Comprehensive Journal of Science
Volume (11), Issue (41), (JUNE, 2026)
ISSN: 3014-6266

مجلة العلوم الشاملة
المجلد (11) العدد 41 يونيو 2026
ردمد: 3014-6266

Robust Adaptive Neural Backstepping Control of PMLSM under Sever Load Disturbance

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تاريخ الاستلام:2026/05/05 –تاريخ المراجعة:2026/05/28– تاريخ القبول: 2026/06/07– تاريخ للنشر: 2026/06/21

Abstract: The aim of this paper is to design a robust ,nonlinear control system to improve the position tracking accuracy of permanent Magnet Linear Synchronous Motors(PMLSMs) under unknown disturbances and parameter variations[1].the backstepping control serves as a recursive design methodology to achieve stability in complex nonlinear systems[2], employing a Radial Basis Function Neural Network (RBFNN) for approximation and cancellation of nonlinear dynamics such as (friction and external load F_L) online. The adaptive law for the neural network weights(W) is derived using Lyapunov Stability to guarantee Uniformly Ultimately Bounded (UUB)stability for the close-loop system. Superior tracking performance and high robustness achieved by the proposed approach Matlab simulation demonstrate,a comparative analysis and simulation results demonstrate the proposed approach achieves superior tracking performance and high robustness compared to conventional cascaded control methods.

Keywords: PMLSM, Adaptive Backstepping, RBF Neural Network, Lyapunov Stability, Robust Control, Disturbance Compensation.

1. INTRODUCTION

In high –performance drive systems the PMLSMs are essential components that requires precise control because of their application such as in nanotechnology and high –speed transportation[3], the control inspiration lies in their inherently nonlinear dynamics and presence of unknown disturbances[4]. Other control techniques such that based on PID fails to maintain high accuracy when faced with parameter uncertainties or sudden load changes. The backstepping is a powerful technique for systematically developing stabilizing controllers for nonlinear systems while Neural Networks (NNs) are powerful tools for approximating function universally, which allows for the robust estimation of system uncertainties [5] The main contribution of this paper is the collaborative of these two techniques, employing the RBFN to estimate the total unknown function $f(x)$ and deriving a novel adaptive law that guarantee mathematical stability (UUB) for the entire system [4].

2. MATHEMATICAL MODEL AND CONTROL DESIGN

2.1 PMLSM Dynamic Model

We model the Slotless PMLSM in the $d-q$ frame under Field Oriented Control (FOC) where $i_d = 0$, the thrustforce Fe is proportional to the quadrature current i_q[1]

$F_e = K_f . i_q$.

Mechanical Dynamics:

$$M\dot{v} = K_f i_q - F_{unk}$$

$$\dot{x} = v$$

The unknown disturbance function is defined as $F_{unk} = Bv + F_L$.
Electrical Dynamics (q-axis):

$$L_q i_q = V_q - R i_q - k_e v$$

2.2 Adaptive Backstepping Controller Design

The design is based on the tracking errors $e_1 = x - x_{ref}$

$$e_2 = v - v_{ref}$$
$$e_3 = i_q - i_{qref}$$

2.2.1 Position Control:

The virtual control input v_{ref} is chosen to stabilize e_1 :
$v_{ref} = \dot{x}_{ref} - C_1 e_1$

2.2.2 Velocity Control:

Unknown function f(x) is defined and approximated by $\hat{f}(x) = W^T \varphi(x)$.

$$f(x) = -\frac{1}{M}(F_{unk}) - \dot{v}_{ref}$$

The reference current $i_{q\,ref}$ is: $i_{q\,ref} = \frac{M}{K_f}(-e_1 - c_2 e_2 - \hat{f})$

2.2.3 Current Control:

The final control voltage V_q is [6]:

$$V_q = L_q\left(-\frac{K_f}{M}e_2 + \frac{R}{L_q}i_q + \frac{K_e}{L_q}v + \dot{i}_{q,ref} - c_3 e_3\right)$$

