

Spiking rate and latency encoding with resonant tunneling diode neuron circuits and design influences

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Neuromorphic computing, inspired by the functionality and efficiency of biological neural systems, holds promise for advancing artificial intelligence and computational paradigms. Resonant tunneling diodes (RTDs), thanks to their ability to generate neuronal dynamical responses, such as excitable spiking and refractoriness, have recently emerged as candidates for use as optoelectronic spiking neurons in novel neuromorphic computing hardware. This work explores the ability of RTD spiking neurons to deliver information encoding mechanisms analogous to those observed in biological neurons, specifically spike firing rate and spike latency encoding. We also report detailed experimental and numerical studies on the impacts that the RTD mesa radius and the circuit inductance and capacitance have on its spiking properties, providing useful information for future design of RTD-based neural networks optimized for ultrafast (greater than gigahertz rate) processing capabilities. Finally, we showcase the application of spike rate encoding in RTD neurons for the ultrafast reconstruction of a eight-level amplitude signal, effectively filtering out the noise.

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I. INTRODUCTION

Within the artificial intelligence landscape, neuromorphic systems are emerging as ensembles of nonlinear nodes that mimic the way biological brains process information. While artificial neural networks were initially emulated serially on standard CPUs—leading to significant breakthroughs in supervised and unsupervised learning [1,2]—the slowing of Moore’s law [3] has emphasized the need for computing platforms that mirror the inherent parallelism occurring in the brain. Both electronic and photonic platforms are under active development, integrating trainable physical parameters and neuronlike units. Examples of neuromorphic electronic hardware include SpiN-Naker from the University of Manchester [4,5], IBM’s

TrueNorth [6], Intel’s Loihi [7], and BrainScaleS from the University of Heidelberg [8]. Neuromorphic photonics, on the other hand, leverages the high speed, low loss, and parallel processing enabled by light, using approaches such as wavelength division multiplexing in both on-chip [9–11] and free-space [12] configurations.

Resonant tunneling diodes (RTDs) have recently gained attention for their operational versatility as optoelectronic spiking neurons. These active semiconductor devices incorporate a double-barrier quantum well (DBQW) structure with layer thicknesses of approximately 10 nm. This preserves the electronic wave function’s phase across the DBQW, enabling interference phenomena at room temperature [13]. RTDs operate analogously to an optical (tunneling in) tunable Fabry-Perot interferometer: Application of a voltage across the DBQW adjusts the Fermi energy of incident electrons, maximizing electron flow tunneling when their energy resonates with the DBQW states. This results in the RTD’s N-shaped current-voltage (I - V) characteristics, with a positive differential resistance (PDR) region from zero volts up to the resonance point (at peak voltage, where the current reaches a local maximum).

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Beyond this, tunneling is inhibited, leading to a negative differential resistance (NDR) region up to the valley voltage where the current reaches a minimum [14]. The resulting highly nonlinear I - V characteristics of RTDs have been used to demonstrate ultrahigh (terahertz-range) bandwidth switching capabilities between the peak and the valley of the I - V curve, making them attractive for communication applications [15,16], and also diverse neuromorphic behaviors. These include excitable spike firing [17,18], refractoriness [19], multipulse bursting [20], oscillatory and chaotic responses [21], flip-flop memory oscillating between spiking and quiescent states [22] or two stable values [23], and regenerative self-feedback operation [24]. These behaviors can be exploited in isolated RTDs or when RTDs are coupled with external optoelectronic elements, such as RTD–laser-diode systems integrated on-chip [17,25]. Despite progress, the encoding mechanisms used by RTD-based neurons and their parallels with their biological counterparts remain underexplored.

This study experimentally explores the spike rate and spike latency encoding mechanisms (at fast nanosecond rates) in RTD neuron circuits, further aligning their functionality with that of biological neurons. We also investigate experimentally and in theory the impact of design parameters, in particular, the RTD cross-section area and the circuit inductance and capacitance, on their neuromorphic rate-encoding properties and potential for ultrafast speed operation at higher than gigahertz rates. These findings will be valuable for guiding the design and training of future neuromorphic hardware based on optoelectronic spiking neurons built with RTDs. Finally, we propose a proof-of-concept application where an eight-level noisy voltage signal is regenerated by an RTD neuron by means of its rate encoding capability.

This paper is structured as follows: Sec. II presents experimental results on the rate and latency encoding capabilities of a single (micrometer-scale) RTD spiking neuron. Section III explores the effects that the mesa radius, inductance, and capacitance, key design parameters, have on the neuromorphic properties and speed of operation of RTD neurons. In Sec. IV we propose a proof-of-concept application for encoding, reconstruction, and noise-filtering of a multilevel signal leveraging the ultrafast spike rate encoding capabilities of RTD neurons. Finally, in Sec. V, we draw our conclusions.

II. INFORMATION ENCODING

We used the setup sketched in Fig. 1 to experimentally investigate the information encoding capabilities of RTD neurons. The I - V characteristic of RTDs is measured through a bias controller (Keysight E36312A), which both sets the desired bias voltage to the RTD and reads the corresponding output current. An arbitrary waveform generator (Keysight M8190A, 12×10^9 samples/s) allows

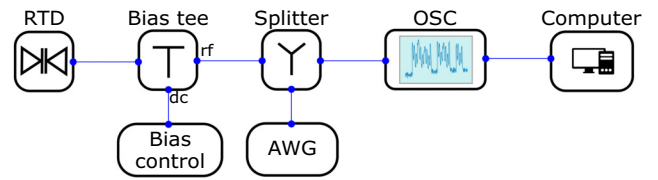


FIG. 1. Experimental setup for probing the RTD. AWG, arbitrary waveform generator; OSC, oscilloscope.

the generation of rf waveforms with voltage pulses that will be used to elicit spiking dynamics in the RTD neuron. These pulses propagate toward a splitter and then a bias tee (0.01–12.4 GHz bandwidth range), where they are combined with the bias dc voltage signal. The temporal dynamical evolution in the system at its fast (spiking) timescales is measured by our directing the rf component of the RTD output to a high-speed oscilloscope (Rohde & Schwarz, 16 GHz bandwidth), which is then connected to a computer for data storage and analysis. All the RTDs in this work were fabricated on a layer stack grown by metal-organic vapor phase epitaxy on a semi-insulating InP substrate. They contain an AlAs(1.7 nm)/(In,Ga)As(5.7 nm)/AlAs(1.7 nm) DBQW structure surrounded by 2 nm undoped (In,Ga)As layers, followed by 50 nm of moderately doped n -(In,Ga)As ($5 \times 10^{16} \text{ cm}^{-3}$) and highly doped n -(In,Ga)As contact layers.

A. Spike rate encoding

The dynamical behavior of an RTD neuron circuit evolves as the bias voltage is moved within the NDR region of its I - V characteristic. With reference to the experimentally measured I - V curve [see Fig. 2(a)] of a single-pillar RTD with a 3 μm mesa radius, the system remains quiescent when biased below the peak voltage ($V_{\text{peak}} = 0.88 \text{ V}$) of the I - V curve. However, surpassing of the peak voltage initiates oscillatory dynamics, which persist until the bias approaches the valley region, beyond which the system becomes quiescent again. When biased within the NDR region, the RTD circuit exhibits self-oscillations with a spikelike profile. This behavior is captured in Fig. 2(b), where the spiking firing rate ν_{spike} of the RTD increases with the bias voltage, nearly doubling from 7 to 12.5 MHz. Additionally, Fig. 2(c) presents representative spiking time traces for three distinct bias scenarios, corresponding to the colored markers in Fig. 2(b). These traces illustrate differing numbers of spikes generated over 0.5 μs , reflecting the correlation between bias voltage and firing rate. Interestingly, the firing rate behavior of the RTD neuron and, in particular, its discontinuity exhibited near the spiking threshold closely resemble those of a class 2 biological neuron, suggesting a biologically inspired mechanism for encoding information in the firing rate. Although more limited with respect to class 1 neurons, which can exhibit

