Stochastic Modeling of Silver Nanowire Networks for Neuromorphic Computing

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Abstract. Self-organizing silver nanowire (AgNW) networks are a promising platform for *in materia* neuromorphic computing. In this work, we present a graph-based simulation framework that combines a dual-node network representation, a sparse-matrix admittance solver, and stochastic junction-level conductance updates to model the electrical evolution of these systems. The model captures qualitative behaviors reported across different percolation regimes, from close-to-percolation activation to smoother over-percolated responses. Our results show that the emergence of filamentary conduction paths, hysteretic current–voltage characteristics, and the associated memory window are strongly influenced by network density and voltage-dependent switching probabilities. Rather than providing a device-specific quantitative fit, the proposed framework offers a computational tool for studying how topology, stochastic switching, and percolation jointly shape the macroscopic electrical response of AgNW networks.

Keywords: silver nanowire networks , percolation , neuromorphic computing , stochastic simulation , memristive networks

Modelado Estocástico de Redes de Nanohilos de Plata para Computación Neuromórfica

Abstract. Las redes autoorganizadas de nanohilos de plata (AgNW) constituyen una plataforma prometedora para la computación neuromórfica *in materia*. En este trabajo presentamos un marco de simulación basado en grafos que combina una representación de red de nodo dual, un resolvedor disperso de matrices de admitancia y actualizaciones estocásticas de conductancia a nivel de juntura para modelar la evolución eléctrica de estos sistemas. El modelo captura comportamientos cualitativos reportados en distintos regímenes de percolación, desde la activación cercana al umbral de percolación hasta respuestas más suaves en redes sobrepercoladas. Nuestros resultados muestran que la emergencia

de caminos conductivos filamentarios, las características histéricas de corriente–voltaje y la ventana de memoria asociada están fuertemente influenciadas por la densidad de red y por probabilidades de conmutación dependientes del voltaje. Más que proporcionar un ajuste cuantitativo específico para un dispositivo, el marco propuesto ofrece una herramienta computacional para estudiar cómo la topología, la conmutación estocástica y la percolación determinan conjuntamente la respuesta eléctrica macroscópica de las redes de AgNW.

Keywords: redes de nanohilos de plata , percolación , computación neuromórfica , simulación estocástica , redes memristivas

1 Introduction

Some new physical systems have emerged as attractive options for neuromorphic computing due to the search for effective, brain-inspired hardware (Marković et al., 2020a). Among these, self-organizing memristive nanowire networks (NWNs) have garnered growing interest as a neuromorphic computing platform. These networks arise from the stochastic assembly of metallic nanowires, where the cross-points function as functional memristive junctions, in contrast to conventional CMOS-based architectures. High connectivity, short-term memory, and synaptic-like plasticity are therefore made possible by their unique interaction between complex topology and internal state dynamics (Kuncic & Nakayama, 2021; Vahl et al., 2024).

Recent studies have highlighted the critical role of the percolation regime in determining the electrical response of AgNW networks Diaz-Schneider et al., 2024; Marković et al., 2020b; Milano et al., 2025; Vahl et al., 2024; Zhu et al., 2021. As demonstrated by Levy et al. Diaz-Schneider et al., 2024, networks operating near the structural percolation threshold exhibit a high-resistance state that requires electrical activation, whereas over-percolated systems are dominated by metallic-like transport. This structural landscape serves as the physical substrate for functional behavior. In this context, Milano and Vahl Milano et al., 2025; Vahl et al., 2024 proposed that these networks undergo "structural plasticity" through the dual mechanisms of reweighting (conductance updates) and rewiring (formation of new paths), effectively emulating the experience-dependent adaptation of biological neural circuits.

From an information-theoretic perspective, the dynamic computational power of these architectures is optimized at the edge of chaos. Zhu et al. Zhu et al., 2021 identified that information flow and storage—quantified by transfer entropy and active information storage—are maximized when a fixed network transitions from a quiescent to an active state under external voltage stimulation. While their work focuses on this dynamic, stimulus-driven critical transition, the relationship between such optimal information dynamics and the underlying static, density-dependent percolation threshold remains to be fully unraveled. We hypothesize

that the structural sweet spot dictated by wire density acts as a prerequisite that scales and optimizes the dynamic range available for such edge-of-chaos transitions.

According to earlier research, these networks might exhibit improved computational characteristics close to the transition(Zhu et al., 2021). Specifically, Zhu et al. (2021) demonstrated that information flow and storage are optimum close to this transition, as measured by transfer entropy and active information storage. These findings support the notion that the functional behavior of NWNs is intimately related to percolation, switching dynamics, and network structure.

