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# High- Precision Optimized Adaptive Neural Backstepping Control for PMLSM under High-Amplitude Trajectories and Severe Load Shocks

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**الملخص**

يقدّم هذا البحث استراتيجية تحكم تكيفية تعتمد على التراجع العصبي لمحركات التزامن الخطية ذات المغناطيس الدائم (PMLSM) العاملة تحت مسارات مرجعية ذات سعة كبيرة واضطرابات خارجية شديدة. يدمج مخطط التحكم المقترح إطار التراجع غير الخطي مع شبكة عصبية من نوع الدوال الأساسية الشعاعية (RBFNN) لتقريب الاضطرابات المجمّعة وتغيرات الحمل آنيًا. ولضمان سلاسة تقدير الاضطرابات ومنع التذبذبات عالية التردد، تم ضبط معاملات الشبكة العصبية بصورة منهجية مع تضمين آلية تسريب (σ-leakage) لمنع انجراف الأوزان. كما يثبت تحليل الاستقرار المعتمد على نظرية ليابونوف (UUB) أن النظام المغلق يحقق الاستقرار الموحّد المحدود في النهاية .وتؤكد نتائج المحاكاة باستخدام برنامج MATLAB قدرة المخطط المقترح على تحقيق دقة تتبع ضمن نطاق الميكرومتر والاستجابة السريعة لاضطرابات الحمل، مما يبرز متانته وقابليته للتطبيق في أنظمة التحكم الحركيه عالية الدقة.

***Abstract***

*This paper proposes an adaptive neural backstepping control strategy for Permanent Magnet Linear Synchronous Motors (PMLSMs) operating under high-amplitude trajectories and severe external disturbances. The control scheme integrates a nonlinear backstepping framework with a Radial Basis Function Neural Network (RBFNN) to online approximate lumped uncertainties and load variations. To ensure smooth disturbance estimation and avoid high-frequency oscillations, the neural parameters are systematically optimized, and a σ-leakage mechanism is employed to prevent neural weight drift. Lyapunov-based analysis guarantees Uniformly Ultimately Bounded (UUB) stability of the closed-loop system. MATLAB simulation results demonstrate micrometer-level tracking accuracy and rapid disturbance rejection under a 0.4 m reference trajectory and a 25 N load disturbance, confirming the robustness and effectiveness of the proposed approach for high-precision motion control applications.*

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

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## 1. Introduction

Permanent Magnet Linear Synchronous Motors (PMLSMs) have become a key enabling technology for high-speed and high-precision motion systems in advanced industrial applications such as semiconductor manufacturing, precision positioning stages, and nano-fabrication. By providing direct-drive actuation, PMLSMs eliminate mechanical transmission components such as ball screws and gear mechanisms, thereby avoiding backlash, friction nonlinearities, and compliance effects. However, the absence of mechanical transmission also makes PMLSMs highly sensitive to system uncertainties, including thrust ripple, parameter variations, friction, and abrupt load disturbances.

Conventional linear control strategies, such as Proportional Integral Derivative (PID) controllers, often fail to satisfy stringent tracking accuracy requirements under large-amplitude trajectories and severe external disturbances. Although sliding mode control (SMC) exhibits strong robustness against uncertainties, its practical implementation is commonly limited by chattering phenomena, which may excite unmodeled dynamics and cause mechanical wear. Backstepping control has emerged as an effective nonlinear design methodology that systematically constructs stabilizing control laws for strict-feedback systems while guaranteeing closed-loop stability through Lyapunov analysis [4]. To further enhance robustness against unknown nonlinearities and external disturbances, adaptive neural network–based control schemes have been widely investigated [2],[7]. In particular, Radial Basis Function Neural Networks (RBFNNs) are attractive due to their universal approximation capability, fast convergence, and simple structure [7]. By embedding RBFNNs into backstepping frameworks, unknown lumped disturbances can be approximated online without requiring precise system models. Nevertheless, the performance of neural backstepping controllers strongly depends on the appropriate selection of neural parameters, such as learning rates, receptive field widths, and weight adaptation mechanisms. Improper tuning may lead to high-frequency oscillations, estimation bias, or neural weight drift.