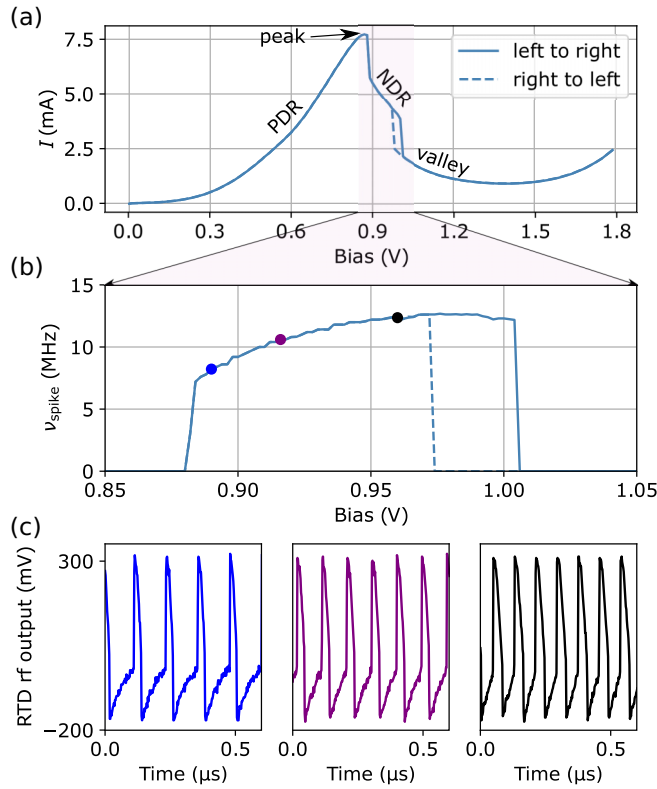


FIG. 2. (a) Experimental I - V characteristics of an RTD with a $3\ \mu\text{m}$ circular mesa radius. (b) Spiking rate variation under dc bias tuned across the NDR region. (c) Examples of spike time traces with increasing firing rate achieved for three bias values within the NDR region, corresponding to the colored circles in (b).

arbitrarily low spiking rates near the threshold, this encoding method is simple yet effective. To use it, the RTD can be biased just below the peak voltage in its I - V characteristic, where it remains quiescent. Input voltage perturbations can then temporarily drive the RTD into the NDR region, enabling spiking. Input pulses of varying intensity modulate the bias within the NDR region, producing spike trains whose firing rates depend on the amplitude of the input pulse. Alternatively, the bias itself can be varied across the NDR region to produce the same spike-rate variations.

For effective information encoding, the duration of the perturbation must be carefully managed. Voltage pulses that are too short may trigger only a single spike (not enough to define a firing rate), while excessively long pulses may generate unnecessary long spike trains, reducing processing speed. An optimal compromise should be achieved by one considering the timescales of the task of interest, and therefore the speed at which information needs to be converted and processed. When the RTD is biased close to but below the peak value (in its I - V curve), the amplitude of the input voltage pulse required to drive the RTD into the NDR region depends on the applied

bias voltage. Consequently, the bias emerges as a trainable parameter during the learning phase of a neuromorphic task. Notably, the three time-series examples in Fig. 2(c) also highlight that while the spike firing rate varies for different bias values within the NDR region, the amplitude of the spike remains constant.

B. Spike latency encoding

Information can also be encoded in the precise timing of a neuron's spike, offering a faster alternative to rate encoding. In this scheme, a single spike can encode information, eliminating the need to generate multiple spikes to define a rate. Specifically, we examined the relationship between the amplitude of an input perturbation and the latency time of the spike it triggers in an RTD neuron circuit. The latter, known as latency encoding, is a powerful mechanism widely used by the brain to extract spatial features from somatosensory, visual, and auditory sensing information [26,27].

Latency encoding is investigated with the same RTD neuron previously used for rate encoding, having a $3\ \mu\text{m}$ mesa radius. Here we bias the RTD below the peak of its I - V curve, thus preparing it in a quiescent state. Then we perturb the RTD with voltage pulses of differing amplitudes but fixed duration, much shorter than the duration of a single spike (and that of its refractory period, approximately 90 ns), to elicit a single spike. Examples of RTD dynamics are shown in Fig. 3. The selected bias is indicated as dashed green lines in the plots in the left column and is expressed in terms of $\delta V = V_{\text{bias}} - V_{\text{peak}}$, i.e., its distance from the peak of the I - V curve ($V_{\text{peak}} = 0.88\ \text{V}$). The temporal profiles of increasing amplitude input pulses with 4 ns duration are shown in the top panel in the right column. Input pulses with amplitude just below the threshold do not trigger any spike (blue time traces in the right panels). Subthreshold pulses (with resolution of 1.25 mV) enable the spike response with a latency given by the time taken to intersect an arbitrary voltage threshold, represented as a horizontal black line. As the input strength increases, the spike is generated first (lower latency). A wider characterization of the spike's latency for input pulses lasting 4 ns and with amplitude increasing from 20 to 251.25 mV in 1.25 mV steps and for different bias conditions δV from -20 to $-230\ \text{mV}$ with a 30 mV step is summarized in Fig. 4. The pulse amplitude used to evoke the RTD spiking response is reported on the x axis, with a step resolution of 1.25 mV. The resulting latency at which spikes are generated is presented in a color map, with white regions indicating quiescent states where no spike is fired by the RTD circuit. The results reveal that the transition from quiescence to spiking RTD dynamics is strongly dependent on both the voltage bias applied to the RTD and the amplitude of the input pulse. For any tested bias, spikes are elicited only when the pulse amplitude approaches or exceeds δV .

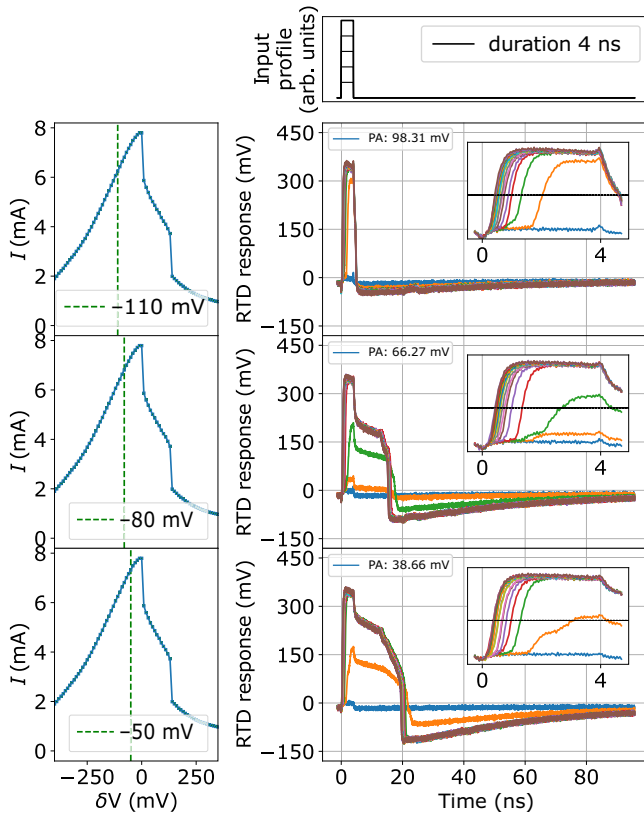


FIG. 3. Examples of experimental RTD rf responses for three bias scenarios (dashed green line in the left panels) far from the peak ($V_{\text{peak}} = 0.88$ V), and input pulses lasting 4 ns and having increasing amplitudes (top-right panel). Blue curves in the right panels describe the quiescent RTD response to input pulses with pulse amplitude (PA) just below the spike activation threshold. Higher-amplitude pulses (with 1.25 mV steps) evoke the RTD spiking response, with a latency that reduces as sketched in the insets.

