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# NEURO-VESICLES: NEUROMODULATION SHOULD BE A DYNAMICAL SYSTEM, NOT A TENSOR DECORATION

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## ABSTRACT

We introduce *Neuro-Vesicles*, a formal framework that augments conventional neural networks with a previously missing computational layer: a dynamical population of mobile, discrete entities that live *alongside* the network rather than *inside* its tensors. Unlike classical neuromodulation mechanisms—which collapse modulation into scaling factors, gating masks, or low-rank parameter shifts—Neuro-Vesicles treat modulation as an explicit stochastic process unfolding on the network graph. Each vesicle is a self-contained object carrying a vector-valued payload, a type label, an internal state, and a finite lifetime. Vesicles are emitted from nodes in response to activations, errors, or meta-signals; migrate across the graph according to learned transition kernels; probabilistically dock at individual nodes; locally alter activations, parameters, learning rules, or external memory through content-dependent release operators; and finally decay or are absorbed.

This event-based interaction layer fundamentally reshapes modulation: vesicles can accumulate, disperse, trigger cascades, carve transient computational pathways, or write structured traces into topological memory. Rather than applying a fixed modulation function at every forward pass, the system exhibits multi-timescale behavior where fast neural computation is continuously shaped by slowly evolving vesicle dynamics. In the limit of many vesicles with short lifetimes, the framework recovers familiar tensor-level conditioning layers such as FiLM, hypernetworks, or attention; in the opposite limit of sparse, long-lived vesicles, it approaches a discrete symbolic system of mobile “agents” that edit computation only at rare but decisive moments.

We present a complete mathematical specification of the Neuro-Vesicle paradigm, including the base network as a directed computational graph; the vesicle state space; emission, migration, docking, release, and decay kernels; the coupled stochastic dynamics linking vesicles and network behavior; a continuous density relaxation for differentiable training; and a reinforcement-learning formulation that treats vesicle control as an overlay policy. We then outline how the same formalism naturally extends to spiking neural networks and neuromorphic hardware such as the Darwin3 chip, yielding a three-part computational architecture—a parameterized network, a topological external memory, and a mobile event-driven dynamical layer—that turns neuromodulation from a tensor decoration into a first-class mechanism of computation.

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## 1 Base Network as a Graph

Figure 1 provides a high-level overview of the Neuro-Vesicle paradigm, from biological neuromodulation to deployment on spiking and neuromorphic systems.

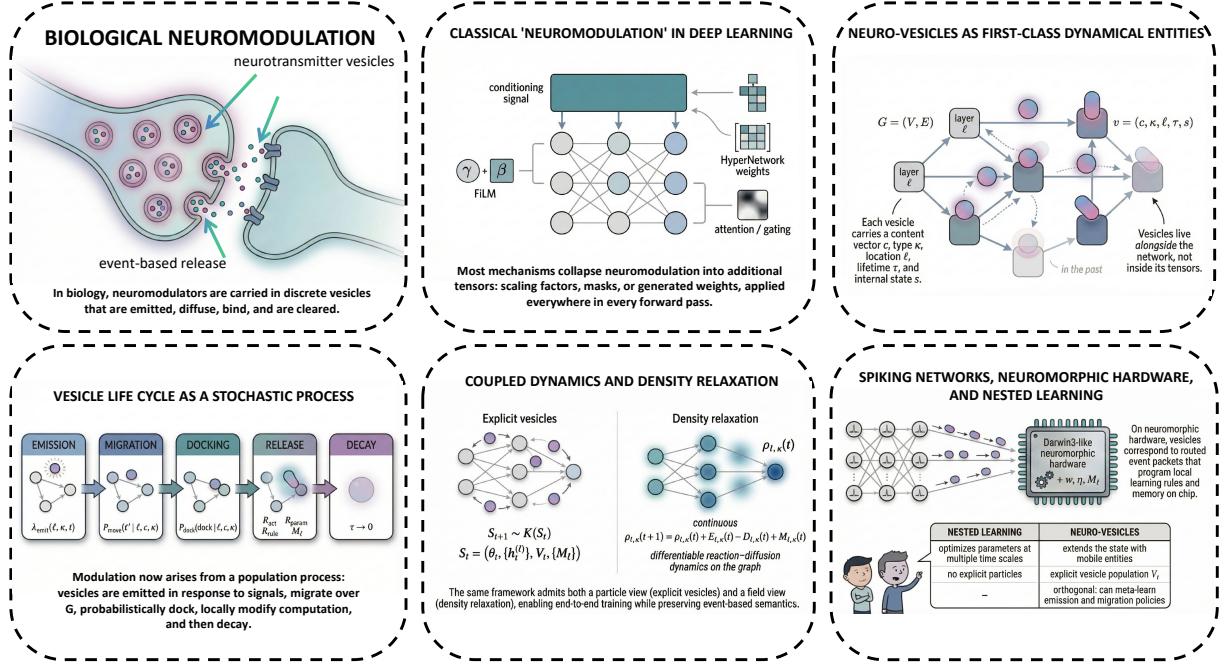


Figure 1: Overview of the Neuro-Vesicle (NV) paradigm. From left to right, the panels illustrate: (a) biological neuromodulation via neurotransmitter vesicles at chemical synapses; (b) classical “neuromodulation” in deep learning implemented as additional tensors (conditioning signals, FiLM layers, HyperNetwork-generated weights, and attention/gating); (c) NVs as first-class dynamical entities—mobile vesicles  $v = (c, \kappa, \ell, \tau, s)$  that move on the network graph  $G = (V, E)$ ; (d) the vesicle life cycle as a stochastic process (emission, migration, docking, release, decay); (e) coupled dynamics of explicit vesicles and their continuous density relaxation on the graph; (f) deployment in spiking neural networks and neuromorphic hardware, and the orthogonal relationship between NVs and nested learning. The bottom legend summarizes the core notation: *Neuro-Vesicle* = (content  $c$ , type  $\kappa$ , location  $\ell$ , lifetime  $\tau$ , state  $s$ ),  $G = (V, E)$  is the network graph substrate, and modulation is emphasized as emerging from vesicle dynamics rather than from extra tensors alone.

The starting point of our framework is deliberately conservative: we do not alter the structure of a standard neural network. Instead, we *re-interpret* it as a substrate on which an additional dynamical layer can live. This avoids confusing the proposed mechanism with yet another architectural tweak, and makes it clear that Neuro-Vesicles are not a replacement for existing models, but an overlay that can, in principle, be added to almost any architecture.

Let a standard feedforward or recurrent neural network be written as a function

$$f_\theta : \mathcal{X} \rightarrow \mathcal{Y}, \quad (1)$$

with parameters  $\theta$  and training distribution  $(x, y) \sim \mathcal{D}$ . We view the network as a directed graph

$$G = (V, E), \quad (2)$$

where each node  $v \in V$  corresponds to a computational module (e.g., a single neuron, a channel, a layer, or a transformer block) and each edge  $(u, v) \in E$  denotes information flow. This graph view is intentionally generic: it covers convolutional stacks, transformers, mixture-of-experts, and even more irregular architectures such as neural program interpreters.

