Abstract—In this article, a nonlinear robust optimal control (NROC) scheme for uncertain two-axis motion control system via adaptive dynamic programming (ADP) and neural networks (NNs) is proposed. The two-axis motion control system is an $X$–$Y$ table actuated by permanent-magnet linear synchronous motor servo drives. First, the motions of the tracking contour in $X$-axis and $Y$-axis of the $X$–$Y$ table are stabilized through feedback linearization control (FLC) laws. However, the control performance may be destroyed due to parameter uncertainties and compounded disturbances. Therefore, to improve the robustness of the control system, an NROC is designed to achieve this purpose. The tracking control problem of the $X$–$Y$ table with uncertainties is transformed to a regulation problem. Then, it is solved by an infinite horizon optimal control using a critic NN. Consequently, the NN is developed via ADP learning algorithm to facilitate the online solution of the Hamilton–Jacobi–Bellman equation corresponding to the nominal system for approximating the optimal control law. The uniform ultimate boundedness of the closed-loop system is proved utilizing the Lyapunov approach and the tracking error asymptotically converges to a residual set. The validation of the proposed control schemes are carried out through experimental analysis. The control algorithms have been implemented using a DSP control board. A comparison of control performances using FLC, adaptive FLC, and FLC-based NROC is investigated. From the experimental results, the dynamic behaviors of the two-axis control system using the proposed FLC-based NROC can achieve robust optimal control performance against parameter uncertainties and compounded disturbances.

Index Terms—Adaptive dynamic programming (ADP), Hamilton–Jacobi–Bellman (HJB), Lyapunov satiability, neural networks (NNs), nonlinear optimal control, permanent-magnet linear synchronous motor (PMLSM), $X$–$Y$ table.

I. INTRODUCTION

The permanent-magnet linear synchronous motor (PMLSM) drive is suitable for high-performance motion control applications and has been widely used for industrial robots, machine tools, micromachining for semiconductor, microelectronics manufacturing equipment, optical pointing devices, and $X$–$Y$ driving devices [1]–[6]. In these applications, PMLSMs are frequently used due to their simple structure, ease of manufacture, high power density, and high thrust to mass ratio, high efficiency, and low thermal losses. The wide variety of applications and increasing use of PMLSM drives make it necessary to come up with fast and reliable motor drive control system design approaches [3]–[5]. The direct drive design based on PMLSM has the following advantages: no backlash and less friction; high speed and high precision in long distance location; simple mechanical construction, resulting in higher reliability and frame stiffness; and high thrust force [3]–[5]. However, the PMLSM is affected by force ripple, parameter variations and external force disturbances. Moreover, the machine can exhibit cogging forces. Therefore, these parameter uncertainties (PUs) should be compensated to achieve high precision control in PMLSM drives.

The major issues considered in the high precision motion control of the $X$–$Y$ table driven by PMLSM servo drives include large variations of physical parameters; unknown nonlinearities such as cogging and ripple forces of PMLSM; uncertain dynamic nonlinearities (e.g., friction described by dynamic models in high precision motion controls), external disturbances, cross-coupled interference and frictional force and control input saturation due to limited capacity of physical actuators. Therefore, the $X$–$Y$ table system is a highly nonlinear time-varying system in practical applications. To deal with these uncertainties and the stochastic disturbances, and to enhance the control performance of the $X$–$Y$ table, different control strategies were adopted in literature [7]–[38]. During the past decade, stringent performance requirements of two-axis control systems driven by PMLSMs have forced control researchers to look beyond traditional linear control theory for more advanced controllers. Several advanced control strategies for PMLSM drives have been developed to achieve significant performance improvement in motion control applications, adaptive control [7]–[12], sliding-mode control...
[13], [14], $H^\infty$ optimal control [15], adaptive fuzzy-neural control [16]–[20], intelligent sliding-mode control [21], [22], and intelligent $H_\infty$ optimal control [23]. In addition, the recurrent-neural network (NN) sliding-mode control [24], fuzzy NN controller with nonlinear disturbance observer [25], backstepping sliding-mode control using an NN [26]–[29], adaptive recurrent neural-network control [30]–[34], nonlinear control [35], $H_2/H_\infty$ adaptive control [36], adaptive nonlinear disturbance observer with wavelet-NN [37], and neural adaptive dynamic surface control [38] have been developed for two-axis motion control systems driven by PMLSM servo drives.

Although the control methods in the literature for the $X$–$Y$ table systems can guarantee the stability, they ignored the optimal control problem. In closed-loop control system design, the stability is essential and is the main objective. A valuable control scheme should not only carry out the stability of the closed-loop system, but also make the cost of the controller as small as possible. Thus, the optimal controller design is more significant in practice. The linear optimal control with quadratic cost can be tackled by solving the well-known Riccati equation. But, the nonlinear optimal control problem always requires solving the HJB equation which involves solving nonlinear partial differential equations [39]. Though, dynamic programming has been used as a conventional method in solving optimization and optimal control problems. But it often suffers from the curse of dimensionality, which was primarily due to the backward-in-time approach. To avoid this difficulty, based on function approximation, such as NNS, adaptive dynamic programming (ADP) was proposed by Werbos [40] as a method to solve optimal control problems forward in time. Therefore, ADP is an efficient technique to solve optimal control problems. According to the classical control theories [41], [42], the optimal control problem can be converted to the solution of HJB equation, which is a nonlinear partial differential equation for continuous-time systems. The ADP approach has been used to solve the optimal tracking control problems [43]–[48]. In addition, online methods to solve the continuous HJB equation were studied for nonlinear affine systems using NNS [49]–[53]. In [54], a nonlinear robust optimal control (NROC) is designed to optimize the performance of the $X$–$Y$ table motion control system.

