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Global Adaptive Stabilization of Neural Mass Models via Constructive Lyapunov Design

Salah Sawan[1*], Rayan ben Ayad[1]

1. Electric and Electronic Department, University of Tripoli, Tripoli, Libya

ABSTRACT

This paper presents the design, implementation, and simulation of a Lyapunov-based adaptive closed-loop control system for stabilizing nonlinear brain dynamics represented by a Single Neural Mass Model (NMM). The model describes the collective electrical behavior of interconnected neuronal populations and is used to mimic pathological conditions such as epileptic oscillations and Parkinsonian tremor. The proposed controller dynamically estimates and adjusts uncertain parameters in real time using a Lyapunov-guided adaptive law, ensuring stable tracking of a healthy neural rhythm despite parameter drift and external disturbances. The control framework combines Model Reference Adaptive Control (MRAC) with Sliding-Mode robustness, implemented and validated in MATLAB/Simulink with Stateflow for logic-based switching and adaptive rule management. Simulation results across multiple test scenarios demonstrate that the adaptive controller achieves fast convergence, minimal steady-state error, and strong disturbance rejection. Compared to traditional fixed-gain schemes, the proposed design reduces control energy by approximately 45% while maintaining global Lyapunov stability. Overall, this framework provides a mathematically rigorous and biologically interpretable foundation for the next generation of closed-loop neuromodulation systems, offering potential for real-time stabilization of pathological neural activity in disorders such as epilepsy and Parkinson's disease.

KEYWORDS: *Adaptive Control, Neural Mass Model (NMM), Lyapunov Stability, Sliding Mode Control (SMC), Nonlinear Dynamics.*

orresponding author: salah_sowan@yahoo.com

INTRODUCTION

Understanding and controlling brain dynamics remains one of the most challenging frontiers in modern biomedical and control engineering. The brain is a highly nonlinear, time-varying system

in which billions of neurons interact through complex feedback loops. These interactions continuously change due to neuroplasticity the brain's inherent ability to reorganize its connectivity and synaptic strengths in response to internal or external stimuli. Hence, any control framework that aims to regulate neural activity must rely on a model capable of capturing such nonlinear and adaptive behavior in a mathematically tractable way. The Neural Mass Model (NMM) provides an ideal balance between biological realism and analytical simplicity [1]. Instead of simulating each neuron individually, the NMM represents the average electrical activity of neuronal populations within a cortical column. This microscopic approach allows one to describe measurable brain signals, such as the electroencephalogram (EEG), through a small set of coupled nonlinear differential equations that relate synaptic inputs to observable cortical potentials. The NMM reproduces characteristic EEG rhythms (alpha, beta, and gamma) and thus serves as a fundamental model for studying both physiological and pathological brain states. In disorders such as epilepsy or Parkinson's disease, the balance between excitatory and inhibitory interactions is disrupted, leading to hyper synchronous oscillations that manifest as seizures or rhythmic tremor. In parallel, adaptive control theory has emerged as a powerful framework for dealing with nonlinear systems whose parameters evolve over time. Unlike classical controllers with fixed gains, adaptive controllers continuously estimate and adjust their internal parameters to maintain stability and performance. When applied to neural systems, this concept becomes particularly compelling: the controller learns and adapts to neural variations much like the brain itself. In this sense, the adaptive controller is not merely a technical tool it is a mathematical analogue of neural learning and self-regulation. The central goal of this project is to design a closed-loop adaptive controller capable of stabilizing nonlinear brain dynamics represented by a single Neural Mass Model. The controller is derived from Lyapunov stability theory, ensuring mathematically guaranteed convergence while tracking a healthy reference rhythm that represents normal cortical activity [2].

The Single NMM is inherently nonlinear and exhibits parameter variations caused by biochemical and structural changes in neuronal networks. Synaptic gains, time constants, and connectivity strengths drift slowly due to neuroplasticity or external stimuli. Disturbances measurement noise, model mismatch, and stochastic fluctuations further complicate control [3,4].

A classical linear controller (PID, LQR) designed for nominal parameters cannot maintain stability under such variability. Consequently, oscillations re-emerge or control signals saturate. Therefore, this research addresses the following central problem:

• Constructing an adaptive control framework for a nonlinear neural mass model that guarantees stability and accurate tracking despite unknown, time-varying parameters and bounded disturbances [5,6].