For notational clarity, we assume the network can be decomposed into  $L$  ordered layers

$$h^{(0)} = x, \quad h^{(l)} = \phi^{(l)}(h^{(l-1)}; \theta^{(l)}), \quad l = 1, \dots, L, \quad (3)$$

with output  $f_\theta(x) = h^{(L)}$ . Here  $h^{(l)}$  is the hidden representation at layer  $l$ ,  $\theta^{(l)}$  are parameters local to that layer, and  $\phi^{(l)}$  is a deterministic mapping (e.g., affine transformation plus nonlinearity, attention block, etc.). The details of  $\phi^{(l)}$  are deliberately abstracted away, because Neuro-Vesicles are defined to act on this layer-wise structure without constraining its internal implementation.

We write the standard training objective as

$$L_{\text{base}}(\theta) = \mathbb{E}_{(x,y) \sim \mathcal{D}} [\ell(f_\theta(x), y)], \quad (4)$$

where  $\ell(\cdot, \cdot)$  is a suitable loss function. In almost all existing work on “neuromodulation” in deep learning, the effect of modulatory signals is implemented as additional terms inside this forward mapping: scaling factors on activations, additive biases, hypernetworks that generate weights, context-dependent attention masks, and so on.<sup>2</sup> Conceptually, all of these live *inside* the tensors and weight matrices, and are updated at the same time scale and with the same gradient flow as the rest of the network.

By contrast, Neuro-Vesicles are designed to form a *separate* dynamical system that runs on top of the graph  $G$ , interacting with but not being reduced to the usual tensor algebra. The aim is to more faithfully capture the idea that neuromodulation is an event-driven, spatially localized, and temporally extended process, rather than just a few extra channels in the forward pass.

## 2 State Space of Neuro-Vesicles

### 2.1 Single Vesicle State

We now describe the basic unit of the proposed dynamical layer. A *Neuro-Vesicle* is a discrete entity

$$v = (\mathbf{c}, \kappa, \ell, \tau, s), \quad (5)$$

with the following components:

- $\mathbf{c} \in \mathbb{R}^{d_c}$ : vesicle content vector (payload), conceptually an artificial neuromodulator embedding. This can be thought of as the analogue of the “chemical content” of a biological vesicle, but here it is entirely abstract and learnable.
- $\kappa \in \{1, \dots, K\}$ : vesicle type (e.g., “families” analogous to different biological neuromodulators). Different types may use different emission rules, migration policies, or release operators.
- $\ell \in V$ : current location on the network graph (node, layer, or module). This makes vesicles spatially grounded: they do not act everywhere at once, but only at the nodes where they happen to be.
- $\tau \in \mathbb{R}^+$ : remaining lifetime. The lifetime induces a natural temporal extent for the influence of a vesicle; once it expires, its direct effects stop, although its past interactions may have long-term consequences via learned parameters and memory.
- $s \in \mathcal{S}$ : optional internal state (e.g., residual release budget, discrete mode, etc.). This allows vesicles to implement multi-stage or stateful interaction protocols, rather than a single one-shot effect.

The space of vesicle states is the product

$$\mathcal{Z} = \mathbb{R}^{d_c} \times \{1, \dots, K\} \times V \times \mathbb{R}^+ \times \mathcal{S}. \quad (6)$$

In particular,  $\mathcal{Z}$  is independent of the dimension of activations or parameters in the base network; this decoupling is crucial for viewing vesicles as first-class entities rather than hidden tensor components.

### 2.2 Configuration of Vesicles

At discrete time  $t \in \mathbb{N}$  (e.g., within or across training steps), the system maintains a finite multiset of vesicles

$$\mathcal{V}_t = \{v_t^{(1)}, v_t^{(2)}, \dots, v_t^{(N_t)}\}, \quad (7)$$

where  $N_t$  is the number of active vesicles at time  $t$ . The cardinality  $N_t$  can vary over time: in some regimes the system may maintain only a handful of vesicles; in others, it may deploy a large “cloud” of vesicles that densely explore the network.

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<sup>2</sup>See, e.g., FiLM layers [1] and HyperNetworks [2] for two influential families of such mechanisms.

We denote the joint state of network and vesicles as

$$S_t = (\theta_t, \{h_t^{(l)}\}_{l=0}^L, \mathcal{V}_t). \quad (8)$$

Here  $\theta_t$  and  $h_t^{(l)}$  may evolve due to training, vesicle interactions, or external updates. Conceptually, Neuro-Vesicles turn the pair  $(\theta_t, \{h_t^{(l)}\})$  into a *medium* on which a second, richer dynamical system  $\mathcal{V}_t$  lives and acts.

### 3 Emission, Migration, Docking, Release, and Decay

We now specify the vesicle dynamics as a composition of stochastic kernels acting on the configuration  $\mathcal{V}_t$ . The main design principle is to mirror the qualitative stages of biological neuromodulation (release, diffusion, binding, action, and clearance), while retaining differentiability and compatibility with standard training pipelines.

#### 3.1 Emission Kernel

Intuitively, emission answers the question: *when and where should a vesicle be created, and with what content and type?* In biological systems, neuromodulators are often released in response to activity patterns, reward signals, or global brain states. We encode this idea via a learned emission intensity.

For each node  $\ell \in V$  and type  $\kappa$ , we define an emission intensity  $\lambda_{\text{emit}}(\ell, \kappa, t)$ , which may depend on local activations, gradients, or meta-variables. A simple parametrization is

$$\lambda_{\text{emit}}(\ell, \kappa, t) = \sigma(u_\kappa^\top \psi_{\text{emit}}(h_t^{(\ell)}, g_t^{(\ell)}, m_t)), \quad (9)$$

where

- $u_\kappa \in \mathbb{R}^{d_e}$  is a type-specific vector,
- $\psi_{\text{emit}}$  is an encoder producing features of local activations  $h_t^{(\ell)}$ , local gradients  $g_t^{(\ell)} = \nabla_{\theta^{(\ell)}} L_t$ , and meta state  $m_t$ ,
- $\sigma(z) = 1/(1 + e^{-z})$  is a sigmoid.

Thus, emission intensity is a learned function of both forward and backward signals, allowing vesicles to be spawned preferentially in regions that are surprising, high-error, or otherwise “interesting” for the task.

Conditioned on  $\lambda_{\text{emit}}(\ell, \kappa, t)$ , we can model the number of new vesicles of type  $\kappa$  emitted at node  $\ell$  as a Poisson random variable

$$N_{\ell, \kappa}^{\text{new}}(t) \sim \text{Poisson}(\lambda_{\text{emit}}(\ell, \kappa, t)). \quad (10)$$

Other emission count distributions (e.g., Bernoulli or bounded count models) are possible; we adopt a Poisson form to emphasize the connection with point processes.

For each such new vesicle, we sample its content, lifetime, and internal state from emission distributions:

$$\mathbf{c}_0 \sim P_c(\cdot | \ell, \kappa, t), \quad (11)$$

$$\tau_0 \sim P_\tau(\cdot | \ell, \kappa, t), \quad (12)$$

$$s_0 \sim P_s(\cdot | \ell, \kappa, t). \quad (13)$$

These distributions can themselves be parameterized neural networks, linking vesicle content to the context that triggered emission.

The emission kernel is then

$$P_{\text{emit}}(\mathcal{V}_t^+ | \mathcal{V}_t, S_t), \quad (14)$$

where  $\mathcal{V}_t^+$  denotes the union of existing and newly emitted vesicles. From a systems viewpoint, this turns each node into a potential generator of information-carrying entities that will later roam the network and intervene in its computations.