Actually, this is the first time that the infinite horizon NROC is developed for an uncertain $X$–$Y$ table system. The aim of this article is to design a NROC scheme for identification and control of uncertain $X$–$Y$ table system. First, the motions of the tracking contour in $X$-axis and $Y$-axis are stabilized through feedback linearization control (FLC) laws. However, the control performance may be destroyed due to PUs, external disturbances, cross-coupling interferences, and frictional forces. Thus, an adaptive FLC (AFLC) is proposed which comprises a FLC and an NN identifier to relax the impractical constraint by approximating the uncertain nonlinear functions of the $X$–$Y$ table system and estimate the upper bound of uncertainties. To overcome the problems of uncertain dynamics and to achieve the optimality and robustness of the control performance, the NROC is proposed. Subsequently, an NN-based online HJB solution via the ADP technique is used to obtain the optimal control inputs. Furthermore, a learning scheme combined with an additional stabilizing term is introduced in the NN weight update policy, which can stabilize the closed-loop system and accelerate the online learning process. The uniform ultimate boundedness of the closed-loop system is proved via the Lyapunov approach. The validity and robustness of the proposed control scheme are verified by experimental results. Finally, the main contributions of this article are concluded as follows.

1) The design and implementation of a novel AFLC with a robust controller via simple NN estimator.
2) The design and implementation of a novel infinite horizon NROC for an uncertain nonlinear $X$–$Y$ table system.
3) The NN weight update policy is combined with additional stabilizing term to speed up the learning process.

This article is organized as follows. Section II presents the dynamic modeling of the $X$–$Y$ table system and the problem formulation. In Section III, the design of FLC and AFLC is given. In Section IV, the NROC design methodology via online HJB solution using ADP and NN as well as the stability analysis is developed. The control algorithms have been implemented using DS1104 control computer. Experimental results are provided in Section V to validate the effectiveness of the proposed NROC. The dynamic performance has been studied under PUs and external disturbances. Conclusions are drawn in Section VI.

II. MATHEMATICAL MODELING OF THE TWO-AXIS $X$–$Y$ TABLE INCLUDING ACTUATOR DYNAMICS

A. Modeling of the Two-Axis $X$–$Y$ Table Driven by PMLSm

Consider the fourth-order dynamic mathematical modeling of the single-axis PMLSM in the synchronously rotating reference frame. During the operation of the $X$–$Y$ table, the parameters are varying as a result of reaction real resistively, air-gap dynamics, phase unbalance, load thrust disturbance, changing temperature, and end effect [36], [37], [54]. With the consideration of all these uncertainties, the perturbed dynamic model based on the field-orientation control (FOC) can be represented in the state form as follows:

$$\dot{x}_1 = \dot{x}_m = v_m$$

$$\dot{x}_2 = \dot{v}_m = -\frac{D}{M}v_m - \frac{1}{M}(F_L + F_f(v_m)) + \frac{K_F}{M}i_{qs} + \Xi_v$$

$$\dot{x}_3 = \dot{i}_{qs} = -\frac{R_s}{L_{qs}}i_{qs} - \frac{\pi}{\tau_p i_{ds}}L_{ds}v_m i_{ds} - \frac{\lambda_{PM}}{\tau_p}L_{qs}v_m + \frac{V_{qs}}{L_{qs}} + \Xi_q$$

$$\dot{x}_4 = \dot{i}_{ds} = -\frac{R_s}{L_{ds}}i_{ds} + \frac{\pi}{\tau_p i_{qs}}L_{qs}v_m i_{qs} + \frac{V_{ds}}{L_{ds}} + \Xi_d$$

where $V_{qs}$, $V_{ds}$, $i_{qs}$, and $i_{ds}$ are the $d$–$q$ axis voltages and currents, respectively. $R_s$ is the phase winding resistance, $L_{ds}$ and $L_{qs}$ are the $d$–$q$ axis inductances, and $\lambda_{PM}$ is the permanent magnet flux linkage, $x_m$, $v_m$ and $P$ are the mover position, the linear velocity, and the number of primary poles, respectively. $F_L$, $F_f$, $M$, $D$, and $K_F$ are the external thrust disturbance, the frictional force, the total mass of the mover, the viscous friction and iron-loss coefficient, and the thrust constant, respectively.
The developed electromagnetic thrust can be expressed as

$$F_e = K_f (\lambda_{ds} i_{qs} + (L_{ds} - L_{qs}) i_{ds} i_{qs}).$$

(5)

Then, using FOC and setting \(d\)-axis current as zero, the electromagnetic thrust is obtained as

$$F_e = K_F i_{qs}$$

(6)

where \(K_f = (3/2) \cdot (P/2) \cdot (\pi/\tau_p)\) is the force constant; \(K_F = K_\lambda \lambda_{PM}\).

The equation of motion of the mover is given by

$$F_e = M \frac{dv_m}{dt} + Dv_m + F_L + F_f(v_m).$$

(7)

The friction force can be formulated as [4]

$$F_f(v_m) = F_C \text{sgn}(v_m)$$

$$+ (F_S - F_C) e^{-\left(\frac{v_m}{v_s}\right)} \text{sgn}(v_m) + K_v v_m$$

(8)

where \(F_C\) is the Coulomb friction, \(F_S\) is the static friction, \(v_s\) is the Striebeck velocity parameter, \(K_v\) is the viscous friction coefficient, and \(\text{sgn}(\cdot)\) is a function. All the parameters in (8) are time varying.

B. Problem Formulation for the Nonlinear X–Y Table System

Consider the mathematical model of the nonlinear uncertain X–Y table system (1)–(8) described by the canonical form as

$$\dot{x}(t) = \Gamma(x, u) = f(x(t)) + g(u(t)) + \Xi(x(t))$$

(9)

where \(x(t) = [x_1, x_2, \ldots, x_n]^T \in \mathbb{R}^n\) is the state vector, \(u(t) = [u_1, u_2, \ldots, u_n]^T \in \mathbb{R}^n\) is the control input vector, \(f(x(t)) \in \mathbb{R}^n\) and \(g(x(t)) \in \mathbb{R}^{n \times n}\) are the system nonlinear functions assumed to be bounded, and assume \(g(x(t))\) is invertible, \(\Xi(x(t))\) is the unknown nonlinear perturbation which has assumed an upper bound \(\|\Xi(x(t))\| \leq \zeta; \|\cdot\|\) is the Euclidean norm and \(\zeta\) is a positive constant. \(f(\cdot)\) and \(g(\cdot)\) are known functions and are differentiable in their arguments with \(f(0) = 0\). Let \(x(0) = x_0\) be the initial state ensuring that \(x = 0\) is equilibrium of (9).