Despite these advances, there is still a need for computational models that connect microscopic junction-level switching with macroscopic electrical observables in a tractable and physically interpretable way. In this work, we present a graph-based stochastic simulation framework to study the electrical evolution of AgNW networks across different percolation regimes. We combine a dual-node representation, sparse-matrix admittance solver and voltage-dependent stochastic switching rules. We investigate how a simple junction dynamics gives the hysteretic I–V characteristics, and the associated memory window. The proposed framework provides a computational tool for exploring how topology, stochastic switching, and percolation jointly determine the macroscopic electrical response of AgNW networks, while offering theoretical support for experimental studies and a basis for future developments in neuromorphic nanowire systems.

2 Methods

The simulation framework is written in Python and uses a modular pipeline that combines graph theory, effective numerical solvers, and stochastic physics. Topological generation, graph mapping, electrical solution, and stochastic state updating are the four primary phases of the procedure.

2.1 Topological Network Generation

The simulation starts by generating N nanowires, modeled as one-dimensional sticks of length L, randomly distributed within a square area $A = 1mm^2$. For each wire i, a center coordinate (x_c, y_c) and an orientation $\theta \in [0, \pi]$ are sampled using a uniform distribution. To identify the nanowires junctions, we look for the geometric intersection.

Two wires i and j form a junction if their segments intersect. The coordinates corresponding to the intersections are stored to define the location of the memristive junctions. Figure 1 shows a NWN with 3000 nanowires, while Fig. 2 shows the random nanowires together with the corresponding intersections marked as red points.

2.2 Dual-Node Graph Mapping

To represent the internal degrees of freedom of the network, we implement a dual-node mapping strategy. Each physical junction J is decomposed into two

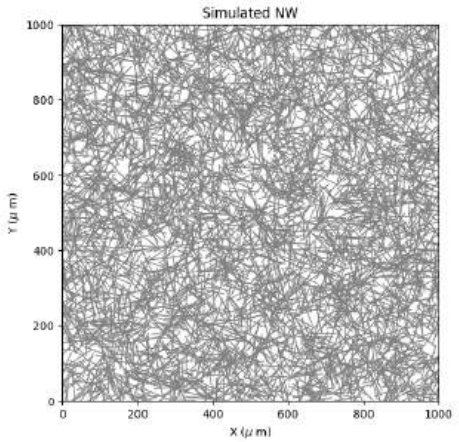

Fig. 1. A stochastically generated network of 3000 nanowires. The area of the square represents an experimental substrate measuring 1 mm × 1 mm.

graph nodes, n_i and n_j, representing the electrical contact points on wire i and wire j, respectively. This allows for a clear distinction between intra-wire and inter-wire transport.

- **Memristor edges:** An edge is created between n_i and n_j, representing the memristive interface. This edge is assigned a dynamic conductance $G \in \{G_{ON}, G_{OFF}\}$. Figure 3 illustrates the physical process by which a conductive channel is formed through the insulating coating of the nanowires, causing the conductive state to change from $G_{OFF} = 1{\times}10^{-9}\,S$ to $G_{ON} = 1{\times}10^{-3}\,S$(Vahl et al., 2024).
- **Resistive segments:** Nodes belonging to the same nanowire are connected via resistive edges. The conductance of these segments is calculated as $G_{seg} = 1/(d \cdot \rho)$, where d is the distance between adjacent junctions along the wire and $\rho = 1.59 \times 10^{-8}\,\Omega\,m$.

2.3 Sparse Matrix Admittance Solver

The electrical state of the network is determined by solving the nodal admittance matrix Y under Kirchhoff's Current Law, following a standard nodal-analysis formulation for electrical networks (Ho et al., 1975). For a network with N_g nodes, the system $Y\mathbf{V} = \mathbf{I}$ is constructed, where the elements of Y are defined as

$$Y_{pq} = \begin{cases} \sum_k G_{pk} & \text{if } p = q, \\ -G_{pq} & \text{if } p \neq q. \end{cases} \tag{1}$$

Due to the high sparsity of the AgNW network, where the number of edges satisfies $E \ll N_g^2$, we use a Compressed Sparse Row (CSR) format for matrix

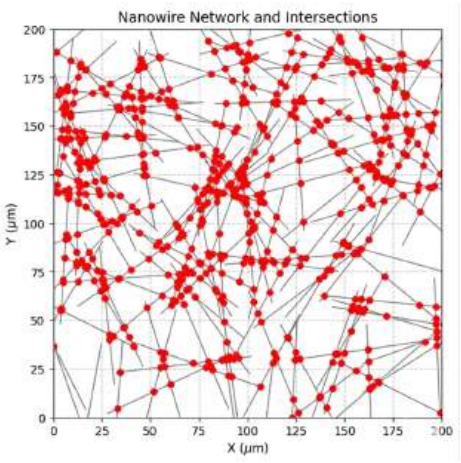

Fig. 2. Randomly generated AgNW layout used as the initial topological configuration before junction extraction.

representation. Boundary conditions are applied by setting $V = V_{in}$ at nodes within the source electrode region and $V = 0$ at the drain region. The system is solved at each time step using the `spsolve` algorithm from SciPy (Virtanen et al., 2020), providing an efficient sparse implementation for networks with thousands of wires.