#### 3.2 Migration Kernel

After emission, vesicles must move. Migration controls how vesicles explore the network topology and which regions they are likely to reach, thereby shaping the spatial pattern of neuromodulatory influence.

Let  $A \in \{0, 1\}^{|V| \times |V|}$  be the adjacency matrix of  $G$ , where  $A_{ij} = 1$  if there is an edge from node  $i$  to node  $j$ . For each type  $\kappa$ , we define a (possibly learnable) transition matrix  $T^{(\kappa)} \in [0, 1]^{|V| \times |V|}$  such that

$$T_{ij}^{(\kappa)} = 0 \quad \text{if } A_{ij} = 0, \quad \sum_j T_{ij}^{(\kappa)} = 1. \quad (15)$$

This captures the “default” migration policy for vesicles of type  $\kappa$ , constrained by the network topology.

Given a vesicle  $v_t = (\mathbf{c}_t, \kappa, \ell_t, \tau_t, s_t)$ , its new location  $\ell_{t+1}$  is sampled as

$$\ell_{t+1} \sim P_{\text{move}}(\cdot \mid \ell_t, \mathbf{c}_t, \kappa, S_t), \quad (16)$$

where a simple instantiation is

$$P_{\text{move}}(\ell' \mid \ell_t, \mathbf{c}_t, \kappa, S_t) \propto T_{\ell_t, \ell'}^{(\kappa)} \cdot \exp\left(\gamma_\kappa \cdot q_{\text{move}}(\ell', \mathbf{c}_t, S_t)\right), \quad (17)$$

with  $\gamma_\kappa$  a temperature parameter and  $q_{\text{move}}$  a score function (e.g., depending on local gradient norm or uncertainty at  $\ell'$ ). In this way, migration can be biased towards regions where intervention is likely to matter more, while still being rooted in the network’s graph structure.

### 3.3 Docking Kernel

Migration alone does not guarantee interaction. Docking decides whether a passing vesicle actually engages with a node or simply passes by. This is a crucial difference from tensor-based modulation: vesicle effects are *event-based*, not continuous.

Given a vesicle at location  $\ell_{t+1}$ , we define the probability that it docks at time  $t + 1$  as

$$p_{\text{dock}} = P_{\text{dock}}(\text{dock} \mid \ell_{t+1}, \mathbf{c}_t, \kappa, S_t) = \sigma\left(w_\kappa^\top \psi_{\text{dock}}(h_{t+1}^{(\ell_{t+1})}, \mathbf{c}_t, s_t)\right), \quad (18)$$

with parameters  $w_\kappa$  and feature encoder  $\psi_{\text{dock}}$ . Here the docking decision can depend on both local activity and vesicle content, allowing, for example, vesicles that “recognize” particular activity patterns to preferentially dock where those patterns occur.

We then sample a Bernoulli variable

$$d_{t+1} \sim \text{Bernoulli}(p_{\text{dock}}). \quad (19)$$

If  $d_{t+1} = 1$ , a release event is triggered.

### 3.4 Release Operators

When a vesicle docks at node  $\ell$ , it releases its content  $\mathbf{c}$  via a set of local operators acting on (i) activations, (ii) parameters, (iii) learning rules, and (iv) external memory. This is the point where Neuro-Vesicles connect back to the familiar machinery of deep learning: they do not replace activations and gradients, but modulate them in structured ways.

**Activation-level release.** Let the pre-activation at node  $\ell$  be  $h^{(\ell)}$ . We define an activation modification operator

$$\mathcal{R}_\ell^{\text{act}} : (h^{(\ell)}, \mathbf{c}, \kappa, s) \mapsto \Delta h^{(\ell)}. \quad (20)$$

A simple form is FiLM-style modulation:

$$(\gamma_\ell, \beta_\ell) = W_{\text{act}}^{(\kappa)} \mathbf{c} + b_{\text{act}}^{(\kappa)}, \quad (21)$$

$$\Delta h^{(\ell)} = \gamma_\ell \odot h^{(\ell)} + \beta_\ell, \quad (22)$$

where  $W_{\text{act}}^{(\kappa)}$  and  $b_{\text{act}}^{(\kappa)}$  are learnable, and  $\odot$  denotes elementwise product. The updated activation is

$$\tilde{h}^{(\ell)} = h^{(\ell)} + \Delta h^{(\ell)}. \quad (23)$$

This recovers familiar modulation mechanisms but makes them conditional on discrete, mobile entities that may or may not be present at  $\ell$  at a given time.

**Parameter-level release.** At the parameter level, we define

$$\mathcal{R}_\ell^{\text{param}} : (\theta^{(\ell)}, \mathbf{c}, \kappa, s) \mapsto \Delta\theta^{(\ell)}. \quad (24)$$

For example, a rank-one update:

$$\mathbf{u}_\ell = U_\ell^{(\kappa)} \mathbf{c}, \quad (25)$$

$$\mathbf{v}_\ell = V_\ell^{(\kappa)} \mathbf{c}, \quad (26)$$

$$\Delta\theta^{(\ell)} = \eta_\ell^{(\kappa)} \mathbf{u}_\ell \mathbf{v}_\ell^\top, \quad (27)$$

with step size  $\eta_\ell^{(\kappa)}$ . The updated parameters are

$$\tilde{\theta}^{(\ell)} = \theta^{(\ell)} + \Delta\theta^{(\ell)}. \quad (28)$$

This provides a mechanism for vesicles to induce localized structural changes in the parameter space, potentially enabling rapid, targeted adaptation.

**Rule-level release.** We allow vesicles to modify the local learning rule at node  $\ell$ . Let the base gradient be

$$g_t^{(\ell)} = \nabla_{\theta^{(\ell)}} L_t. \quad (29)$$

We define a vesicle-conditioned gradient

$$\tilde{g}_t^{(\ell)} = \mathcal{R}_\ell^{\text{rule}}(g_t^{(\ell)}, \mathbf{c}, \kappa, s), \quad (30)$$

for example

$$\tilde{g}_t^{(\ell)} = \alpha^{(\ell)}(\mathbf{c}) \odot g_t^{(\ell)} + \beta^{(\ell)}(\mathbf{c}), \quad (31)$$

where  $\alpha^{(\ell)}(\mathbf{c})$  and  $\beta^{(\ell)}(\mathbf{c})$  are outputs of learnable functions of  $\mathbf{c}$ . The parameter update becomes

$$\theta_{t+1}^{(\ell)} = \theta_t^{(\ell)} - \eta_t^{(\ell)} \tilde{g}_t^{(\ell)}, \quad (32)$$

with possibly vesicle-dependent learning rate  $\eta_t^{(\ell)} = \eta^{(\ell)}(\mathbf{c})$ . This explicitly separates the *what* (the gradient signal) from the *how* (the update rule), allowing vesicles to shape the latter.