The detailed description for the perturbed dynamical model of practical nonlinear systems (9) can be expressed in the following state-space form:

$$\dot{x}_1(t) = f_1(x(t)) + g_1(x_1) x_2 + \Xi_1(x(t))$$

$$\dot{x}_2(t) = f_2(x(t)) + g_2(x_1, x_2) x_3 + \Xi_2(x(t))$$

$$\vdots$$

$$\dot{x}_i(t) = f_i(x(t)) + g_i(x_1, x_2, \ldots, x_i) x_{i+1} + \Xi_i(x(t))$$

(10)

$$\vdots$$

$$\dot{x}_n(t) = f_n(x(t)) + g_n(x) u + \Xi_n(x(t))$$

where \(i = 1, 2, \ldots, n-1, x = [x_1, x_2, \ldots, x_n]^T\) is the state vector, and \(u(t)\) is the control input. The \(f_i, g_i, i = 1, 2, \ldots, n\) are smooth functions and virtual control-gain functions, respectively. \(\Xi_i(x(t)), i = 1, 2, \ldots, n\) are bounded uncertainties consisting of unknown modeling errors, parameter variations, frictional force, cross-axis coupling interferences, and external thrust disturbances.

The motivation of our approach comes from the cascade control structure. By looking at the X–Y table system dynamic model (1)–(4), a very special structure is noticed. According to (1)–(4), (9)–(10), the dynamic model can be considered as two nonlinear systems in cascade as given in (11) and (12). The mover position \(x_m(t)\) is regulated to control subsystem (1)–(2), (11) and construct the desired commands \(v_m\) and \(i_{qs}\). In addition, the \(d-q\) axis currents \(i_{qs}, i_{ds}\) are regulated to control subsystem (3)–(4), (12) to construct the actual control inputs \(V_{qs}\) and \(V_{ds}\):

$$\dot{X}_{OL}(t) = F_{OL}(x(t)) + G_{OL} U_{OL}(t) + \Xi_{OL}(x(t))$$

(11)

$$\dot{X}_{IL}(t) = F_{IL}(x(t)) + G_{IL} U_{IL}(t) + \Xi_{IL}(x(t))$$

(12)

$$F_{OL}(x(t)) = \begin{bmatrix} f_1(x) \\ f_2(x) \end{bmatrix} = \begin{bmatrix} - \frac{R_s}{L_{qs}} i_{qs} - \frac{\pi}{\tau_p} \frac{L_{ds}}{L_{qs}} i_{ds} - \frac{\pi}{\tau_p} \lambda_{PM} v_m \\ - \frac{R_s}{L_{ds}} i_{ds} + \frac{\pi}{\tau_p} \frac{L_{qs}}{L_{ds}} v_m i_{qs} \end{bmatrix}$$

(13a)

$$F_{IL}(x(t)) = \begin{bmatrix} f_3(x) \\ f_4(x) \end{bmatrix}$$

where

$$G_{OL}(x) = \begin{bmatrix} 1 & 0 \\ 0 & K_F / M \end{bmatrix}$$

(14a)

$$G_{IL}(x) = \begin{bmatrix} 1 / L_{qs} & 0 \\ 0 & 1 / L_{ds} \end{bmatrix}$$

(14b)

$$U_{OL} = [v_m^T i_{qs}^T]^T$$

(15a)

$$U_{IL} = [u_{qs} u_{ds}^T]^T$$

(15b)

$$\Xi_{OL}(x(t)) = \begin{bmatrix} \Xi_1(x(t)) \\ \Xi_2(x(t)) \end{bmatrix}$$

$$\Xi_{IL}(x(t)) = \begin{bmatrix} \Xi_3(x(t)) \\ \Xi_4(x(t)) \end{bmatrix}$$

(16a)

where

$$x(t) = [x_1 x_2 x_3 x_4]^T = [x_m v_m i_{qs} i_{ds}]^T$$

is the state vector, \(\Xi_1, \Xi_2, \Xi_3, \Xi_4\) denote the lumped PUs; \(\Delta R_s\), \(\Delta L_{qs}\), \(\Delta L_{ds}\), \(\Delta M\), \(\Delta D\), \(\Delta F_{IL}\), and \(\Delta K_F\) are the uncertainties introduced by the system parameters; \(w_m, w_{qs}, w_{dt}\) expresses the external disturbances in practical applications, respectively. The \(F_{OL}, F_{IL}, G_{OL}, \) and \(G_{IL}\) are nonlinear functions for outer and inner subsystems (11)–(12). \(\Xi_{OL}\) and \(\Xi_{IL}\) are the uncertainties of outer and inner subsystems too. The \(g_{OL}\) and \(g_{IL}\) are positive-definite matrices.
Remark 1: In the X–Y table dynamic modeling formulated by (1)–(8) with all uncertainties, it is obvious that the existence of nonlinearities due to the multiplied linear velocity of the mover and d–q axis current terms as well as the flux-linkage term. In addition, there exist nonlinearities due to the nonlinear characteristics of the current-regulated pulse width modulation (CRPWM) inverter. Moreover, the parameter variations also increase the nonlinearities and degrade the control performance or even destroy the stability of the system. Hence, nonlinearities, parameter variations, and external thrust disturbances should be eliminated or limited in an attenuation level. This is a significant reason for the complexity and difficulty to design a robust control scheme that realizes real-time stabilization and accurate control simultaneously. Fortunately, the overall nonlinear dependence could be considered into the lumped uncertainties (16) and the proposed controller should be robust enough to tolerate these uncertainties. In this article, a cascade control structure including inner and outer control loops as shown in Fig. 1 is proposed for stabilization and accurate control of nonlinear X–Y table system. In this control system, the feedback mover position \( x_m(t) \) through the outer control loop generates the desired velocity, \( v_m^* \), and thrust, \( i_{qs}^* \), commands. In addition, the feedback d–q axis currents through the inner control loops generate the actual input voltages \( V_{qs} \) and \( V_{ds} \). The aim of the inner control loop is to design a NROC–IL law with NN identifier so that d–q axis currents can fit the command currents and construct the actual control input voltage. In the outer control loop, the NROC–OL law with NN identifier is designed so that mover position tracks the reference mover position and the tracking error converges to zero.

