2003 International Symposium on Advanced Intelligent Systems
September 25-28, 2003, Jeju, Korea

Predictive Control for Linear Motor Conveyance Positioning System using DR-FNN

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***Abstract* – In the maritime container terminal, LMTT (Linear Motor-based Transfer Technology) is horizontal transfer system for the yard automation, which has been proposed to take the place of AGV (Automated Guided Vehicle). The system is based on PMLSM (Permanent Magnetic Linear Synchronous Motor) that is consists of stator modules on the rail and shuttle car (mover). Because of large variant of mover's weight by loading and unloading containers, the difference of each characteristic of stator modules, and a stator module's trouble etc., LMCPS (Linear Motor Conveyance Positioning System) is considered as that the system is changed its model suddenly and variously. In this paper, we will introduce the soft-computing method of a multi-step prediction control for LMCPS using DR-FNN (Dynamically-constructed Recurrent Fuzzy Neural Network). The proposed control system is used two networks for multi-step prediction. Consequently, the system has an ability to adapt for external disturbance, cogging force, force ripple, and sudden changes of itself.**

I. INTRODUCTIONS

LMTT (Linear Motor-based Transfer Technology) is horizontal transfer system in the maritime container terminal for the port automation. For the port automation, many technologies have been developed until now. As the yard automation technology, one of them, the known well AGV (Automated Guided Vehicle) system was proposed. But AGV system had various problems that included the difficulty of control, complexity, low speed, heavy weight, low position accuracy, etc. Above all, the main problem was the part of navigation that had difficulty to apply in the whole system and to work together with other systems. Recently, LMTT has been developed to solve these problems. LMTT is based on the concept of linear motor and rail structure. The main benefits of LMTT include the high force density, no need for sub-systems, and, most importantly, the high precision and accuracy associated with the simplicity in mechanical structure[1,2].

In this paper, we will introduce the control strategy for the positioning system of LMTT, by the name of LMCPS (Linear Motor Conveyance Positioning System). The system is considered PMLSM (Permanent Magnetic Linear Synchronous Motor) that is consists of stator modules on the rail and mover (shuttle car). Because of large variant of mover's weight by loading and unloading containers, the difference of each characteristic of stator modules, and a stator module's default etc., LMCPS is able to consider as that the system is changed its model suddenly and variously. Then, we will introduce the soft-computing method of a multi-step prediction control for LMCPS using DR-FNN (Dynamically-constructed Recurrent Fuzzy Neural Network).

The proposed control system is used the network that is based on FNN (fuzzy neural network). It is composed of the structure of neural network that have the fuzzy inference ability and the recurrent loops. In addition, it has ability to adjust the structure of network. Layers in the network are consisted of the adjustable number of nodes which act a role such as the membership function or rule base. We use two units of DR-FNN and each network has two output nodes in the system. One is a predicted system output, another is a predicted reference signal, and others are control input signals from each other network. Then the system has an ability to adapt for the external disturbance, cogging force, force ripple, and sudden changes of itself by unifying network weights of controller and emulator.

II. LINEAR MOTOR CONVEYANCE POSITIONING SYSTEM

The system consists of a substructure (guide rail, stator modules), shuttle cars (mover), and a control system. The motor style is permanent magnet synchronous linear motor as shown by figure 1.

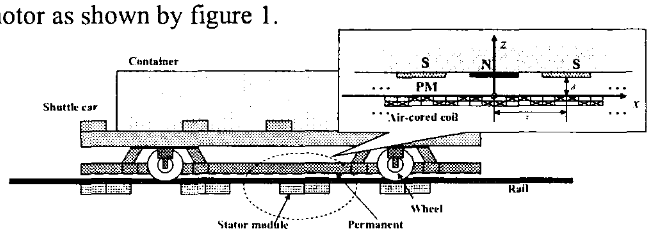

Fig. 1. PMLSM-based LMCPS

Because of permanent magnets are installed under the plate of shuttle car. Then no power cables and other devices are required onto the shuttle car. LMCPS is able to start modeling from the general PMLSM as follows[3,4].

$$\left.\begin{aligned} v_q &= R_s i_q + p\lambda_q + \omega_e \lambda_d \\ v_d &= R_s i_d + p\lambda_d + \omega_e \lambda_q \end{aligned}\right\} \tag{1}$$

Flux linkages for each axis, angular velocities, and electric linear velocity are represented by equation (2).

$$\lambda_q = L_q i_q,\ \lambda_d = L_d i_d + \lambda_{PM} \tag{2}$$

$$\omega_e = n_p \omega_r,\ \omega_r = \pi v / \tau$$

$$v_e = n_p v = 2\tau f_e$$

Electromagnetic power is represented by the following.