Although several neural backstepping approaches for motor drive systems have been reported in the literature, most existing works focus on moderate operating conditions or lack a systematic discussion on neural parameter optimization under large-amplitude motion and severe load shocks [6]. In addition, many studies validate their approaches under limited disturbance levels, which may not reflect harsh industrial environments.

**The main contributions of this paper can be summarized as follows:**

1. An optimized adaptive neural backstepping control scheme is developed for PMLSMs operating under high-amplitude reference trajectories (0.4 m) and severe load disturbances (25 N), representing harsh operating conditions rarely addressed in existing literature.
2. A systematic tuning strategy for the RBFNN learning rate and receptive field variance is introduced to suppress high-frequency oscillations while ensuring fast and smooth disturbance estimation.
3. A σ-leakage–based weight adaptation mechanism is incorporated to prevent neural weight drift and guarantee bounded parameter estimation during long-term operation.
4. A rigorous Lyapunov-based analysis [4],[5] is provided to prove Uniformly Ultimately Bounded (UUB) stability of the closed-loop system under lumped uncertainties.
5. Extensive MATLAB simulations demonstrate microammeter-level tracking accuracy and rapid recovery from severe load shocks without oscillatory behaviour.

The overall control architecture of the proposed adaptive neural backstepping scheme for the PMLSM is illustrated in Figure. 1.

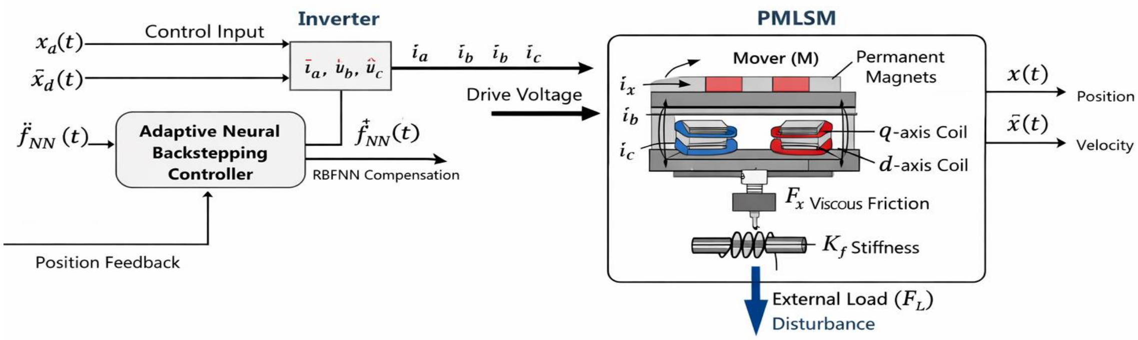


Figure.1. Block diagram of the proposed adaptive neural backstepping controlled PMLSM system

## 2. Mathematical Modelling of the PMLSM

### 2.1 System Description and Assumptions

The dynamic model of the Permanent Magnet Linear Synchronous Motor (PMLSM) is formulated under the standard Field Oriented Control (FOC) assumption, where the direct-axis current is regulated to zero $(i_d = 0)$. This assumption decouples the thrust force from the magnetic flux dynamics and allows the electromagnetic thrust to be directly controlled through the quadrature-axis current.

### 2.2 Electromechanical Dynamics

Under the FOC framework, the electromagnetic thrust force generated by the PMLSM can be expressed as

$$F_e = K_f . i_q = K_f . u \tag{1}$$

where $F_e$ (N) denotes the electromagnetic thrust force, $i_q$ (A) is the $q$-axis current, and $K_f$ (N/A) represents the thrust force constant.

The mechanical dynamics of the mover are governed by the following equation:

$$d(t) + F_e = \dot{x}B + \ddot{x}M \tag{2}$$

where x (m) denotes the linear position of the mover, $\dot{x}$ (m/s) and $\ddot{x}$(m/s$^2$) represent the velocity and acceleration, respectively. The parameters M (kg) and B (N·s/m) denote the mover mass and viscous friction coefficient. The term $d(t)$ represents the lumped disturbance, which includes unmodeled dynamics, thrust ripple, friction nonlinearities, parameter uncertainties, and external load variations.