Assumption 1: The states of the X–Y table driven by PMLSM servo drives are available for feedback.

III. FLC System

A. Design of the FLC

The control problem is to find a control law so that the X–Y table system trajectory \( x(t) \) can track the desired trajectory \( x_d(t) \) in the presence of unknown dynamics and compounded disturbances. Assume that the system in (9) is controllable and feedback linearizable [57]. The tracking error \( e(t) \) and the filtered tracking error dynamics \( r(t) \) are chosen as

\[
e(t) = x_d(t) - x(t)
\]

\[
r(t) = e^{n-1} + k_{n-1}e^{n-2} + \cdots + k_1e = k_l^T e.
\]

If the nonlinear functions \( f(x(t)) \) and \( g \) are well known, then the control input can be designed as

\[
u_{FLC}(t) = g^{-1} \left[ -f(x) - \sum_{i=1}^{n-1} k_i e_{(i+1)}^{(n)} + x_d^{(n)} - \zeta \text{sgn}(r) \right]
\]

where \( k_i \) is the gain matrix to be designed for the best transient control performance, the control gain \( \zeta \) is concerned with the upper bound of uncertainty vector \( \Xi(x(t)) \) and \( \text{sgn}(r) \) represents the sign function of each element in the filtered error vector \( r \). According to the Lyapunov theorem [56], the stability of the FLC scheme can be guaranteed. But, the upper bound of PUs and external disturbances needs to be determined in advance.
to construct the FLC algorithm. The exact upper bound in the FLC algorithm cannot be obtained in practical applications. Furthermore, the conservative selection of a high control gain can induce a large amount of chattering. However, the parameters of the functions $f(x(t))$ and $g$ and the unknown disturbance are not precisely known such that the FLC law in (19) cannot be implemented. So, to relax the impractical constraint, an NN identifier is utilized to approximate the uncertain nonlinear function $\Xi(x(t))$ and estimate the upper bound of uncertainties $\zeta$. Therefore, an AFLC is proposed in the following section.

B. Design of the AFLC

The control objective is to design an AFLC scheme which specifying the approximation of $\Xi(x(t))$ and $\zeta$.

**Theorem 1:** Consider the $X-Y$ table represented by (9) with uncertain nonlinear functions $\Xi(x(t))$ which is approximated as (22), the AFLC is designed as (20), (23) in which the adaptation laws of the NN estimators are designed as (29)–(31). The AFLC law is designed as

$$u_{\text{AFLC}}(t) = g^{-1} \left[ -f(x) - \sum_{i=1}^{n-1} k_i e_{(i+1)} + x_d^{(n)} - \hat{\Xi}(x) - \zeta \text{sgn}(r) \right].$$

(20)

Using an NN estimator, the uncertainty $\Xi$ can be represented as

$$\Xi = W^T \Psi + \varepsilon$$

(21)

where $\varepsilon$ is a minimum reconstructed error. The NN functional estimate of $\Xi$ is given by

$$\hat{\Xi} = \hat{W}^T \Psi$$

(22)

where $\hat{W}$ are estimates of the ideal weight value. The Lyapunov method is applied to derive the reinforcement adaptive learning rules for the weight values. Since these adaptive learning rules are formulated from the stability analysis of the controlled $X-Y$ table, the system performance can be guaranteed for the closed-loop control.

**Assumption 2:** Let the input $x = [x_1, x_2, \ldots, x_d]^T$ of the NN belongs to a compact set $\Sigma_W$ and the NN is used to approximate the nonlinear function $\Xi(x(t))$. The optimal parameter vector $W^*$ of the $\hat{W}(\cdot)$ is given by

$$W^* = \arg \min_{W \in \Sigma_W} \left[ \sup_{x \in \Sigma_W} \| \Xi(x) - \hat{\Xi} \| \right]$$

(23)

where $\Sigma_W$ are compact sets of suitable bounds on $\hat{W}$ and it is assumed that $W^*$ is restricted to $\Sigma_W$.

The AFLC, $u_{\text{AFLC}}(t)$, in (20) is rewritten as

$$u_{\text{AFLC}}(t) = \frac{-f(x) - \sum_{i=1}^{n-1} k_i e_{(i+1)} + x_d^{(n)} - \hat{W}^T \Psi - \hat{u}_r}{g}$$

(24)

where $\hat{u}_r$ is a robust controller which is designed to compensate the minimum approximation error of the NN uncertainty identifier. To develop the robust controller, the minimum approximation error $\varepsilon$ is defined as

$$\varepsilon = (\hat{\Xi} - \Xi).$$

(25)

The absolute value of the minimum approximation error $\varepsilon$ is bounded by known positive value, $\zeta$ (i.e., $| \varepsilon | < \zeta$).

Using (20), (24), and (9), the error dynamic equation is obtained as follows:

$$\dot{\varepsilon} = -ke + \hat{\Xi} - \Xi - \hat{u}_r$$

$$= -ke + [\hat{W}^T \Psi + \varepsilon - \hat{u}_r].$$

(26)

Choose the Lyapunov function candidate as

$$V(t) = \frac{1}{2} \varepsilon^2 + \frac{1}{2g} tr(\hat{W}^T \hat{W})$$

(27)

where $\eta$ is a learning rate. Using (25) and (26), the derivative of $V(t)$ is given by

$$\dot{V}(t) = e^T \dot{\varepsilon} + \frac{1}{\eta} tr(\hat{W}^T \hat{W})$$

$$= -ke^2 + e[\hat{W}^T \Psi + \varepsilon - \hat{u}_r] + (1/\eta) tr(\hat{W}^T \hat{W})$$

$$= -ke^2 + e[\varepsilon - \hat{u}_r] + e\hat{W}^T \Psi + (1/\eta) tr(\hat{W}^T \hat{W}).$$

(28)

To satisfy $\dot{V}(t) \leq 0$, the updated law $\dot{\hat{W}}$ and the robust controller $\hat{u}_r$ are designed as

$$\dot{\hat{W}} = -\eta_w \hat{\Psi}$$

(29)

$$\hat{u}_r = \hat{\Psi} \text{sgn}(e)$$

(30)

$$\zeta = \eta_e$$

(31)

where $\eta_w$ and $\eta_e$ are positive constants; $W$ is the weight vector, and $\Psi$ is the firing strength vector, respectively. $\zeta$ is the online estimated value of the uncertain term $\zeta$.

