Fuzzy Neural Network Control for a Reaction Force Compensation Linear Motor Motion Stage

Kyung Ho Yang1 · Hyeong-Joon Ahn2

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Abstract
Technological progress and market expansion in the semiconductor industry require ultra-precise and high-speed processing and motion systems. However, even though reaction force compensation (RFC) linear motor motion stages help reduce the transmitted reaction force, the residual vibration of the movable magnet track after motion acts as a disturbance, affecting settling time and tracking performance. To address this issue, this study introduces a fuzzy neural network controller for an RFC linear motor motion stage. Since non-linear factors, such as frictional forces from guide rails, make it difficult to accurately model the system, a Nonlinear Autoregressive Neural Network (NARX) is used to identify the nonlinearity from displacement and servo control outputs. The fuzzy logic controller, which takes into account the error and error rate, is then combined with the inverse model controller of NARX. Finally, the fuzzy neural network controllers are integrated with the existing PIV (proportional-integral-velocity) control in feedforward configurations. The experiments demonstrate the potential performance improvements of the proposed approach over the PIV controllers.

Keywords Linear motor motion stage · Reaction force compensation · Motion control · Fuzzy logic · Artificial neural network

List of Symbols

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>b</td>
<td>Bias Unit</td>
</tr>
<tr>
<td>Cmt</td>
<td>Damping of the Magnet Track</td>
</tr>
<tr>
<td>D</td>
<td>Input Delay</td>
</tr>
<tr>
<td>de/dt</td>
<td>Following Error Rate of the Mover</td>
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<tr>
<td>e</td>
<td>Following Error of the Mover</td>
</tr>
<tr>
<td>Ft</td>
<td>Thrust Force of the Mover</td>
</tr>
<tr>
<td>i</td>
<td>Motor Input Current</td>
</tr>
<tr>
<td>Kmt</td>
<td>Stiffness of the Magnet Track</td>
</tr>
<tr>
<td>Mt</td>
<td>Mass of the Mover</td>
</tr>
<tr>
<td>Mmt</td>
<td>Mass of the Magnet Track</td>
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<tr>
<td>NARX</td>
<td>Nonlinear Autoregressive Neural Network</td>
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<tr>
<td>p</td>
<td>Fuzzy Compensation</td>
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<tr>
<td>PIV</td>
<td>Proportional-Integral-Velocity</td>
</tr>
<tr>
<td>u</td>
<td>Servo Controller Output</td>
</tr>
<tr>
<td>uc</td>
<td>Fuzzy-NARX Output</td>
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<tr>
<td>uPIV</td>
<td>PIV Controller Output</td>
</tr>
<tr>
<td>W</td>
<td>Weight</td>
</tr>
<tr>
<td>xmt</td>
<td>Position of Magnet Track</td>
</tr>
<tr>
<td>xmt,Ref</td>
<td>Actual Position of the Mover</td>
</tr>
<tr>
<td>xmt,Ref</td>
<td>Position Reference Command</td>
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1 Introduction

In the 21st century, alongside the evolution of semiconductor technology and the burgeoning market demand, motion stages utilized in semiconductor manufacturing processes necessitate high-speed capabilities and ultra-precision [1]. In semiconductor lithography equipment, extreme performance is essential, necessitating long-distance travel at high speeds and precise handling of up to 230 wafers per hour, with accuracies measured in nanometers [2].

When the mover of a motion stage undergoes rapid acceleration and deceleration, it generates significant reaction forces transmitted to the base, which leads to residual vibration of the system base and adversely affect production quality and
equipment lifespan [3]. To address this issue, reaction force compensation (RFC) linear motor motion stages utilize a movable magnetic track connected to the base through a spring to alleviate the transmitted reaction force [4-6]. However, the residual vibration of the movable magnet track after motion serves as a disturbance, compromising settling time and tracking performance. Consequently, various control strategies are currently under investigation to tackle these challenges [7,8].

The motion stage’s movers, supported by linear guides, face friction, introducing nonlinearity and decreasing position accuracy. Conventional linear controls struggle to effectively compensate for the nonlinearity due to challenges in obtaining accurate nominal models.

There is an increasing demand for advanced control strategies to address these nonlinear challenges [9-12]. Nonlinear control techniques such as sliding mode control (SMC) and adaptive robust control (ARC) are widely used. SMC is favored for motion stages due to easy implementation and high robustness [9-11]. However, SMC can only guarantee asymptotic convergence, and may produce unstable control signal or chattering. Although ARC offers strong robustness against uncertainties and nonlinearities, it requires high mathematical rigor [12].

