

Cross-Platform Autonomous Control of Minimal Kitaev Chains

David van Driel^{1,*}, Rouven Koch^{1,2}, Vincent P. M. Sietses¹, Sebastiaan L. D. ten Haaf¹, Chun-Xiao Liu,¹ Francesco Zatelli¹, Bart Roovers¹, Alberto Bordin,¹ Nick van Loo¹, Guanzhong Wang,¹ Jan Cornelis Wolff,¹ Grzegorz P. Mazur,¹ Tom Dvir¹, Ivan Kulesh,¹ Qingzhen Wang¹, A. Mert Bozkurt,¹ Sasa Gazibegovic,³ Ghada Badawy,³ Erik P. A. M. Bakkers,³ Michael Wimmer,¹ Srijit Goswami¹, Jose L. Lado², Leo P. Kouwenhoven,¹ and Eliska Greplova^{1,†}

¹*QuTech and Kavli Institute of NanoScience, Delft University of Technology, 2600 GA Delft, The Netherlands*

²*Department of Applied Physics, Aalto University, 02150 Espoo, Finland*

³*Department of Applied Physics, Eindhoven University of Technology, 5600 MB Eindhoven, The Netherlands*



(Received 31 May 2024; accepted 4 June 2026; published 28 July 2026)

Contemporary quantum devices are reaching new limits in size and complexity, allowing for the experimental exploration of emergent quantum modes. However, this increased complexity introduces significant challenges in device tuning and control. Here, we demonstrate autonomous tuning of emergent Poor Man's Majorana zero modes in a minimal realization of a Kitaev chain. We achieve this task using cross-platform transfer learning. First, we train a tuning model on a theory model. Next, we retrain it using a Kitaev chain realization in a two-dimensional electron gas. Finally, we apply this model to tune a Kitaev chain realized in quantum dots coupled through a semiconductor-superconductor section in a one-dimensional nanowire. Utilizing a convolutional neural network, we predict the tunneling and Cooper pair splitting rates from differential conductance measurements, employing these predictions to adjust the electrochemical potential to a Poor Man's Majorana sweet spot. The algorithm successfully converges to an immediate vicinity of a sweet spot (within ± 1.5 mV in 67.6% of attempts and within ± 4.5 mV in 80.9% of cases), typically finding a sweet spot in 45 min or less. This advancement is a stepping stone toward autonomous tuning of emergent modes in interacting systems, and toward foundational tuning machine learning models that can be deployed across a range of experimental platforms.

DOI: [10.1103/ryll-qb42](https://doi.org/10.1103/ryll-qb42)

I. INTRODUCTION

Mesoscopic quantum devices are promising for both quantum computing [1–3] and quantum simulation [4–8] due to the flexibility and scalability in the design and fabrication. However, a challenge in terms of control and tuning emerges as these devices reach larger sizes. In other words, the scalability of solid-state quantum devices comes with the price of complex quantum control requirements. There are two main lines of inquiry toward solving these challenges either based on (1) the development of effective models that can be embedded into the experimental control protocols [9,10] or (2) data-driven machine learning (ML) approaches that are trained to extract key features and make predictions directly on the measured data [11–23]. The latter technique has shown success in cases where precise theoretical modeling is challenging or when the algorithmic application of effective model is prohibitive due to its complexity. In instances where there is a sufficient amount of training data available, ML models

show impressive generalization with respect to noise and, once trained, rapid evaluation speed that allows for embedding into the existing experimental workflows [24].

In particular, ML techniques have been widely deployed for tasks pertaining to the operation of semiconductor quantum dots (QDs) [24]. In this context, ML methods have been applied with promising results that simplify device operation and reach comparable accuracy to experienced human operators [25]. The key challenges in the field can be grouped into two broader categories [26]: (1) building foundational models that generalize well to a large set of platforms and devices, and (2) demonstrating the utility of machine learning approaches beyond smaller-scale devices with relatively simple charge stability diagrams (CSDs) and a comparably low number of parameters.

In the present work, we design, benchmark, and experimentally demonstrate an ML-based method that addresses both these challenges simultaneously: We devise an autonomous tune-up protocol that achieves the emergence of Poor Man's Majorana modes (PMMs), and we deploy the protocol without using data from the experimental platform we wish to tune. Specifically, we concentrate on the experimental realization of PMMs that are predicted to manifest as emergent quasiparticles in a one-dimensional (1D) Kitaev chain [27,28]. Kitaev chains have been modeled in various forms, including both spinless and spinful variants [27,29–37]. By tuning up complex emergent modes, we take a step beyond what has been established in autonomous state

*Contact author: D.vanDriel@tudelft.nl

†Contact author: e.greplova@tudelft.nl

Published by the American Physical Society under the terms of the [Creative Commons Attribution 4.0 International](https://creativecommons.org/licenses/by/4.0/) license. Further distribution of this work must maintain attribution to the author(s) and the published article's title, journal citation, and DOI.

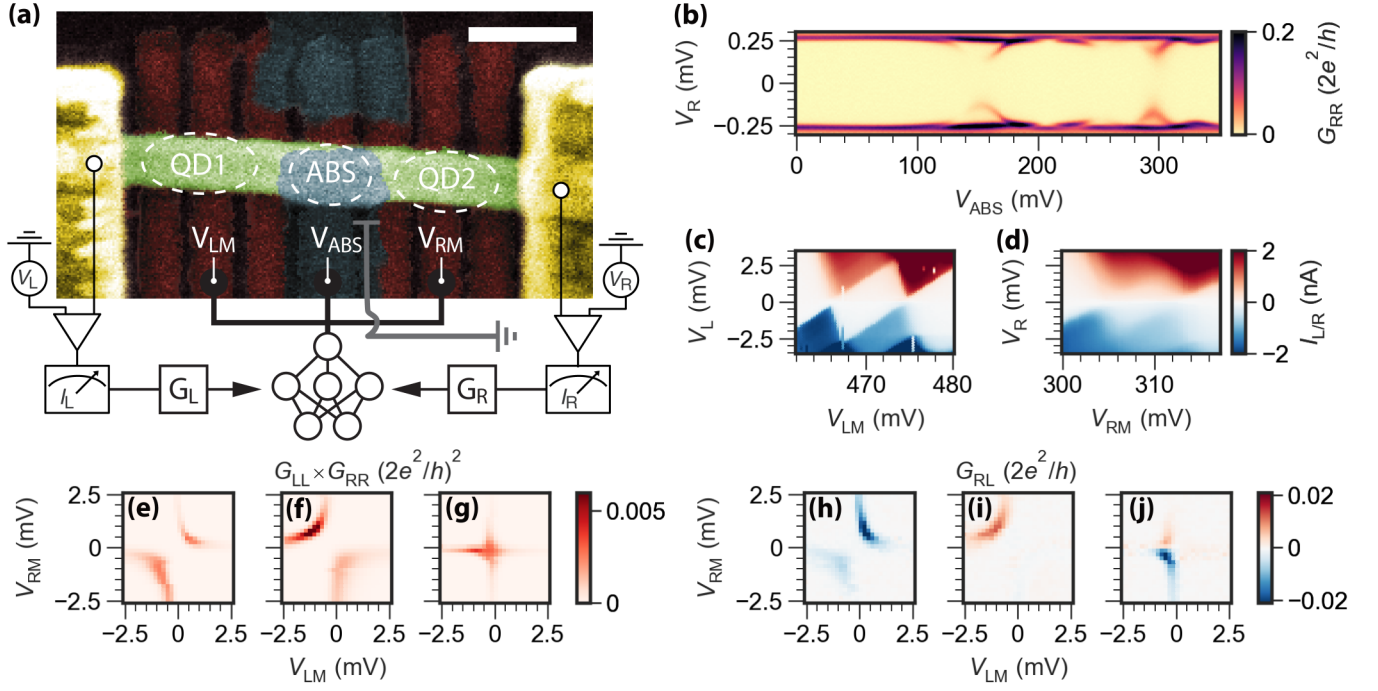


FIG. 1. Device A setup and characterization. (a) False color SEM micrograph of our device and the circuit. An InSb nanowire (green) is contacted by a grounded Al shell (blue) and two normal leads (yellow). The nanowire is placed on bottom gates (red). The relevant gate voltages are indicated by text. Both normal leads can be voltage-biased independently with respect to the grounded Al. (b) Local differential conductance measured from the right lead, G_{RR} , for varying hybrid plunger gate voltage, V_{ABS} , and V_R at $B = 0$ T. (c) The current measured at the left lead, I_L , for varying plunger gate voltage of the left QD, V_{LM} , and bias voltage applied to the left lead, V_L . (d) The current measured at the right lead, I_R , for varying plunger gate voltage of the right QD, V_{RM} , and bias voltage applied to the right lead, V_R . (e)–(g) The product of the left and right differential conductance, $G_{LL} \times G_{RR}$, for varying V_{LM} and V_{RM} at $V_L = V_R = 0$ V. The measurements were performed at V_{ABS} values of 85, 104, and 115 mV, respectively. (h)–(j) Nonlocal conductance, $G_{RL} = dI_R/dV_L$ for varying V_{LM} and V_{RM} . The data were measured simultaneously with panels (e)–(g).

preparation previously. Moreover, we achieve this tuning in a cross-platform transfer learning setting. Specifically, we consider three objects during testing and training of our ML algorithm: a theoretical model of the Kitaev chain, a Kitaev chain experimental realization in chain of quantum dots coupled to superconductor in a one-dimensional nanowire (Device A), and a Kitaev chain experimental realization based on two-dimensional electron gas (2DEG) (Device B). We train the tuning algorithm on theoretical model, retrain on a small number of data acquired from Device B, and then apply and evaluate its performance on Device A.