The closer the bias is to the peak, i.e., $\delta V \rightarrow 0$, the lower is the perturbation amplitude needed to bring the device into the NDR region of the I - V curve, and elicit a spike. The latency of the spike is inversely proportional to the input pulse amplitude for a range of a few millivolts just above the threshold voltage. Spikes are fired with the longest delay for input amplitudes just above the threshold, and earlier for larger amplitudes, rapidly reaching a plateau for all biases δV considered. Moreover, this behavior is consistently reproduced in all other measures with different pulse durations investigated (2, 1, and 0.5 ns, not shown), indicating a mechanism where the timing of the spike depends on both a restricted range of pulse amplitude values (of just a few millivolts) above the threshold and the operating bias. Given this reduced input voltage range, we conclude that this encoding mechanism works only for differentiation of closely-time-resolved input pulses. We show in the following that tuning just the circuitry inductance allows subnanosecond spikes while leaving almost unchanged the

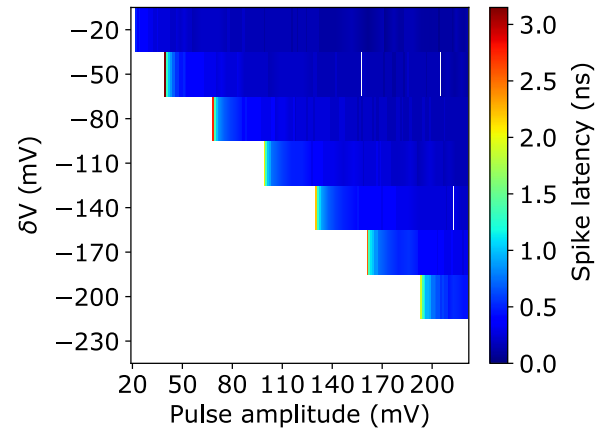


FIG. 4. Spike latency map for different configurations of bias $\delta V = V_{\text{bias}} - V_{\text{peak}}$ (y axis) and input pulse amplitude (x axis). The input pulse has a duration of 4 ns. When its amplitude is not sufficiently strong to elicit an RTD spike response, the delay is not defined, appearing as a white box.

integration time. Within this scenario, latency up to 3 ns can play a major role, enabling spike latency encoding [28] and time-to-first-spike protocols. For example, latency encoding is used to extract spatial information from sensory data in biological neurons [26,27]. Similarly, an array of RTDs with each one firing with different latencies may be studied in future designs. Although the sensing voltage range would be restricted to only a few millivolts, according to Fig. 4, this range could be widened by one designing a matrix of RTDs, having different bias lines per row. In this way, each row of RTDs would be highly sensitive in a restricted but different voltage range.

Figure 3 shows that the spike profile is influenced by the applied voltage. For $\delta V = -110$ mV (second row in Fig. 3) the RTD responses resemble an amplified version of the input pulse. However, for bias closer to the peak ($\delta V = -80$ mV and $\delta V = -50$ mV, third and fourth rows in Fig. 3, respectively), the same amplified input pulse is also followed by distinct discharge and recovery phases, lasting approximately 90 ns. The recovery period is linked to the relative refractory period [19] of the RTD neuron's circuit. In this period, similarly to biological neurons, the system is less likely excitable from new input stimuli. Therefore, Fig. 3 reveals that our simply tuning the bias allows the RTD operation to be switched from an amplifier to a neuron incorporating a refractory time. These are novel and fundamental details to account for when one is designing and optimizing neuromorphic hardware relying on RTD neurons, strengthening once again the importance of considering the bias as a critical trainable parameter. As a final detail, it is worth noting that spikes generated through perturbations in the PDR share qualitative features with those produced when the device is biased in its NDR and without perturbations [see Fig. 2(c)]. In both cases,

the spike evolution is described by two fast and two slow phases, but when the device is biased in the PDR, an amplified profile of the input pulse emerges in between the first fast phase and subsequent slow phase. Moreover, while continuous spiking is achieved when the bias is set within the NDR, the PDR allows only a number of spikes limited by the single pulse duration.

III. INFLUENCE OF RTD DESIGN PARAMETERS

In this section we study the influence of key system parameters, such as the RTD mesa radius and the overall circuit inductance and capacitance, in the spike encoding properties of RTD neurons. The insights provide valuable guidance for the future development of neuromorphic optoelectronic hardware architectures built with RTD neurons at their core.

A. RTD mesa radius

Previous studies have shown that RTDs having a circular mesa shape with larger radii allow more current to flow through the DBQW, resulting in shifted I - V characteristics [29,30]. However, the specific effects of mesa radius on the spiking behavior of RTDs remain unexplored. To address this, RTDs with mesa radii of 2, 3, 4, and 5 μm were experimentally characterized in terms of their I - V curves, spike amplitudes, and firing rates. The results, summarized in Fig. 5, reveal key trends and implications for future optimized RTD designs. The I - V characteristics of the RTDs are displayed in Fig. 5(a), showing a quasisymmetric behavior around the origin since the layer stack and overall fabricated RTD structure were targeted as symmetric as possible. RTDs with larger mesa radii exhibit a shift in their I - V characteristics toward higher currents, consistent with the increased flow of electrons through the DBQW [29,30]. Additionally, larger mesa radii expand the NDR region, widening the spiking region. The corresponding spike amplitude A_{spike} and firing rate ν_{spike} when the RTDs are biased across their NDR regions are shown in Figs. 5(b) and 5(c), respectively. The left panel in Fig. 5(b) shows an enlargement of the NDR regions under reverse bias, while the right panel shows an enlargement of the NDR regions under forward bias operation. The spike amplitudes and firing rates are zero outside the NDR regions but become nonzero within these regions, confirming the presence of spiking activity. Notably, RTDs designed with larger radii fire electrical spikes having a larger amplitude, as the limit cycle orbit extends across the wider NDR region shown in Fig. 5(a); see Sec. III B. The spike amplitude remains constant across the NDR region, independently on the RTD mesa radius, and is more pronounced under reverse bias configurations. Conversely, larger mesa radii reduce the firing rate [Fig. 5(c)], demonstrating an inverse relationship between spike amplitude and firing rate. Notably, Fig. 5(c) also highlights that RTDs

with larger radii exhibit more restricted firing rate ranges spread over broader NDR regions. These devices are better suited for detecting external stimuli and maintaining consistent firing rates, even in noisy environments, due to their robustness regarding input voltage fluctuations. In contrast, RTDs with smaller radii offer wider firing rate ranges and hence encoding possibilities but are more susceptible to noise, making them ideal for tasks requiring stimulus distinction based on the firing rate. However, we note that the RTD with $r = 2 \mu\text{m}$ does not fully follow these trends. It exhibits a narrower firing range than the $r = 3 \mu\text{m}$ device and shifted onsets of its NDR regions. We speculate that the observed deviation may arise from increased parasitic resistance due to fabrication-induced variability. While the mesa size can be controlled relatively well (variability of a few hundred nanometers), the metalization via lift-off is more susceptible to stronger process variability (several hundreds of nanometers).

These findings have significant implications for neural network design. RTD neurons with smaller radii can specialize in tasks requiring diverse firing rates, while larger-radius RTDs are advantageous in noisy environments or when signal amplification is necessary. Networks can incorporate subnetworks tailored to specific functions, using RTDs with differing mesa radii. For example, spikes traveling through noisy network regions can be amplified by cascading RTDs with increasing radii, calibrated to generate higher-amplitude spikes as needed. This modular approach increases the network's robustness and adaptability for complex computational tasks.

B. RTD circuit inductance and capacitance

In this section we explore how to increase the spiking rate of RTD neurons measured experimentally by tuning key circuit parameters. This analysis is performed numerically in order to have access to variables not directly accessible in the experiments, such as rapid current variations during the RTD spiking dynamics, and to provide a deeper understanding of the system. The RTD circuit scheme we refer to is shown in Fig. 6. By applying Kirchhoff's laws to the circuit, one obtains

$$C \frac{dV(t)}{dt} = I - f(V(t)), \quad (1)$$

$$L \frac{dI(t)}{dt} = V_0 - V(t) - RI(t), \quad (2)$$

where $V(t)$ and $I(t)$ indicate the voltage and the total current across the RTD and the capacitor with capacitance C , while R and L indicate the circuit resistance and inductance, respectively. $L = L_{\text{RTD}} + L_{\text{ext}}$ and $C = C_{\text{RTD}} + C_{\text{ext}}$ account for RTD intrinsic (L_{RTD} and C_{RTD}) and external (L_{ext} and C_{ext}) components, with the latter aiming to extend the tunability of the RTD neuron circuit. The function $f(V)$