**External-memory release.** Each node  $\ell$  additionally maintains an external memory state  $M_\ell$ . We define a write operator

$$M_\ell \leftarrow \text{Write}_\ell(M_\ell, \mathbf{c}, \kappa, s), \quad (33)$$

and a read operator used during forward/backward computation

$$r_\ell = \text{Read}_\ell(M_\ell), \quad (34)$$

which can be injected into the computation at  $\ell$ , e.g.,

$$h_{\text{extended}}^{(\ell)} = h^{(\ell)} \oplus r_\ell. \quad (35)$$

By design, the triple  $(\theta, \{M_\ell\}, \mathcal{V}_t)$  forms a richer state than parameters alone. Vesicles can then be seen as agents that write structured traces into this topological memory, leaving behind *spatially localized* signatures of past events.

**Combined release effect.** Let  $\mathcal{V}_{t,\ell}^{\text{dock}}$  be the set of vesicles that dock at node  $\ell$  at time  $t$ . The total activation update at  $\ell$  is

$$\Delta h_{\text{total}}^{(\ell)} = \sum_{v \in \mathcal{V}_{t,\ell}^{\text{dock}}} \mathcal{R}_\ell^{\text{act}}(h^{(\ell)}, \mathbf{c}_v, \kappa_v, s_v), \quad (36)$$

and similarly for parameters and memory. Thus, multiple vesicles can cooperate or interfere at a single node, leading to rich combinatorial patterns of modulation.

### 3.5 Decay Kernel

Finally, vesicles must not persist indefinitely, or the system would degenerate into a static, densely populated field. Decay enforces a finite temporal horizon for vesicle influence.

Vesicle lifetime  $\tau$  decays over time according to

$$\tau_{t+1} = \tau_t - \Delta t + \epsilon_{\text{noise}}, \quad (37)$$

where  $\epsilon_{\text{noise}}$  can model stochastic fluctuations. A vesicle is removed when

$$\tau_{t+1} \leq 0 \quad \text{or} \quad \text{Absorb}(v_{t+1}) = 1, \quad (38)$$

where  $\text{Absorb}(\cdot)$  is an optional learned or deterministic absorption condition (e.g., explicit “clearance” operations at specific nodes). This ensures that vesicle dynamics remain non-trivial and that the system does not accumulate obsolete entities.

## 4 Coupled Dynamics of Network and Vesicles

At a high level, the joint system forms a stochastic dynamical process

$$S_{t+1} \sim \mathcal{K}(S_t), \quad (39)$$

where the transition kernel  $\mathcal{K}$  factorizes into:

1. *Base forward pass:*

$$h_t^{(0)} = x_t, \quad h_t^{(l)} = \phi^{(l)}(h_t^{(l-1)}; \theta_t^{(l)}). \quad (40)$$

This is the standard computation of the underlying network.

2. *Emission:*

$$\mathcal{V}_t \xrightarrow{P_{\text{emit}}} \mathcal{V}_t^+. \quad (41)$$

New vesicles are spawned based on current activity and gradients.

3. *Migration:*

$$v_t^{(n)} \xrightarrow{P_{\text{move}}} v_{t+1/3}^{(n)}. \quad (42)$$

Existing vesicles move across the graph according to their type and content.

4. *Docking and release:*

$$v_{t+1/3}^{(n)} \xrightarrow{P_{\text{dock}}, \mathcal{R}} v_{t+2/3}^{(n)}, \quad h_t^{(l)}, \theta_t^{(l)}, M_\ell \mapsto \tilde{h}_t^{(l)}, \tilde{\theta}_t^{(l)}, \tilde{M}_\ell. \quad (43)$$

Docking events trigger local modifications of activations, parameters, learning rules, and memory.

5. *Decay:*

$$v_{t+2/3}^{(n)} \xrightarrow{\text{decay}} v_{t+1}^{(n)}, \quad (44)$$

keeping only vesicles with  $\tau_{t+1}^{(n)} > 0$ .

6. *Parameter update* (for training):

$$\theta_{t+1} = \theta_t - \eta_t \nabla_{\theta_t} L(\tilde{h}_t^{(L)}, y_t), \quad (45)$$

where  $\tilde{h}_t^{(L)}$  is the vesicle-modified output.

Thus, vesicle dynamics and network learning are tightly coupled. The network provides the substrate and gradients that drive emission and migration; vesicles, in turn, shape the effective computation and learning rule experienced by the network.

## 5 Density Relaxation

Exact discrete vesicle dynamics can be expensive or non-differentiable. We therefore consider a continuous relaxation in which vesicles are represented by densities. This serves both as a practical approximation and as a conceptual link between the discrete entity view and more classical continuous fields.

### 5.1 Vesicle Density and Mean Content

For each node  $\ell$  and type  $\kappa$ , define a scalar density  $\rho_{\ell,\kappa}(t)$  and a mean content vector  $\mathbf{C}_{\ell,\kappa}(t)$ . Intuitively,

$$\rho_{\ell,\kappa}(t) \approx \mathbb{E}[N_{\ell,\kappa}(t)], \quad (46)$$

and

$$\mathbf{C}_{\ell,\kappa}(t) \approx \mathbb{E}\left[\sum_{n \in \mathcal{I}_{\ell,\kappa}(t)} \mathbf{c}_t^{(n)}\right], \quad (47)$$

where  $\mathcal{I}_{\ell,\kappa}(t)$  indexes vesicles of type  $\kappa$  at node  $\ell$ . In this picture, vesicles are no longer tracked individually; instead, we track how much “vesicle mass” and content of each type resides at each node.

## 5.2 Dynamics of the Density Field

We write the density update as

$$\rho_{\ell,\kappa}(t+1) = \rho_{\ell,\kappa}(t) + E_{\ell,\kappa}(t) - D_{\ell,\kappa}(t) + M_{\ell,\kappa}(t), \quad (48)$$

where:

- $E_{\ell,\kappa}(t)$  is the emission term,
- $D_{\ell,\kappa}(t)$  is the decay/absorption term,
- $M_{\ell,\kappa}(t)$  is the net migration term.

A simple differentiable parameterization is:

$$E_{\ell,\kappa}(t) = \lambda_{\text{emit}}(\ell, \kappa, t), \quad (49)$$

$$D_{\ell,\kappa}(t) = \delta_\kappa \rho_{\ell,\kappa}(t), \quad (50)$$

$$M_{\ell,\kappa}(t) = \sum_i \rho_{i,\kappa}(t) \tilde{T}_{i \rightarrow \ell}^{(\kappa)} - \rho_{\ell,\kappa}(t) \sum_j \tilde{T}_{\ell \rightarrow j}^{(\kappa)}, \quad (51)$$

where  $\delta_\kappa \geq 0$  is a decay rate and  $\tilde{T}^{(\kappa)}$  is a differentiable transition matrix (e.g., softmax over neighbor scores). This is a discrete-time reaction–diffusion system over the graph  $G$ , parameterized by neural networks.

In vector form for a fixed type  $\kappa$ ,

$$\boldsymbol{\rho}_\kappa(t+1) = \boldsymbol{\rho}_\kappa(t) + \boldsymbol{\lambda}_{\text{emit},\kappa}(t) - \delta_\kappa \boldsymbol{\rho}_\kappa(t) + (T^{(\kappa)\top} - I) \boldsymbol{\rho}_\kappa(t), \quad (52)$$

where  $\boldsymbol{\rho}_\kappa(t) \in \mathbb{R}^{|V|}$ . This formulation is fully differentiable and can be trained jointly with the base network using standard gradient descent.

