Offline Neural Plasticity Homeostasis (ONPH) - Computational Modeling Specification

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Simulation Environment: Python 3.9 / NumPy / SciPy

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1. Model Overview

This simulation model aims to verify the theoretical consistency of the core dynamical equations within the ONPH hypothesis. We constructed a **Stochastic Differential Equation (SDE)** model to simulate the dynamic evolution of synaptic weights during the "Wake-Sleep" cycle2.

This model is not a precise physical simulation of biological neurons (e.g., Hodgkin-Huxley model), but rather a **Phenomenological Modeling** of synaptic plasticity rules. Its core purpose is to verify the following three theoretical inferences3:

1. **Bidirectional Adjudication Mechanism:** Whether Wake Confirmation is a necessary condition for long-term consolidation4.
2. **Active Forgetting:** Whether Homeostatic Downscaling can effectively clear unconfirmed noise memories5.
3. **Instinct Preservation:** Whether Endogenous Activation can prevent the disuse atrophy of instinctual circuits6.

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2. Core Dynamics

The evolution of synaptic weight W_{ij} follows the update rule below for discrete time steps7:

$$W_{t+1} = \mathrm{Clip}(W_t + \Delta W_{wake} + \Delta W_{sleep} + \epsilon, 0, 1)$$

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2.1 Wake Phase Update

Weight changes during the wake phase are determined by Hebbian input and the Wake Confirmation Gain9:

$$\Delta W_{wake} = \gamma \cdot C(w)$$

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- γ **(Gamma):** Wake Confirmation Gain Coefficient. Simulates the gating effect of neuromodulators (e.g., Dopamine) on LTP11.
- $C(w)$ **(Confirmation Input):** External behavioral input signal12.
  - For the **Consolidation Group**: $C(w) > 0$ (Simulating review/re-exposure)13.
  - For the **Forgetting Group**: $C(w) = 0$ (No review)14.

2.2 Sleep Phase Update

Weight changes during the sleep phase are determined by the ONPH core equation15:

$$\Delta W_{sleep} = \alpha \cdot R(s) - \beta \cdot D(t) + \delta \cdot I(g)$$

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- α **(Alpha):** Offline Replay Gain. Simulates the intensity of Hippocampal-Cortical Replay17.
  - $R(s)$ **(Replay Probability):** Modeled as a Sigmoid function of the current synaptic weight: $R(s) \propto \frac{1}{1+e^{-k(W-W_{0})}}$18.
- β **(Beta):** Homeostatic Downscaling Factor. Simulates the synaptic scaling pressure proposed by the SHY hypothesis19.
- δ **(Delta):** Instinct Preservation Coefficient20.
  - $I(g)$ **(Instinct Weight):** Genetically encoded baseline weight (1.0 for the Instinct Group, 0.0 for others)21.

2.3 Random Noise

- $\epsilon \sim N(0, \sigma^2)$**:** Simulates the inherent synaptic noise in biological systems22.

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3. Parameter Calibration

To explore the boundary conditions of the model, we performed a parameter space search and selected the following parameter set to simulate healthy nervous system function23:

Parameter	Symbol	Set Value	Biological Interpretation
Replay Gain	α	**0.20**	Simulates the induction efficiency of LTP during SWS/REM sleep. The value must be higher than the homeostatic pressure to allow consolidation.
Homeostatic Downscaling	β	**0.18**	Simulates the exponential decay of synaptic weights. This value is set high (0.18) to ensure that unconfirmed memories are effectively cleared (validating Active Forgetting).
Wake Confirmation	γ	**0.65**	Simulates the weight of behavioral feedback during the wake phase. A high value indicates that wake confirmation plays a decisive role in overcoming homeostatic pressure.
Instinct Weight	δ	**0.15**	Simulates gene-driven baseline activation. This value is sufficient to counteract the decay caused by β.
Noise Level	σ	**0.08**	Simulates the randomness of synaptic transmission.

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Calibration Note: We found that when $\beta < 0.12$, the system fails to effectively clear noise memories (forgetting curve stagnation); when $\gamma < 0.4$, valid memories fail to overcome downscaling pressure. The current parameter combination represents an optimal system state with high Signal-to-Noise Ratio (SNR) screening capabilities25.

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4. Experiment Design

We employed the **Monte Carlo Method** for simulation with a sample size of $N = 10,000$26.

Experimental Groups 27

1. **Scenario A (Consolidation):** Simulating high-value memory. Strong input is given on Day 1, followed by exponentially decaying wake confirmation signals28.
2. **Scenario B (Forgetting):** Simulating noise memory. Input is given only on Day 1, with no subsequent wake confirmation29.
3. **Scenario C (Instinct):** Simulating instinctual circuits. No wake input, but possesses high endogenous instinct weight ($I_g = 1.0$)30.

Statistical Test 31

An independent samples t-test (Student's t-test) was used to compare inter-group differences on Day 3, with the significance level set at $\alpha = 0.05$32.