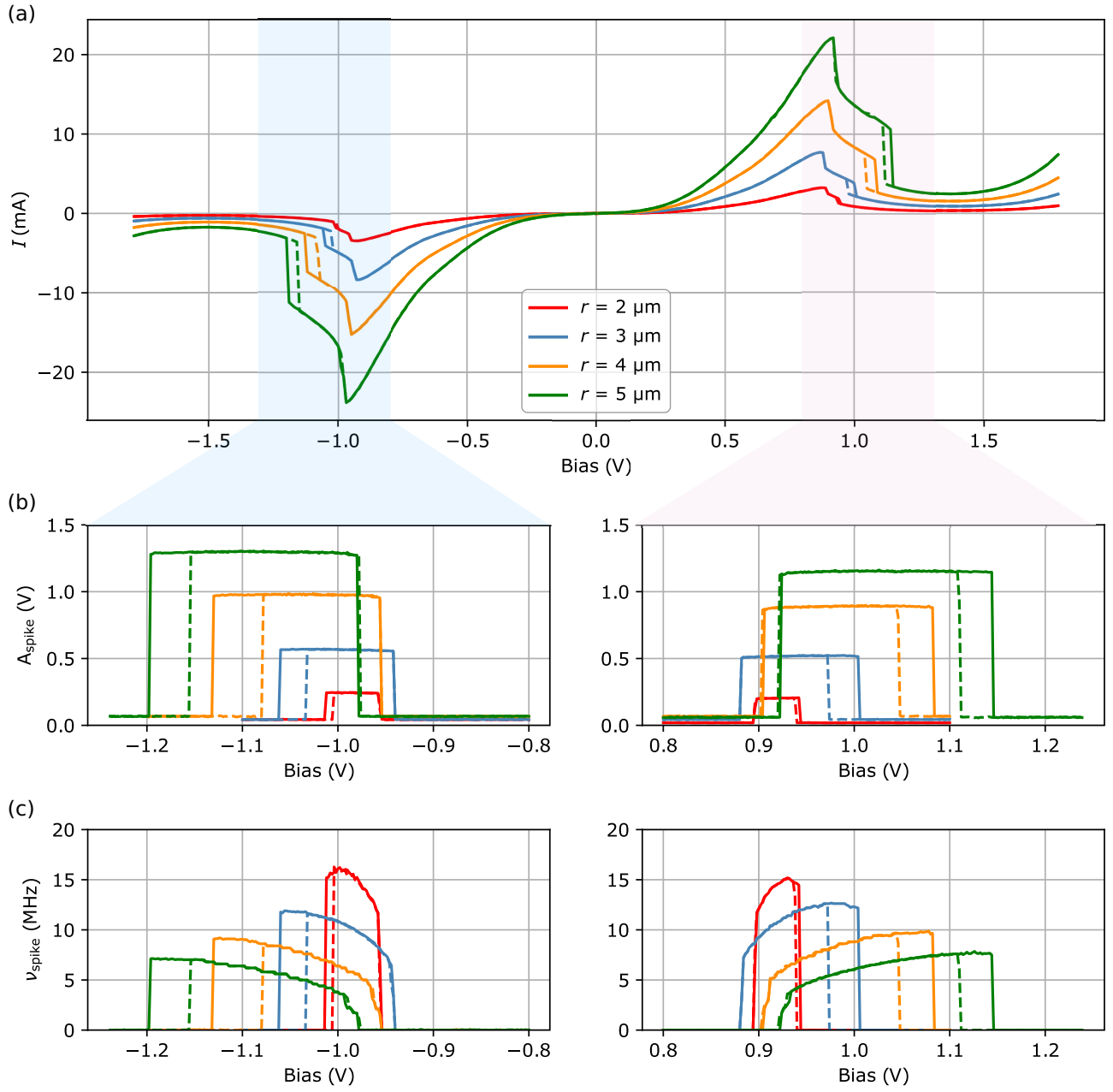


FIG. 5. (a) Experimental I - V characteristics of RTDs having different circular mesa radii. (b) Amplitude of the spike A_{spike} and (c) firing rate ν_{spike} exhibited by RTDs with different mesa radii when biased across their correspondent NDR regions.

appearing in Eq. (1) describes the RTD I - V characteristics with an expression derived directly from the quantum model in Ref. [31]:

$$f(V) = a \ln \left[\frac{1 + e^{(q/k_B T)(b-c+n_1 V)}}{1 + e^{(q/k_B T)(b-c-n_1 V)}} \right] \times \left[\frac{\pi}{2} + \tan^{-1} \left(\frac{c - n_1 V}{d} \right) \right] + h [e^{(q/k_B T)n_2 V} - 1], \quad (3)$$

where T is the temperature, q_e the electron charge, and k_B the Boltzmann constant, while a , b , c , d , n_1 , n_2 , and h depend on the RTD epilayer properties (e.g., geometry and doping levels) [31]. These are chosen to fit the experimental I - V characteristic of the RTD having a mesa radius of $3 \mu\text{m}$. The fit, shown as a green curve in Fig. 7, accounts for all experimental data (blue dots) and, in particular, for the sharp NDR transition just after the peak. The fit does not consider NDR points related to spiking activity (and some valley points labeled by red crosses in Fig. 7). Given f , the I - V characteristics accounting for the circuit

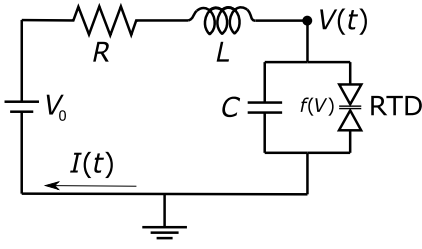


FIG. 6. RTD circuit scheme, described by an I - V function $f(V)$ coupled to circuit parameters R , L , and C . The inductance $L = L_{\text{RTD}} + L_{\text{ext}}$ and capacitance $C = C_{\text{RTD}} + C_{\text{ext}}$ account for RTD intrinsic (L_{RTD} and C_{RTD}) and external (L_{ext} and C_{ext} , the latter parallel to C_{RTD}) components that expand the tunability of the RTD neuron circuit.

parameters can be extracted by integration of Eqs. (1) and (2) for different dc bias voltages V_0 and averaging over the corresponding simulated output-time trace $I(t)$, with use of this current value in the I - V . Note that this procedure resembles the average value of $I(t)$ measured experimentally for each bias by the current reader connected to the dc port of the bias tee, due to its limited bandwidth relative to the fast RTD spiking dynamics (see Fig. 1). Figures 8(a) and 8(b) show the simulated I - V characteristics and corresponding spiking rate maps, respectively, for four inductance values ranging over 4 orders of magnitude, from $L = 2 \times 10^{-9}$ H to $L = 2000 \times 10^{-9}$ H (corresponding to the four columns in Fig. 8). Each I - V curve in Fig. 8(a) is measured by the integration of Eqs. (1) and (2) being repeated for dc bias voltage V_0 [x axis in Fig. 8(a)] from 0 to 2.08 V (continuous light-blue line) and vice versa (dashed light-blue line). Figure 8(a) also shows as a green line the fit function $f(V)$ [Eq. (3)] used in the simulations, for reference. The same function f is used in all simulations.

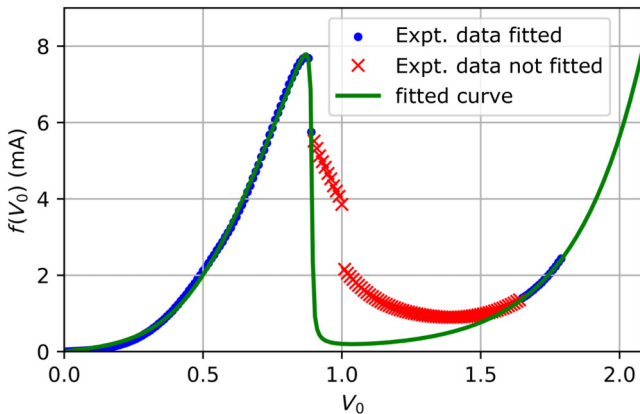


FIG. 7. Fit of $f(V)$ to the experimental I - V characteristic of the RTD with 3 μm radius. The simulation parameters are $a = 8.18 \times 10^{-4}$ A, $b = 8.535 \times 10^{-2}$ V, $c = 18.432 \times 10^{-2}$ V, $d = 7.209 \times 10^{-4}$ V, $n_1 = 0.2066$, $n_2 = 0.1055$, and $h = 1.6025 \times 10^{-6}$ A.