The system is solved at each time step using the direct sparse solver spsolve from the SciPy library (utilizing the SuperLU architecture with COLAMD column permutation to minimize fill-in). While iterative solvers (e.g., GMRES) offer lower memory footprints for massive systems, a direct solver was selected due to the moderate size of the network graph ($N_g \approx 3000$) and the high ill-conditioning of the admittance matrix Y, which arises from the multi-order-of-magnitude contrast between G_{ON} and G_{OFF}. Under these conditions, the direct method guarantees numerical stability, exact convergence, and superior execution computational speed per time step without the need for complex preconditioning.

2.4 Stochastic Switching Dynamics

Once the system of nodal equations $\mathbf{YV} = \mathbf{I}_{ext}$ is solved at each discrete time step using the direct sparse solver, the local electrical state of the network is fully determined. Specifically, the local current I_{ij} flowing through a memristive edge (junction) connecting two internal nodes n_i and n_j is calculated directly via the local Ohm's law:

$$I_{ij} = G_{ij} \cdot (V_i - V_j) \tag{2}$$

where G_{ij} is the instantaneous conductance of the junction, and V_i, V_j are the respective nodal voltages extracted from the solution vector $\mathbf{V}$.

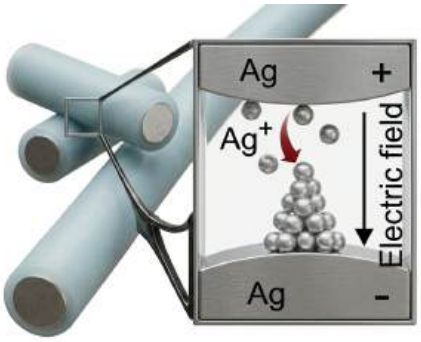

Fig. 3. Schematic representation of the generation of a conductive channel at the junction of two silver nanowires through PVP coating.*Source: Prepared by the authors.*

The simulation evolves in discrete time steps Δt. At each step, the voltage drop across every memristive edge, $V_{mem} = |V_i - V_j|$, is evaluated. The transition between G_{OFF} and G_{ON} (SET process) is modeled phenomenologically through a stochastic probability P_{SET}, consistent with threshold-driven junction activation in AgNW networks (Diaz-Alvarez et al., 2019),

$$P_{SET}(V_{mem}) = \Delta t P_0 \max(0, 1 - \exp\left[-\alpha(V_{mem} - V_{th})\right]), \tag{3}$$

where $P_0 \Delta t \ll 1$, α is the voltage sensitivity, and V_{th} is the threshold voltage. Conversely, the RESET process, representing filamentary instability or rupture, is modeled phenomenologically as a current-dependent decay,

$$P_{RESET}(I_{mem}) = \min\left(1, \Delta t P_{decay}(I_{mem})^2\right), \tag{4}$$

where $I_{mem} = |I_{ij}|$ is the local current flowing through the junction. This dual stochastic mechanism allows the network to display both deterministic trajectories and stochastic jumps, capturing key features of the complex dynamics reported in neuromorphic nanowire systems (Mambretti et al., 2022; Milano et al., 2025). Algorithm 1 summarizes the full simulation workflow, from the generation of the nanowire geometry to the stochastic update of junction states.

In the following we present a brief description of the simulation's pipeline:

In table 1 we present the parameters used in the simulation. To ensure numerical reproducibility and statistical soundness, the stochastic components of the simulation are governed by a deterministic pseudo-random number generator (implemented in the `numpy.random` library), initialized with a fixed seed for regression control. At each discrete time step Δt, the switching state of each individual memristive junction is evaluated independently via a Bernoulli trial; a random float r is sampled from a uniform distribution $r \sim \mathcal{U}(0, 1)$, and the state transition occurs if and only if $r < P_{SET}$ (or $r < P_{RESET}$).