## 5.3 Expected Release Under the Density Approximation

Under the density model, the expected activation update at node  $\ell$  can be approximated as

$$\mathbb{E}[\Delta h_{\text{total}}^{(\ell)}(t)] \approx \sum_\kappa \rho_{\ell,\kappa}(t) \cdot \bar{\mathcal{R}}_{\ell,\kappa}^{\text{act}}(h_t^{(\ell)}, \mathbf{C}_{\ell,\kappa}(t)), \quad (53)$$

where  $\bar{\mathcal{R}}_{\ell,\kappa}^{\text{act}}$  is the mean effect of a vesicle of type  $\kappa$  with average content  $\mathbf{C}_{\ell,\kappa}(t)$ . Analogous expressions can be written for parameter-level and rule-level effects.

This yields a fully differentiable surrogate system for training. Once trained, one can either keep this continuous version, or use it as a proposal distribution from which discrete vesicles are sampled, bridging between field-like and particle-like descriptions.

## 6 Neuro-Vesicles for Spiking Neural Networks and Neuromorphic Hardware

The preceding sections treated the base network abstractly, without assuming a particular neuron model. We now show that Neuro-Vesicles are especially natural in the context of spiking neural networks (SNNs) and neuromorphic hardware, where computation is already event-driven and time-resolved [3, 6, 7].

### 6.1 Spiking Dynamics and Eligibility Traces

Consider a recurrent SNN with neurons indexed by  $i$ , membrane potentials  $u_i(t)$ , and spike trains  $s_i(t) = \sum_k \delta(t - t_i^k)$ , where  $t_i^k$  are spike times. A simple leaky integrate-and-fire model reads

$$\tau_m \frac{du_i(t)}{dt} = -u_i(t) + \sum_j w_{ij} (s_j * \kappa)(t) + I_i(t), \quad (54)$$

with membrane time constant  $\tau_m$ , synaptic kernel  $\kappa$ , and external current  $I_i(t)$ . Spikes are generated when  $u_i(t)$  crosses threshold and then reset.

For learning in SNNs, many biologically motivated rules are *three-factor* schemes of the form

$$\Delta w_{ij}(t) \propto e_{ij}(t) m(t), \quad (55)$$

where  $e_{ij}(t)$  is an eligibility trace computed from pre- and post-synaptic activity, and  $m(t)$  is a modulatory signal encoding reward, surprise, or context [11, 12, 13, 15]. Eligibility traces evolve according to local dynamics, e.g.,

$$\tau_e \frac{de_{ij}(t)}{dt} = -e_{ij}(t) + F(s_i(t), s_j(t)), \quad (56)$$

where  $F$  encodes spike-timing-dependent plasticity (STDP).

In many existing models, the modulatory term  $m(t)$  is either a scalar global signal (“dopamine level”) or a fixed field over neurons [12, 13]. Neuro-Vesicles provide a way to *materialize* this modulatory signal as a population of discrete entities moving on the SNN graph.

## 6.2 Vesicle-Carried Modulatory Fields

To couple vesicles to SNN plasticity, we associate with each synapse  $w_{ij}$  a modulatory field  $m_{ij}(t)$  defined as the aggregated influence of vesicles in the neighborhood of the synapse. One concrete instantiation is

$$m_{ij}(t) = \sum_{\kappa} \sum_{v \in \mathcal{V}_t} \mathbf{1}[\ell_v \in \mathcal{N}(i, j)] \alpha_{\kappa}(\mathbf{c}_v, s_v), \quad (57)$$

where  $\mathcal{N}(i, j)$  is a local region of the graph (e.g., the pre- and post-synaptic neurons and their immediate neighbors),  $\mathbf{1}[\cdot]$  is an indicator, and  $\alpha_{\kappa}$  maps vesicle content and state to a scalar modulation strength. The synaptic update then becomes

$$\Delta w_{ij}(t) = \eta e_{ij}(t) m_{ij}(t), \quad (58)$$

so that only those synapses lying in the current trajectory of vesicles receive strong updates.

In this picture, vesicles realize a *structured* modulatory field: rather than emitting a global broadcast signal, the system can route modulation selectively along particular pathways. For example, vesicles generated in a “reward” circuit could migrate along recurrent loops implicated in the current task, biasing credit assignment towards these loops while leaving unrelated circuits untouched, in line with ideas from cell-type-specific neuromodulation [12].

## 6.3 Event-Driven Vesicle Dynamics

Spiking simulations, especially on neuromorphic chips, are often event-driven: neuron state is updated only at spike times. Neuro-Vesicles can be integrated into this framework by letting their dynamics advance only in response to discrete events. For instance, let  $\mathcal{T} = \{t^1, t^2, \dots\}$  be the ordered set of spike times in the network. Between events, vesicles simply age:

$$\tau^{(n)}(t^{k+1}) = \tau^{(n)}(t^k) - (t^{k+1} - t^k), \quad (59)$$

and migration/emission/docking are computed only at event times  $t^k$ , using the current pattern of spikes in a local window.

This naturally aligns vesicle updates with the temporal granularity of SNN hardware simulators and avoids unnecessary computation at idle times. Moreover, vesicles can themselves emit modulatory spikes into dedicated channels, so that their actions are indistinguishable from ordinary spike events at the level of hardware primitives.

## 6.4 Mapping to Darwin3 and Other Neuromorphic Chips

Neuromorphic chips such as TrueNorth [4], Loihi [5], and Darwin3 [10] have demonstrated that large-scale SNNs with on-chip learning are feasible at competitive energy budgets [6, 8, 9]. Darwin3, in particular, supports up to 2.35 million spiking neurons and over 100 million synapses per chip, and exposes a domain-specific instruction set architecture (ISA) that allows flexible on-chip learning rules and custom synapse models [10].

At a high level, Neuro-Vesicles can be compiled onto such hardware by treating vesicles as *soft processes* that are implemented by auxiliary neuron populations and configurable synapses:

- **Emission** can be realized by neuron populations that monitor local spikes and error proxies, triggering the creation of new “vesicle neurons” whose state encodes  $\mathbf{c}$ ,  $\kappa$ , and  $\tau$ .
- **Migration** corresponds to routing spikes from vesicle neurons to different parts of the chip over time. On Darwin3, this can be expressed using its packet-based routing fabric and ISA-level support for programmable spike forwarding.
- **Docking and release** are implemented as synaptic connections from vesicle neurons onto target neurons and synapses, using the chip’s programmable learning engine to modulate weight updates and local currents [5, 10].

- **Decay** is handled by letting vesicle neurons follow leaky dynamics; once their internal potential falls below a threshold, they stop emitting spikes and are effectively cleared.

For example, suppose Darwin3 supports a generic synaptic plasticity update of the form

$$\Delta w_{ij} = A_{\text{pre}} \text{STDP}_{\text{pre}}(t) + A_{\text{post}} \text{STDP}_{\text{post}}(t) + A_{\text{mod}} \text{STDP}_{\text{mod}}(t), \quad (60)$$

where the last term is gated by a modulatory spike train. A Neuro-Vesicle implementation can set  $A_{\text{mod}} = \alpha_\kappa(\mathbf{c})$  for vesicles of type  $\kappa$ , and let these vesicles emit spikes into the modulatory channel whenever they dock near synapse  $w_{ij}$ . Thus, the vesicle dynamics define *which* synapses see strong modulatory input and *when*, while the on-chip learning engine handles the local pre/post computations.