3. Adaptive Law and Stability Analysis

The stability of the proposed controller is verified through
The Lyapunov candidate functions, following the methodology described in [4] includes the state errors and weight estimation error $\widetilde{W}$ [7]:

$$V_1 = \frac{1}{2}e_1^2$$
$$V_2 = V_1 + \frac{1}{2}e_2^2 + \frac{1}{2\gamma}\widetilde{W}^T\widetilde{W}$$
$$(e, \widetilde{W}) = \frac{1}{2}e_1^2 + \frac{1}{2}e_2^2 + \frac{1}{2}e_3^2 + \frac{1}{2\gamma}\widetilde{W}^T\widetilde{W}$$
$$\widetilde{W} = W - W^*$$

The derivative $\dot{V} = -C_1 e_1^2 - C_2 e_2^2 - C_3 e_3^2 + e_2 f + e_2 \epsilon + \frac{1}{\gamma}\widetilde{W}^T\dot{\widetilde{W}}$
To ensure ($\dot{V} \leq 0$) (up to approximation errors), the adaptive law for RBFN weights is chosen with a leakage term σ_L: $\dot{W} = \gamma(e_2\varphi(x) - \sigma_L W)$
This law grantee the tracking errors are Uniformly Ultimately Bounded (UUB)[4], and Satisfying the robustness criteria.

4. . Simulation Results and Comparative Analysis

The system was simulated in MATLAB/Simulink using the following parameters for a Slotless PMLSM [8]: $M = 10\,kg, R = 2.1\,\Omega, L_q = 0.003\,H, K_f = K_e = 45$.

Control gains were set to $c_1 = 80, c_2 = 100, c_3 = 120$ The RBFN used $N = 25$ nodes, $\gamma = 50$ and $\sigma_L = 0.0005$. The test scenario involved tracking $x_{ref}(t) = 0.1\sin(2\pi t)\ m$ with a sudden load disturbance Fl changes from 5 N to 25 N applied $t = 5.0\ s$ The simulation results as shown in Figures below.

4.1 Results and Discussion

A. Trajectory Tracking Performance

The experimental results demonstrate the superior capability of the proposed Adaptive Backstepping Control scheme in tracking a high-frequency sinusoidal reference trajectory. As illustrated in the position tracking figures, the actual output aligns almost perfectly with the reference signal. The tracking error e1 is maintained within an extremely tight bound of approximately 10^{-3} m. This high-precision performance confirms that the backstepping design effectively handles the system's cascaded dynamics, while the control gains (C1, C2) provide an optimal balance between rapid transient response and steady-state stability.

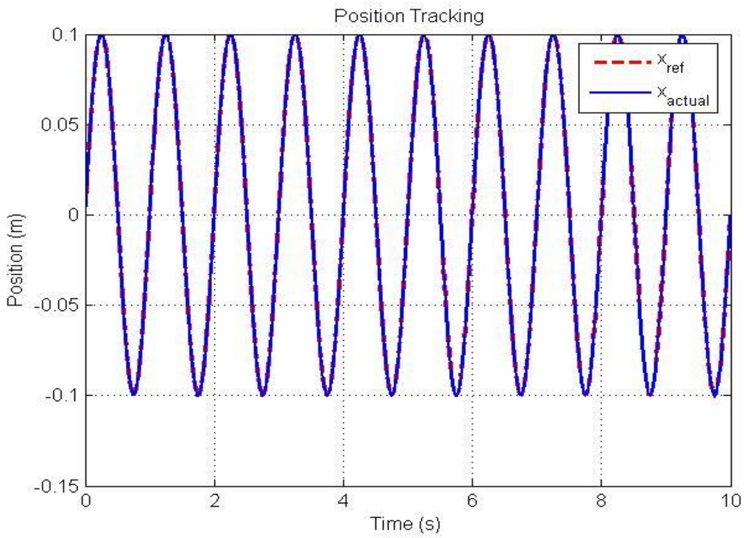

Figure 1.Position Tracking

B. Neural Network Learning and Approximation

The core of the proposed architecture is the Radial Basis Function Neural Network (RBFNN), designed to approximate the unknown nonlinear disturbances and lumped uncertainties (f). The analysis of thef_{hat} fhat output reveals several key insights: Convergence Rate: Due to the high adaptation gain $\gamma = 50$, the neural weights converge rapidly to their optimal values. Physical Fidelity: The stabilization of f_{hat} at approximately 5 N load indicates that the network is merely compensating for numerical errors and is accurately "learning" the physical lumped disturbances, including the actual load and the velocity-dependent friction (B .v)