### 2.3 lumped disturbance Representation

The lumped disturbance $d(t)$ aggregates unmodeled dynamics, thrust ripple, nonlinear friction effects, parameter uncertainties, and external load disturbances. It is assumed that the is bounded such that:

$$|d(t)| \leq d_{max} \tag{3}$$

where $d_{max}$ is an unknown positive constant.

This matched disturbance enters the system through the same channel as the control input, which motivates the use of adaptive neural approximation within the backstepping framework.

### 2.4 State-Space Representation

To facilitate the recursive backstepping controller design, the state variables are defined as:

$$x = x_1 \ \ , \dot{x} = x_2 \tag{4}$$

The PMLSM dynamics can then be rewritten in strict-feedback form as:

$$x_2 = \dot{x_1} \tag{5}$$

$$d(t)\frac{1}{M} + x_2\frac{B}{M} - i_q\frac{k_f}{M} = \dot{x_2} \tag{6}$$

This state-space representation is well suited for adaptive backstepping control and enables the integration of neural network–based approximation for the unknown disturbance term.

### 2.5 System Parameters

The physical parameters of the PMLSM used in the simulations are summarized in Table I. These parameters correspond to a typical industrial linear motor and are assumed to be constant throughout the control process.

**Table I: physical Parameters of the PMLSM**

| Parameter | Symbol | Value | Unit |
|---|---|---|---|
| Mover Mass | M | 10 | Kg |
| Resistance | $R_s$ | 2.1 | Ω |
| Inductance | $L_q$ | 0.003 | Mh |
| Force Constant | $K_f$ | 45 | N/A |
| Magnetic Flux | $\emptyset_f$ | 0.08 | Wb |
| Viscous Friction | B | 10 | N.s/m |
| Pole Pitch | $\tau$ | 0.001 | M |

## 3. CONTROLLER DESIGN AND NEURAL OPTIMIZATION

### **3.1** Backstepping Controller Design

Based on the strict-feedback model in (5),(6), a recursive backstepping approach is employed to design a stabilizing control law for the PMLSM. The objective is to ensure accurate tracking of the desired position trajectory $x_d(t)$ in the presence of lumped uncertainties.

Define the tracking errors:

$$e - x_1 = e_1 \tag{7}$$

Consider the first Lyapunov candidate:

$$\frac{1}{2}e_1^2 = V_1 \tag{8}$$

Choose the virtual control:

$$C_1 e_1 - \dot{x}_\propto = \propto \tag{9}$$

Define the second error variable:

$$\propto - x_2 = e_2 \tag{10}$$

Extend the Lyapunov function:

$$\frac{1}{2}e_2^2 + V_1 = V_2 \tag{11}$$

The time derivative of leads to the following control law:

$$\left(C_1 \dot{e}_1 - C_2 e_2 + d\dot{(\ddot{t})} - \ddot{x_\propto}\right)\frac{M}{K_f} = i_q \tag{12}$$

where $C_1, C_2 > 0$are design gains.

**3.2 RBF Neural Network Disturbance Approximation**

The unknown lumped disturbance d(t) is approximated online using a Radial Basis Function Neural Network (RBFNN) due to its universal approximation capability.

$$d(t) = \varepsilon + W^{T*}\emptyset(x) \tag{13}$$

where: $W^*$: ideal weight vector.

$\emptyset(x)$: Gaussian basis functions.
$\varepsilon$: bounded approximation error.

The estimated disturbance is: $d(t) = W^{T*}\emptyset(x)$ (14)

**3.3 Neural Adaptation Law with σ-Leakage**

To avoid parameter drift and ensure bounded weight estimation, a σ-leakage–based adaptation law is adopted:

$$\widehat{W} = \gamma\varphi(x)e_2 - \sigma_{leak}\,\dot{\widehat{W}} \tag{15}$$

This modification introduces a stabilizing damping term that guarantees boundedness even under persistent excitation.

### 3.4 Neural Parameter Optimization

The selection of neural parameters critically affects disturbance estimation accuracy and closed-loop performance, particularly under large-amplitude trajectories and severe load disturbances. In adaptive neural backstepping control, improper tuning of the learning rate, receptive field width, or weight adaptation mechanism may lead to high-frequency oscillations, slow convergence, or neural weight drift, thereby degrading tracking precision and robustness.