Because Darwin3’s ISA is explicitly designed to support new learning rules [10], implementing Neuro-Vesicles does not require changing the chip, only supplying a compiler and runtime that map vesicle processes onto instruction sequences. This is conceptually similar to how existing compilers map abstract learning algorithms like e-prop onto neuromorphic substrates [11].

## 6.5 Algorithmic Synergies

Embedding Neuro-Vesicles in SNNs and neuromorphic hardware yields several potential synergies with existing algorithmic work:

- **Credit assignment.** Vesicle-mediated three-factor learning offers a unifying view of algorithms such as e-prop [11], MDGL [12], and NACA [13]: in each case, the modulatory factor can be seen as arising from a vesicle field with different emission/migration rules.
- **Temporal processing.** Recent work shows that neuromodulated oscillations improve temporal robustness in SNNs [14]. Vesicles provide a way to generate and route such oscillatory modulation, for instance by letting vesicle content encode phase and frequency.
- **Continual learning and task gating.** Neuromodulation-assisted credit assignment can mitigate catastrophic forgetting by selectively tagging synapses with task-specific traces [13]. Vesicles extend this idea by allowing task-specific modulatory entities to persist and move between subnetworks, effectively implementing mobile task gates.

In all these cases, the SNN and chip-level primitives remain largely unchanged; what is new is the *organizational layer* that decides where modulatory resources flow over time. We view Neuro-Vesicles as a candidate abstraction for that layer.

## 7 Neuro-Vesicles as an RL-Controlled Overlay

An alternative view treats vesicle dynamics as a policy in a Markov decision process layered on top of the base network. This perspective is particularly natural when one wants vesicle dynamics to explicitly optimize a long-term objective such as sample efficiency, robustness, or meta-learning performance.

### 7.1 State, Actions, and Policy

Define the combined state at time  $t$  as

$$s_t = (x_t, y_t, \{h_t^{(l)}\}_l, \theta_t, \mathcal{V}_t, \{M_\ell\}_\ell). \quad (61)$$

We define a vesicle control action  $a_t$  as a collection of operations:

$$a_t = (a_t^{\text{emit}}, a_t^{\text{move}}, a_t^{\text{dock}}, a_t^{\text{release}}), \quad (62)$$

specifying where to emit vesicles, how to move them, when to dock, and which release operators to apply. Each component may itself be structured and high-dimensional.

A parameterized policy  $\pi_\phi$  defines

$$a_t \sim \pi_\phi(a_t \mid s_t). \quad (63)$$

The environment dynamics (base network and stochastic transitions) are captured in a transition kernel  $P(S_{t+1} \mid S_t, a_t)$ . From this viewpoint, vesicle control is a meta-controller that operates on top of a differentiable world model (the base network and its learning dynamics).

## 7.2 Objective and Policy Gradient

Let the per-step reward be a function of performance and regularization, e.g.,

$$r_t = -\ell(f_{\theta_t}(x_t), y_t) - \Omega(\mathcal{V}_t), \quad (64)$$

where  $\Omega(\mathcal{V}_t)$  penalizes excessive vesicle usage. The objective is the expected discounted return

$$J(\phi) = \mathbb{E}_{\pi_\phi} \left[ \sum_{t=0}^{\infty} \gamma^t r_t \right], \quad (65)$$

with discount factor  $0 < \gamma \leq 1$ . Using REINFORCE, the gradient is

$$\nabla_\phi J(\phi) = \mathbb{E}_{\pi_\phi} \left[ \sum_{t=0}^{\infty} \nabla_\phi \log \pi_\phi(a_t | s_t) (R_t - b_t) \right], \quad (66)$$

where  $R_t = \sum_{k=t}^{\infty} \gamma^{k-t} r_k$  and  $b_t$  is a baseline (e.g., a learned value function). Thus, vesicle emission, migration, docking, and release can be learned to optimize downstream performance, not just through induced gradients but also through explicit exploration in the space of neuromodulatory strategies.

## 8 Minimal Prototype With Explicit Vesicles

Finally, we summarize a minimal explicit implementation at a single time scale (e.g., per training step). The goal here is not to be optimal, but to demonstrate that the proposed formalism can be instantiated with standard deep learning tooling.

### 8.1 Configuration Update

We maintain a list

$$\mathcal{V}_t = \{(\mathbf{c}_t^{(n)}, \kappa^{(n)}, \ell_t^{(n)}, \tau_t^{(n)}, s_t^{(n)})\}_{n=1}^{N_t}. \quad (67)$$

For each training step on a mini-batch  $(x_t, y_t)$ , we perform:

1. Forward pass through the base network, obtaining  $\{h_t^{(l)}\}$  and loss  $L_t$ . Here, no modification is needed to the original architecture.
2. Emission: sample new vesicles using (9) and the emission distributions, and add them to  $\mathcal{V}_t$ . In a simple implementation, one might cap the maximum number of vesicles emitted per layer per step.
3. Migration: for each vesicle  $n$ , sample new location using (17). This can be implemented as a categorical sampling over neighbors.
4. Docking: for each vesicle  $n$ , compute docking probability via (18); if docked, apply activation/parameter/memory release operators and optionally update its internal state  $s_t^{(n)}$ . The release operators can be implemented as small auxiliary networks that transform  $\mathbf{c}_t^{(n)}$  into modulation parameters.
5. Decay: for each vesicle  $n$ , update lifetime and remove it if  $\tau_t^{(n)} \leq 0$ . In practice, this corresponds to deleting entries from a list or masking them out.
6. Parameter update: compute gradients (possibly rule-modulated) and update  $\theta$  with an optimizer of choice. The presence of vesicles changes the effective loss surface and update rule, but requires no modification to the optimizer itself.

Even this minimal prototype exhibits all defining properties of the Neuro-Vesicle paradigm: (i) explicit discrete vesicle entities, (ii) migration on the network topology, (iii) event-based docking and release, and (iv) coupling between vesicle dynamics and learning. More sophisticated implementations can build on this scaffold by adding multiple time scales, more expressive release operators, or explicit meta-learning of vesicle controllers.

## 9 Discussion: Gaps in Existing Neuromodulation and Originality of Neuro-Vesicles

We briefly situate Neuro-Vesicles in the broader landscape of “neuromodulation-inspired” mechanisms in deep learning, and clarify what conceptual gap this framework aims to fill.

Most existing approaches that claim neuromodulatory inspiration reduce the idea to one of the following patterns:

- scalar or vector gates that multiplicatively scale activations or features,
- FiLM-style affine transformations conditioned on context,
- hypernetworks that generate weights as a function of side information,
- attention mechanisms that reweight contributions from different sources.

While powerful and widely useful, all of these mechanisms are ultimately realized as *additional terms inside the tensor computation*: they live in the same space, at the same time scale, and with the same update mechanism as ordinary activations and parameters [1, 2, 16]. From this perspective, neuromodulation is treated as a “tensor decoration”—an extra dimension, an extra channel, or an extra learned function in the forward pass.

The proposed Neuro-Vesicle framework challenges this implicit assumption by positing that neuromodulation should instead be understood as a *separate dynamical system* that:

1. has its own state space (the vesicle configuration),
2. has its own dynamics (emission, migration, docking, decay),
3. interacts with the base network through localized, event-based release operations.