Our method relies on conductance measurements of charge stability diagrams and works on any platform that supports them. The PMMs in a Kitaev chain originate from two distinct physical processes. A convolutional neural network (CNN) identifies the dominant process. At the voltage configuration where these two processes are equal, the PMMs emerge and we refer to this point as the sweet spot. The output of this initial classification is then used as an input for a gradient descent algorithm that minimizes the distance to the sweet spot by adjusting the device's gate voltages. We find that our algorithm is able to successfully converge to the vicinity of the sweet spot in the voltage space where the PMMs are predicted to emerge. Specifically, 67.6% of tuning runs converge within ± 1.5 mV, and 80.9% converge within ± 4.5 mV of a known sweet spot.

This work is organized as follows: First, we explain the details and characterization of the two-dot Kitaev chain we aim to tune. Then, we describe all the stages of the tuning algorithm: the theory model, the validation and retraining of the model on Device B, and finally its application to Device A. Then, we summarize the ML algorithm performance and assess and summarize our findings in the discussion and conclusion sections. We refer readers to a complementary submission by Benestad *et al.* that simulates a tuning algorithm based on additional sensor quantum dots coupled to a minimal Kitaev chain [38].

II. DEVICE A CHARACTERIZATION

In this section, we describe Device A, on which we demonstrate the tuning algorithm. The device is a semiconductor nanowire designed to be a minimal Kitaev chain, consisting of two QDs coupled by a semiconductor-superconductor segment, as in the first experimental Kitaev chain realization [28]. Minimal Kitaev chains are predicted to host non-Abelian statistics, enabling quantum information operations such as fusion, braiding, and qubit formation [35,39,40]. We show a false-color scanning electron microscopy (SEM) micrograph of Device A in Fig. 1(a). The nanowire (green) is deposited on bottom finger gates (red), and contacted by normal Cr/Au (yellow) contacts at its ends. The middle section of the nanowire, the hybrid, is contacted by a grounded Al shell

(blue). Further details pertaining to the device fabrication can be found in Refs. [41,42].

The left and right normal leads can be biased with respect to the grounded Al with voltages V_L and V_R , respectively. The current running through the left lead (I_L) and through the right lead (I_R) can be measured independently. Unless explicitly indicated, we do not apply an external magnetic field. Using standard lock-in detection, we obtain the local and nonlocal differential conductances [43]:

$$\begin{aligned} G_{LL} &= dI_L/dV_L, & G_{RR} &= dI_R/dV_R, \\ G_{RL} &= dI_R/dV_L, & G_{LR} &= dI_L/dV_R. \end{aligned}$$

Measurements of the local conductances, G_{LL} and G_{RR} , for varying V_{LM} and V_{RM} are used as an input for a CNN that predicts the rates of elastic cotunneling (ECT) and crossed Andreev reflection (CAR) between the two QDs (see Appendix A for details on the CNN architecture). The PMMs appear when the ECT and CAR rates are equal [28,29,44]. The prediction from the CNN is then used as input for a gradient descent algorithm that adjusts V_{ABS} until the rates are equal, marking a sweet spot. While we could have equally used G_{RL} and G_{LR} as input for the CNN, measurements of nonlocal conductance require a multiterminal setup that does not scale well for longer Kitaev chains.

First, we characterize the spectrum of the hybrid segment by accumulating electrons in the InSb nanowire and defining tunnel barriers using the two gates directly next to the hybrid segment. In Fig. 1(b), we show G_{RR} for varying V_R and hybrid plunger gate voltage, V_{ABS} . A hard superconducting gap is seen over the entire gate voltage range. Multiple discrete states are observed in this range, whose gate dependence is typical for Andreev bound states (ABSs). Then, we change the tunnel gate voltages to define QDs to the left and right of the hybrid. We control their electrochemical potentials by varying the plunger gate voltages V_{LM} and V_{RM} . We characterize the left QD by varying V_{LM} and V_L while measuring I_L as shown in Fig. 1(c). For small bias voltage, the current is fully suppressed due to the Coulomb blockade, and as the bias increases we see current appearing in the form of Coulomb diamonds. Additionally, we notice that a gap has opened around the Fermi level due to the superconducting Al. We also perform an analogous measurement of the right QD as shown in Fig. 1(d). Here, the Coulomb diamonds are more difficult to resolve than in Fig. 1(c), which we attribute to a stronger tunnel coupling to the superconductor [45].

After defining the QDs, we set $V_{ABS} = 85$ mV and measure CSDs. Figure 1(e), shows the correlated local conductance, $G_{LL}G_{RR}$, for varying V_{LM} and V_{RM} . This correlated conductance is only finite when transport processes involve both QDs. Therefore, it filters out features that are local to only one QD, such as Andreev reflection. We see an avoided crossing that indicates hybridization between the left and right QD levels. Figure 1(h) shows the nonlocal conductance, G_{RL} , that was measured simultaneously. The negative sign of G_{RL} indicates that the ECT rate is greater than the CAR rate, which is confirmed by the antidiagonal avoided crossing [28]. Figures 1(f) and 1(i) show $G_{LL}G_{RR}$ and G_{RL} , respectively, for varying V_{LM} and V_{RM} at $V_{ABS} = 104$ mV. Here, the avoided crossing is now diagonal and the sign of G_{RL} is positive,

indicating that CAR dominates over ECT. Figures 1(g) and 1(j) show $G_{LL}G_{RR}$ and G_{RL} at $V_{ABS} = 115$ mV. There is no avoided crossing in the CSD anymore, and G_{RL} has both negative and positive values, which is characteristic of the sweet spot where the ECT and CAR rates are equal.

III. TUNING ALGORITHM

A. Theory model

To train a CNN to predict the CAR and ECT rates from CSDs, we construct an effective model of the system to simulate transport data. We model the device in Fig. 1(a) as a three-site system, where the semiconductor-superconductor hybrid segment is treated as an individual site, as shown in Fig. 2(a). The couplings between the two QDs are mediated by ABSs in the hybrid segment. A more detailed description of the theory model and Hamiltonian can be found in Appendix B. We can write the effective interaction Hamiltonian for the QDs in the occupation basis as

$$H_T = \sum_{\sigma, \eta = \uparrow, \downarrow} (t_{\sigma\eta} c_{DL\sigma}^\dagger c_{DR\eta} + \Delta_{\sigma\eta} c_{DL\sigma}^\dagger c_{DR\eta}^\dagger) + \text{H.c.} \quad (1)$$

The operators $c_{DL/DR}^\dagger$ ($c_{DL/DR}$) create (annihilate) an electron in each of the QDs. $t_{\sigma\eta}$ and $\Delta_{\sigma\eta}$ are the ECT and CAR couplings between the two QDs with corresponding spins in the left and right QDs, σ and η , respectively. Coupling to the ABS results in an induced gap on each QD, leading us to model them as Yu-Shiba-Rusinov (YSR) states [46–48]. We add the QDs' electrochemical potential and charging energy to Eq. (1) to obtain the full Hamiltonian [see Eq. (B1) for details]. We then perform a Bogoliubov transformation to account for the particle-hole symmetry on the QDs, and write an effective Hamiltonian for two coupled YSR states in the limit of infinite Zeeman splitting as

$$\begin{aligned} H_{\text{eff}} &= \delta\epsilon_L f_L^\dagger f_L + \delta\epsilon_R f_R^\dagger f_R \\ &+ t(f_L^\dagger f_R + f_R^\dagger f_L) + \Delta(f_L^\dagger f_R^\dagger + f_L f_R). \end{aligned} \quad (2)$$

The operators $f_{L/R}^\dagger$ ($f_{L/R}$) create (annihilate) a quasiparticle in each QD, that is, a superposition of electron and hole components. Here, $\delta\epsilon_{L/R}$ are the energies of the YSR states, and t and Δ are the generalized effective couplings for the odd- and even-parity states, respectively. While t and Δ correspond to ECT and CAR for normal QDs, this is no longer the case for YSR states. Due to local Andreev reflection, ECT can now also couple the global even-parity states, and CAR the odd states (see Appendix B for details). We note that Eq. (2) is a spinless Hamiltonian when expressed in terms of the YSR states for which localized Majorana zero modes (MZMs) will emerge at $t = \Delta$. On the other hand, at zero field, the odd states are spin degenerate and Eq. (2) is no longer valid. However, the system has a sweet spot at $t = \tilde{\Delta}(B=0) = \sqrt{2}\Delta$. Here, the presence of high charging energy in the quantum dots leads to the emergence of Majorana Kramers pairs that are protected against local perturbations but have an additional degeneracy (see Ref. [49] for details). The CSD in the sweet spot is identical for zero and infinite Zeeman energy. As a result, we can train the CNN on the spinless Hamiltonian in Eq. (2) and recognize sweet spots both in the absence and