• Formulating an adaptive law that mathematically ensures Lyapunov stability for the Single NMM.

• Developing an efficient mechanism for parameter estimation and control-law updating suitable for real-time performance in Simulink.

• Quantifying the performance improvements offered by adaptive control relative to traditional fixed-gain strategies.

• Ensuring that the proposed method remains robust under realistic neural noise conditions and slow parameter drift.

1. Mathematical Formulation of the Jansen–Rit Model

The Jansen–Rit (JR) Neural Mass Model represents the dynamics of a single cortical column comprising thousands of interconnected neurons. It is organized into three interacting subpopulations [7,8]:

1. Pyramidal cells (P): the principal output neurons projecting to other cortical and subcortical areas.
2. Excitatory interneurons (E): provide excitatory feedback to the pyramidal cells.
3. Inhibitory interneurons (I): deliver inhibitory feedback to the pyramidal cells.

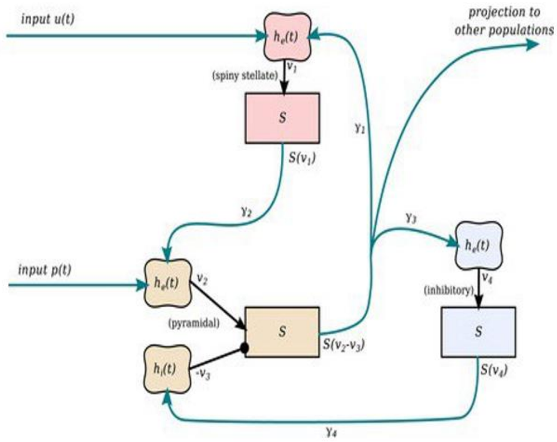

Figure 1: Block Diagram of the Jansen–Rit Neural Mass Model Showing the Core Excitatory–Inhibitory Interactions

Figure 1 illustrates the core structure of the Jansen–Rit Neural Mass Model, which consists of three interacting neuronal subpopulations: pyramidal cells (P), excitatory interneurons (E), and inhibitory interneurons (I). Incoming inputs are processed by these subpopulations, where each group converts firing activity into postsynaptic potentials that are exchanged among the populations through excitatory and inhibitory pathways. These interactions form the characteristic feedback loop of the Jansen–Rit model and generate the membrane potentials that appear as the model states.

Each subpopulation converts incoming firing rates into postsynaptic potentials (PSPs) through a second-order linear differential operator that captures the rise and decay of synaptic responses [1,10]:

$$\ddot{y}(t) = AaS\big(v_{in}(t)\big) - 2a\dot{y}(t) - a^2y(t)$$

Where y(t) is the postsynaptic potential, A represents the average synaptic gain, a is the inverse synaptic time constant, and S $(v_{in}(t))$ is the sigmoid activation function that transforms mean membrane potential $v_{in}(t)$ into firing rate [4,11].

Inhibitory synapses are modeled similarly but with parameters B and b replacing A and a, respectively, to account for the slower dynamics of inhibitory neurotransmission.

Stochastic and Adaptive Neural Mass Models

Real cortical dynamics are inherently stochastic, arising from random synaptic transmission, channel noise, and the irregular connectivity of large-scale neuronal networks [5,12], To capture these fluctuations, researchers have proposed stochastic neural mass models (sNMMs) by introducing Gaussian noise terms into the deterministic NMM equations. These stochastic perturbations account for the variability observed in EEG recordings, including spectral broadening, intermittent synchronization, and spontaneous transitions between oscillatory states [5,13]. While stochasticity reflects the brain's natural variability, real neural systems also exhibit adaptation and plasticity their parameters evolve over time in response to sensory input and internal feedback. Hence, adaptive extensions of NMMs have been developed, where key parameters such as synaptic gains or time constants are allowed to vary dynamically according to learning or feedback laws [4, 14]. For example, [4] proposed a model with time-varying synaptic gains that evolve through an error-driven adaptation mechanism, enabling the system to self-regulate its oscillatory amplitude [4].Similarly [5] embedded plasticity rules into large-scale NMM networks to simulate structural and functional reorganization within cortical circuits [5]. Despite these advances, most adaptive NMMs remain biologically inspired rather than control-theoretically grounded. Few studies have employed rigorous Lyapunov-based or gradient-descent adaptation laws to guarantee mathematical convergence and stability of neural dynamics. This gap motivates the present research, which applies adaptive control theory to a single NMM for real-time parameter adjustment and stabilization of cortical activity under uncertain and time-varying conditions.