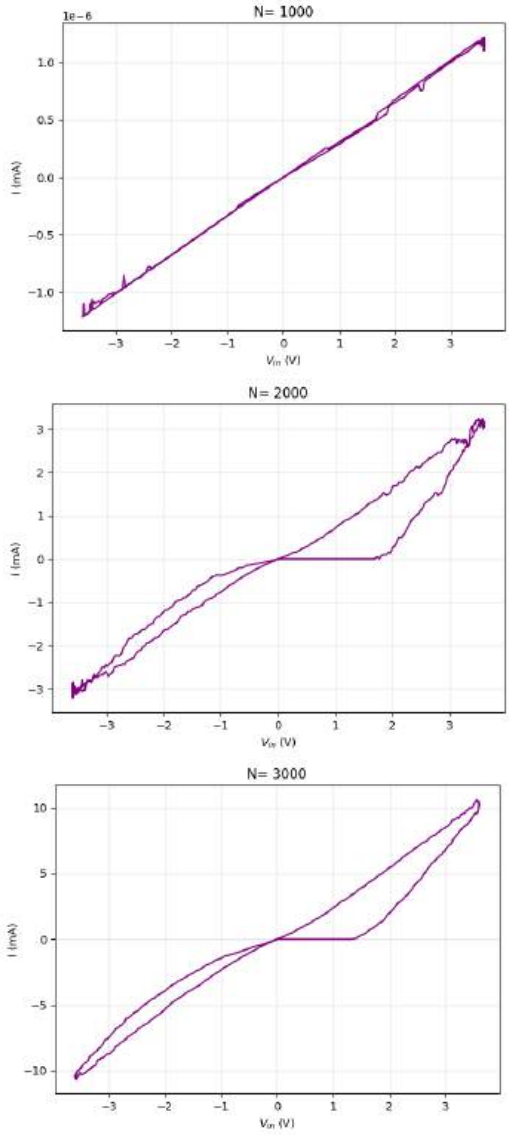

Fig. 4. Representative hysteresis curves of the AgNW network under cyclic voltage stimulation for different wire densities.

Algorithm 1 AgNW Network Simulation Pipeline

Input: N wires, $V_{in}(t)$, G_{ON}, G_{OFF}, Δt
Generate wire geometry and identify intersections
Build dual-node graph $G(V, E)$
for each step $t = 0$ to T **do**
    Update matrix Y with current conductance values
    Solve $Y\mathbf{V} = \mathbf{I}$ for nodal voltages
    Calculate I_{in} and total network conductance
    for each memristive edge $e \in E$ **do**
        Compute P_{SET} or P_{RESET}
        Update the state of G_e stochastically
    end for
end for

Table 1. Simulation and Physical Parameters used in this work.

Parameter	Description	Value
L	Nanowire length	70 μm
A	Substrate Area	1 mm^2
Δt	Simulation time step	10^{-3} s
$\Delta t P_0$	SET probability	0.4
α	Voltage sensitivity	1 V^{-1}
V_{th}	Threshold voltage	0.01 V
$\Delta t P_{decay}$	Decay rate coeff.	0.01
T	Number of steps per cycle	50000
V_{in}	Voltage ramp amplitude	3.6 V

3 Results and Discussion

The macroscopic electrical response of the AgNW network is characterized by pinched hysteresis loops in the current–voltage (I–V) plane, a hallmark of memristive behavior. Our simulations reproduce the qualitative evolution of the I–V response across different wire densities, capturing the transition from weakly hysteretic to strongly nonlinear regimes associated with the collective switching of internal junctions.

The emergence of hysteresis in our model is driven by the voltage-dependent stochastic transition probability P_{SET}. As the input voltage V_{in} follows a sinusoidal ramp, the local potential drops across memristive edges trigger a cascading activation of junctions. In Fig. 4 we show the I–V curves corresponding to $N = 1000$, $N = 2000$, and $N = 3000$. For $N = 1000$, the response is almost linear and exhibits little hysteresis. For $N = 2000$, the hysteresis loop becomes clearly visible and characteristic current spikes emerge, revealing an intermittent switching regime in which a small number of active junctions strongly affects the global conductance. For $N = 3000$, the hysteretic response becomes smoother and more continuous, consistent with a denser network in which multiple conductive pathways contribute simultaneously to transport. These trends are qualitatively