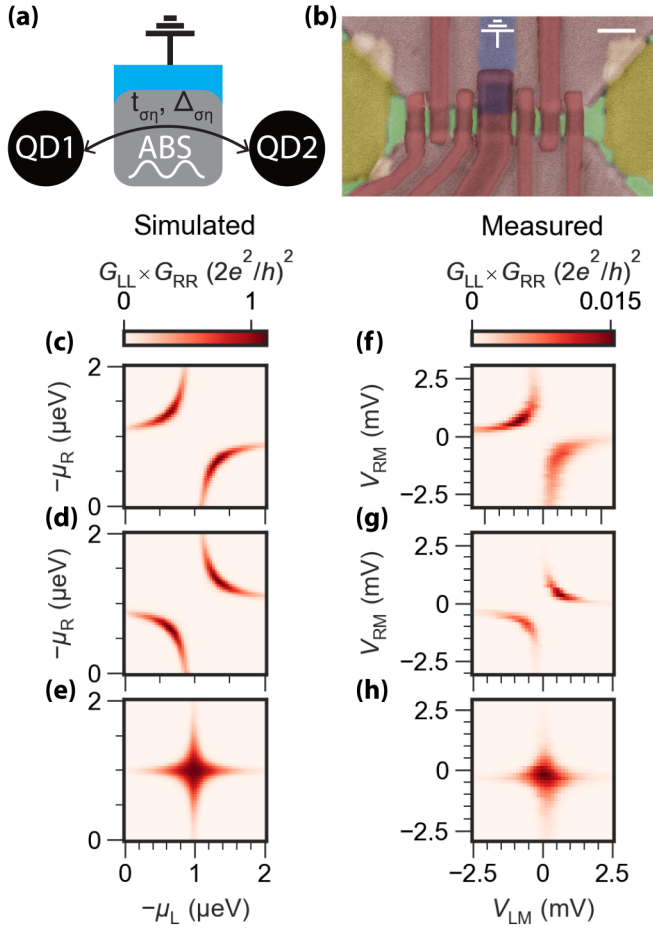


FIG. 2. Device B charge stability diagrams and simulations. (a) Schematic overview of the model system. Two QDs are coupled by an ABS in a semiconductor (gray) coupled to a grounded superconductor (blue). (b) False color SEM image of Device B. A 1D channel is defined in the InAsSb (green) using a top and bottom depletion gate (light red). The InAsSb is contacted in the middle by a grounded Al strip (blue). QDs are defined on the left and right of this hybrid segment using finger gates (darker red). The InAsSb channel is contacted from the sides by two Ti/Au leads (yellow). Scale bar is 200 nm. (c)–(e) Simulated conductance, $G_{LL} \times G_{RR}$ at zero energy, for varying chemical potential of the left and right quantum dots, μ_L and μ_R . These were generated for $(t - \Delta)/(t + \Delta) = \{-1/3, 1/3, 0\}$, respectively. (f)–(h) Measured $G_{LL} \times G_{RR}$, for varying V_{LM} and V_{RM} at $V_L = V_R = 0$ V for Device B. The CNN predicts $(t - \Delta)/(t + \Delta) = \{-0.31, 0.31, 0.01\}$ for these, respectively.

in the presence of a magnetic field. We shall refer to the renormalized and field-dependent parameter $\tilde{\Delta}(B)$ as Δ , to ensure that $t = \Delta$ corresponds to a sweet spot for all magnetic field values. We have further validated our approach using a spinful Hamiltonian model (Appendix I), confirming that the main conclusions remain unchanged.

Equation (2) allows us to compute CSDs using the Mahaux-Weidenmüller formula and the scattering matrix formalism [50] (see Appendix B for more details). We generate CSDs for varying values of t and Δ , and show three examples in Figs. 2(c)–2(e). We label each generated CSD with $(t - \Delta)/(t + \Delta)$ and train the CNN to predict these labels on 6000 examples (see Appendix B for details on the training

set). We use this ratio for labeling, as it is a dimensionless quantity and scales with the interaction strength $t + \Delta$ of the QDs. In principle, we could have used $\sqrt{8|t^2 - \Delta^2|}$, which is directly proportional to the distance between the hyperbolas of the avoided crossing in the CSDs [51]. However, there is a scaling factor that depends on the measurement resolution, the lever arm of the gates, and the range of V_{LM} and V_{RM} . To eliminate the necessity to manually scale an absolute quantity, we choose the dimensionless ratio, $(t - \Delta)/(t + \Delta)$.

B. Model validation and retraining on Device B

To develop a cross-platform tuning algorithm, we require the CNN predictions to generalize across different device types. Before applying the CNN to Device A, we first perform measurements on Device B, which was fabricated on an InAsSb-Al two-dimensional electron gas, shown in Fig. 2(b) (see also Ref. [51]). Here, a quasi-1D channel is defined by two large depletion gates. Gate-defined QDs are created on the left and right of a region proximitized by a thin Al strip (blue), using fabrication methods detailed in Ref. [52]. The same measurement setup is used as for Device A. In Figs. 2(f)–2(h), we show three example CSDs measured at different V_{ABS} values using Device B. These CSDs are used as inputs for our trained CNN, yielding predictions for $(t - \Delta)/(t + \Delta)$ of $-0.31, 0.31, 0.01$, respectively. The experimental CSDs closely resemble the generated ones in Figs. 2(c)–2(e), which we manually matched with the experimental ones by setting $(t - \Delta)/(t + \Delta) = \{-1/3, 1/3, 0\}$, respectively.

As t and Δ represent the ECT and CAR rates, validating the CNN predictions requires determining these rates quantitatively. We extract them by performing bias spectroscopy at the V_{LM}, V_{RM} values corresponding to the center of the (avoided) crossing of the CSDs. Typically, each spectrum consists of four conductance peaks [53]: two inner peaks separated by $|t - \Delta|$ and two outer peaks separated by $t + \Delta$ (see Appendix C for details on the labeling procedure). The ratio of the peak distances can then be used to calculate $(t - \Delta)/(t + \Delta)$, which is combined with the corresponding CSD to constitute one labeled dataset.

Figure 3(a) compares the $(t - \Delta)/(t + \Delta)$ values obtained experimentally with those predicted by the CNN for a range of V_{ABS} values. The CNN predictions (red markers) generally match the values extracted from bias spectroscopy (black markers), with small deviations around $(t - \Delta)/(t + \Delta) = 0$. We note that the labeled data imply that $(t - \Delta)/(t + \Delta) = 0$ for a range of V_{ABS} values. However, only the CSD shown in Fig. 3(d) indicates a clear sweet spot. We attribute this apparent plateau of $(t - \Delta)/(t + \Delta) = 0$ to the influence of multiple, overlapping ABSs in the hybrid section of Device B (see extended data Fig. 1(e) of Ref. [51]). In addition, our labeling procedure is limited by tunnel broadening and temperature (see Appendix C). We stress that the CNN has not been trained on any experimental data for these predictions. To improve the accuracy of the CNN, we retrain it on a part of the experimental data that we manually labeled. For retraining, we use 51 labeled CSDs that were randomly sampled from Fig. 3(a), which is significantly fewer than the 6000 theory datasets initially used to train the CNN (see Appendix B for details). As labeling experimental data are

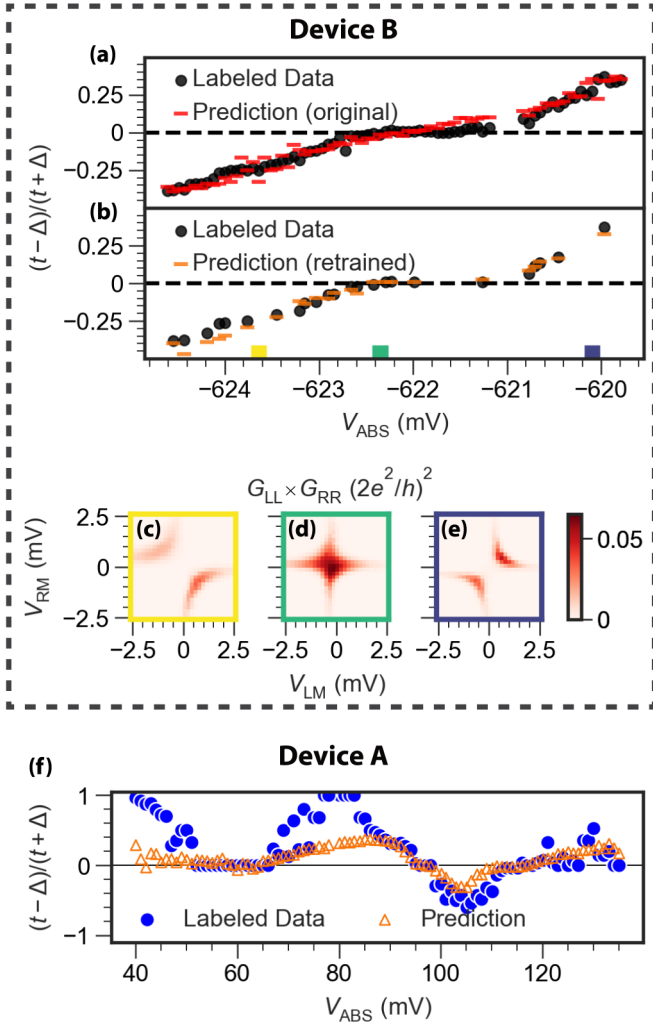


FIG. 3. Convolutional neural network retraining and predictions. (a) The weighted ratio of elastic cotunneling (t) and crossed Andreev reflection (Δ) rates, $(t - \Delta)/(t + \Delta)$, for varying V_{ABS} for Device B. The black markers indicate experimentally labeled data and the red markers are the CNN predictions. (b) $(t - \Delta)/(t + \Delta)$ of a subset of test data of panel (a) after retraining the CNN on experimental data. The black markers indicate experimentally labeled data and the orange markers are the predictions of the retrained CNN. (c)–(e) The product of the left and right differential conductance, $G_{\text{LL}} \times G_{\text{RR}}$, for varying V_{LM} and V_{RM} at $V_L = V_R = 0$ V for Device B. The measurements were performed at the V_{ABS} values indicated by colored marks in panel (b). (f) $(t - \Delta)/(t + \Delta)$ for varying V_{ABS} for Device A. The blue markers indicate experimentally labeled data, and the orange markers are the retrained CNN predictions.

intensive and time consuming, it is crucial to minimize the number of labeled CSDs required to retrain the CNN.