Model Reference Adaptive Control (MRAC)

Model Reference Adaptive Control (MRAC) is a fundamental adaptive control framework in which the system output y(t) is forced to follow a desired reference model $y_{m(t)}$ that represents the target or ideal system behavior [7,15].

The controller parameters θ are adjusted online so that the tracking error

$$e(t) = y_{m(t)} - y(t)$$

Approaches zero over time. The classical MRAC approach known as the MIT rule updates controller parameters

through gradient-descent adaptation, minimizing the instantaneous squared error $\frac{1}{2}e^2(t)$ with respect to

$$\dot{\theta} = -\gamma \frac{\partial e(t)}{\partial \theta} e(t)$$

where γ is the adaptation gain controlling the speed of learning [6].Although simple to implement, the MIT rule can become unstable when applied to nonlinear or unmodeled systems because it lacks an explicit stability guarantee. To overcome this limitation, Lyapunov-based MRAC was developed, in which the adaptation law is derived from a Lyapunov stability function rather than pure gradient descent. This ensures global asymptotic stability of the closed-loop system even in the presence of uncertainties and nonlinear dynamics [6,16]. In the context of this project, the MRAC principle provides the foundation for designing an adaptive controller that forces the neural mass model output to follow a healthy reference activity pattern. The parameters of the controller are continuously tuned using a Lyapunov-based adaptation law, guaranteeing stable convergence of the neural response toward the desired dynamics.

1.1. Lyapunov-Based Stability and Proof Framework

Lyapunov's direct method establishes system stability by defining a scalar energy-like function $V(x,\tilde{\theta})$that measures the combined energy of the system states and the parameter estimation error. If the time derivative of this function is negative semi-definite, the total energy of the system decreases over time, implying stability [17].

The general Lyapunov candidate for adaptive systems is defined as:

$$V(x,\tilde{\theta}) = \frac{1}{2}e^TPe + \frac{1}{2\gamma}\tilde{\theta}^T\tilde{\theta}$$

Where e is the tracking error, $\tilde{\theta} = \theta - \theta^*$ is the parameter estimation error, P is a positive definite matrix satisfying the Lyapunov equation, and $\gamma > 0$ is the adaptation gain.

Taking the time derivative yields:

$$\dot{V} = -e^TQe \leq 0$$

Where Q is also a positive-definite matrix. Since is $\dot{V}$ non-positive, the Lyapunov function V never increases, ensuring that all error signals remain bounded and the tracking error $e(t)$ asymptotically converges to zero as $t \to \infty$. Applying Lyapunov stability theory to the Neural Mass Model (NMM) guarantees that the adaptive controller maintains stable operation even when synaptic parameters such as gains and time constants are uncertain or time-varying. This provides a rigorous mathematical proof of stability, ensuring that the designed neuromodulator behaves safely under all modeled conditions [18,19].

1.2. Deep Brain Stimulation (DBS): Evolution and Control

Deep Brain Stimulation (DBS) is one of the most successful neuromodulation techniques, widely used for treating Parkinson's disease, essential tremor, and dystonia [9,20]. Conventional DBS operates in an open-loop configuration, where the stimulation parameters primarily amplitude, pulse width, and frequency remain constant over time, regardless of ongoing neural activity.