This leads to several distinctive properties:

- **Entity-based modulation:** modulatory signals are carried by discrete entities that can be counted, tracked, and analyzed, rather than being diffused across all neurons.
- **Topological locality:** vesicle effects depend on the paths they take on the network graph, making neuromodulation sensitive to architecture in a way that pure tensor algebra is not.
- **Temporal extension and memory:** vesicles have lifetimes and internal states, allowing them to implement multi-step protocols and leaving traces in external memory.
- **Decoupled learning rules:** by acting at the level of gradients and update rules, vesicles can reshape how learning happens, not just what is represented.

Of course, this added expressivity comes with potential drawbacks and open questions:

- **Complexity:** the vesicle state space is large, and naïve implementations may incur non-trivial overhead in memory and computation, especially on conventional GPUs.
- **Stability:** if vesicle emission and migration are not well regulated, the system may become unstable, with too many vesicles or highly chaotic dynamics. Density relaxations and RL-based controllers are two possible tools for regularizing this behavior.
- **Identifiability:** different combinations of emission, migration, and release policies may produce similar behavioral effects, making interpretation and analysis challenging.
- **Task alignment:** not all tasks may benefit from such a rich neuromodulatory layer; identifying regimes where Neuro-Vesicles are strictly beneficial is an important empirical question, particularly for temporal processing and continual learning in SNNs [11, 14, 13].

Despite these challenges, we argue that treating neuromodulation as a dynamical layer of mobile entities—rather than a minor tweak to tensor operations—opens a qualitatively new design space for deep learning systems, with potential implications for continual learning, credit assignment, hierarchical reasoning, and deployment on large-scale neuromorphic computers such as Darwin3 and its successors [10, 6, 7].

## 10 Conclusion

We have proposed Neuro-Vesicles as a concrete, mathematically grounded realization of the idea that neuromodulation should be modeled as a dynamical system on top of neural networks, not merely as extra parameters inside them. By introducing a population of mobile, discrete vesicle entities with their own state, dynamics, and interaction operators, we obtain a framework that simultaneously: (i) recovers many existing conditioning mechanisms as limiting cases; (ii) suggests new algorithmic possibilities for spiking neural networks and neuromorphic hardware; and (iii) affords a richer vocabulary for thinking about how learning rules can be reconfigured in space and time.

The present work is intentionally theory-heavy and experiment-light. Our goal is to articulate a sufficiently detailed formalism that future empirical work can build upon it: small-scale prototypes on conventional GPUs, efficient event-driven implementations on neuromorphic chips like Darwin3, and biologically grounded models connecting vesicle

dynamics to recent theories of credit assignment in the brain [16, 12, 13, 11]. We hope that this perspective will help bridge the gap between abstract neuromodulatory ideas and concrete, programmable mechanisms in artificial neural systems.

## Appendix

### A Relation to Nested Learning and Other Modulatory Frameworks

This appendix clarifies how the proposed Neuro-Vesicle (NV) framework relates to existing work on nested learning and neuromodulation-inspired mechanisms in deep learning and neuromorphic computing. In short, Neuro-Vesicles are *complementary* rather than competing: nested-learning methods primarily reorganize *optimization* across multiple time scales, whereas Neuro-Vesicles enlarge the *state space* of the model with an explicit population of mobile entities that implement event-based neuromodulation on the network graph.

#### A.1 Conceptual Comparison

Nested learning views a learning system as a hierarchy of nested optimization problems operating at different time scales: a fast learner adapts parameters on short horizons, while slower learners adapt the fast learner, its objectives, or its inductive biases over longer horizons. In this picture, all relevant quantities—parameters, optimizer states, meta-parameters—live in a continuous parameter space and are updated by gradient-based (or gradient-like) methods at their respective frequencies. A typical nested-learning stack might consist of: (i) task-level parameters updated every batch, (ii) a meta-learner updating learning rates, regularization coefficients, or initializations over many tasks, and (iii) an even slower outer loop that tunes the meta-learner itself. All of these levels are described within the same calculus of differentiable optimization: the system remains a collection of tensors plus associated update rules, with nesting expressed through compositionality of objectives and gradients.

From this perspective, “structure” enters primarily through the way objectives are factorized and the way gradients are propagated across levels. There is no separate ontology beyond parameters and their updates: a meta-parameter is still just a vector or matrix, and its effect on the fast learner is mediated by differentiable computation graphs. Even when nested learning is applied to recurrent networks or spiking networks, the nested components modify how the existing units learn, not what kinds of entities exist in the state space.

By contrast, Neuro-Vesicles introduce an additional dynamical layer whose state space is the configuration of vesicles  $\mathcal{V}_t = \{(\mathbf{c}, \kappa, \ell, \tau, s)\}$ . This layer is not a new level of optimization, but a population of discrete entities that migrate on the network graph and interact with computation only through *event-based docking and release*. In other words, NVs change *what* the system is made of, not only *how fast* different parts of it are optimized. Each vesicle persists over multiple forward and backward passes, moves between layers, and decides stochastically whether to intervene at a given location. The relevant operations are therefore not just gradient steps but also birth, movement, interaction, and death of individual particles.

Crucially, the base optimizer may still be standard backpropagation or any nested learning algorithm; the vesicle dynamics are orthogonal and can sit *on top of* those choices. A nested learner can update  $\theta_t$  and meta-parameters that govern  $P_{\text{emit}}$  or  $P_{\text{move}}$ , while the vesicle population  $\mathcal{V}_t$  evolves as a stochastic process coupled to the network state. This yields a clear separation of concerns: nested learning organizes the hierarchy of optimization problems, whereas Neuro-Vesicles enlarge the state space with explicit mobile entities that realize neuromodulation as a spatiotemporal process on the graph  $G = (V, E)$ . In the limit where vesicle counts are very high and lifetimes are very short, the NV layer degenerates to an effectively continuous field that can be absorbed into tensor-level modulation; in the opposite limit of sparse, long-lived vesicles, the system resembles a network of neural modules coupled to a small set of mobile “agents” that carry and deploy modulatory information at discrete times and places—a regime that has no direct analogue in classical nested-learning formulations.

Seen from this perspective, nested learning sculpts a vector field over the space of parameters and meta-parameters, while Neuro-Vesicles sculpt a distribution over *trajectories* of vesicles moving on the network graph. The two mechanisms therefore operate on different geometric objects: gradients drive continuous flows in  $\theta_t$ , whereas vesicle birth, migration, docking, and decay induce piecewise-stochastic jumps in  $\mathcal{V}_t$ . When combined, the overall system lives in a hybrid space  $(\theta_t, \mathcal{V}_t)$  where slow, smooth optimization and fast, event-based neuromodulation coexist. This hybrid view makes it explicit that one can meta-learn the statistics of vesicle dynamics (e.g., sparsity, coverage, or preferred paths on  $G$ ) using nested-learning objectives, without ever reducing vesicles themselves to yet another tensor in the forward pass.

## A.2 Axes of Difference

Table 1 summarizes high-level conceptual differences between Neuro-Vesicles, nested learning, and more classical tensor-level neuromodulation (e.g., FiLM, hypernetworks).