In this study, the neural and controller parameters were systematically selected to ensure fast disturbance estimation, smooth transient response, and long-term stability under harsh operating conditions. Specifically, the proportional and velocity gains were tuned to provide sufficient tracking stiffness and effective error damping without inducing overshoot during high-amplitude motion. The RBF neural network learning rate was chosen to enable rapid online adaptation to abrupt load disturbances, while the receptive field variance was adjusted to suppress high-frequency oscillations and ensure smooth disturbance approximation [1][3]. Moreover, a σ-leakage–based weight adaptation mechanism was incorporated to prevent neural weight drift and guarantee bounded parameter estimation during prolonged operation. The number of neurons and the distribution range of the RBF centers were selected to provide adequate estimation resolution while fully covering the expected operating region of the system. The optimized controller and neural network parameters adopted in this paper, along with their respective roles in the control system, are summarized in Table II**.**

**Table II: Optimized Controller & RBFNN parameters**.

| Parameter | Symbol | Final Value | Role in System |
|---|---|---|---|
| Position Gain | C1 | 100 | Proportional tracking stiffness |
| Velocity Gain | C2 | 120 | Error damping and recovery |
| Adaption Gain | $\gamma$ | 35 | Neural network learning rate |
| RBF Variance | $\sigma^2$ | 20 | Neural receptive field width |
| Leakage Factor | $\sigma_{leak}$ | 0.0001 | Weight drift prevention |
| Number of Neurons | N | 11 | Estimation resolution |
| RBF Canter Range | C | [-1.5, 1.5] | Covering the 0.4 m state-space |

## 4. LYAPUNOV STABILITY ANALYSIS

This section provides a rigorous Lyapunov-based stability analysis for the proposed adaptive neural backstepping controller and proves that all closed-loop signals are Uniformly Ultimately Bounded (UUB).

### 4.1 LYAPUNOV Candidate Function

$$V = \frac{1}{2}e_1^2 + \frac{1}{2}e_2^2 + \frac{1}{2\gamma}\widetilde{W}^T\widetilde{W} \tag{16}$$

Where $\widetilde{W} = W^* - \widehat{W}$ . Taking the derivative

$$\dot{V} = e_1\dot{e}_1 + e_2\dot{e}_2 - \frac{1}{\gamma}\widetilde{W}^T\dot{\widehat{W}} \tag{17}$$

Substituting the error dynamics :

$$\dot{V} = e_1(-c_1e_1 + e_2) + e_2\left(-c_2e_2 - e_1 + \left(f - \hat{f}\right)\right) - \frac{1}{\gamma}\widetilde{W}^T\dot{\widehat{W}} \tag{18}$$

Using the adaptation law

$$\dot{\widehat{W}} = \gamma(e_2S(x) - \sigma_{leak}\widehat{W}) \tag{19}$$

has been obtained ;

$$\dot{V} = -c_1e_1^2 - c_2e_2^2 - \sigma_{leak}\widetilde{W}^T\widehat{W} + \epsilon e_2 \tag{20}$$

This inequality ensures that the system is Uniformly Ultimately Bounded (UUB), preventing weight drift through the sigma-leakage term [4,5].

### 4.2 Uniform Ultimate Boundedness

From (20), it follows that all closed-loop signals are Uniformly Ultimately Bounded, and the tracking errors converge to a compact set defined by:

$$\sqrt{\frac{\Delta}{\lambda_{min}(\varphi)}} \geq \|Z\| \tag{21}$$

This bound can be made arbitrarily small by appropriate selection of:

- controller gains $C_1$,$C_2$.
- neural adaptation parameters $\gamma$ and $\sigma_{leak}$.

### 4.5 Physical Interpretation

The UUB property guarantees that the position and velocity tracking errors remain within a small neighborhood around zero despite large reference amplitudes and severe load disturbances [1],[5]. The σ-leakage term plays a critical role in preventing neural weight drift, thereby ensuring long-term stability and robustness of the PMLSM drive system.