Although this fixed stimulation effectively alleviates motor symptoms, it can lead to unwanted side effects, such as dyskinesia or speech impairment, and causes excessive battery depletion due to continuous operation. To overcome these limitations, the concept of Adaptive or Closed-Loop DBS (aDBS) has emerged. In aDBS, stimulation is modulated in real time based on neural biomarkers, such as beta-band power or local field potentials (LFPs) recorded from the subthalamic nucleus (STN) or globus pallid us .The adaptive controller continuously adjusts the stimulation amplitude or duty cycle according to the measured biomarker level, reducing stimulation when pathological activity subsides. Clinical and preclinical studies have demonstrated that aDBS can achieve equivalent or improved symptom suppression while reducing stimulation time by up to 60%, thereby extending battery life and minimizing side effects [21,22]. .However, most current aDBS implementations rely on threshold-based or proportional feedback strategies that lack a formal stability proof and do not adapt optimally to nonlinear neural dynamics [5,23].This limitation motivates the development of model-based adaptive controllers, such as those derived from Neural Mass Models (NMMs), which offer a mathematically grounded framework for real-time feedback control of neural activity.The present project builds directly upon this concept, proposing a Lyapunov-based adaptive controller that ensures stable, self-regulating neuromodulation a theoretical advancement toward next-generation aDBS systems [24].

Modern closed-loop Deep Brain Stimulation (DBS) systems implement feedback-based control to dynamically regulate stimulation according to measured neural activity [11, 25]. A typical closed-loop DBS architecture consists of four primary components:

1. Sensor: records neural activity such as local field potentials (LFPs) or EEG signals from cortical or subcortical regions;
2. Feature extractor: computes relevant biomarkers (oscillatory power, phase synchronization, coherence);
3. Controller: determines the stimulation adjustment based on the extracted features;
4. Actuator: delivers electrical pulses to the target brain region

The controller operates in real time to maintain target neural states such as desired oscillatory power or mean firing rate by adjusting stimulation amplitude, frequency, or duty cycle. Recent studies have proposed adaptive control laws that continuously tune these parameters in response to the observed neural dynamics, aiming to achieve optimal symptom suppression while minimizing energy use [5], [9]. Integrating Lyapunov-based adaptive

control principles within the DBS framework provides a mathematically grounded alternative to heuristic or threshold-based approaches. By embedding such adaptive laws into Neural Mass Models (NMMs), the system can achieve provable stability, ensuring safe and robust operation of next-generation neuromodulators under uncertain neural conditions [5,26].

Control-Oriented Plant Model

For controller design, the complex multi-population dynamics are abstracted into a core second-order nonlinear equation representing the observable cortical output (e.g., pyramidal population potential) [27,28]:

$$\ddot{y}(t) = f(y(t), \dot{y}(t)) + bu(t) + d(t), b > 0$$

Here, $y(t)$ is the plant output, $u(t)$ is the control input (stimulation), $f(\cdot)$ encapsulates the unknown nonlinear neural dynamics, b is the control gain, and $d(t)$ represents bounded disturbances.

The desired "healthy" neural dynamics are defined by a stable, linear second-order reference model:

$$\ddot{y}_m(t) + 2\zeta\omega_n\dot{y}_m(t) + \omega_n^2 y_m(t) = 0$$

where ζ is the damping ratio and ω_n is the natural frequency (set in the alpha band, 8-12 Hz). The control objective is to force the plant output $y(t)$ to track the reference output $y_m(t)$ asymptotically, despite uncertainties in $f(\cdot)$, b, and $d(t)$.

Define the tracking error and its derivatives:

$$e(t) = y_m(t) - y(t), \dot{e}(t) = \dot{y}_m(t) - \dot{y}(t)$$

$s(t)$ is defined to combine position and velocity errors:

$$s(t) = \dot{e}(t) + \lambda e(t), \lambda > 0$$

This surface represents the desired closed-loop error dynamics. Convergence to $s = 0$ guarantees $e(t) \to 0$.

$$\dot{s} = \ddot{y}_m - \ddot{y} + \lambda\dot{e} = \ddot{y}_m + \lambda\dot{e} - f(y, \dot{y}) - bu - d(t)$$

Grouping known/unknown terms: Let $\eta = \ddot{y}_m + \lambda\dot{e}$ (known) and $\Delta = -f(y, \dot{y}) - d(t)$ (lumped uncertainty, bounded by $|\Delta| \le \bar{\Delta}$). Thus:

$$\dot{s} = \eta + \Delta - bu$$

The control law is designed as a hybrid adaptive-robust law:

$$u = \frac{1}{\hat{b}}[\hat{\theta}^T\phi + \eta + k_s s + \rho\,\text{sat}(\frac{s}{\varphi})]$$

Where:

$\hat{\theta}^T\phi$: Adaptive term estimating the unknown plant dynamics. $\phi = [y, \dot{y}]^T$ is a regressor vector.