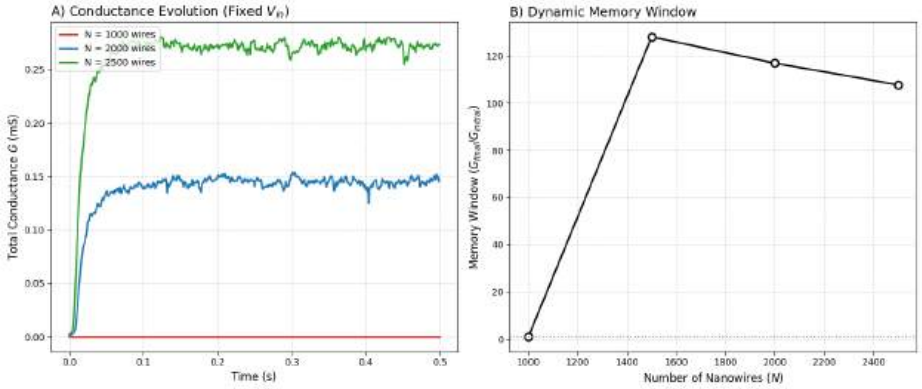

Fig. 5. Left: Conductivity as a function of time. Right: memory window as a function of the number of nanowires.

consistent with the contrast between close-to-percolation and over-percolated regimes reported by Diaz-Schneider et al. (2024).

Within this framework, hysteresis arises from the formation of preferential conduction filaments that persist even as the voltage decreases, creating the characteristic memory opening in the I–V plane. The model describes this behavior as the result of a competition between deterministic field-driven filament formation and stochastic current-driven decay (P_{RESET}), in qualitative agreement with the stochastic dynamical systems framework discussed by Milano et al. (2025).

The morphology of the hysteresis loop undergoes a significant transformation as network density varies, providing insight into the reconfiguration capacity of the system. At low densities, the hysteresis loops are wider and exhibit sharp, discrete jumps in current. This digital-like switching reflects a regime in which the global conductance is highly sensitive to the state of a few critical junctions. In this case, the G_{ON}/G_{OFF} ratio is maximized, indicating a large but potentially fragile memory window. In denser networks, by contrast, the hysteresis loops become softer and more Ohmic.

The evolution of the network's global conductance ratio ($G_{final}/G_{initial}$), hereafter referred to as the memory window, provides an operational measure of the contrast between low- and high-conductance network states. As shown in Fig. 5, the explored simulations suggest that this quantity reaches a maximum in the vicinity of the percolation threshold ($N \approx 1200$). In this sparse regime, the network's connectivity is precarious and global electrical transport is governed by a minimal number of critical junctions. Following the framework proposed by Diaz-Schneider et al. (2024), these close-to-percolation realizations require significant electrical activation to establish the first stable conduction paths. In this state, the transition of a single memristive junction from G_{OFF} to G_{ON} can induce large changes in the total network conductance, since there are no redundant metallic paths that bypass the switching event.

As the wire density N increases into the over-percolated regime, we observe a gradual degradation of the memory window. This behavior can be explained by the emergence of redundant transport pathways. In dense networks, the contribution of individual memristive switching events is diluted by the presence of numerous parallel metallic routes that remain in a high-conductance state or act as parasitic resistances. This interpretation is consistent with the structural plasticity mechanisms discussed by Milano et al. (2025).

Overall, the simulated I–V profiles are qualitatively consistent with the experimental trends reported by Diaz-Schneider et al. (2024), particularly in the contrast between close-to-percolation activation and smoother over-percolated responses. Rather than providing a quantitative fit to a specific device, the present model offers a computational framework for exploring how topology, stochastic switching dynamics, and percolation jointly shape the macroscopic electrical response of AgNW networks. In this sense, the results point to a trade-off between robustness and reconfigurability: sparse networks exhibit large conductance contrast but are more fragile, whereas denser networks are more stable but less sensitive to the state of individual junctions.

4 Conclusion

In summary, we developed a graph-based simulation framework to investigate the electrical and functional response of self-assembling silver nanowire networks across different percolation regimes. By combining a dual-node mapping strategy with a sparse-matrix admittance solver and stochastic junction-level switching rules, the model captures how microscopic conductance updates give rise to macroscopic hysteretic behavior. Our results indicate that the memory window, quantified through the $G_{final}/G_{initial}$ ratio, is strongly conditioned by network density and is maximized in simulations near the percolation threshold, where a small number of critical junctions can dominate long-range transport. As the network becomes more densely connected, this sensitivity is progressively reduced by the emergence of redundant conductive pathways. Rather than providing a device-specific quantitative fit, the present study offers a computational framework for examining the interplay between topology, stochastic switching, and percolation in AgNW networks. These results support the use of graph-based stochastic modeling as a useful framework for interpreting and complementing experimental studies on neuromorphic nanowire substrates, while also helping identify operating regimes of interest for further developments.

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Integrity: During the preparation of this paper, the authors used Gemini to improve the language and readability of the manuscript. After using this tool, the authors reviewed and edited the content and assume full responsibility for the content of the publication.

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