Then, for any initial conditions satisfying Assumption 2, the adjustable weight $\hat{W}$ of the closed-loop system is uniformly ultimately bounded (UUB) and may be kept at arbitrary small constant. The stability proof of the AFLC is given in [54]. But due to the estimation of uncertain dynamics, the computation burden of the AFLC is very high. So, to overcome this problem and to optimize the control performance of the two-axis motion control system, the FLC based on the NROC is proposed. In the proposed controller, the term $\zeta \text{sgn}(e)$ is replaced by an optimal auxiliary control function $\hat{u}(x)$ which will be designed in Section IV.

IV. ROBUST OPTIMAL CONTROL DESIGN METHODOLOGY USING ONLINE ADAPTIVE DYNAMIC PROGRAMMING

A. Problem Formulation

It should be pointed out that although the control design methods in the literature for the $X-Y$ table systems can guarantee the stability, but they ignored the optimal control problem. In closed-loop control system design, the stability is essential and is the main objective. A valuable control scheme should not only carry out the stability of the closed-loop system, but also make
the cost of the controller as small as possible. Thus, the optimal controller design is more significant in practice. The structure of the proposed NROC for high dynamic performance X–Y table system is shown in Fig. 1. The control objective is to design an NROC scheme such that the output can track a reference contour and the closed-loop system is stable in the presence of PUs and external disturbances. In addition, all errors are UUB and the cost function is minimized. Besides, the magnitude of the tracking error can be arbitrary small as \( t \to \infty \). The NROC law is designed as

\[
\mathbf{u}_{\text{NROC}}(t) = \mathbf{g}^{-1} \left[ -f(x) - \sum_{i=1}^{n-1} k_i \mathbf{e}_{i+1} \right. \\
\left. + x_d^{(n)} - \hat{u}(x) \right]
\]  

(32)

where \( \hat{u}(x) \) is the approximate of optimal auxiliary control function \( u^*(x) \) which will be designed in the next section. Defining the nominal system corresponding to the perturbed dynamic model (10) in a standard form of nonlinear system as

\[
\dot{x}(t) = \mathbf{\Gamma}(x, u) = f(x(t)) + gu(t).
\]  

(33)

Assume that \( (f(x(t)) + gu(t)) \) is Lipschitz continuous on set \( \Omega \) in \( \mathbb{R}^n \) containing the origin and the system (1)–(4), (33) is controllable.

Assumption 3: Assume that the nonlinear dynamic uncertainty \( \Xi(x(t)) \) has the form [51], [53], [54]

\[
\Xi(x) = \Lambda(x) d(x)
\]  

(34)

\[
d^T(x)d(x) \leq h^T(x)h(x)
\]  

(35)

where \( \Lambda(\cdot) \in \mathbb{R}^{n \times r} \) is the known function denoting the structure of the uncertainty, \( d(\cdot) \in \mathbb{R}^r \) is uncertain function with \( d(0) = 0 \), and \( h(\cdot) \in \mathbb{R}^n \) is a given function with \( h(0) = 0 \).

For the two-axis motion control system, the infinite horizon cost function is considered as

\[
\mathbf{V}(x_0, u) = \int_0^\infty \mathbf{U}(x(\tau), u(\tau)) d\tau
\]  

(36)

where \( \mathbf{U}(x, u) = x^T Q x + u^T R u, \) both \( Q = Q^T > 0 \) and \( R = R^T > 0 \) are positive-definite symmetric matrices. The optimal cost function of system (33) can be formulated as

\[
V^*(x_0, u) = \min_{w \in \mathbb{R}^r} \int_0^\infty \mathbf{U}(x(\tau), u(\tau)) d\tau.
\]  

(37)

B. Robust Optimal Control

The aim of this section is to design an auxiliary optimal feedback control function \( u(x) \) and determine a finite upper bound function \( \varphi(u) < \infty \) by solving the cost function, such that the closed-loop system is robustly stable and the cost function (36) satisfies \( V \leq \varphi \). The robust optimal control problem of system (9) can be transformed into the optimal control problem of its corresponding analytical dynamic model via a modified HJB equation. This means that the robust optimal control policy can be obtained by solving the modified HJB equation using the ADP. The unknown nonlinear lumped parameter uncertainty \( \Xi(x(t)) \) may destroy the stability of the control system and hence it needs to be handled carefully. The robust approximate optimal control is derived based on the modified cost function as follows.