## 5. SIMULATION RESULTS AND DISCUSSION

### 5.1 Simulation Setup

To evaluate the effectiveness of the proposed adaptive neural backstepping controller under harsh operating conditions, extensive MATLAB/Simulink simulations were conducted using the PMLSM parameters listed in Table I. The reference trajectory was selected as a large-

amplitude sinusoidal motion with a peak displacement of 0.4 m, representing a demanding scenario commonly encountered in high-speed precision positioning systems.
A sudden external load disturbance of 25 N was applied to the system to emulate severe payload variation and external shocks, corresponding to a 500% increase relative to nominal operating conditions. This scenario constitutes a worst-case condition for many conventional controllers.

### 5.2 Trajectory Tracking Performance

Figure. 2 illustrates the position tracking performance of the PMLSM under the proposed control strategy. It can be observed that the actual position closely follows the high-amplitude sinusoidal reference with negligible steady-state error. The steady-state tracking error is confined within the micrometer range, indicating high dynamic stiffness and precise motion control.
The smooth tracking behavior confirms the effectiveness of the backstepping framework in shaping the closed-loop error dynamics, while the neural compensator actively suppresses the effect of lumped uncertainties.

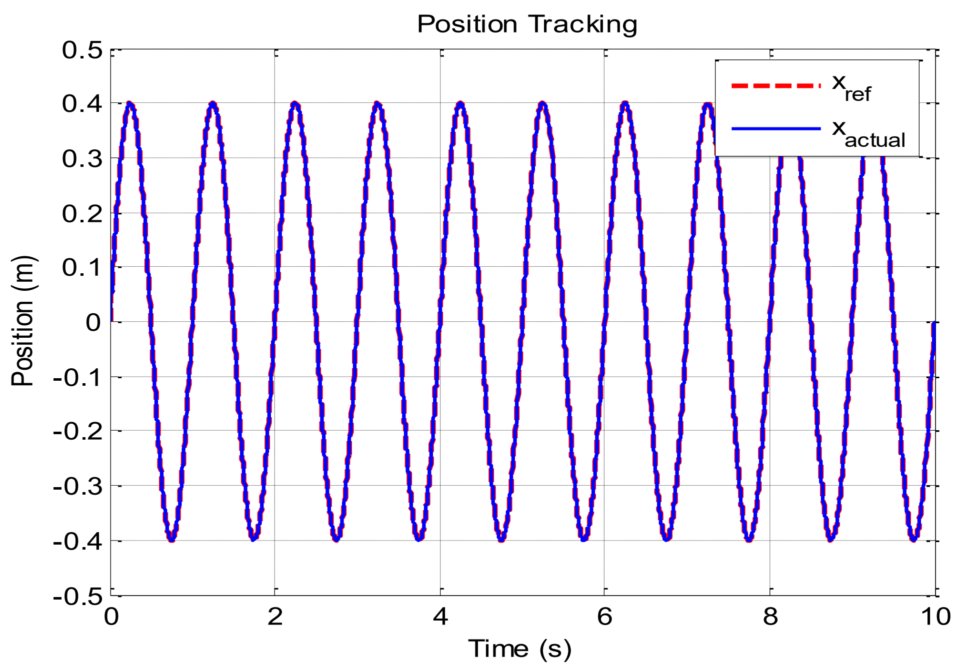


Figure. 2. Sinusoidal Reference Tracking Performance of the Motor

### 5.3 Robustness Against Load Disturbances

At t=2 s, a sudden load disturbance of 25 N is applied to the system. As shown in Figure. 3, a transient deviation occurs immediately following the disturbance; however, the controller rapidly compensates for the applied load, and the tracking error converges back to its bounded neighborhood within approximately 0.15 s without oscillatory behavior.

This fast recovery validates the role of the optimized neural learning rate (γ=35), which enables rapid disturbance estimation while maintaining smooth system response.

