $\eta = 0.001 \sim 0.05$.

VII. Conclusions

In this paper we have proposed the neuro-PID control algorithms based on the neural network of layered type. This control method is robust with parameter change and noise as well as the environmental condition. Therefore, we can apply the neuro-PID controller to many kinds of control problems, for example, process control, regulator problem, serbo-problem etc. Among them we have applied the torque and speed control problems of PIVOT electrical vehicle (PIVOT) which has been develped by Shikoku Electric power Ltd, in Japan.

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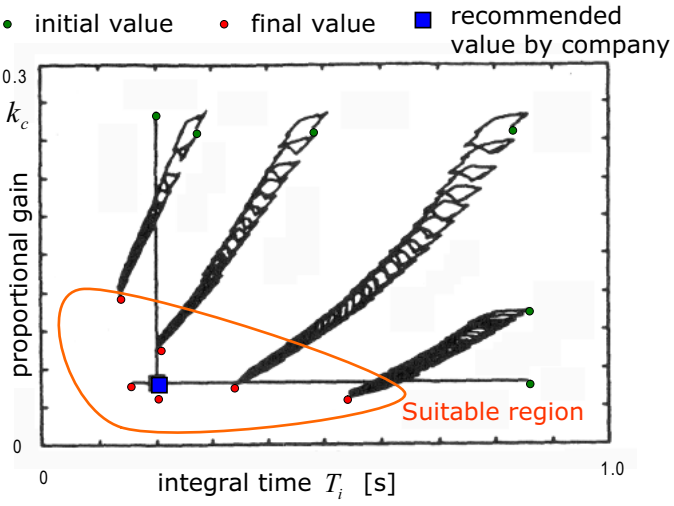

Figure 18. PID control gains.

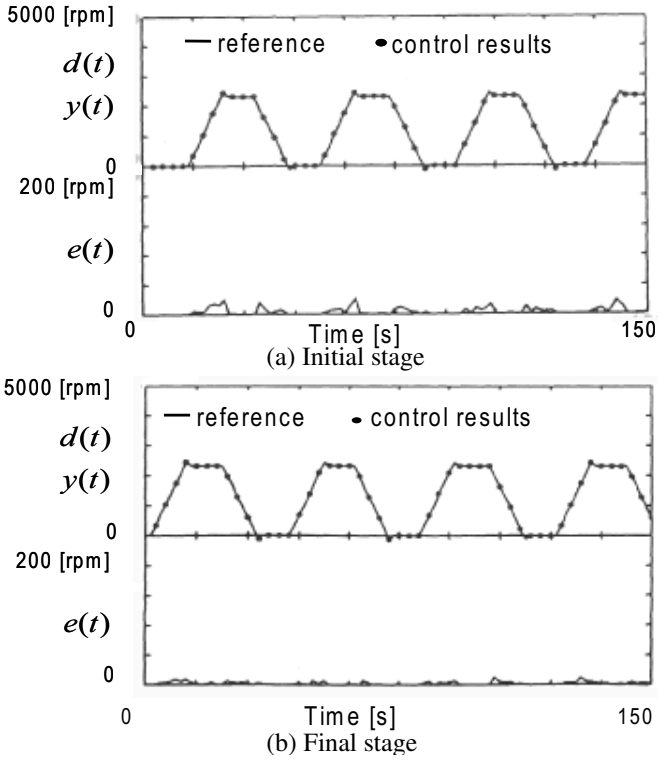

Figure 19. Speed control for four modes case.

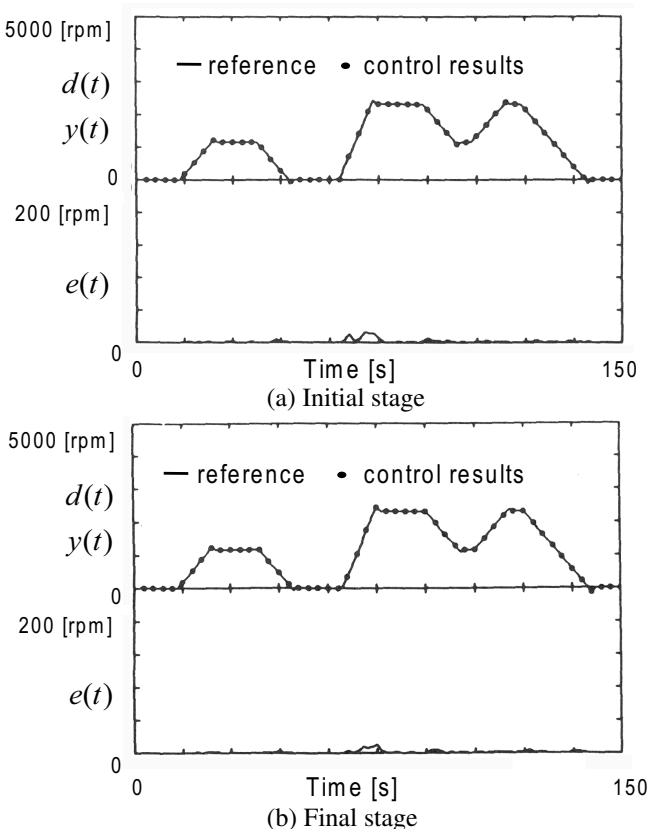

Figure 20. Speed control for eleven mode case.

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