We first note that all four inductance scenarios studied allow spiking regimes [$v_{\text{spike}} \neq 0$ in Fig. 8(b)] when the RTD is biased within the NDR region of the corresponding I - V curve [Fig. 8(a)], and in agreement with the experimental findings in Fig. 2. Notably, the NDR regions are also where the effects of circuit parameters are more pronounced, leading to deviations from $f(V)$. Remarkably, the NDR region excluded from the experimental fit of $f(V)$ in Fig. 7 naturally emerges when $f(V)$ is coupled to the circuit through Eqs. (2) and (3). This suggests that the RTD spiking dynamics in the NDR region is an excitable process relying on resonance tunneling effects within the DBQW (assumed to be instantaneous in the model), with timescales linked to the RTD neuron circuit parameters. Increasing the inductance by a factor of 10 reduces the firing rate range by a factor of 10, from $v_{\text{spike}} \approx 10$ GHz for $L = 2$ nH down to $v_{\text{spike}} \approx 10$ MHz for $L = 2$ μH , as shown in Fig. 8(b). The reduction in firing rate with increasing L is also shown by the temporal spiking responses plotted in Fig. 8(c), under a 0.94 V bias [a value that belongs to the NDR regions of all four inductance scenarios investigated—see the pairs of colored dots in Figs. 8(a) and 8(b)]. To grasp the physical origins behind the lower firing speed for larger inductance in the RTD circuit, the starting point is to map the (voltage) spiking temporal traces [for example, the ones in Fig. 8(c), obtained under a 0.94 V bias] in their corresponding limit cycle in the I - V plane [see the colored orbits in Fig. 8(a)], and observe that not only the voltage $V(t)$ but also the current $I(t)$ across the RTD is subject to variations during the spike evolution. While for the $L = 2$ nH case, the orbit is more rounded [Fig. 8(a), leftmost panel] and described by a smooth oscillation over time [Fig. 8(c), leftmost panel], for larger L the orbit becomes stiffer, with emerging slow-fast temporal spike profiles, as predicted by the smaller stiffness coefficient $\mu = \sqrt{C/L}$ obtained for larger L [20]. By observing the limit cycle trajectories linked to a spike profile [see Fig. 8(a), $L \geq 20$ nH], we can recognize four stages: two stages where $V(t)$ experiences a larger variation, while $I(t)$ is left almost constant, and two stages where both $V(t)$ and $I(t)$ vary steadily [20]. The inductance opposes current variations in the form of an opposite electromotive force ($V_{0,L} = -LdI/dt$) and affects therefore the two stages of the spike evolution with wider current variation. On the other hand, the fast voltage phases of the spike evolution are controlled by the capacitance C of the RTD neuron circuit. We studied this dependence by performing simulations where C was varied over 4 orders of magnitude, from 2.5 to 2500 fF, while L was left fixed at $L = 20$ nH. We assume that is the external component C_{ext} of C varying, while the intrinsic component C_{RTD} , linked to the RTD mesa radius, is the same. In this way all I - V characteristics show the same peak current. The results, shown in Fig. 9, describe smoother spike fast phases with increasing C , with a maximum spike rate reduction of less than a

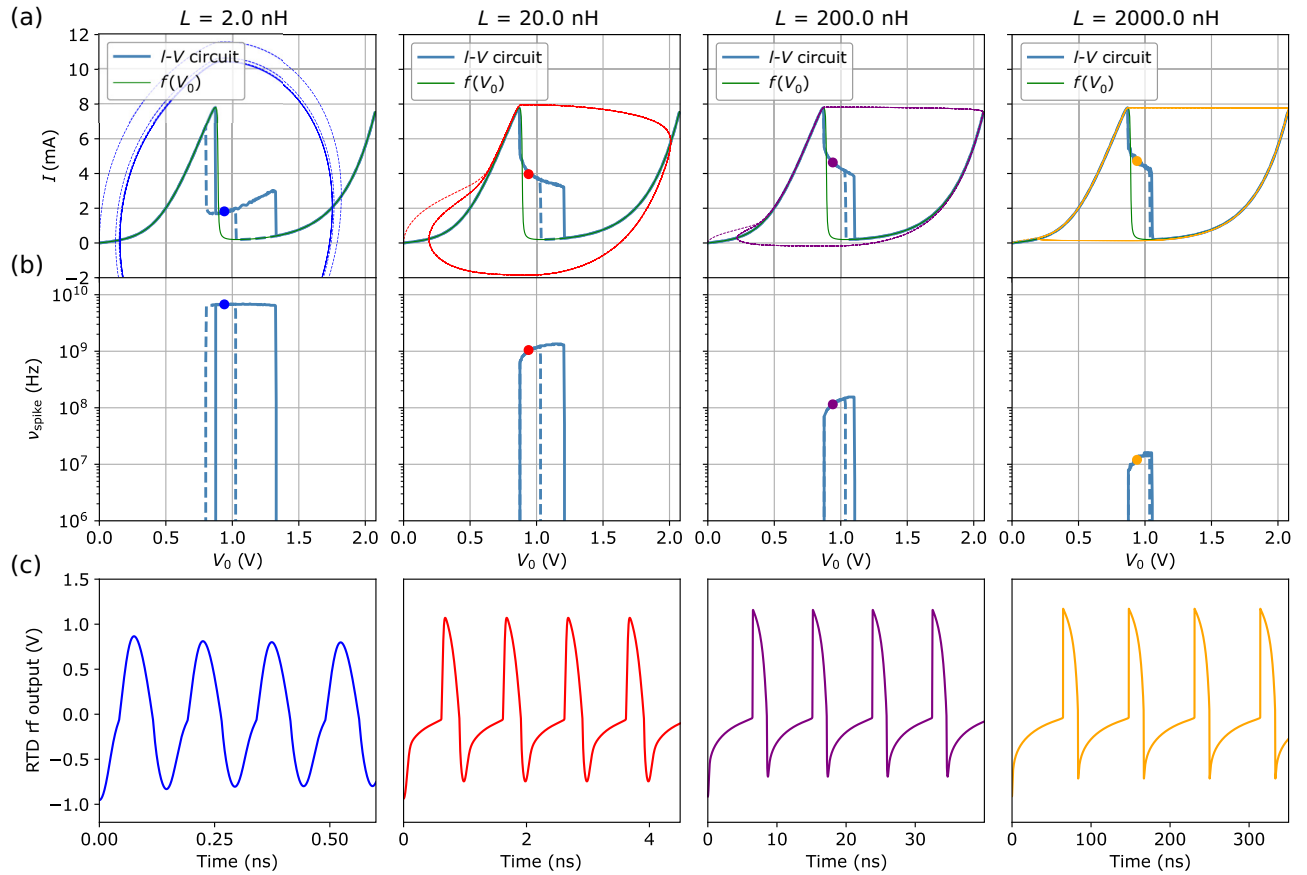


FIG. 8. Simulations of an RTD neuron circuit with four different inductance values L , indicated at the top of each column, and capacitance C fixed at 250×10^{-15} F and resistance R fixed at $0.1 \, \Omega$. In (a), the I - V circuit characteristics were evaluated by our averaging the output current $I(t)$ over a long simulation time (long enough to allow multiple spikes) at each corresponding voltage bias V_0 (blue curve). These results are compared with the RTD's pure quantum mechanical description f across all bias values V_0 (green curve). The simulation times are 8, 20, 200, and 500 ns for the four respective values of L . A highlighted colored orbit illustrates the evolution of $V(t)$ and $I(t)$ during a spike for $V_0 = 0.94$ V. (b) Dependency of the firing rate on L . (c) Spiking evolution $V(t)$ over time for a bias V_0 of 0.94 V, a value belonging to the NDR region for all four inductance scenarios. Note that different timescales are used for the x axis.

factor of 10 [much less than 10^4 obtained by variation of L in Fig. 8(b) by 4 orders of magnitude]. Since the first fast phase of the spike evolution links to the integration time of the RTD neuron [32], the capacitance becomes a parameter that allows slightly to change the neuron property. Critically, as the stiffness coefficient $\mu = \sqrt{C/L}$ increases, either by decrease of L [as in Fig. 8(a), left panels] and speeding up of the slow current phases, or by increase of C [as in Fig. 9(a), right panels] and slowing down of the fast voltage phase, the RTD spike gradually loses its slow-fast phases, flattening the corresponding firing rate variation within the NDR region [Figs. 8(b) and 9(b), respectively]. Consequently, this removes any rate encoding capability of the RTD neuron circuit.