The orange markers in Fig. 3(b) show the predictions of the retrained CNN applied to a test set of 24 previously unseen experimental CSDs. We observe that the predicted values of $(t - \Delta)/(t + \Delta)$ are closer to the values extracted from spectroscopy compared to the predictions of the CNN that was trained on the simulated data only. In Figs. 3(c)–3(e), we show the CSDs measured for Device B for V_{ABS} values indicated by the colored marks in panel (b). We see that the avoided crossings in panels (c) and (e) have reversed direction, which agrees

with the predicted sign change of $(t - \Delta)/(t + \Delta)$ shown in Fig. 3(b). The Coulomb resonances form a cross in Fig. 3(d), which is consistent with the predicted $(t - \Delta)/(t + \Delta) \approx 0$ and indicates a sweet spot.

C. Transfer learning: Application of the algorithm on Device A

Before discussing the CNN's performance on Device A, it is crucial to note that we only retrained it on experimental data from Device B. The ability of machine learning algorithms to generalize is vital, making them highly effective for analyzing noisy experimental datasets. In Fig. 3(a), we assessed the performance of a CNN that was trained on a theoretical model only, which may not fully capture the nuances of experimental data. We now consider a different type of generalization, namely, the machine learning model's ability to adapt from one device to another. Eliminating the need for device-specific retraining offers a significant advantage in time.

We now apply the CNN that was trained on theory simulations and retrained on all 75 experimental datasets from Device B (2DEG) to Device A (nanowire) as shown in Fig. 1(a). The blue markers in Fig. 3(f) show the $(t - \Delta)/(t + \Delta)$ values that we have extracted experimentally from Device A using the same method as for Device B. The orange markers show the corresponding predictions of the CNN. To compensate for differences in the conductance of the CSD measurements, we regularize the CNN predictions (see Appendix E for details). We see excellent agreement with the experimental data for small $(t - \Delta)/(t + \Delta)$. Most importantly, there is good agreement for the values of V_{ABS} at which the $(t - \Delta)/(t + \Delta)$ ratio changes sign, indicating a sweet spot. Around $V_{\text{ABS}} \approx 50$ mV, the CNN predicts values close to 0, which is not in agreement with the labeled data. We attribute this to the left QD interacting strongly with the ABS, which exceeds the simplified model used for generating training data (see Appendix D for details).

For V_{ABS} values close to 40 and 80 mV, the labeled data indicate $(t - \Delta)/(t + \Delta) \approx 1$, while the CNN predictions are considerably lower. Here, $\Delta \ll t$, which makes it challenging to resolve the pairs of conductance peaks at $(t - \Delta)$ and $(t + \Delta)$ in bias spectroscopy, leading to a ratio of one (see Appendix C for details). As the CNN predictions do not depend on peak spacing or measurement resolution, it predicts lower values of $(t - \Delta)/(t + \Delta)$ compared to the labeled data. The CNN predictions also mildly differ from the labeled data around $V_{\text{ABS}} \approx 130$ mV as well. We attribute this to a low interaction strength, $(t + \Delta)$, which causes the ratio $(t - \Delta)/(t + \Delta)$ to become large. As the CNN was trained and retrained predominantly on strongly interacting QDs, it generalizes less well to the device with low $(t + \Delta)$. We conclude that the CNN can correctly identify $t \approx \Delta$ when the QD does not strongly hybridize with the ABS, and when the QD-QD interaction strength is at least larger than the measurement resolution.

D. Gradient descent voltage optimization

Each CNN prediction of $(t - \Delta)/(t + \Delta)$ is incorporated into a gradient descent algorithm that sets a new value of the voltage V_{ABS} . The algorithm minimizes the cost function

$f(V_{\text{ABS}}) = |(t - \Delta)/(t + \Delta)|$ until it reaches a value below a set tolerance. In each step, n , the algorithm computes the following quantities [54]:

$$\begin{aligned} \langle g \rangle_n &= \frac{1}{N} \sum_{i=n-N}^n \frac{f(V_{\text{ABS}})_i - f(V_{\text{ABS}})_{i-1}}{V_{\text{ABS}}^i - V_{\text{ABS}}^{i-1}}, \\ v^{n+1} &= kv^n + (1 - k) \langle g \rangle_n, \\ V_{\text{ABS}}^{n+1} &= V_{\text{ABS}}^n - \eta v^{n+1}. \end{aligned} \quad (3)$$

Here, $\langle g \rangle_n$ is the gradient of the objective function, which is computed after the n th measurement, averaged over the past N measurements. The velocity v^{n+1} is a mixture of the previous velocity v^n and gradient $\langle g \rangle_n$, weighted by the momentum, k . The change in V_{ABS} is then determined by v^{n+1} , scaled by the learning rate η . These steps are repeated until $f(V_{\text{ABS}}) < \tau$, where τ is the tolerance set for each run. We note that in the first step of the algorithm, V_{ABS} is changed by a pseudorandom number drawn from a Gaussian distribution with a standard deviation of 1, and an amplitude of 1.2 mV. This first step is on the order of typical V_{ABS} changes made by the algorithm. The minimal change of V_{ABS} is set by the 60 μV resolution of our digital-analog converters. We limit the maximal change to 5 mV, to prevent large shifts of the QD levels due to cross-capacitance. See Appendix F for details on the algorithm, the choices of τ and η , and the algorithm pseudocode.

We now apply the automated tuning algorithm to Device A. Figure 4(a) shows the gate voltages, V_{ABS} , set by the algorithm for a run that converged below tolerance in eight steps. Figure 4(b) shows the values of $(t - \Delta)/(t + \Delta)$ predicted by the CNN. Here, the blue horizontal lines indicate the ideal tolerance, $\tau = 0.01$, set before the run. We show the CSDs for each step in Fig. 4(c) and see that the direction of the avoided crossing reverses between steps 4 and 5. This indicates that $(t - \Delta)/(t + \Delta)$ changes sign, which is confirmed by the CNN predictions in panel (b). Due to the momentum term k in the gradient descent algorithm [Eq. (3)], the algorithm first proceeds to lower V_{ABS} values before the velocity term changes sign. The CNN converges below the tolerance at measurement eight, which we can confirm as a sweet spot by identifying a cross in the last panel of Fig. 4(c). In this run, the automated tuning was able to correctly identify the sweet spot, as well as vary V_{ABS} to find it. We show an example of a run that did not converge successfully in Appendix H.

IV. TUNING ALGORITHM PERFORMANCE

A. Zero field algorithm performance

The example run shown in Fig. 4 converged in eight steps and was chosen as a representative example. To assess the performance of the algorithm more quantitatively, we repeat the tuning procedure 15 times and initialize it at different starting values of the gate voltage V_{ABS} . We limit each run to a maximum of 25 measurements (not including the initial measurement) in order to restrict the total run-time of the experiment. We chose the number of iterations based on the operation time of the presented experiment. In general, this variable can be set by the user and will be specific to the data collection time and other experimental timescales. The

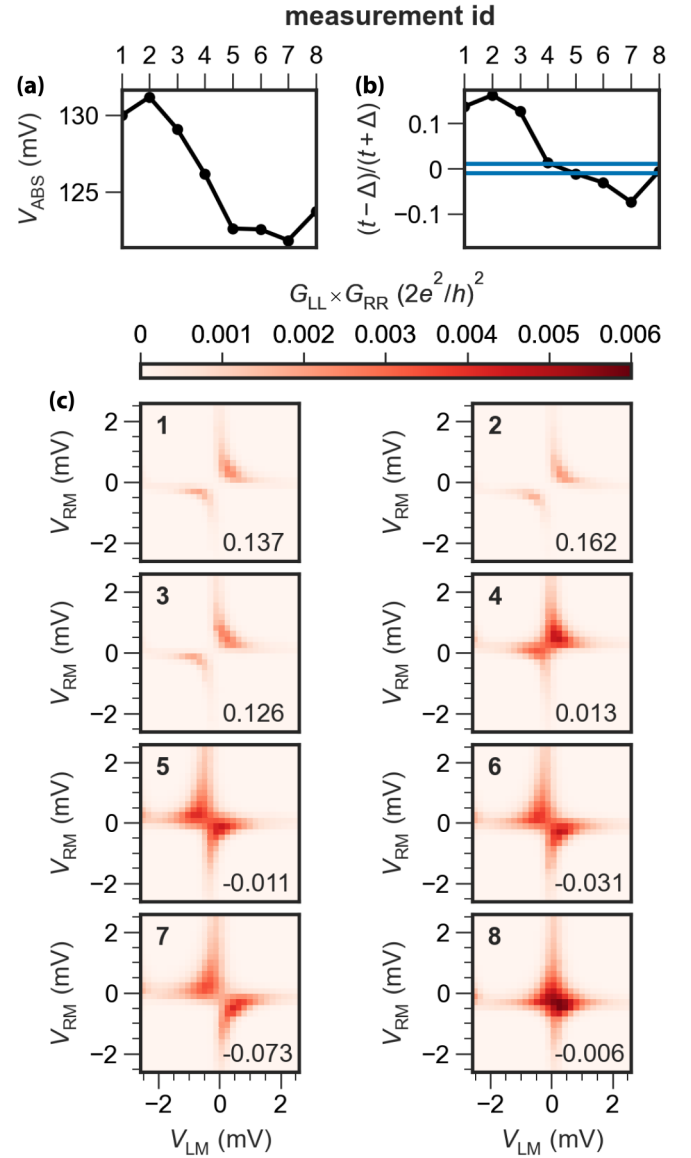


FIG. 4. Example of an automated tuning run of Device A. (a) The hybrid plunger gate voltage, V_{ABS} , for each measurement. (b) Prediction of the weighted ratio of elastic cotunneling and crossed Andreev reflection, $(t - \Delta)/(t + \Delta)$, for each measurement. The horizontal, blue lines indicate the tolerance set before the run. (c) $G_{\text{LL}} \times G_{\text{RR}}$, for varying V_{LM} and V_{RM} for subsequent measurements. The measurement IDs are indicated by the bold text in the top left corner. The predicted value of $(t - \Delta)/(t + \Delta)$ is indicated in the bottom right corner.

algorithm is run at zero external magnetic field as all measurements shown above.