**Theorem 2:** Assume that there exists a positive and differentiable cost function \( V(x) \) for all \( x \neq 0 \) with \( V(0) = 0 \), a bounded function \( \Theta(x) \) satisfying \( \Theta(x) \geq 0 \) and a feedback control function \( u(x) \) such that

\[
(\nabla V(x))^{T} \mathbf{\Gamma}(x, u) \leq (\nabla V(x))^{T} \mathbf{\Gamma}(x, u) + \Theta(x)
\]  

(38)

\[
\nabla V(x))^{T} \mathbf{\Gamma}(x, u) + \Theta(x) < 0, \quad x \neq 0
\]  

(39)

\[
U(x, u) + (\nabla V(x))^{T} \mathbf{\Gamma}(x, u) + \Theta(x) = 0
\]  

(40)

where \( \nabla V(x) = \partial V(x)/\partial x \) denotes the partial derivative of the cost function \( V(x) \) with respect to \( x \). Define a positive bounded function

\[
\Theta(x) = h^T(x)h(x) + \frac{1}{4}(\nabla V(x)\Lambda(x)\Lambda(x)^T \nabla V(x))
\]  

(41)

where \( h(\cdot) \) is a function satisfying \( d^T(x)d(x) \leq h^T(x)h(x) \). The modified cost function is given by

\[
V(x_0, u) = \int_0^\infty \{U(x(\tau), u(x(\tau))) + \Theta(x(\tau))\} d\tau.
\]  

(42)

We can find that the modified cost function satisfies

\[
V(x_0, u) = V(x_0) \geq \tilde{V}(x_0, u).
\]  

(43)

As a result, we can find an optimal auxiliary control function \( u(x) \) to make the system (9) asymptotically stable according to the modified cost function (42). The optimal auxiliary control law can be obtained by applying the stationary condition \( \partial H(x, u, \nabla V(x))/\partial u = 0 \), which yields

\[
u^*(x) = -\frac{1}{2} R^{-1}g^T \nabla V^*(x).
\]  

(44)

**Proof of Theorem 2:** The proof of Theorem 2 is given in [54].

C. Design of the Infinite Horizon Robust Optimal Control

In this section, an infinite horizon robust optimal control design via online HJB solution using ADP is presented for the X–Y table system. According the universal approximation property [50]–[54], a single-layer critic NN with time-invariant activation function is constructed to approximate the modified cost function on a compact set \( \Omega \) as follows:

\[
V(x) = W_c^T \Phi_c(x) + \varepsilon_c(x)
\]  

(45)

where \( W_c \in \mathbb{R}^n \) is the ideal NN weight, \( \Phi_c \in \mathbb{R}^n \) is the time-invariant activation function, \( \kappa \) is the number of neurons in the hidden layer, and \( \varepsilon_c(x) \) is the unknown reconstruction error of the NN. The NN weights and the reconstruction error \( \varepsilon_c(x) \) are assumed to be upper bound as \( ||W_c|| \leq W_M \) and \( ||\varepsilon_c(x)|| \leq \varepsilon_M \).

The gradient of the cost function is given by

\[
\nabla V(x) = (\nabla \Phi_c(x))^T W_c + \varepsilon_c(x)
\]  

(46)

where \( \nabla \Phi_c(x) = \partial \Phi_c(x)/\partial x \) and \( \nabla \varepsilon_c(x) = \partial \varepsilon_c(x)/\partial x \) the gradient of the activation function and the NN reconstruction error, respectively. The gradient of \( \varepsilon_c(x) \) is assumed to satisfy \( ||\nabla \varepsilon_c(x)|| \leq \varepsilon_M \).

Assumption 4: The weight vector \( W_c \), the reconstruction error \( \varepsilon_c(x) \) and its gradient \( \nabla \varepsilon_c(x) \) and the gradient \( \nabla \Phi_c(x) \) are all bounded on a compact set \( \Omega \).
A critic NN is used to approximate the cost function in terms of the estimated weights as

$$\hat{V}(x) = \hat{W}_c^T \Phi_c(x).$$  \hspace{1cm} (47)

Consequently, the gradient of the estimated cost function is

$$\nabla \hat{V}(x) = (\nabla \Phi_c(x))^T \hat{W}_c$$  \hspace{1cm} (48)

where $\nabla \hat{V}(x) = \partial \hat{V}(x)/\partial x$.

In addition, from the optimal control law (44) and (48), the approximate optimal auxiliary control law can be obtained in terms of the estimated cost function as

$$\hat{u}(x) = -(1/2)R^{-1}g^T(\nabla \Phi_c(x))^T \hat{W}_c.$$  \hspace{1cm} (49)

The proof of the infinite horizon robust optimal control and the critic NN update weights is given in [54].

The structure of the proposed infinite-horizon optimal control for the two-axis motion control system is shown in Fig. 2 and the flowchart of the implementation process using critic NN is illustrated in Fig. 3.

D. Stability Analysis of the Robust Optimal Control System

In this section, the stability analysis of the closed-loop system using the critic NN is presented using the Lyapunov theory. The UUB of the error dynamics of the critic NN weight estimation error and the closed-loop system based on the approximate optimal control will be proved using the Lyapunov approach.

Theorem 3: Consider the two-axis motion control system driven PMSLM drives with model uncertainties represented by (9) and Assumption 3. The optimal control law is given by (49) and the critic NN weights are tuned by (50). Then, the critic NN weight estimation error $\hat{W}_c$ and states of the closed-loop system are UUB

$$\dot{\hat{W}}_c = -\eta_c \frac{\partial E_c}{\partial \hat{W}_c}$$

$$\dot{\hat{W}}_c = -\frac{1}{2} \eta_c \psi(x, \hat{u})(\nabla \Phi_c(x))^T g R^{-1} g^T(\nabla J_s(x))$$  \hspace{1cm} (50)

$$\dot{\hat{W}}_c = -\hat{W}_c = \eta_c e_c \frac{\partial e_c}{\partial \hat{W}_c}$$

$$\dot{\hat{W}}_c = -(1/2)\eta_c \psi(x, \hat{u})(\nabla \Phi_c(x))^T g R^{-1} g^T(\nabla J_s(x)).$$  \hspace{1cm} (51)

Proof of Theorem 3: The proof is given in [54].