The inductance and capacitance studies presented above are part of a broader analysis over a wider set of L and C combinations in the RTD circuit. These results are summarized in Fig. 10, which shows how the mean spiking

rate $\bar{\nu}_{\text{spike}}$ across the NDR region and the corresponding spiking rate range $\Delta \nu_{\text{spike}}$ evolve as L is varied. Each colored line in Fig. 10 represents a different fixed capacitance scenario. When $\Delta \nu_{\text{spike}} > 0$, the RTD circuit supports rate encoding over the NDR region. When ν_{spike} remains constant over the NDR region, as seen in the leftmost panel in Fig. 8(b), the circuit no longer exhibits rate encoding. Figure 10 shows that $\bar{\nu}_{\text{spike}}$ increases linearly as L decreases for all capacitances analyzed. This linearity bends as soon as the RTD circuit no longer exhibits a firing rate range ($\Delta \nu_{\text{spike}} = 0$), i.e., when ν_{spike} is approximately constant within the NDR region. At this point, the circuit has lost the fast-slow dynamics characteristic of a spike, as seen in the leftmost panel in Fig. 8(c).

Further decrease of the inductance L still increases the oscillation rate, but with a different linear coefficient than with the RTD exhibiting a spike profile. Notably, the rate becomes strongly influenced also by the capacitance C

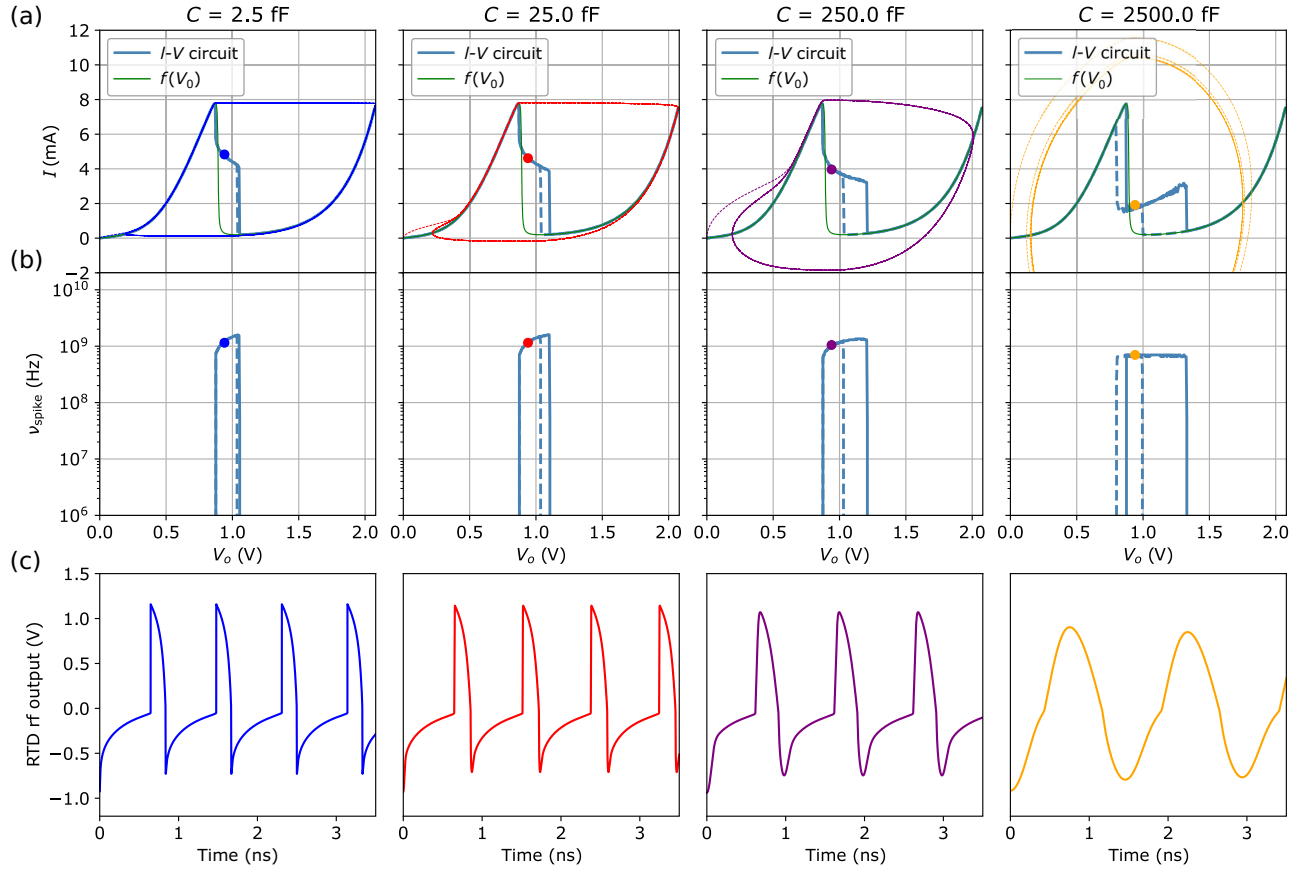


FIG. 9. Simulations of an RTD neuron circuit with four different capacitance values C , indicated at the top of each column, and inductance L fixed at 20×10^{-9} H and resistance R fixed at 0.1Ω . In (a), the I - V circuit characteristics were evaluated by our averaging the output current $I(t)$ over a long simulation time (long enough to allow multiple spikes) at each corresponding voltage bias V_0 (blue curve). These results are compared with the RTD's pure quantum mechanical description f across all bias values V_0 (green curve). The simulation time is 20 ns for all four capacitance scenarios. A highlighted colored orbit illustrates the evolution of $V(t)$ and $I(t)$ during a spike for $V_0 = 0.94$ V. (b) Dependency of the firing rate on C . (c) Spiking evolution $V(t)$ over time for a bias V_0 of 0.94 V, a value belonging to the NDR region for all four capacitance scenarios.

when L is below the critical point, i.e. when the circuit is oscillating, resuming the expected $1/\sqrt{LC}$ dependence of an LC oscillator (see, for instance, $L = 10^{-11}$ H in Fig. 10). Furthermore, Fig. 10 shows that the use of a lower capacitance (e.g., $C = 2.5 \times 10^{-15}$ F, blue line) shifts the transition point to smaller values of L , thereby extending the rate encoding capabilities of the RTD circuit ($\Delta\nu > 0$) at higher speed.

These results underscore the importance of careful calibration of the inductance, capacitance, and stiffness coefficient when one is designing RTD-based neuromorphic systems to achieve the desired spike operational speed and firing rate variability within the NDR region. Moreover, these findings are complementary to the earlier discussions on the impact of the RTD mesa radius. Specifically, the observed firing rate variations across RTDs having diverse mesa radii [see Fig. 5(c)] align with the findings of the numerical capacitance study. Since the RTD intrinsic capacitance increases with the mesa radius, it slightly

impacts the firing rate. Additionally, a higher capacitance corresponds to a higher stiffness coefficient, which our simulations indicate progressively constrains the firing rate variation within the NDR region. This explains the reduced firing rate variability in RTDs with larger mesa radii. Moreover, both inductance and capacitance affect the width of the bistable region at the end of the NDR region, providing tuning capabilities for spiking memory effects [22]. Together, these insights provide a deeper understanding of how circuit and device-level parameters influence RTD spiking dynamics. Notably, the inductance study reported in Fig. 8 shows that for $L = 2 \mu\text{H}$ the RTD I - V curve, the spike firing rate, and the widths of the NDR and bistability regions closely match the experimental data in Fig. 2. However, such an inductance would require an impractical large on-chip transmission line. We therefore attribute this inductance to the instrumentation connected to our RTD. Specifically, the bias tee in Fig. 1, which has a bandwidth of 10 MHz to 12 GHz and an estimated

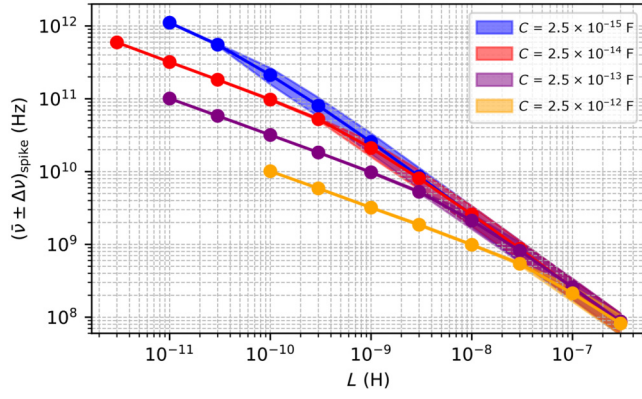


FIG. 10. Mean spiking rate $\bar{v}_{\text{spike}}$ over the NDR region and corresponding firing rate range Δv over the NDR region as a function of the inductance L for different capacitance C values in the RTD circuit.

internal inductance of a few microhenries, appears to be the limiting factor for the experimentally observed spiking rate. Consequently, fitting $f(V)$ to the experimental NDR region (red crosses in Fig. 7) would inherently account for these experimental circuitry effects, even before coupling to the circuit parameters via Eqs. (1) and (2), leading to deviations between numerical and experimental results.