We calculate the time elapsed between the start and end of each run and plot histograms for different starting V_{ABS} values in Fig. 5(a). The dark blue bars indicate runs where the algorithm identified a sweet spot by finding $f(V_{\text{ABS}}) < 0.01$ within 25 measurements. The sea green bars indicate runs where the algorithm identified a sweet spot, with higher tolerance, $0.01 < f(V_{\text{ABS}}) < 0.021$, within 25 measurements. For the light blue bars, the algorithm did not converge with $f(V_{\text{ABS}}) < 0.021$ within 25 measurements. We note that this

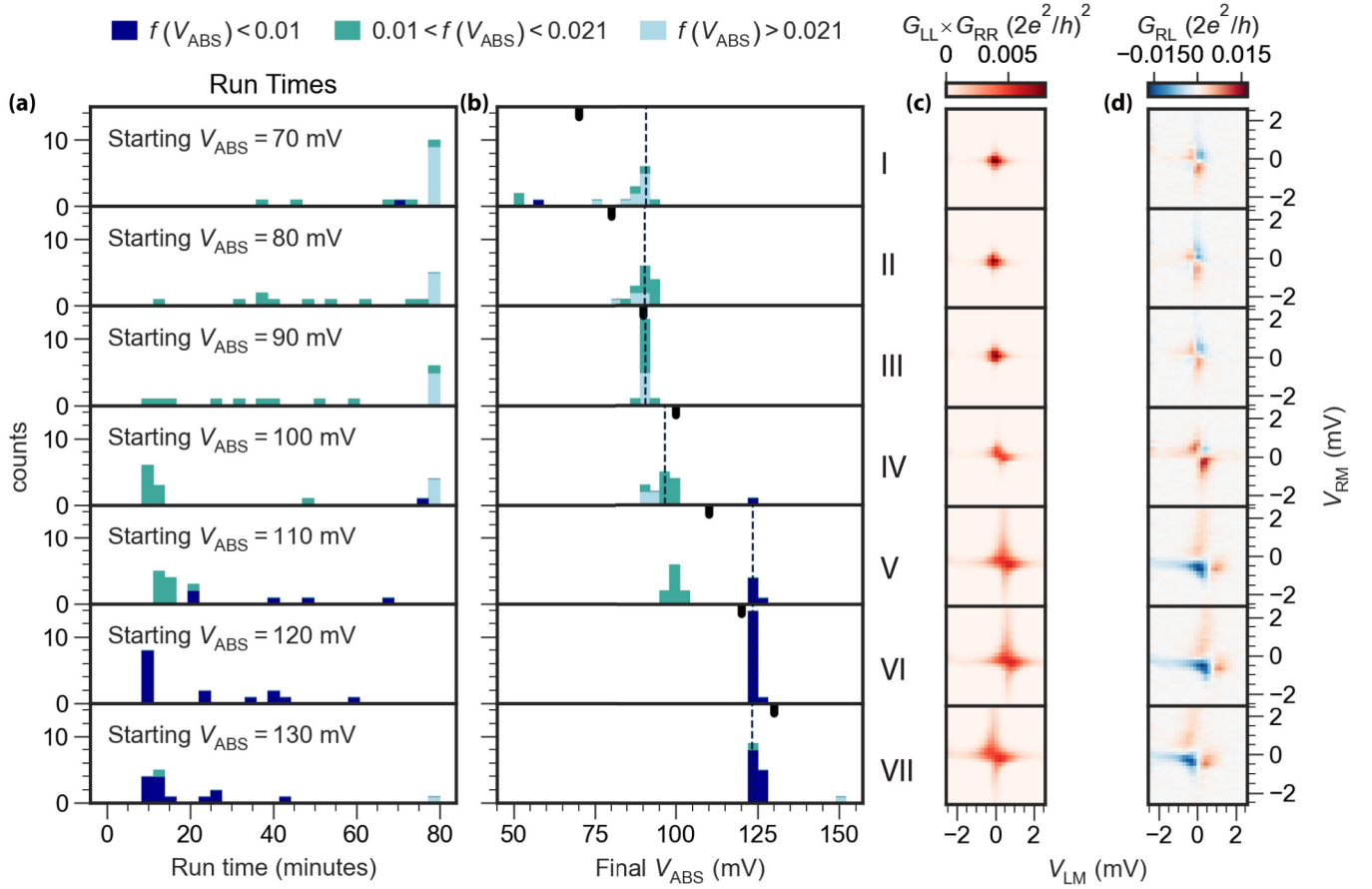


FIG. 5. Run times and V_{ABS} values at which the algorithm converges for zero applied magnetic field. We set a learning rate $\eta = 2 \times 10^{-4}$, a momentum $k = 0.5$, and a tolerance $\tau = 1 \times 10^{-2}$. (a) Histograms of the run-time of the gradient descent algorithm, for different starting V_{ABS} values. The dark blue bars indicate which runs converged with an objective function $f(V_{\text{ABS}}) = |(t - \Delta)/(t + \Delta)| < 0.01$. The sea green bars indicate convergence with $0.01 < f(V_{\text{ABS}}) < 0.021$. Light blue bars indicate runs that did not converge with $f(V_{\text{ABS}}) < 0.021$ within 25 iterations. (b) Histograms of the V_{ABS} values for which the algorithm found the lowest $f(V_{\text{ABS}})$, for different starting V_{ABS} values. The black marks at the top of the figures indicate the starting V_{ABS} value. The dashed, vertical line indicates the V_{ABS} value closest to the greatest histogram peak with the lowest $f(V_{\text{ABS}})$. (c) $G_{\text{LL}} \times G_{\text{RR}}$, for varying V_{LM} and V_{RM} , measured at the V_{ABS} value indicated by the dashed, vertical line in panel (b). (d) $G_{\text{RL}} = dI_R/dV_L$ for varying V_{LM} and V_{RM} , for different starting V_{ABS} values. The data were measured simultaneously with $G_{\text{LL}} \times G_{\text{RR}}$ in panel (c).

does not exclude a sweet spot, as will be discussed below. Most of the runs that start from $V_{\text{ABS}} = 70$ mV do not converge within 25 measurements. In contrast, nearly all runs starting from $V_{\text{ABS}} = 130$ mV do converge, most of them within 20 min. This is a result of limiting each run to 25 measurements, as runs that start from $V_{\text{ABS}} = 70$ mV are farther away from a sweet spot and need more iterations to converge at a sweet spot.

In Fig. 5(b), we show histograms of the V_{ABS} values for which the algorithm found the lowest $f(V_{\text{ABS}})$. For starting V_{ABS} values of 70, 80, and 90 mV (rows I–III), most runs end at $V_{\text{ABS}} \approx 90.5$ mV. We can inspect the CSDs measured at these gate values to determine whether they correspond to sweet spots. Figure 5(c) shows $G_{\text{LL}} \times G_{\text{RR}}$, for varying V_{LM} and V_{RM} at ending V_{ABS} values indicated by the vertical dashed lines in panel (b). We see that for Fig. 5(c)(I–III), the QD levels hybridize to form a cross, which is consistent with a sweet spot. The corresponding G_{RL} measurements in Fig. 5(d) show both signs of nonlocal conductance, which confirms that $t = \Delta$ [28]. Most of the runs starting from $V_{\text{ABS}} = 100$ mV (row

IV) converge in 20 min, with the majority ending at $V_{\text{ABS}} = 96.5$ mV. From panels (c) and (d), we see that the QD levels do not form a cross, and the nonlocal conductance is mostly positive. We conclude that the algorithm incorrectly identifies this charge stability diagram as a sweet spot. The confirmation that the algorithm-discovered sweet spot indeed hosts PMMs can be performed via spectroscopic measurements [28]. We provide the spectroscopic data for both Devices A and B in Appendix G.

Runs that start from $V_{\text{ABS}} = 110$ mV (row V) converge with $0.01 < f(V_{\text{ABS}}) < 0.021$ at $V_{\text{ABS}} = 99.5$ mV and with $f(V_{\text{ABS}}) < 0.01$ at $V_{\text{ABS}} = 123.5$ mV. We can see that the latter is close to a sweet spot, with $t \gtrsim \Delta$, as seen from the predominantly negative values of G_{RL} . The peak at $V_{\text{ABS}} = 99.5$ mV is close to the V_{ABS} ending values of the runs that started at $V_{\text{ABS}} = 100$ mV runs and does not correspond to a sweet spot. We define 90.5 and 123.5 mV as sweet spots, based on the charge stability measurements. We note that the runs that did not converge with $f(V_{\text{ABS}})$ below tolerance (light blue) are clearly peaked around the sweet spot at 90.5 mV.