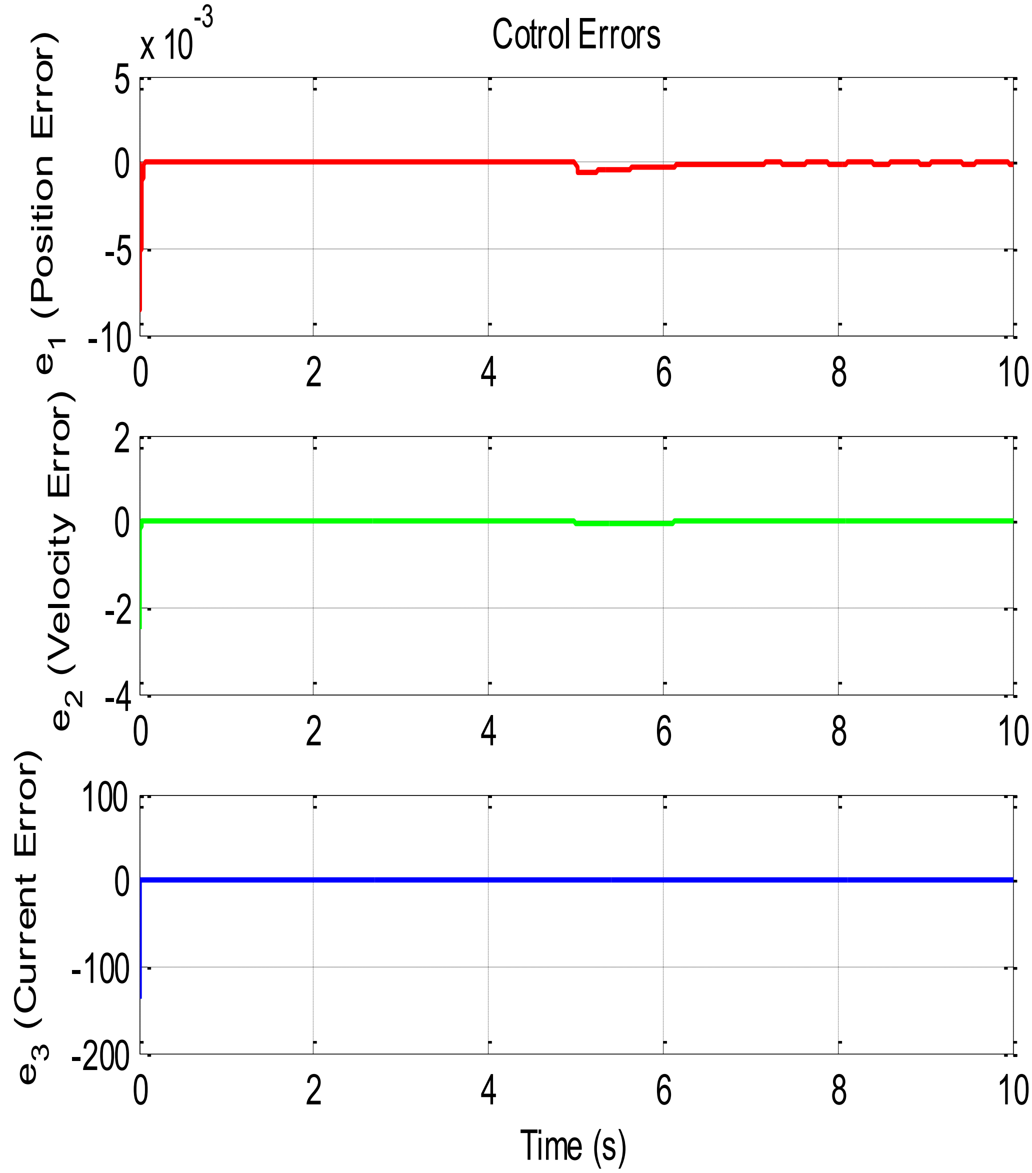


Figure. 3. Effect of Fast Learning Rate (γ=35) on Load Disturbance Rejection.

### 5.4 Neural Disturbance Estimation Performance

Figure. 4 describe the estimated disturbance generated by the RBFNN in comparison with the actual applied load. The estimated signal accurately converges to the true disturbance magnitude of (N=25) with a smooth transient profile and minimal steady-state bias.

The incorporation of the σ-leakage term ($\sigma_{leak}=10^{-4}$) effectively prevents neural weight drift, which is commonly observed in standard RBFNN-based controllers, thereby ensuring long-term estimation stability.