IV. RATE ENCODING EXAMPLE

Figure 11 shows an example of the RTD spike rate encoding scheme applied to a randomly generated word of eight-level symbols. Each level is mapped to a bias voltage within the NDR region of the RTD neuron circuit, so that each level elicits a different spiking rate. This demonstration is conducted numerically because the bandwidth limitation of the bias tee in the current setup restricts input pulse durations to approximately 20 ns before filtering effects become significant. This duration is insufficient to produce multiple spikes and establish a spike rate. Instead, we consider an RTD with circuit parameters of $L = 20$ nH and $C = 250$ fF, as characterized in Fig. 9, yielding a spike rate range between 0.65 GHz and 1.35 GHz.

The bias voltage across the RTD was varied between eight voltage levels within the NDR region between 0.95 V and 1.15 V (spaced such that the resulting spike rates at each level were equally spaced), with each level held for 5 ns to allow several spikes. This modulation is shown in Fig. 11(a). Figure 11(b) shows the response of the RTD with spikes occurring at rates according to the applied bias voltage. The instantaneous spiking rate was approximated from the voltage trace by the inverse of the interspike interval calculated at each spike (i.e., the difference between the time of a spike and the time of the preceding spike). Figure 11(c) shows the approximate spike rate at the moment of each spike, recreating the eight-level word input to the bias

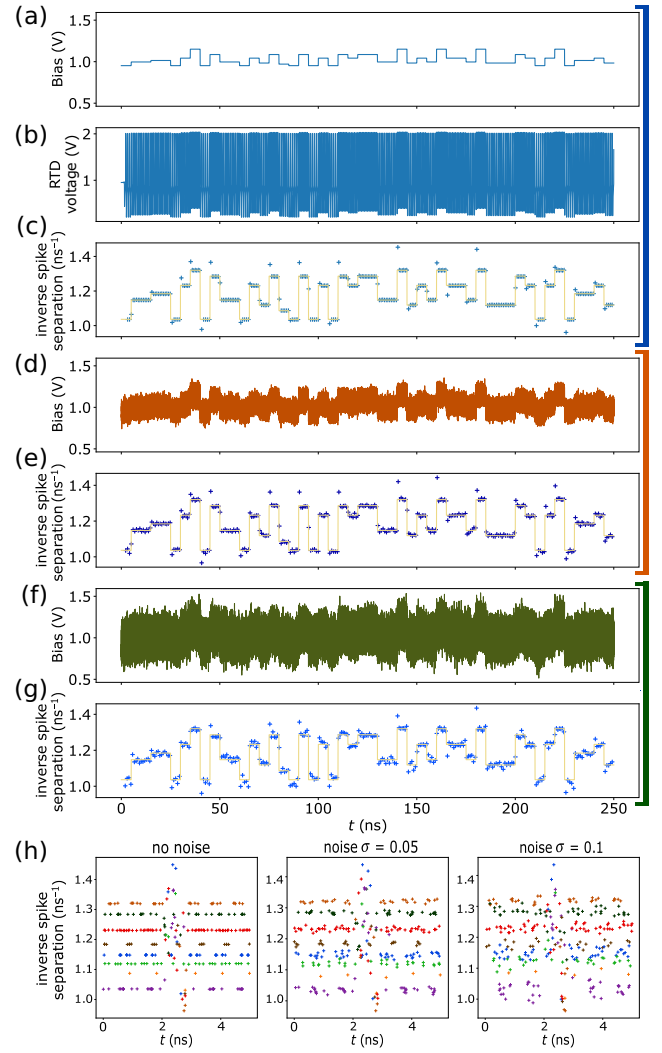


FIG. 11. Simulation of a spike rate encoding of an eight-level word. (a) Modulation of the bias voltage to the RTD. Each symbol was held for 5 ns. (b) Voltage across the RTD, showing the constant spiking at different rates, according to the bias modulation. (c) Reconstruction of the signal from the spike interval. At the time of occurrence of each spike, the reciprocal of the time since the previous spike is plotted to approximate the inverse of the spike rate, recovering the modulation signal. (d),(f) Original modulation signal with normally distributed noise (standard deviation $\sigma = 0.05$ V and $\sigma = 0.1$ V) added. (e),(g) Reconstruction of the signal by inverse spike interval, showing a good reconstruction of the non-noisy signal, and (h) corresponding eye diagram. Gold lines in (c),(e),(g) show the target function to recover.

modulation. The visible outliers are the result of the transitive state as the RTD spike rate moves from one level to the other. Additionally, the spike rate encoding was performed on a noisy version of the original modulation. Gaussian noise with zero mean and a standard deviation σ of 0.05 V [Fig. 11(d)] and 0.1 V [Fig. 11(f)] was added to the voltage modulation. Since the frequency of the noise is

much higher than the spiking frequency, the RTD spike rate encoding effectively filters out the noise and can reconstruct well the signal from the inverse spike interval [Figs. 11(e) and 11(g)]. The number of levels that can be used for rate encoding is determined by the level of noise in the input. In our case, the eye diagrams created for the different noise scenarios [see Fig. 11(h)] show that for low (or no) noise, the eight levels remain distinguishable, whereas for high noise, they have significant overlap. Use of fewer levels would avoid this overlap at high noise values; however, this would transmit less information. This suggests the ability to effectively encode and decode noisy signals at high bit rate with spiking RTD neurons.

V. CONCLUSION

This work investigates experimentally and in theory the neuromorphic properties of RTD spiking neurons, emphasizing their potential for spike-based encoding mechanisms. The spike firing rate of an RTD can be tuned by adjustment of the bias across the NDR region of its I - V characteristic, providing a basis for spike firing rate encoding. Additionally, we investigated encoding information using the latency time of spike firing in response to input stimuli. The study reveals a highly selective mechanism where only input pulses within a narrow amplitude range, on the order of a few millivolts above the spiking threshold, result in differentiated firing delays. This selectivity can be further controlled by fine-tuning of the RTD bias, potentially enabling time-to-first-spike protocols in faster, optimized RTD neuron circuits. However, for bias below but far from the peak of the I - V curve, we also find that the elicited spikes show a weaker recovery phase (independently of the input pulse amplitude), which makes it easier to bypass the refractory period of the device.

The influence of RTD mesa radius and circuit inductance on spiking dynamics was also analyzed. RTDs with smaller radii are more suitable for firing rate encoding, as they offer a broader firing rate range. In contrast, larger-radius RTDs, which have a narrower firing rate range spread across a wider NDR region, are better suited for operation in noisy environments due to their robustness regarding voltage fluctuations. These results link to the higher capacitance of RTDs with a larger mesa radius, which is numerically shown to slightly control the fast voltage phase time of the spike evolution. On the other hand, the inductance in the circuit resists the wide current variations during the spike evolution and significantly impacts the RTD's spike response by limiting the firing rate. In this way, the operational speed is controlled mainly by the inductance of the circuit, with possibilities to be fine-tuned by the capacitance. Both the inductance and the capacitance also tune the bistability width at the end of the NDR region, which is critical for spiking flip-flop memory effects [22]. Moreover, the stiffness coefficient

also needs proper calibration, as a higher stiffness coefficient gradually smooths the slow-fast dynamics during the spike evolution, removing the firing rate capability within the NDR region. These findings provide valuable guidance for the design of RTD-based neuromorphic systems, potentially co-working with external photonic hardware such as photodetectors [22], offering exciting potential for photonic-electronic neuromorphic hardware.

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G.D. performed the experimental and numerical study of RTDs. D.O.-N. realized the numerical application of rate encoding. J.F., V.D.-C., and E.M. designed the RTDs, which were then fabricated at Eindhoven University of Technology. J.R. and X.P. helped set up the laboratory experiment. J.F. and B.R. supported the numerical analysis. A.H. supervised the work. All authors contributed to the revision of the manuscript.

DATA AVAILABILITY

The data that support the findings of this article are openly available [33].