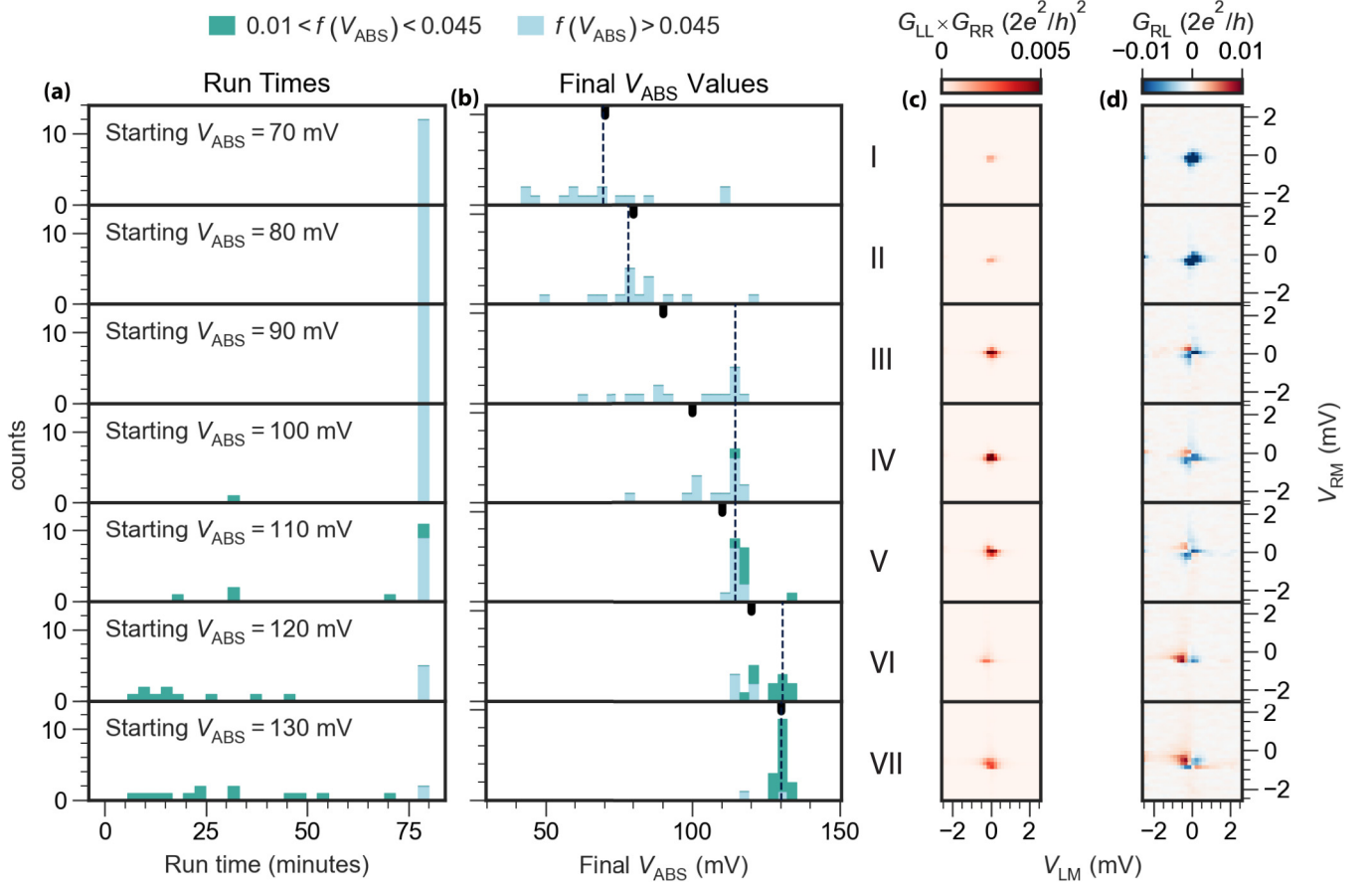


FIG. 6. Run times and V_{ABS} values at which the algorithm converged for $B = 150$ mT. We set a learning rate $\eta = 2 \times 10^{-4}$, a momentum $k = 0.5$, and a tolerance $\tau = 1 \times 10^{-2}$. (a) Histograms of the run-time of the gradient descent algorithm, for different starting V_{ABS} values. The sea green bars indicate which runs converged with an objective function $0.01 < f(V_{\text{ABS}}) < 0.021$. The light blue bars indicate runs that did not converge with $f(V_{\text{ABS}}) < 0.021$ within 25 iterations. (b) Histograms of the V_{ABS} values for which the algorithm found the lowest $f(V_{\text{ABS}})$, for different starting V_{ABS} values. The black marks at the top of the figures indicate the starting V_{ABS} value. The dashed, vertical line indicates the V_{ABS} value closest to the greatest histogram peak with the lowest $f(V_{\text{ABS}})$. (c) $G_{\text{LL}} \times G_{\text{RR}}$, for varying V_{LM} and V_{RM} , measured at the V_{ABS} value indicated by the dashed, vertical line in panel (b). (d) $G_{\text{RL}} = dI_R/dV_L$ for varying V_{LM} and V_{RM} , for different starting V_{ABS} values. The data were measured simultaneously with $G_{\text{LL}} \times G_{\text{RR}}$ in panel (c).

We attribute the higher value of $f(V_{\text{ABS}})$ here to a weaker interaction strength than at the other sweet spot at 123.5 mV. Averaging all runs over the varying starting V_{ABS} values, 67.6% of runs converge in the immediate vicinity of a sweet spot within ± 1.5 mV, and 80.9% of runs converge within ± 4.5 mV of an independently verified sweet spot. Averaging over all starting V_{ABS} values, the algorithm converges within ± 4.5 mV of a sweet spot in 45 min. This is sufficiently fast to be beneficial to experimentalists that are tuning Kitaev chain devices into a sweet spot.

B. Finite field algorithm performance

In the previous section, we found sweet spots in the absence of an external magnetic field. In this case, the emerging Poor Man's Majorana zero modes are Kramers pairs, which retain the protection against local perturbations, but have an additional degeneracy due to time-reversal symmetry [49]. This degeneracy has no impact on the demonstration of the automated tuning algorithm in the previous section, as the CSDs look identical to the spin-polarized result when

the charging energy of the QDs is large compared to the parent gap. We now break time-reversal symmetry by applying an external field $B = 150$ mT along the nanowire axis, to test whether our algorithm works both in the absence and in the presence of magnetic field. The magnetic field Zeeman splits the ABSs in addition to the QDs and lowers their energy. To compensate for the resulting increased hybridization between the QDs and ABS, we raise the tunnel barriers between them using electrostatic gates.

We repeat the automated tuning algorithm for 15 times at different starting values of voltage V_{ABS} each. We, again, limit each run to a maximum of 25 measurements (not including the initial measurement) and show histograms of the run times in Fig. 6(a). In Fig. 6(a) (I–III), we see that none of the runs converge with $f(V_{\text{ABS}}) < 0.045$ within 80 min. The corresponding histograms in Fig. 6(b) show a broader distribution than for $B = 0$ T, as seen in Fig. 5(b). The runs that start from V_{ABS} values of 110, 120, and 130 mV (rows V–VII) converge with $0.01 < f(V_{\text{ABS}}) < 0.045$ more frequently, and the resulting histograms in Fig. 6(b) are more clustered.

The CSDs in Figs. 6(c) and 6(d) indicate that the interaction between the QDs is significantly weaker than for $B = 0$ T, as seen from the smaller avoided crossings. We attribute this to the stronger tunnel barriers we had to set to compensate for the lower ABS energy. This leads to generally larger values of $(t - \Delta)/(t + \Delta)$, as the denominator becomes smaller. In addition, our regularization procedure of the CNN predictions leads to a larger $f(V_{\text{ABS}})$ when the conductance is low.

We attribute the worse convergence of the algorithm to the weaker QD-QD interaction. Nonetheless, we see from Fig. 6(d) that a number of peaks of the histograms in panel (b) correspond to sweet spots. We further note that $G_{LL}G_{RR}$ is the input for the CNN, which does not have the added information of G_{RL} . Based on the CSDs measured using $G_{LL}G_{RR}$ in Fig. 6(c) alone, it is hard for an experimentalist to identify a sweet spot. Defining 114.26 and 130.44 mV as sweet spots based on the measurements of G_{RL} , we find that 45.7% of the runs converge within ± 1.62 mV, and 60% converge within ± 4.85 mV of these sweet spots. In this case, the algorithm can be run numerous times to gather statistics. The value of V_{ABS} that is converged upon most frequently will then indicate an optimal sweet spot. While the performance at finite magnetic field is worse than the algorithm's performance at $B = 0$ T, we note that the CNN was trained only on strongly interacting data (see Appendix B). We also note that we chose the same tolerance for $f(V_{\text{ABS}})$ as for Fig. 5, while the QD-QD interaction was weaker. These two aspects mean that the algorithm will find less $f(V_{\text{ABS}})$ values below tolerance than before. We conclude that the algorithm can partially generalize to previously unseen experimental data in the weakly interacting regime. It can then be run multiple times to statistically identify sweet spots.

C. Finite field CNN validation

To further evaluate the CNN classifier's performance on finite field data, we test it on measurements from an additional device. Specifically, we use data collected at finite magnetic field from a second 2DEG device—referred to as Device B in Ref. [51]—which is identical in design to the Device B used in this work. Figure 7(a) displays the values of $t^2 - \Delta^2$ extracted from CSDs measured at $B = 80$ mT. As bias spectroscopy was not performed for each in-plane magnetic field angle, we cannot independently extract t and Δ . However, we can still extract and compare the quantity $t^2 - \Delta^2$. The point $t^2 - \Delta^2 = 0$ corresponds to a sweet spot, as can be seen from the corresponding CSD in Fig. 7(c), combined with the avoided crossings pointing along different diagonals in Figs. 7(b) and 7(d).