Intelligent controls, like fuzzy logic and artificial neural network (NN), have demonstrated their efficacy across various control strategies. Fuzzy logic encapsulates control algorithms, incorporating expert judgment and ambiguity in an if-then format, thereby facilitating control capable of handling uncertainty and imprecise information [13-17].

Artificial NN are extensively employed for modeling nonlinear systems due to their adeptness in learning intricate data patterns and forecasting their variations [18-25]. Notably, NARX (nonlinear autoregressive exogenous model), a type of recurrent NN, stands out for its structure, which incorporates feedback from output neurons rather than hidden neurons, thereby avoiding computational disadvantages. Research has explored NARX to compensate for the nonlinearity of motion stages [26].

This paper presents a fuzzy NN controller for an RFC linear motor motion stage. Nonlinear factors, such as friction from guide rails, hinder accurate nominal modeling, prompting the use of NARX to identify the nonlinear nature from displacement and servo control. A fuzzy logic controller, designed with error and error rate, is combined with the inverse model controller of NARX. Finally, the fuzzy NN controllers are integrated with the existing PIV control in feedforward configurations. The proposed fuzzy NN control demonstrates significant improvements in peak errors for both forward and backward paths, achieving a 53.4% reduction and a 27.4% reduction, respectively, compared to conventional PIV control. Moreover, the mean square error is reduced by 34.7%.

2 RFC Linear Motor Motion Stage and Motion Controller

2.1 RFC Linear Motor Motion Stage

Fig. 1 illustrates the schematic diagram of the RFC linear motor motion stage. The mathematical equations of the mover and magnet track are shown in Eqs. (1) and (2), respectively. RFC linear motor motion stages employ a movable magnetic track connected to the base via a spring to mitigate transmitted reaction forces. That is, the thrust force \( F_T \) is divided into inertial force of the magnet track \( M_{mt} \ddot{x}_{mt} \) and the transmitted reaction force \( K_{mt} \dot{x}_{mt} \) and \( C_{mt} \dot{x}_{mt} \).

\[
M_{mt} \ddot{x}_{mt} = F_T
\]

\[
M_{mt} \ddot{x}_{mt} + K_{mt} x_{mt} + C_{mt} \dot{x}_{mt} = F_T
\]

2.2 Experimental Setup

Fig. 2 depicts the experimental setup of the RFC linear motor motion stage, comprising an ironless linear motor (Justek, JTKL3638), a servo driver (CDHD2-0082AEC2), a linear sine encoder (Heidenhain), custom hall sensors, a unipolar (Justek, JTED-1000), and a Simulink real-time controller. Table 1 outlines the specifications of the linear motor. The linear encoder for position control has a resolution of 0.05 μm, while the digital hall sensor for commutation offers a

![Fig. 1 Schematic diagram of RFC linear motor motion stage](image)

![Fig. 2 Experimental set-up](image)

<table>
<thead>
<tr>
<th>Table 1 Specifications of the linear motor</th>
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<tbody>
<tr>
<td>Continuous / Peak force</td>
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<tr>
<td>Continuous / Peak current</td>
</tr>
<tr>
<td>Force constant</td>
</tr>
<tr>
<td>Back EMF constant (phase to phase)</td>
</tr>
<tr>
<td>Coil mass</td>
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<tr>
<td>Max. speed</td>
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</table>
resolution of 15 μm. The industrial PC for real-time control features an I3-3229 CPU, MB970F main board, 4 GB DDR3 RAM, and 500 GB HDD. PCI-6251 (NI) is installed on the PC to gather the encoder signal, converted from the linear sine encoder by the unipolarator.

2.3 Motion Controller

In Fig. 3, a comparison between the conventional motion control and the proposed fuzzy NN controller is presented. The proposed controller integrates fuzzy logic and artificial NN components with existing PIV position control. Notably, the NARX serves dual roles in system identification and control within the proposed framework.

3 Simulink Real-time Intelligent Motion Control System

3.1 System Identification with NARX

The nonlinear dynamic model of the RFC linear motor motion stage can be identified using NARX. The goal is to compensate for nonlinear elements such as guide friction using trained NARX. Fig. 4 illustrates a sample data for training the NN. Various data sets are collected with ±30% variations of the nominal PIV gain and ±50% variations of nominal stroke. The position data of the mover served as input, while the PIV servo control was utilized as output during the training process. The block diagram of the NARX is depicted in Fig. 5. Training involved two hidden layers, each comprising 10 neurons. The NN is trained up to 591 epochs and the mean square error (MSE) is $1.1 \times 10^{-4}$, as shown in Fig. 6(a).