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- [1] C. D. Schuman, S. R. Kulkarni, M. Parsa, J. P. Mitchell, P. Date, and B. Kay, Opportunities for neuromorphic computing algorithms and applications, *Nat. Comput. Sci.* **2**, 10 (2022).
 - [2] J. K. Eshraghian, M. Ward, E. O. Neftci, X. Wang, G. Lenz, G. Dwivedi, M. Bennamoun, D. S. Jeong, and W. D. Lu, Training spiking neural networks using lessons from deep learning, *Proc. IEEE* **111**, 1016 (2023).
 - [3] M. M. Waldrop, The chips are down for Moore's law, *Nat. News* **530**, 144 (2016).
 - [4] S. B. Furber, F. Galluppi, S. Temple, and L. A. Plana, The SpiNNaker project, *Proc. IEEE* **102**, 652 (2014).
 - [5] E. Painkras, L. A. Plana, J. Garside, S. Temple, F. Galluppi, C. Patterson, D. R. Lester, A. D. Brown, and S. B. Furber, SpiNNaker: A 1-W 18-core system-on-chip for massively-parallel neural network simulation, *IEEE J. Solid-State Circuits* **48**, 1943 (2013).
 - [6] M. V. DeBole, B. Taba, A. Amir, F. Akopyan, A. Andreopoulos, W. P. Risk, J. Kusnitz, C. O. Otero, T. K. Nayak, R. Appuswamy *et al.*, TrueNorth: Accelerating from zero to 64 million neurons in 10 years, *Computer* **52**, 20 (2019).
 - [7] M. Davies, N. Srinivasa, T.-H. Lin, G. Chinya, Y. Cao, S. H. Choday, G. Dimou, P. Joshi, N. Imam, S. Jain *et al.*, Loihi:

- A neuromorphic manycore processor with on-chip learning, *IEEE Micro* **38**, 82 (2018).
- [8] J. Schemmel, L. Kriener, P. Müller, and K. Meier, in *2017 International Joint Conference on Neural Networks (IJCNN)* (IEEE, Anchorage, AK, USA, 2017), pp. 2217–2226.
- [9] F. Ashtiani, A. J. Geers, and F. Aflatouni, An on-chip photonic deep neural network for image classification, *Nature* **606**, 501 (2022).
- [10] S. Biasi, R. Franchi, L. Cerini, and L. Pavesi, An array of microresonators as a photonic extreme learning machine, *APL Photonics* **8**, 096105 (2023).
- [11] J. Feldmann, N. Youngblood, C. D. Wright, H. Bhaskaran, and W. H. Pernice, All-optical spiking neurosynaptic networks with self-learning capabilities, *Nature* **569**, 208 (2019).
- [12] X. Lin, Y. Rivenson, N. T. Yardimci, M. Veli, Y. Luo, M. Jarrahi, and A. Ozcan, All-optical machine learning using diffractive deep neural networks, *Science* **361**, 1004 (2018).
- [13] D. K. Ferry, *Transport in Semiconductor Mesoscopic Devices* (IOP Publishing, Bristol, UK, 2020).
- [14] C. Ironside, B. Romeira, and J. Figueiredo, *Resonant Tunneling Diode Photonics Devices and Applications* (IOP Publishing, Bristol, UK, 2023).
- [15] D. Cimbri, J. Wang, A. Al-Khalidi, and E. Wasige, Resonant tunneling diodes high-speed terahertz wireless communications - A review, *IEEE Trans. Terahertz Sci. Technol.* **12**, 226 (2022).
- [16] Y. Nishida, N. Nishigami, S. Diebold, J. Kim, M. Fujita, and T. Nagatsuma, Terahertz coherent receiver using a single resonant tunnelling diode, *Sci. Rep.* **9**, 18125 (2019).
- [17] B. Romeira, J. Javaloyes, C. N. Ironside, J. M. Figueiredo, S. Balle, and O. Piro, Excitability and optical pulse generation in semiconductor lasers driven by resonant tunneling diode photo-detectors, *Opt. Express* **21**, 20931 (2013).
- [18] M. Hejda, J. A. Alanis, I. Ortega-Piwonka, J. Lourenço, J. Figueiredo, J. Javaloyes, B. Romeira, and A. Hurtado, Resonant tunneling diode nano-optoelectronic excitable nodes for neuromorphic spike-based information processing, *Phys. Rev. Appl.* **17**, 024072 (2022).
- [19] M. Hejda, E. Malysheva, D. Owen-Newns, Q. R. Ali Al-Taai, W. Zhang, I. Ortega-Piwonka, J. Javaloyes, E. Wasige, V. Dolores-Calzadilla, J. M. Figueiredo *et al.*, Artificial optoelectronic spiking neuron based on a resonant tunnelling diode coupled to a vertical cavity surface emitting laser, *Nanophotonics* **12**, 857 (2023).
- [20] I. Ortega-Piwonka, O. Piro, J. Figueiredo, B. Romeira, and J. Javaloyes, Bursting and excitability in neuromorphic resonant tunneling diodes, *Phys. Rev. Appl.* **15**, 034017 (2021).
- [21] B. Romeira, R. Avó, J. Javaloyes, S. Balle, C. N. Ironside, and J. M. Figueiredo, Stochastic induced dynamics in neuromorphic optoelectronic oscillators, *Opt. Quantum Electron.* **46**, 1391 (2014).
- [22] G. Donati, D. Owen-Newns, J. Robertson, E. Malysheva, A. Adair, J. Figueiredo, B. Romeira, V. Dolores-Calzadilla, and A. Hurtado, Spiking flip-flop memory in resonant tunnelling diode neurons, *Phys. Rev. Lett.* **133**, 267301 (2024).
- [23] K. Sano, K. Murata, T. Otsuji, T. Akeyoshi, N. Shimizu, and E. Sano, An 80-Gb/s optoelectronic delayed flip-flop IC using resonant tunneling diodes and uni-traveling-carrier photodiode, *IEEE J. Solid-State Circuits* **36**, 281 (2001).
- [24] B. Romeira, J. M. Figueiredo, and J. Javaloyes, Delay dynamics of neuromorphic optoelectronic nanoscale resonators: Perspectives and applications, *Chaos* **27**, 114323 (2017).
- [25] T. J. Slight and C. N. Ironside, Investigation into the integration of a resonant tunnelling diode and an optical communications laser: Model and experiment, *IEEE J. Quantum Electron.* **43**, 580 (2007).
- [26] B. J. Richmond, L. M. Optican, M. Podell, and H. Spitzer, Temporal encoding of two-dimensional patterns by single units in primate inferior temporal cortex. I. Response characteristics, *J. Neurophysiol.* **57**, 132 (1987).
- [27] J. C. Middlebrooks, A. E. Clock, L. Xu, and D. M. Green, A panoramic code for sound location by cortical neurons, *Science* **264**, 842 (1994).
- [28] R. Talukder, A. Skalli, X. Porte, S. Thorpe, and D. Brunner, A spiking photonic neural network of 40,000 neurons, trained with rank-order coding for leveraging sparsity, *arXiv:2411.19209*.
- [29] J. L. Figueiredo, C. N. Ironside, and C. R. Stanley, Electric field switching in a resonant tunneling diode electroabsorption modulator, *IEEE J. Quantum Electron.* **37**, 1547 (2001).
- [30] B. Romeira, R. R. Adão, J. B. Nieder, Q. Al-Taai, W. Zhang, R. H. Hadfield, E. Wasige, M. Hejda, A. Hurtado, E. Malysheva *et al.*, Brain-inspired nanophotonic spike computing: Challenges and prospects, *Neuromorphic Comput. Eng.* **3**, 033001 (2023).
- [31] J. Schulman, H. De Los Santos, and D. Chow, Physics-based RTD current-voltage equation, *IEEE Electron Device Lett.* **17**, 220 (1996).
- [32] J. Robertson, D. Black, G. Donati, Q. R. A. Al-Taai, E. Malysheva, B. Romeira, J. Figueiredo, V. D. Calzadilla, E. Wasige, and A. Hurtado, Ultrafast and compact photonic-electronic leaky integrate-and-fire circuits based upon resonant tunnelling diodes, *arXiv:2501.17133*.
- [33] G. Donati, Data for: “Spiking rate and latency encoding with resonant tunnelling diode neuron circuits and design influences” (2025), <https://doi.org/10.15129/fa675685-5b03-4866-a532-c291411f6ffc>.