V. EXPERIMENTAL VALIDATION OF THE TWO-AXIS X–Y TABLE MOTION CONTROL SYSTEM

In order to investigate the effectiveness of the proposed NROC with ADP and NNs, the implementation of the control algorithms are carried out using MATLAB/SIMULINK based on the control system shown in Figs. 1–4. A dSPACE DS1104 control board, which is based on an MPC8240 64-bit floating-point
A hardware experimental prototype of the two-axis motion control system was tested to validate the high performance of the developed NROC scheme compared to the FLC and AFLC schemes. The laboratory tests were performed based on the control schemes presented in Figs. 1–4. To verify the performance, the proposed FLC, AFLC, and NROC schemes are applied to control the X–Y table system. Some experimental results are introduced using two cases of PUs which are the nominal case (Case 1: $M_x = M_y = M$ and $F_{Lx} = F_{Ly} = 25$ N) and the parameter variation case (Case 2: $M_x = M_y = 3M$ and $F_{Lx} = F_{Ly} = 75$ N). The experimental results of the dynamic performance for the proposed NROC schemes due to rhombus reference contour are predicted as shown in Figs. 5–7 at both cases of PU and subsequent loading. The dynamic response of the reference and actual rhombus contours in X–Y axis is shown in Fig. 5. The dynamic performance of the X–Y table system involving reference and actual motion tracking response, the motion tracking errors, the reference and actual velocity tracking response, the velocity tracking errors, the reference and actual control effort, and the adaptive motion/velocity signals due to rhombus contour in X-axis at Case 1 of PU are depicted in Fig. 6(a). The dynamic responses at Case 2 of PU
are illustrated in Fig. 6(b). The dynamic performance including the same previous responses due to rhombus contour in $Y$-axis at Cases 1 and 2 of PU is given in Fig. 7. The experimental results of the dynamic performance for the proposed NROC due to rhombus reference contour are predicted as shown in Figs. 8–10 at both cases of PU and subsequent loading. From these results, favorable tracking responses and robust control characteristics are achieved at both cases of PU. Therefore, the proposed NROC has verified its preferable performance for the $X$-$Y$ table system with greatly improved characteristics to a great extent when uncertainties occur. Consequently, it was proved that the developed NROC design accomplishes the precision demands, robustness, and suitability for high-performance $X$-$Y$ table motion control system in practical applications.
TABLE I
PERFORMANCE MEASURES OF THE FLC FOR THE TWO-AXIS MOTION CONTROL SYSTEM

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Tracking Errors (µm)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Maximum</td>
<td>Average</td>
</tr>
<tr>
<td>Case (1)</td>
<td>84.15</td>
<td>71.61</td>
</tr>
<tr>
<td>Case (2)</td>
<td>99.85</td>
<td>85.25</td>
</tr>
</tbody>
</table>

TABLE II
PERFORMANCE MEASURES OF THE AFLC FOR THE TWO-AXIS MOTION CONTROL SYSTEM

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Tracking Errors (µm)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Maximum</td>
<td>Average</td>
</tr>
<tr>
<td>Case (1)</td>
<td>39.18</td>
<td>37.85</td>
</tr>
<tr>
<td>Case (2)</td>
<td>47.65</td>
<td>42.34</td>
</tr>
</tbody>
</table>

TABLE III
PERFORMANCE MEASURES OF THE NROC FOR THE TWO-AXIS MOTION CONTROL SYSTEM

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Tracking Errors (µm)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Maximum</td>
<td>Average</td>
</tr>
<tr>
<td>Case (1)</td>
<td>13.11</td>
<td>12.24</td>
</tr>
<tr>
<td>Case (2)</td>
<td>15.12</td>
<td>14.84</td>
</tr>
</tbody>
</table>

TABLE IV
PERCENTAGE REDUCTION OF TRACKING ERRORS FOR THE AFLC WITH REGARD TO FLC FOR THE TWO-AXIS MOTION CONTROL SYSTEM

<table>
<thead>
<tr>
<th>Parameter</th>
<th>% RTE</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Maximum</td>
<td>Average</td>
</tr>
<tr>
<td>Case (1)</td>
<td>53.44 %</td>
<td>47.14 %</td>
</tr>
<tr>
<td>Case (2)</td>
<td>52.28 %</td>
<td>50.33 %</td>
</tr>
</tbody>
</table>

TABLE V
PERCENTAGE REDUCTION OF TRACKING ERRORS FOR THE NROC WITH REGARD TO FLC FOR THE TWO-AXIS MOTION CONTROL SYSTEM

<table>
<thead>
<tr>
<th>Parameter</th>
<th>% RTE</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Maximum</td>
<td>Average</td>
</tr>
<tr>
<td>Case (1)</td>
<td>84.42 %</td>
<td>82.91 %</td>
</tr>
<tr>
<td>Case (2)</td>
<td>84.86 %</td>
<td>82.59 %</td>
</tr>
</tbody>
</table>

B. Evaluation of Control Performance

To evaluate the performance of the X–Y table motion control system, the maximum tracking error, TE_{max}, the average tracking error, TE_{mean}, and the standard deviation of the tracking error, T_{sd}, are defined in [54]. To further investigate the performance improvement, the performance evaluations of the FLC, AFLC, and NROC at PUs are compared and summarized in Tables I, II, and III, which include the maximum, the average and the standard deviation of the tracking errors at the two cases of parameters uncertainties. In addition, the percentage reduction in the tracking errors (%RTE) for AFLC and NROC schemes with regard to FLC at the same operating conditions is summarized in Tables IV and V using the following relation:

\[
%\text{RTE} = \left(1 - \frac{TE_{C}}{TE_{FLC}}\right) \times 100 \tag{54}
\]

where TE_{C} is the tracking errors using the proposed controller and TE_{FLC} is the tracking errors using the FLC.

From these results shown in Tables IV and V, it is obvious that the high values of the tracking errors have been successfully reduced by the NROC scheme. Therefore, the NROC possesses the robust control characteristics and can control the X–Y table system effectively.