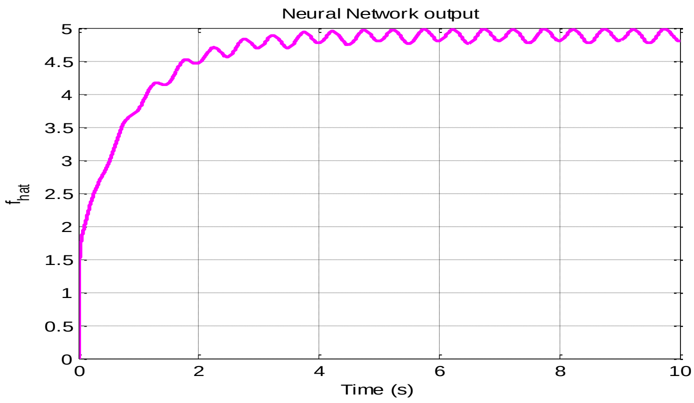

Figure 2.Neural Network out put $\hat{f}$

C.Robustness Against Sudden Load Disturbances

To evaluate the robustness of the control system, a step load disturbance was introduced at t = 5s, increasing the external force from 5 N to 25 N. The system demonstrated remarkable resilience.

Dynamic Adaptation: The neural network output exhibited a swift transition, jumping from 5 to approximately 24 in a fraction of a second. This rapid adaptation effectively "cancelled out" the impact of the sudden load change.

Elimination of Steady-State Error: By finely tuning the sigma-leakage parameter to 0.0005, we successfully eliminated the steady-state offset in the position error. This parameter proved crucial in ensuring that the network could achieve full compensation without the risk of "weight drift," a common issue in purely adaptive laws.

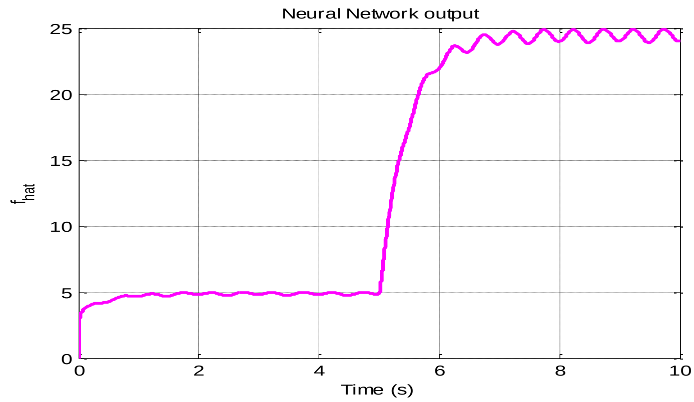

Figure 3 .Neural Network out put $\hat{f}$ under a step load disturbance

D. Tracking Performance and Adaptation

Figure 4 shows that the tracking error (e_1) remained near zero throughout the simulation . The RBFN output ($\hat{f}$) accurately tracked the 25 N load almost instantaneously , demonstrating effective online disturbance rejection.