The red markers in Fig. 7(a) show the values of $(t - \Delta)/(t + \Delta)$ predicted by the CNN based on the measured CSDs. We see that the CNN predictions closely follow $t^2 - \Delta^2$, albeit with a difference in scale. The equality

$$t^2 - \Delta^2 = (t + \Delta)^2 \times \frac{t - \Delta}{t + \Delta}$$

implies that the two quantities differ by a factor of $(t + \Delta)^2$. As there is strong agreement between the labeled data and predictions [black and red dots in Fig. 7(a)] and the transition point is predicted correctly, we conclude that the CNN does work at finite magnetic fields. We note that the CSDs in

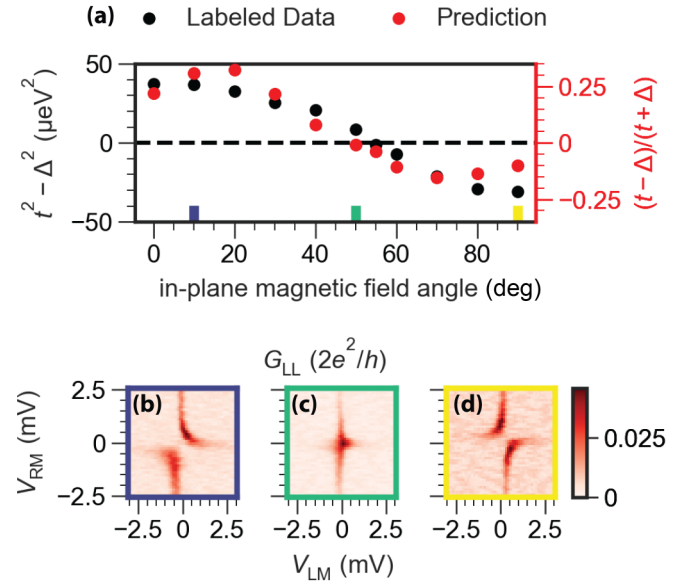


FIG. 7. Convolutional neural network predictions of CSDs measured at $B = 80$ mT on the device investigated in the main text of Ref. [51]. (a) Labeled and predicted couplings for varying in-plane magnetic field angle at fixed V_{ABS} . Black markers: $t^2 - \Delta^2$ obtained by calculating the distance between the hyperbola in measured CSDs, adapted from Fig. 2(d) of Ref. [51]. Red markers: $(t - \Delta)/(t + \Delta)$ predictions by the CNN of the CSDs, after training on the Device B data. (b)–(d) G_{LL} , for varying V_{LM} and V_{RM} , measured at values of the in-plane magnetic field angle indicated by the colored ticks in panel (a).

Figs. 7(b)–7(d) show stronger interaction than the corresponding ones of Figs. 6(c) and 6(d). The worse performance of the tuning algorithm at finite field can possibly be explained by a lack of weakly interacting quantum dot data in the training sets.

V. DISCUSSION

Currently, the algorithm converges within ± 4.5 mV of a sweet spot in 45 min, which is generally faster than the time duration for manually tuning to a sweet spot. Since the CNN predictions and gradient descent algorithm calculations are nearly instantaneous, the run-time is dominated by the dc conductance measurements. Performing rf reflectometry measurements is significantly faster and was used to explore a multidimensional parameter space in semiconductor-superconductor devices before [55]. We believe that the algorithm can converge significantly faster, provided that it is possible to train the CNN on rf reflectometry data generated from theoretical models instead of dc conductance presented here. Also, we note that we start the algorithm from tuned-up QDs in a region of V_{ABS} where ABSs are visible in the spectroscopy measurements. Ideally, the algorithm should also include tuning the QDs and ABSs to have interaction, which also takes a significant amount of time. We note that there are several automated tuning algorithms for forming double quantum dots in literature [14,17,20,25]. Adapting these algorithms and integrating them into the tuning routine presented here would additionally increase speed of Kitaev chain devices' tune-up.

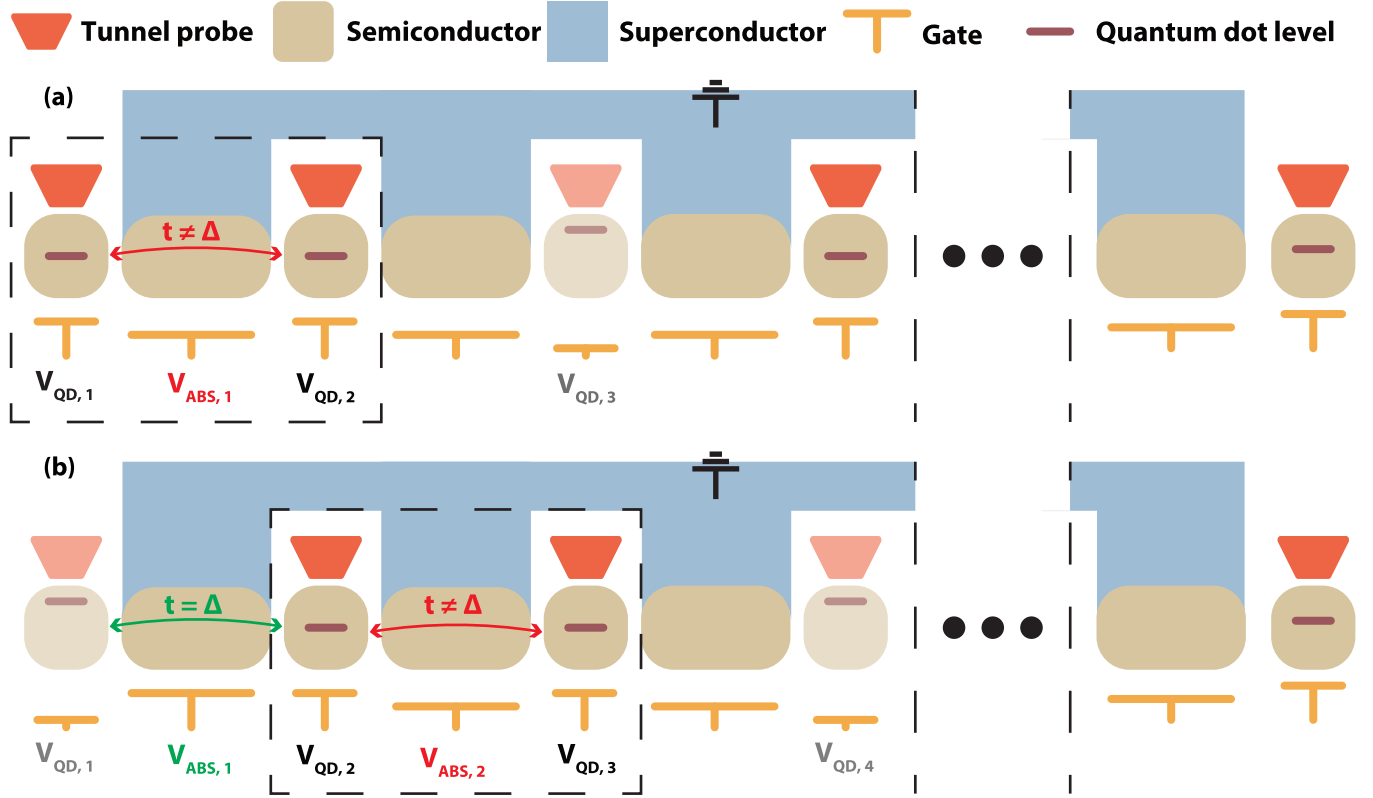


FIG. 8. Protocol for automated tuning of Kitaev chains of arbitrary length, based on sequentially tuning unit cells to $t = \Delta$. Orange-red trapezoids indicate tunnel probes, beige rectangles indicate semiconductor sections, blue is the grounded superconductor, yellow is the electrostatic gates, and brown is the QD levels. Tunnel barriers between the QDs and hybrid sections are omitted for clarity. (a) Step 1 in the tuning algorithm, in which none of the pairwise interactions is sweet spot ($t \neq \Delta$). The leftmost two QDs are tuned into the sweet spot by the algorithm, by varying $V_{\text{ABS},1}$. The tuning unit cell is indicated by the dashed rectangle. This pair of QDs is isolated from the rest of the chain by detuning the next QD above the gap using $V_{\text{QD},3}$. (b) Step 2 in the tuning algorithm, where the first pair now fulfills $t = \Delta$. The tuning unit cell is now isolated from other parts of the chains by detuning both QDs 1 and 4.

VI. OUTLOOK

We have demonstrated the automatic tune-up of a minimal, two-site Kitaev chain. While this is a necessary first step, longer chains are needed to realize a topological phase transition [29] or a parity qubit with appreciable coherence times [56,57]. Extending the chain to host Poor Man's Majorana zero modes at its edges requires tuning additional couplings between QDs. Crucially, the Kitaev chain model only demands that the condition $t = \Delta$ be satisfied pairwise, between adjacent sites [27,58]. This reduces the tuning of an N -site Kitaev chain to setting $N - 1$ pairwise couplings to $t = \Delta$. Since our algorithm can successfully tune a two-QD system to $t = \Delta$, it can be extended to Kitaev chains of arbitrary lengths under the right conditions.

In Fig. 8, we propose how our pairwise sweet spot tuning algorithm can be extended to become an automated N -site Kitaev chain tuning protocol. This builds on the assumption that tuning one unit cell to the $t = \Delta$ condition is similar to tuning a minimal Kitaev chain to the sweet spot, which has been proposed in Ref. [59]. The proposed device is a 2DEG with normal leads acting as tunnel probes for each QD. The hybrid sections between the QDs host ABSs and are proximitized by a single, grounded superconductor. In addition to tunnel barriers, local electrostatic plunger gates can be used to control the hybrid section and QD electrostatic potentials.

In Fig. 8(a), starting from the left end of the chain, CSDs of the first QD pair can be measured using the corresponding tunnel probes. For large enough detuning of the third QD, the leftmost pair reduces to an effective two-site Kitaev chain [60]. The algorithm presented in this work can then be used to set the first pair to $t = \Delta$ within this tuning unit cell indicated by the dashed rectangle. In finding a $V_{\text{ABS},1}$ value corresponding to a sweet spot, we effectively choose a phase for the couplings that needs to be matched by every subsequent pair in the chain.