Dimension	Neuro-Vesicles <sup>†</sup>	Nested Learning / tensor-level modulation <sup>‡</sup>
CORE OBJECT	Explicit vesicle entities $v = (\mathbf{c}, \kappa, \ell, \tau, s)$ forming a population $\mathcal{V}_t$ .	Parameters, optimizer states, and meta-parameters arranged into nested learners; no new first-class entities beyond continuous parameter vectors.
VIEW OF NEURO-MODULATION	Event-driven interventions triggered by vesicle docking and release; modulation is a stochastic dynamical process on the network graph.	Deterministic functions inside the forward/backward pass (e.g., FiLM, hypernetworks, attention) or slower meta-updates to parameters/optimizers.
REPRESENTATION TYPE	<i>Particle-based</i> : vesicles live on top of the network graph, can be counted, tracked, and individually inspected.	<i>Field-based</i> : all information is encoded in continuous tensors and optimizer states.
TIME SCALES	Multiple time scales arise from vesicle lifetimes $\tau$ , emission intensities $\lambda_{\text{emit}}$ , and migration dynamics; fast neural computation is shaped by slower vesicle dynamics.	Multiple time scales arise from nested optimization levels or different update frequencies of parameters/meta-parameters.
TOPOLOGY USAGE	Migration kernel $P_{\text{move}}$ and density dynamics explicitly depend on the graph $G = (V, E)$ , realizing a reaction-diffusion process over the architecture.	Topology mainly enters through the static computation graph; there is no explicit notion of mobile entities moving along edges.
INTERFACE TO LEARNING RULES	Vesicles can modify activations, parameters, and local learning rules through $\mathcal{R}_{\ell}^{\text{act}}, \mathcal{R}_{\ell}^{\text{param}}, \mathcal{R}_{\ell}^{\text{rule}}$ , and write to external memory $M_{\ell}$ .	Nested learners adjust loss functions, regularizers, optimizers, or meta-parameters; tensor-level modulation alters activations via affine transforms, gates, or generated weights.
LIMIT CASES	Dense, short-lived vesicles recover classical tensor-level conditioning layers; sparse, long-lived vesicles approximate mobile symbolic agents that edit computation at rare, decisive events.	Changing nesting depth alters how many levels of optimization are modeled, but does not introduce explicit mobile entities or event-based computation.

Table 1: High-level comparison between the proposed Neuro-Vesicle framework and existing approaches based on nested learning or tensor-level neuromodulation.

<sup>†</sup> NV = Neuro-Vesicles (this work). <sup>‡</sup> Includes nested-learning formulations and FiLM/hypernetwork-style tensor modulation.

## A.3 Mathematical and Dynamical View

From a mathematical perspective, Neuro-Vesicles and nested learning emphasize different primitives. Table 2 contrasts the two at the level of their formal objects and update rules.

Aspect	Neuro-Vesicles*	Nested Learning <sup>§</sup>
State space	Joint state $S_t = (\theta_t, \{h_t^{(l)}\}_l, \mathcal{V}_t, \{M_\ell\}_\ell)$ combining parameters, activations, vesicles, and external memories.	Hierarchy of parameter and meta-parameter spaces $\{\theta_t^{(k)}\}_k$ , often organized as nested learners with different update frequencies.
Core dynamics	Stochastic kernel $\mathcal{K}$ factorizing into emission, migration, docking, release, and decay; vesicles evolve as a Markov process on $G$ .	Nested optimization problems $\min_{\theta^{(K)}} \dots \min_{\theta^{(1)}} L(\theta^{(1)}, \dots, \theta^{(K)})$ , with each level updated by an optimizer (gradient-based or not).
Coupling to learning	Local operators $\mathcal{R}_\ell^{\text{act}}, \mathcal{R}_\ell^{\text{param}}, \mathcal{R}_\ell^{\text{rule}}$ alter activations, parameters, and learning rules in an event-based way.	Upper levels influence lower ones through meta-gradients or implicit differentiation, adjusting objectives, regularizers, or optimizers over long horizons.
Continuous relaxation	Graph-based reaction-diffusion dynamics for vesicle densities $\rho_{\ell, \kappa}(t)$ and mean contents $\mathbf{C}_{\ell, \kappa}(t)$ , fully differentiable.	Relaxations typically appear in the form of bi-level optimization approximations (e.g., truncated backprop, surrogate meta-gradients).

Table 2: Mathematical and dynamical contrast between Neuro-Vesicles and nested learning.

\* Emphasizes an *entity-based* (particle) dynamical view. <sup>§</sup> Emphasizes a *hierarchical* (multi-level) optimization view.

#### A.4 Spiking and Neuromorphic Deployment

A major motivation for Neuro-Vesicles is their compatibility with spiking neural networks (SNNs) and neuromorphic hardware. Because vesicles are defined as mobile, event-driven entities on the network graph, they map naturally to routed packets or special spike types in chips such as Darwin3. Table 3 focuses on this deployment angle.

Hardware-related axis	Neuro-Vesicles on SNN/neuromorphic*	Nested Learning / standard modulation <sup>°</sup>
Physical realization	Vesicles can be implemented as tagged spike packets or messages carrying payload $c$ and type $\kappa$ , routed by the on-chip network (e.g., Darwin3 ISA).	Primarily realized in software training loops; hardware mapping relies on chosen local learning rules (e.g., STDP, three-factor rules) without explicit packet-level entities.
Locality and routing	Migration kernel naturally matches event routing fabric; vesicles can follow specific paths, enabling structured topological memory and localized neuromodulation.	Topology mainly constrains synaptic connectivity; no explicit mechanism for mobile “modulatory packets” that traverse the chip.
Programmability	Release operators can be bound to microcode or instructions that modify synaptic weights, neuron parameters, or on-chip learning rates when vesicles dock.	Programmability typically lives at the level of which plasticity rule is implemented in hardware; fine-grained, stateful modulation must be encoded indirectly in those rules.
Use cases	On-chip continual learning, task-specific modulation, targeted credit assignment, and structural plasticity controlled by vesicle trajectories.	Meta-learning of learning rates, regularizers, or objectives in offline training; on-chip deployment mainly uses fixed rules optimized during training.

Table 3: Comparison of how Neuro-Vesicles and nested learning relate to spiking neural networks and neuromorphic hardware deployments.

\* Entity-based, packet-level neuromodulation well aligned with event-driven hardware. <sup>°</sup> Optimization-centric view with less direct exposure at the packet/spike level.

### A.5 Orthogonality and Potential Synergy

Because nested learning reorganizes *how* parameters and meta-parameters are optimized, while Neuro-Vesicles extend *what* constitutes the state of the system, the two perspectives are orthogonal. In principle, vesicle emission and migration kernels  $P_{\text{emit}}$  and  $P_{\text{move}}$  could themselves form a slower nested level, or nested objectives could be defined over long-horizon statistics of vesicle configurations (e.g., sparsity, coverage of the graph, or information flow patterns). Conversely, vesicles can endow nested-learning systems with a concrete, topology-aware mechanism for implementing neuromodulatory signals in spiking neural networks and neuromorphic hardware.

This separation of concerns—optimization hierarchy versus entity-based dynamical layer—is precisely what enables Neuro-Vesicles to serve as a drop-in, extensible neuromodulatory primitive that can coexist with a wide range of existing training frameworks, including nested learning, meta-learning, and three-factor plasticity rules.

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