$$P_e = F_e v_e = 3n_p\{\lambda_d i_q + (L_d - L_q) i_d i_q\}\omega_e / 2 \tag{3}$$

Electromagnetic force is represented by the following.

$$F_e = 3\pi n_p\{\lambda_d i_q + (L_d - L_q) i_d i_q\} / 2\tau \tag{4}$$

Force equation is represented by the following.

$$F_e = 3\pi\lambda_{PM} i_q / 2\tau \tag{5}$$

Simplified PMLSM drive system is able to describe by the following.

$$F_e = K_f i_q^* \tag{6}$$

$$K_f = 3\pi n_p \lambda_{PM} / 2\tau \tag{7}$$

The simplified shuttle car's dynamic equation is represented by the following.

$$F_e = Mpv + Dv + F_L \tag{8}$$

The gain K_f is scale factor between input current and thrust force. But, if the force ripple and the interval of stator module are considered, it can be modified K_f to nonlinear function as equation (9).

$$K_f(d) = K_{f0} + K_{ripple}(d) \tag{9}$$

$K_{ripple}(d)$ is the function of force ripple effect as shown by equation (10), which is caused by the condition of install of stator modules, the change of distance, and the winding self-inductance varies.

$$\begin{aligned} K_{ripple}(d) = K_{f0}\{&0.03 \cdot \sin(2\pi d / P + \pi / 4) \\ &+ 0.038 \cdot \sin(6\pi d / P + 0.09\pi)\} \end{aligned} \tag{10}$$

F_L is considered as shown by equation (11). Here, f_{dis} is the white noise and the cogging force is described as equation (12).

$$F_L = f_{cogging} + f_{dis} \tag{11}$$

$$\begin{aligned} f_{cogging} = K_s\{&(15\sin(2\pi \cdot d / P + \pi / 4) \\ &+ (20\sin(6\pi \cdot d / P + 0.09\pi)\} \end{aligned} \tag{12}$$

Because of the shuttle car weight change by loading and unloading container and the interval of stator modules, coefficients M and D are needed to consider as the nonlinear function $M(t)$, $D(t)$ respectively. Then, the modified shuttle car's dynamics is described by equation (13) consequently. The whole system configuration is can be described by figure 2.

$$\ddot{x} = \frac{(K_{f0} + K_{ripple})u(t) - D(t)\dot{x} - f_{cogging} - f_{dis}}{M(t)} \tag{13}$$

Table 1. Parameters

v_d, v_q	d-q axis voltages
i_d, i_q	d-q axis currents
R_s	phase winding resistance
L_d, L_q	d-q axis inductances
ω_r	angular velocity of the mover
ω_e	electrical angular velocity
λ_{PM}	permanent magnet flux linkage
n_p	number of primary poles
p	Differential operator
v	linear velocity of the mover
d, x	distance (mover's position)
τ	pole pitch
v_e	electric linear velocity
f_e	electric frequency
M	total mass of the moving element system
D	viscous friction and iron-loss coefficient
F_L	external disturbance term

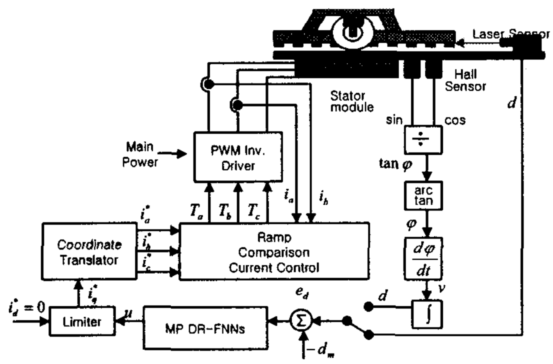

Fig. 2. LMCPS and driver system configuration

III. DR-FNN UNIT

As well known, the fuzzy inference system with the structure of neural network is very suitable for emulating human behaviors which have a robustness and stability by learning[3,4]. In this paper, the structure of network is composed of having two input and output nodes respectively. In the proposed control system, two networks are used as the controller and emulator. Figure 3 shows DR-FNN that is used the emulator unit.

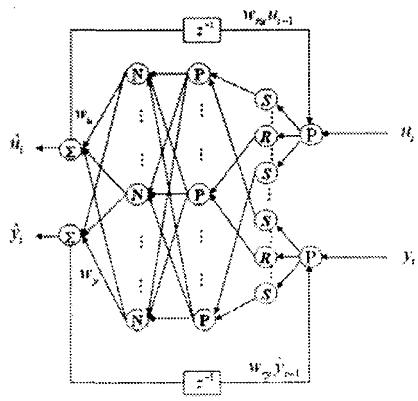

Fig. 3. DR-FNN unit

One of the output nodes is prediction of plant output for one-step ahead, and the other is the predicted control input u . And inputs are recurrent delayed values of control input and system output about p-step time index backward. The network can be considered the recurrent style. Because outputs are used inputs these are delayed in next time index.