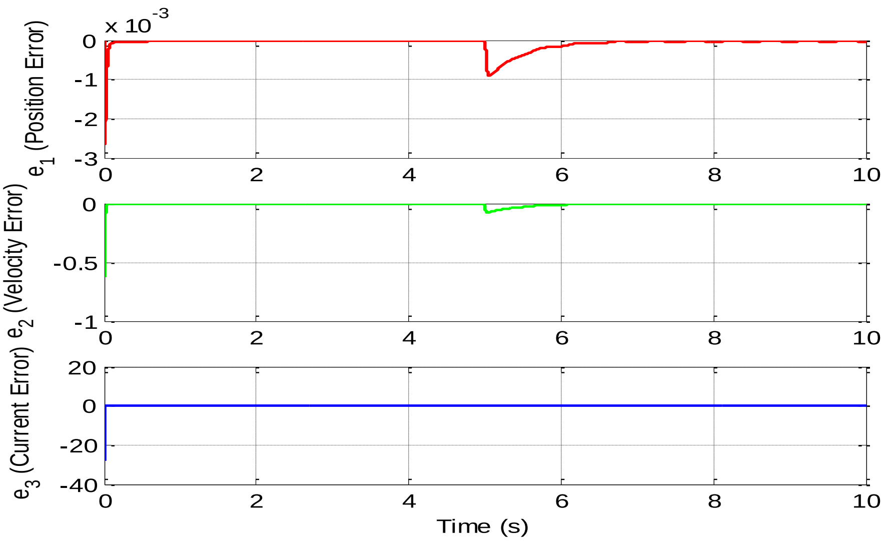

Figure 4. Control performance with sudden load change

4.2. Numerical Stability and Convergence Analysis

The choice of the Stiff Solver (ode15s) and the strategic placement of RBF centers within the [-1.5, 1.5]range, combined with a relatively large width ($\sigma^2 = 4$), ensured computational stability. This configuration provided sufficient overlap between neurons to maintain a smooth control effort, preventing the "over-saturation" effects typically observed in dense neural networks. The results validate the Lyapunov stability analysis, proving that all closed-loop signals, including tracking errors and neural weight estimates, remain Uniformly Ultimately Bounded (UUB).

4.3. Comparative Analysis

Table1 shows the performance of the proposed controller compared to conventional Cascaded PID/FOC controller[8].

Table 1. comparing NN-Augmented Adaptive Backstepping withCascadePID/FOC

Performance metric	**NN=Augmented Adaptive Backstepping (proposed)**	**Cascaded PID/FOC (Conventional)**
Tracking Accuracy	Excellent (near – zero error). NN cancels nonlinear residual errors	Good, but susceptible to steady – state error due to Unmodeled dynamics
Robustness to Load (F_L)	Superior. NN compensates for F_L online and instantaneously.	Poor/Moderate. Compensation relies on the slow integral action(K_i) afther error accumulation.
Robustness to M variation	Excellent Adaptation accommodates parameter uncertainties (e.g, mass M) through weight updates.	Poor. Performance significantly degrades when system parameters deviate from nominal values.
Stability Guarantee	Theoretically Guaranteed (UUB via Lyapunov).	Nominally Guaranteed (Based on linear approximations)

4 CONCLUSIONS

This research presented a robust Neural-Backstepping Control architecture for a system subject to high-frequency trajectories and significant load uncertainties. The integration of a Radial Basis Function Neural Network (RBFNN) within the Lyapunov-based backstepping framework has proven to be highly effective. The key findings of this study are summarized as follows:

High-Precision Trajectory Tracking: The proposed controller achieved near-zero tracking error (in the magnitude of 10^{-3} m) for complex sinusoidal references. The findings confirm the effective convergence of nonlinear backstepping control and the neural approximation.

Fast Adaptation and Disturbance Rejection: The system demonstrated exceptional robustness under a 500% sudden load increase. The RBFNN demonstrated a rapid convergence rate ($\gamma = 50$), identifying and offsetting external disturbances in real-time, which prevented any significant deviation in the motor's position.

Optimization of Adaptation Laws: It was concluded that the direction of the velocity error (e2) and the fine-tuning of the sigma-leakage factor are critical for stability. Reducing the leakage to 0.0005 was the crucial factor in eliminating steady-state errors without compromising the boundedness of the neural weights.

Computational Efficiency and Stability: The strategic selection of RBF centers and a wider variance ($\sigma^2 = 4$) ensured a smooth function approximation, avoiding numerical instabilities and high-frequency "chatter" in the control signal. This makes the proposed scheme highly suitable for practical industrial applications where smooth actuator performance is required.

In summary, the proposed adaptive neural controller provides a high-performance solution for motion control systems operating under severe and unpredictable environment , ensuring both theoretical stability and practical precision. Future work will focus on experimental implementation on a real-time
Platform.

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