3.2 Hyper Parameters Optimization

To enhance the performance of NARX, the hyperparameters such as the number of neurons, hidden layers, learning rate, delay time, training function, and activation function are tuned. During the tuning, MSE was selected as the loss function. Initially, the number of neurons in the hidden layer was set to 10, the number of hidden layers and neurons were determined sequentially. The selected hyper parameters are shown in Table 2 and the MSE after the optimization is shown in Fig. 6(b). The MSE decreased from $1.1 \times 10^{-4}$ to $7.4165 \times 10^{-8}$.

![Fig. 3 Block diagram of motion controllers](image)

![Fig. 4 Training data](image)

![Fig. 5 Structure of NARX](image)

![Fig. 6 MSE during the training](image)

<table>
<thead>
<tr>
<th>Table 2 Hyper-parameters</th>
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<tbody>
<tr>
<td>Hidden layers</td>
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<tr>
<td>Neurons</td>
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<td>Training function</td>
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<td>Activation function</td>
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<td>Performance</td>
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</table>
3.3 Fuzzy Logic Controller Design

The fuzzy logic controller was employed to dynamically adjust the weighting of the artificial NN controller using the command following performance of the RFC motion stage. Based on the motion error and its derivative of the RFC motion stage of Fig. 7, three criteria were set to determine the fuzzy rules as follows.

1) Compensate for the error at the start of the acceleration.
2) Minimize errors in convergence sections.
3) Prevent errors from exceeding the reference value.

The membership function of the input and output of the fuzzy logic controller was shown in Fig. 8 while the fuzzy rules can be set as shown in Table 3. Given the substantial error observed during the initial acceleration phase, it falls within the categories of NB (Negative Big), NM (Negative Middle), PB (Positive Big), and PM (Positive Middle).

Consequently, the output of the fuzzy logic controller is maximized during this segment. For NS (Negative Small), ZO (Zero), and PS (Positive Small) error categories, corresponding to the convergence section, the output of the fuzzy logic controller is set to zero. Furthermore, in NO (Negative Over) and PO (Positive Over) error sections, where errors exceed those of the existing PIV controller, the output of the fuzzy logic controller is also set to zero. The designed fuzzy surface is shown in Fig. 9.

4 Experiments and Results

4.1 Motion Profile

To evaluate the motion control performance, a motion profile of maximum speed 218.75 mm/s, maximum acceleration 751.32 mm/s$^2$, and stroke 100 mm was used and shown in Fig. 10.

4.2 Comparison of Control Performance

Following error and control output of each controller for the given motion profile are shown in Fig. 11. The fuzzy NN controller effectively compensated for frictional forces,
particularly at the beginning of acceleration. The peak following errors of the forward and backward moves were improved by 53.4% (22.2 → 10.35 μm) and 27.4% (23.5 → 17.08 μm), respectively. The position error after the motion is shown in Fig. 12 and the settling time decreases from 0.148 s to 0.037 s. Furthermore, Fig. 13 illustrates MSEs of the forward, backward and total move of two controllers. MSEs of the forward and the backward moves are improved by 58.1% (12.86 → 5.39 μm²) and 10.84% (12.59 → 11.22 μm²), respectively, while that of the total move is improved by 34.7% (4.25 → 2.77 μm²).

5 Conclusion

In this paper, a fuzzy NN controller for a RFC linear motor motion stage was investigated. Non-linear factors, such as frictional forces from guide rails, hinder accurate nominal modeling, prompting the use of NARX to identify the nonlinear nature from displacement and servo control outputs. A fuzzy logic controller, designed with error and error rate, is combined with the inverse model controller of NARX. Finally, the fuzzy NN controllers are integrated with the existing PIV control in feedforward configurations. The proposed fuzzy NN control demonstrates significant improvements in peak errors for both forward and backward moves, achieving a 53.4% reduction and a 27.4% reduction, respectively, compared to conventional PIV control. Moreover, the MSE is reduced by 34.7%. The proposed method includes not only accurate identification with NARX, but also nonlinear compensation with fuzzy and NN, which makes it more powerful than the existing control method.

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References


**Kyung Ho Yang** is currently combined Master’s student in the Department of Mechanical Engineering, Graduate School, Soongsil University. His research interest is linear motor control.

**Hyeong-Joon Ahn** received B.S., M.S. and Ph.D. degrees from Seoul National University, Korea in 1995, 1997 and 2001, respectively. He was research associate in University of Virginia, 2002 and is currently a professor at School of Mechanical Eng., Soongsil University. Dr. Ahn’s research interests are in the area of mechatronics, sensors, actuators, control and precision machine design.