C. Comparison of Control Performance

The performance evaluation of the different control schemes, FLC, AFLC, and NROC, is depicted in Fig. 11. The various comparative performance measures with respect to FLC show that the proposed NROC provides lower tracking errors by: 84.42% and 84.86% for maximum errors at Cases 1 and 2, respectively; 92.91% and 82.59% for average errors at Cases 1 and 2, respectively; 81.17% and 83.72% for standard deviation errors at Cases 1 and 2, respectively. In regards to AFLC compared to FLC, the averages of the maximum, average, standard deviation tracking errors are decreased by 53.44%, 47.14%, and
TABLE VI
Performance Evaluation Analogy of the X–Y Table Control System

<table>
<thead>
<tr>
<th>Controller</th>
<th>Errors (μm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Maximum</td>
</tr>
<tr>
<td>FLC (current paper)</td>
<td>84.13</td>
</tr>
<tr>
<td>AFLC (current paper)</td>
<td>39.18</td>
</tr>
<tr>
<td>NROC (current paper)</td>
<td>11.11</td>
</tr>
<tr>
<td>Recurrent neural network sliding-mode control (RNNSMC) [25]</td>
<td>22.11</td>
</tr>
<tr>
<td>Recurrent fuzzy neural network nonlinear disturbance observer (RFNNCNDNDO) [25]</td>
<td>26.05</td>
</tr>
<tr>
<td>Backstepping sliding-mode control (BSMC) [26]</td>
<td>50.80</td>
</tr>
<tr>
<td>Intelligent backstepping sliding-mode control (IBSMC) [26]</td>
<td>25.40</td>
</tr>
<tr>
<td>Fuzzy neural network control (FNNC) [27]</td>
<td>60.71</td>
</tr>
<tr>
<td>Recurrent fuzzy neural network control (RFNNC) [27]</td>
<td>17.20</td>
</tr>
<tr>
<td>Recurrent fuzzy neural network sliding-mode control (RFNNSMC) [27]</td>
<td>31.90</td>
</tr>
<tr>
<td>Filtering-type sliding-mode control (FSC) [29]</td>
<td>74.39</td>
</tr>
<tr>
<td>Filtering-type sliding-mode control with a radial basis function network (FSCRBFN) [29]</td>
<td>27.33</td>
</tr>
<tr>
<td>Optimal computed torque control (OCTC) [35], [38]</td>
<td>60.25</td>
</tr>
<tr>
<td>Dynamic surface control (DSC) [35], [38]</td>
<td>35.48</td>
</tr>
<tr>
<td>Adaptive dynamic surface control (ADSC) [35], [38]</td>
<td>22.58</td>
</tr>
<tr>
<td>Robust adaptive dynamic surface control (RADSC) [35], [38]</td>
<td>12.50</td>
</tr>
<tr>
<td>Feedback linearization control-nonlinear disturbance observer (FLC-NDO) [36]</td>
<td>54.69</td>
</tr>
<tr>
<td>Adaptive nonlinear disturbance observer (ANDO) [36]</td>
<td>17.23</td>
</tr>
<tr>
<td>Fuzzy wavelet neural network control (FWNNC) [37]</td>
<td>62.90</td>
</tr>
<tr>
<td>Intelligent adaptive tracking control system (IATCS) [37]</td>
<td>16.11</td>
</tr>
</tbody>
</table>

TABLE VII
Comparison of FLC, AFLC, and NROC Control Schemes

<table>
<thead>
<tr>
<th>Control Scheme</th>
<th>Robustness</th>
<th>Learning Ability</th>
<th>Tracking Speed</th>
<th>Computation Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>FLC</td>
<td>Fair</td>
<td>None</td>
<td>Slow</td>
<td>Low</td>
</tr>
<tr>
<td>AFLC</td>
<td>Good</td>
<td>Online</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>NROC</td>
<td>Favorable</td>
<td>Online</td>
<td>Fast</td>
<td>Medium</td>
</tr>
</tbody>
</table>

41.74% at Case 1 of PUs, respectively. As well, the averages of the maximum, average, standard deviation tracking errors are decreased by 52.28%, 50.33%, and 37.07%, respectively; at Case 2 of PUs are achieved for AFLC compared to FLC. The percentage reductions of the tracking errors utilizing the AFLC and the proposed NROC schemes compared to the FLC scheme are shown in Fig. 12. The comparative analysis of the control performance is illustrated in Tables I–III. Furthermore, Tables IV and V depict the improvement in the tracking errors using the AFLC and the proposed NROC in comparison to the FLC. In Table VI, the performance evaluation of the proposed FLC, AFLC, and NROC schemes along with prior research work is provided. It is evident that the proposed NROC provides better dynamic performance under PUs. The comparison between FLC, AFLC, and NROC schemes according to the robustness, the learning ability, the tracking speed, and the computation burden is given in Table VII. It is apparent that the performance measures of the two-axis X–Y table motion control system are significantly enhanced with the proposed NROC scheme. Consequently, the developed NROC scheme with ADP and NNs fulfills the high precision demands. Thus, the proposed control scheme has verified its superiority for the motion control of the X–Y table system for practical applications.

VI. CONCLUSION

This article proposed a NROC scheme via ADP and NNs for the X–Y table system actuated by PMLSM servo drives for achieving high-precision performance which guarantees the robustness in the presence of PUs. First, the FLC scheme is designed to stabilize the X–Y table system. Furthermore, the conservative selection of the high control gain in the FLC algorithm can induce a large amount of chattering. In addition, the performance of the X–Y table may be destroyed due to PUs. To overcome these problems, an AFLC is proposed which combines an NN identifier to approximate the uncertainties of the X–Y table and estimate the upper bound of uncertainties exists in the FLC law. Then, to optimize the control performance, a NROC scheme is developed via ADP technique to facilitate the online solution of the HJB equation using critic NN for approximating the optimal control law. As well, the learning scheme combined with an additional stabilizing term is introduced in the critic NN weight update policy, which can stabilize the closed-loop system and accelerate the online learning process. The UUB of the closed-loop system is also proved via the Lyapunov approach. The robust optimal control performance of the X–Y table system is verified by experimental results. In conclusion, the main contribution of this article can be summarized as: a novel NROC scheme is successfully developed, implemented, and applied for the X–Y table system to achieve robust and optimal control performance considering external force disturbance, frictional force, cross-axis coupling interferences, and PU.
Fig. 12. Percentage reduction of tracking errors using AFLC and NROC control schemes with regard to FLC scheme for the two-axis motion control system. (a) $T_{E_{\text{max}}}$. (b) $T_{E_{\text{mean}}}$. (c) $T_{E_{\text{ad}}}$. reduction.

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