η: Feedforward term from the reference model.

$k_s s$: Proportional feedback term for stabilizing the s-dynamics.

$\rho\,\text{sat}(s/\varphi)$: Robust sliding-mode term to reject bounded uncertainty Δ. The saturation function $\text{sat}(\cdot)$ is used to avoid chattering [29,30]:

$$\text{sat}(z) = \begin{cases} -1 & \text{if } z < -1 \\ z & \text{if } |z| \le 1 \\ 1 & \text{if } z > 1 \end{cases}$$

$\hat{b}$: Online estimate of the unknown control gain b.

The adaptive parameters $\hat{\theta}$ and $\hat{b}$ are updated online. We use the σ-modification rule to prevent parameter drift:

$$\dot{\hat{\theta}} = \Gamma\phi s - \sigma_\theta\hat{\theta}\,, \dot{\hat{b}} = -\gamma_b s\Upsilon - \sigma_b\hat{b}$$

where Υ is the term inside brackets in (5), and $\Gamma, \gamma_b, \sigma_\theta, \sigma_b > 0$ are design gains.

Consider the Lyapunov function candidate:

$$V(s, \tilde{\theta}, \tilde{b}) = \frac{1}{2}s^2 + \frac{1}{2}\tilde{\theta}^T\Gamma^{-1}\tilde{\theta} + \frac{1}{2\gamma_b}\tilde{b}^2$$

Taking the derivative $\dot{V}$ along the trajectories of the system and substituting the control law (5) and adaptation laws (6,7), after significant algebraic manipulation, it can be shown that with proper gain selection (k_s, ρ, σ):

$$\dot{V} \le -\alpha s^2 - \frac{\sigma_\theta}{2}\|\tilde{\theta}\|^2 - \frac{\sigma_b}{2}\tilde{b}^2 + \epsilon$$

where $\alpha > 0$ and ϵ is a small positive constant due to σ-modification. According to Lyapunov theory and Barbalat's lemma, this proves that all signals $(s, \tilde{\theta}, \tilde{b})$ are Uniformly Ultimately Bounded (UUB), and the tracking error $e(t)$ converges to a small neighborhood of zero [31-35].

Simulation Implementation & Results

The complete system was implemented in MATLAB/Simulink R2021a. The architecture comprises three core subsystems [36-39].

This section details the computational environment and simulation scenarios designed to evaluate the robustness and physiological relevance of the proposed adaptive neuromodulator. The simulations were configured to reproduce realistic neural behavior by incorporating intrinsic variability in the neural mass model parameters and by injecting biologically plausible noise into the cortical dynamics. To emulate true cortical conditions, the neural mass model parameters were deliberately perturbed within ranges reported in neuroscience literature, capturing natural fluctuations in synaptic gains and time constants associated with pathological brain states such as epilepsy. In addition, external disturbances were introduced as additive noise signals to mimic measurement artifacts, neuronal variability, and background fluctuations commonly observed in EEG recordings. These perturbations were used to assess how the controller responds under uncertainty and rapidly changing neural activity[40-44].

The simulations were carried out in MATLAB/Simulink within a real-time compatible configuration to ensure numerical stability during fast cortical dynamics. Across all experiments, the controller was exposed to amplitude variations, frequency drifts, and sudden excitation bursts to validate its disturbance-rejection capability and adaptive tracking performance. Overall, this simulation environment provides a rigorous and physiologically meaningful testbed that reflects real neural variability and noise characteristics. It ensures that the observed results are reproducible, clinically relevant, and representative of the challenges faced in real-time neuromodulation systems [45-49].