Layer 1 is input layer for the linguistic variables. Layer 2 (MFu) is consisted of the membership function that have nodes based on RBF (Radial Basis Function). In case of j=1 and u, for two nodes of edged side in layer 2, the membership function get the shape of sigmoid function, and these are optimized automatically by the back-propagation method. The output of membership function is presented by equation (14) in the second layer.

$$\mu_{ij}(x_i) = \exp\left[-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}\right] \quad (14)$$

(i= 1, 2,...,r, j= 2,...,u-1)

Where, x_i is the product between the current input and delayed output. x_1 and x_2 are presented by equation (15) and (16) respectively.

$$x_1(t) = u(t) \cdot w_{ru} \cdot \hat{u}(t-1) \quad (15)$$

$$x_2(t) = y(t) \cdot w_{ru} \cdot \hat{y}(t-1) \quad (16)$$

Third layer is IF-part for fuzzy rules. For the j-th rule R_j, its output is described by equation (17) in third layer.

$$R_k = \exp\left[-\frac{\sum_{i=1}^{2p}(x_i - c_{ij})^2}{\sum_{i=1}^{2p}\sigma_{ij}^2}\right] \quad (17)$$

The normalized output of third layer was calculated in layer 4. It can be expressed by equation (18).

$$N_k = \frac{R_k}{\sum_{l=1}^{N} R_l} \quad (18)$$

The fifth (output) layer computes outputs of consequence part. Control input and predicted plant output are calculated by equation (19) and (20) respectively.

$$\hat{u}(t) = \sum_{k=1}^{N} w_{1,k} \cdot N_k \quad (19)$$

$$\hat{y}(t) = \sum_{k=1}^{N} w_{2,k} \cdot N_k \quad (20)$$

IV. MULTI-STEP PREDICTIVE CONTROL SCHEME

For one-step prediction, DR-FNN is constructed beside plant as an emulator style. It performs not only controller but also act of on-line identifier by two outputs from network. The system can obtain predictions of reference input signal $\hat{y}_d$ and the other control input $\hat{u}$. Then, system has two control inputs protruded from controller and emulator. Respectively these are named by $\hat{u}_c$ and $\hat{u}_e$. To equal system output to reference signal, networks are trained its weights by control input error e_u between these, such as Widrow's method[5,6]. Each network of controller and emulator is trained twice for control input by e_u and performance error e_p as equation (21) and (22). It is the difference between system output and reference signal at the current time.

$$\left.\begin{aligned} &e_u = u_c(t-1) - u_e(t-1), \quad E_u = \frac{1}{2}e_u^2 \\ &w_{l,k}(t+1) = w_{l,k}(t) + \eta\left(-\frac{\partial E_u}{\partial w_{l,k}}\right) \end{aligned}\right\} \quad (21)$$

$$\left.\begin{aligned} &e_p = y_c(t) - y(t), \quad E_p = \frac{1}{2}e_p^2 \\ &w'_{l,k}(t+1) = w'_{l,k}(t) + \eta\left(-\frac{\partial E_p}{\partial w'_{l,k}}\right) \end{aligned}\right\} \quad (22)$$

Where, $w_{l,k}$ is updated first for control input signal in networks of controller and emulator. The weight ($w'_{l,k}$) is updated once more. The predicted reference input signal $\hat{y}_d$ and the predicted plant output $\hat{y}$ are trained by e_{yd} and e_d respectively. Figure 4 is presented the proposed control system.

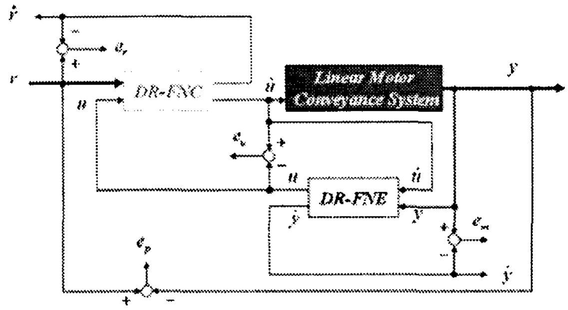

Fig. 4. Control system with DFNN controller and emulator

To improve the adaptability in this case, the proposed control scheme is regarded as the predicted next step system input because two units of DR-FNN are used as a controller and emulator as shown by figure 5. In the part of controller, if DR-FNC were trained enough by the various patterns of reference input signals, network can simulate without the plant virtually using predicted next reference input. Even though network was trained well for some known patterns also, input is the value that can not be guarantee absolutely. Because, reference input can be decided by unknown pattern.