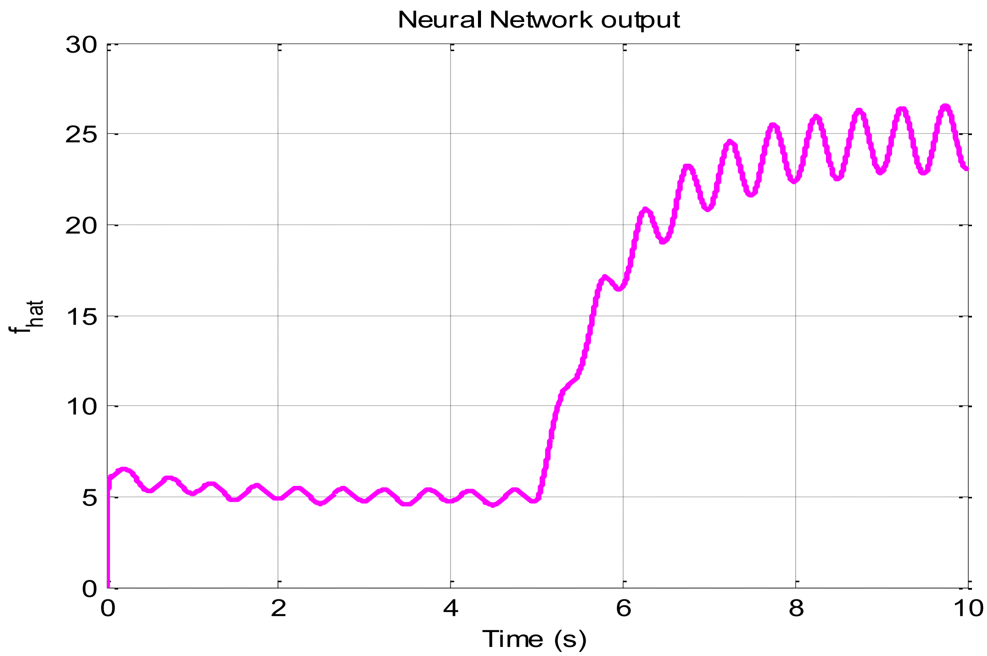


Figure. 4. Transient Response to a Sudden Load Change

### 5.5 Discussion and Theoretical Consistency

The bounded tracking errors observed in all simulation scenarios are consistent with the Uniform Ultimate Boundedness (UUB) property established in the Lyapunov analysis. The ultimate bound of the tracking error remains small despite large reference amplitudes and severe load disturbances, confirming the theoretical predictions.

Moreover, the absence of high-frequency oscillations highlights the effectiveness of the optimized neural parameters and distinguishes the proposed approach from conventional adaptive neural controllers with aggressive learning rates.

## 6. CONCLUSION

This paper presented an optimized adaptive neural backstepping control strategy for Permanent Magnet Linear Synchronous Motors operating under high-amplitude trajectories and severe load disturbances. By integrating a recursive backstepping framework with an RBF neural network, the proposed controller effectively compensates for lumped uncertainties arising from unmodeled dynamics, friction nonlinearities, and abrupt load variations.

A systematic tuning of the neural learning rate and receptive field variance was introduced to achieve a favorable trade-off between fast disturbance estimation and smooth closed-loop response. Furthermore, the incorporation of a σ-leakage–based adaptation mechanism successfully prevented neural weight drift and ensured long-term bounded parameter estimation.

A rigorous Lyapunov-based analysis proved Uniformly Ultimately Bounded stability of the closed-loop system, providing theoretical guarantees that are consistent with the observed simulation results. Extensive MATLAB simulations under a large-amplitude reference trajectory of 0.4 m and a sudden 25 N load disturbance demonstrated micrometer-level tracking accuracy, rapid disturbance rejection, and the absence of oscillatory behavior.

Owing to its robustness, stability guarantees, and practical tuning guidelines, the proposed control scheme constitutes a strong candidate for high-precision industrial motion control applications. Future work will focus on experimental validation and extension of the proposed framework to multi-axis linear motor systems and real-time hardware implementation.

## 8. Conflict of Interest

*The authors declare that there are no conflicts of interest.*

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