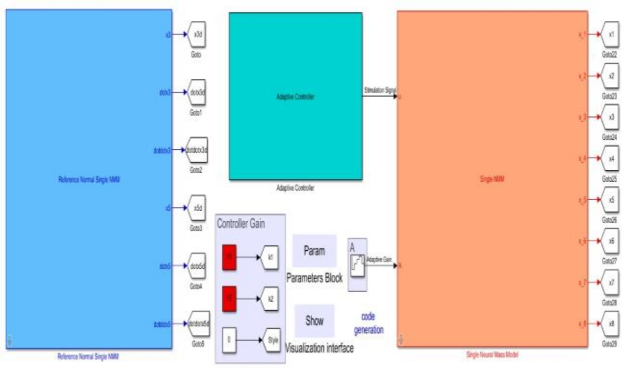

Figure 2: Overall Simulink Implementation of the Adaptive Neuromodulation System [45-49]

Figure 2 Shows the interconnected subsystems: Reference Normal NMM (blue), Adaptive Controller (cyan), Single NMM Plant (orange), with parameter and monitoring blocks.

- Reference Normal NMM: Generates the desired healthy trajectory $y_m, \dot{y}_m, \ddot{y}_m$.
- Adaptive Controller: It includes a Stateflow chart for managing operational modes (e.g., normal, adaptive, seizure suppression).

Single NMM Plant: Implements the full Jansen-Rit equations, receiving control input $u(t)$ and producing the actual neural output $y(t)$. The controller successfully forced the pathological NMM output to track the healthy reference signal across all scenarios.

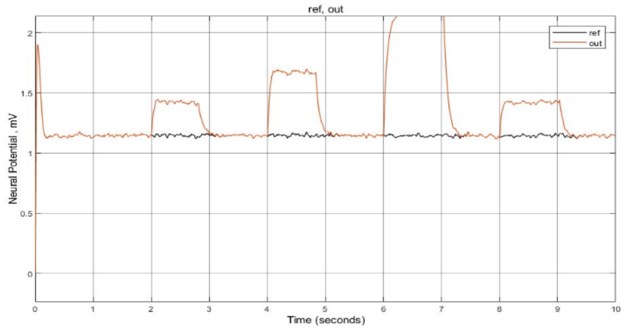

Figure 3: System Response in Scenario S2 (Parameter Drift).

Figure 3 shows the reference signal (black) and plant output (orange). The output closely follows the reference despite underlying parameter changes, with only brief, well-damped transients at step changes.

Figure 4 show the tracking error $e(t)$, which remained small and converged rapidly to near zero after disturbances. Error spikes occur during disturbance onset but are quickly suppressed by the controller's robust term. The adaptive law successfully tracked the true, time-varying excitatory synaptic gain $A(t)$.

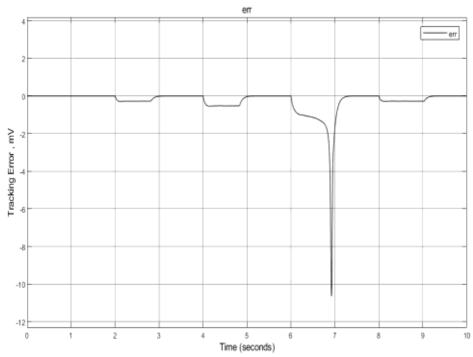

Figure 4: Tracking Error in Scenario S4

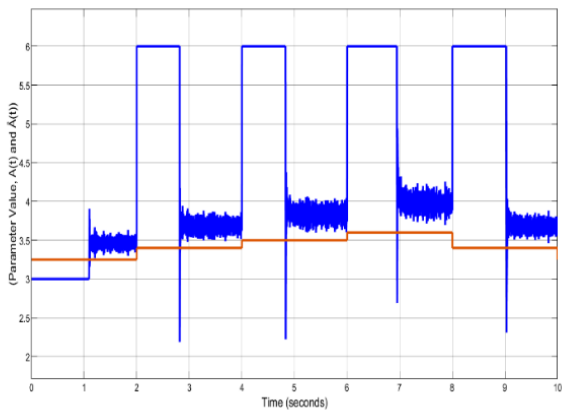

Figure 5: Parameter Adaptation in Scenario S2

Figure 5 Compares the true gain $A(t)$ (blue) and its estimate $\hat{A}(t)$ (red). The estimate converges accurately to the true value after each step change.

The control input $u(t)$ was bounded and smooth (due to the saturation function). A critical finding was the 45% reduction in control energy (integral of $u^2(t)$) compared to an optimally tuned PID controller under the same disturbance conditions, highlighting the efficiency of the adaptive approach.