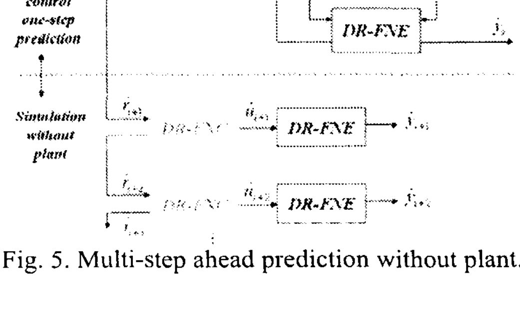

Fig. 5. Multi-step ahead prediction without plant.

V. SIMULATION AND RESULTS

In the simulation, we set the stator module's length and the gap between each module on 3m, 2m respectively. In the plant of LMCPS, Runge-Kutta's method of order 4 was used and its sample time was 0.5ms. And the control time interval was set up 5ms and the pole pitch P was set up 0.3m..

The scenario is same as following. (1) The empty shuttle car goes until the point of 33m and comes again. (2) The container of 40ton is loaded at 50sec. (3) The loaded car shuttles until 55m. The case of figure 6(a) is the description of response for the distance of shuttle car using fixed parameters and control the parameter at learned FNN in advance, (b) is result of by using the FNN of recurrent type and regulation node about the position and the velocity respectively. By same method, (c) is result of separating to 16 node start from 5 membership functions. According as go to (c) from (a), it is improved the response characteristics and reinforced steep weight change of the system and effect of cogging force and stator module. The dotted line is a reference and a solid line is a change of the distance.

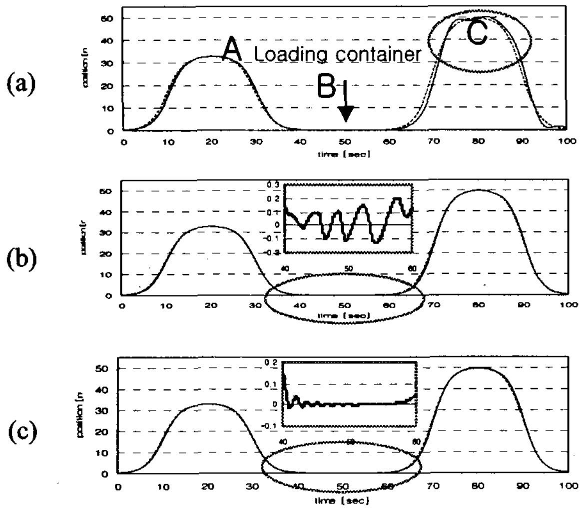

Fig. 6. Reference trajectory and responses of shuttle car

Figure 7 and 8 show the change of the control input and distance error. The maximum position error is less than 1.8cm and the average is about 0.8cm in the stop area.

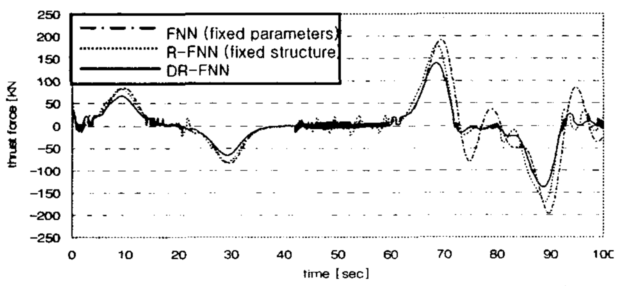

Fig. 7. Variations of thrust force

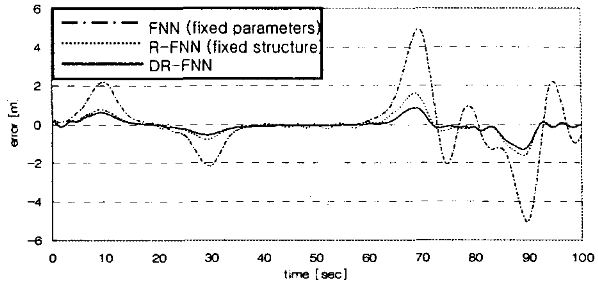

Fig. 8. Results of the distance error

VI. CONCLUSIONS

In this study, we modeled LMTT system by modifying the general PMLSM and adding with the considerable various disturbances. In LMTT, the system included various kinds of problems to control such as cogging force, force ripple, external disturbances, the variation of mover weight, the periodic lack of thrust force, etc. To improve the positioning accuracy and reduce the energy consumption, we proposed a control system that has multi-step predictable structure using two DR-FNN units. In case of using DR-FNN, there are improvements of 68%, 3% than supervised FNN, R-FNN respectively in position accuracy. By multi-step predictable structure, the amount of control input (thrust force) was reduced about 13%, 8% than FNN, R-FNN respectively.

ACKNOWLEDGMENTS

The work was supported by the National Research Laboratory Program of the Korean Ministry of Science & Technology (MOST).

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