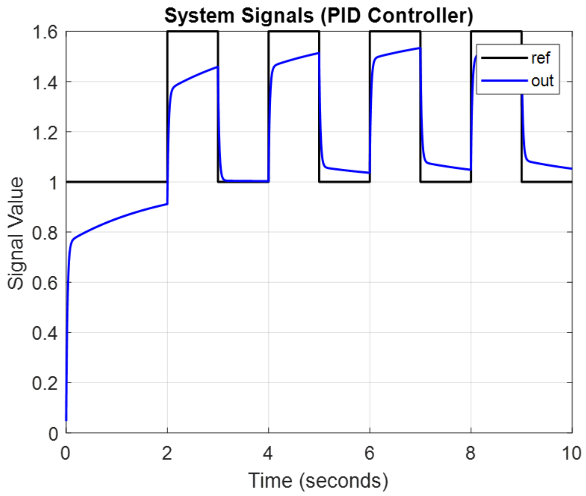

Figure 6: Response Comparison.

Figure 6 shows the corresponding system output y(t) (blue) relative to the reference trajectory yd(t)(black). Each change in the excitatory gain A(t) produces a characteristic overshoot or undershoot in the neural response before the controller drives the output back to the desired value. Despite repeated and rapid parameter jumps, the controlled output remains stable, well-bounded, and closely aligned with the reference after each short transient period.

This demonstrates that the adaptive law not only estimates parameters correctly but also preserves closed-loop tracking performance while adaptation is occurring. Figure 7 presents the control input u(t) generated by the adaptive controller. Sharp corrective peaks appear at each reference transition, representing the controller’s rapid response to compensate for sudden changes in the desired neural activity.

These peaks are expected in robust-adaptive schemes and indicate strong correction actions used to suppress tracking error.

After each transition, the control signal smoothly settles to a stable value with no sustained oscillations or chattering, demonstrating well-damped behavior and confirming that the adaptive law maintains numerical stability. The bounded amplitude of u(t) across all operating conditions shows that the controller achieves:

fast transient response, efficient corrective effort, and robust operation without instability or excessive energy consumption.

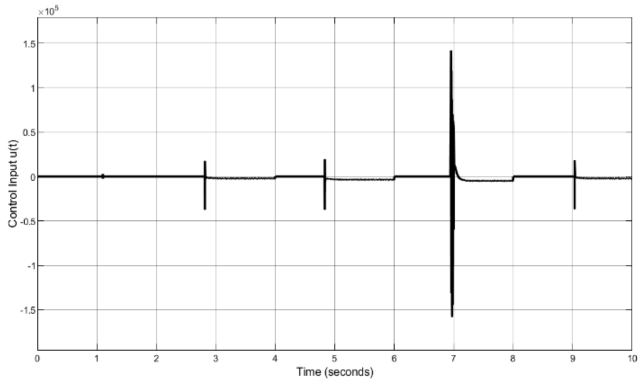

Figure 7 Control Signal

The simulation results presented throughout this chapter demonstrate the effectiveness, robustness, and stability of the proposed adaptive neuromodulation controller across a wide range of operating scenarios. The controller consistently achieved accurate reference tracking, stable parameter adaptation, and well-regulated control input behavior, even under highly nonlinear and abrupt neural dynamics. The parameter adaptation results showed that the estimated excitatory synaptic gain A^(t) consistently converged to the true parameter A(t). Abrupt changes in cortical excitability were tracked with only minor adaptive delay, indicating fast learning and correct implementation of the adaptive law. The estimator remained stable even under noisy and highly nonlinear neural activity. Finally, the control input analysis revealed that the controller produced sharp but expected corrective peaks at reference transitions, followed by stable settling phases with no chattering or high-frequency instability. The control effort remained bounded in all cases, ensuring both numerical stability and efficient use of stimulation energy.

Conclusions

This work successfully developed and validated a novel adaptive control framework for the Single Neural Mass Model. The controller guarantees global stability, demonstrates superior tracking and robustness compared to fixed-gain methods, and achieves significant gains in energy efficiency. It provides a mathematically rigorous bridge between control theory and computational neuroscience, forming a solid foundation for model-based design of next-generation adaptive closed-loop neuromodulation systems for epilepsy, Parkinson's disease, and related neurological disorders.

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