In Fig. 8(b), the leftmost pair of QDs has been tuned to the sweet spot. Before tuning the interaction between QDs 2 and 3, we isolate the pair by detuning QDs 1 and 4. The tuning unit cell has been moved forward by one step and can be treated as an effective two-site Kitaev chain again. The algorithm can then be used to find a $V_{\text{ABS},2}$ value for which $t = \Delta$ for this pair. In the example of Fig. 8(b), this protocol is implemented as follows. First, $V_{\text{ABS},2}$ is varied until a sweet spot between QD2 and QD3 is reached. Then, $V_{\text{QD},1}$ is set such that the QD level is on resonance with QD2 and QD3, creating a three-site chain. As we have now added a site, the phase difference across the superconducting segments becomes relevant, as it affects the relative phase of tunnel couplings between QD2 and QD3. The protection of the Kitaev chain is maximal when there is no phase difference between neighboring sites [61].

To probe this phase difference, we follow the steps outlined in Ref. [59]. First, $V_{\text{QD},3}$ is varied while the differential conductance of QD3 is measured. In the case of a robust zero-bias conductance peak, a zero phase has formed, and the next pair (QD3–QD4) can be added to the chain. In the case of a zero-bias peak in the local conductance of QD3 that splits due to $V_{\text{QD},3}$, a sweet spot at a different $V_{\text{ABS},2}$ value is needed to obtain a relative zero phase.

When no magnetic flux is threaded through the loop between the first two hybrid sections, a phase difference can still arise between the t and Δ terms of the two QD pairs [29] (either 0 or π). In the case of a π -phase difference, a domain wall is created, preventing the formation of a gapped bulk in the chain [60,61]. As a result, the MZMs lose their protection against local perturbations given by longer Kitaev chains. Having tuned to a $t = \Delta$ sweet spot for a newly added QD, we must thus check the relative phase of the newly found sweet spot. This can be achieved through finite-bias spectroscopy, as detailed in Refs. [59,62]. If the phase constitutes a π phase, all that is needed to remove the domain wall is to repeat the tuning protocol for a sweet spot at a neighboring V_{ABS} value, which induces another π shift.

When using this additional protocol step, a sign-ordered Kitaev chain of arbitrary size can be tuned to host MZMs at its edges without an external flux [59]. This can be combined with the algorithm presented in this work to do so autonomously.

VII. CONCLUSION

We have shown that a supervised machine learning algorithm can predict $(t - \Delta)/(t + \Delta)$ from the charge stability diagrams of a minimal Kitaev chain. The algorithm was first trained on data generated from a theoretical model and was shown to generalize well to conductance measurements of a two-dimensional electron gas device. After retraining on a part of this experimental data, the predictions of $(t - \Delta)/(t + \Delta)$ became significantly closer to the experimentally extracted values. The retrained algorithm demonstrated strong generalization to conductance measurements obtained from a nanowire device, achieving good accuracy across different architectures.

A gradient descent algorithm was then used to drive the nanowire device into a sweet spot by changing V_{ABS} , based on the predictions of $(t - \Delta)/(t + \Delta)$. Note that the CNN was not retrained on data from this device. When the QD-QD interaction is strong, the algorithm converges at two sweet spots with different $t + \Delta$ values, which is reflected in the value of $f(V_{\text{ABS}})$ at convergence. At finite external magnetic field, we had to decrease the QD-QD interaction because of the lower ABS energy. As a result, fewer runs converged, which we attribute to the bias toward strong QD-QD interaction in the training and retraining data. However, a number of peaks in the ending V_{ABS} histogram coincide with sweet spots, which shows that the CNN does, to a degree, generalize to weak interaction. When benchmarking the CNN on a previously unseen finite field dataset from two-dimensional electron gas device, its predictions matched well with the experimentally obtained data. From this, we conclude that the CNN can

fundamentally work at finite field, as long as the QD-QD coupling is strong enough.

Finally, we present a protocol to autonomously tune up Kitaev chains of arbitrary lengths automating the protocol proposed in Ref. [59]. Our automated tuning algorithm can successfully drive a minimal Kitaev chain into a sweet spot. Tuning and monitoring multiple sweet spots is required for quantum information experiments involving Majorana zero modes. Our work paves the way for tuning up more complicated Kitaev chain devices that are required for braiding, anyon fusion, and other quantum information experiments [35,39].

ACKNOWLEDGMENTS

This work has been supported by the Dutch Organization for Scientific Research (NWO), Microsoft Corporation Station Q, Academy of Finland Projects No. 331342 and No. 358088, and the Jane and Aatos Erkkö Foundation. This publication is part of the project Engineered Topological Quantum Networks (with Project No. VI.Veni.212.278) of the research program NWO Talent Programme Veni Science domain 2021, which is financed by the Dutch Research Council (NWO). S.G. and M.W. acknowledge financial support from the Horizon Europe Framework Program of the European Commission through the European Innovation Council Pathfinder Grant No. 101115315 (QuKiT). We thank Di Xiao, Candice Thomas, and Michael J Manfra for providing the 2DEG wafers.

D.v.D., F.Z., A.B., G.P.M., N.v.L., G.P.M., B.R., G.W., and J.C.W. fabricated the nanowire device. S.L.D.t.H., I.K., and Q.W. fabricated the two-dimensional electron gas device. V.S., S.L.D.t.H., and D.v.D. performed the electrical measurements. R.K. and J.L.L. designed and trained the neural network, with input from E.G. S.L.D.t.H., R.K., D.V.D., and E.G. designed the experiment. S.L.D.t.H., R.K., and D.v.D. analyzed the data. D.v.D., S.L.D.t.H., R.K., J.L.L., and E.G. prepared the manuscript with input from all authors. T.D., S. Goswami, J.L.L., L.P.K., and E.G. supervised the project. C.X.L. and A.M.B. developed the theoretical model with input from M.W. G.B., S.G., and E.P.A.M.B. performed InSb nanowire growth.

DATA AVAILABILITY

All raw data in the publication, analysis code, plotting code, and spectroscopy labeling code are available in Refs. [63]. This paper is supplemented by a GitLab repository with all the code and data necessary to reproduce our results available in Ref. [64].

APPENDIX A: CNN ARCHITECTURE

Convolutional neural networks are designed for efficient data analysis, especially for visual tasks such as image recognition. Unlike traditional fully connected neural networks, CNNs utilize convolutions to process information in imagelike datasets. These enhance their capacity to handle spatially correlated information present among pixels in imagelike datasets [65,66]. The architectural framework of

TABLE I. Architecture of the CNN.

CNN classifier	
Layer	Output shape
Input	(28, 28, 1)
Conv2D	(28, 28, 32)
MaxPooling2D	(14, 14, 32)
Conv2D	(14, 14, 64)
MaxPooling2D	(7, 7, 64)
Flatten	(3136)
Concatenate ^a	(6272)
Dense	(128)
Dense	(1)
Total parameters	840, 705

^aWe are using a dual-input framework for the first six layers.

CNNs leverages spatial relations within the data through locally connected layers that improve the computational efficiency by neglecting correlations between distant data points.

At the foundation of CNNs are trainable convolutional filters that are crucial for capturing spatial correlations in the data set. The filter size is a hyperparameter of the network architecture and, therefore, adaptable to specific problem sets. Furthermore, to reduce the complexity and number of parameters, CNNs integrate dimensionality reduction techniques such as pooling operations [67]. These operations allow us to preserve essential features and increase computational efficiency at the same time.

The architecture of the CNN to make prediction in this work is shown in Table I. The network architecture employed in this study comprises a total of nine layers. The initial six layers constitute the convolutional segment of the network, followed by a flattening operation and the subsequent utilization of a fully connected NN. The initial six layers operate within a dual-input framework, where two independent and unconnected CNNs can process different images, such as G_{LL} and G_{RR} (or nonlocal conductance $G_{LR/RL}$), and integrate them in the subsequent NN segment. Notably, in the current research, the dual-input framework is not exploited, as we preprocess the data by multiplying G_{LL} with G_{RR} . However, the dual-input framework is kept for the sake of generalization that allows us to adapt the CNNs and tuning algorithm to different inputs in future research.

APPENDIX B: CNN TRAINING

In this work, we are utilizing a two-step training process for the CNN. The first step involves training with a dataset generated through numerical calculations, while the second step involves retraining using a smaller set of experimental conductance data.

1. Kitaev chain effective model

We are modeling the double quantum dot system coupled by a semiconductor-superconductor hybrid segment as a two-site Kitaev chain. The couplings between the quantum dots are mediated by ABSs in the hybrid segment. From a theory point

of view, the system can be seen as three-site model where the hybrid segment gets treated as site. We are following the work of Ref. [32] and refer there for a more detailed description of the theory model. The corresponding Hamiltonian of the three-site model takes the form [33,44,68]

$$\begin{aligned}
 H &= H_D + H_S + H_T, \\
 H_D &= \sum_{a=L,R} (\varepsilon_{Da} + E_{ZDa}) n_{Da\uparrow} + (\varepsilon_{Da} - E_{ZDa}) n_{Da\downarrow} \\
 &\quad + U_{Da} n_{Da\uparrow} n_{Da\downarrow}, \\
 H_S &= \varepsilon_A (n_{A\uparrow} + n_{A\downarrow}) + \Delta_0 (c_{A\uparrow} c_{A\downarrow} + c_{A\downarrow}^\dagger c_{A\uparrow}^\dagger), \\
 H_T &= \sum_{\sigma=\uparrow,\downarrow} (t_L c_{A\sigma}^\dagger c_{DL\sigma} + \sigma t_{Lso} c_{A\sigma}^\dagger c_{DL\sigma} \\
 &\quad + t_R c_{DR\sigma}^\dagger c_{A\sigma} + \sigma t_{Rso} c_{DR\sigma}^\dagger c_{A\sigma}) + \text{H.c.} \quad (\text{B1})
 \end{aligned}$$

The Hamiltonian can be split into three parts, the quantum dot Hamiltonian, H_D , the hybrid segment with the ABSs, H_S , and the tunnel coupling between ABS and quantum dots, H_T . H_D contains the orbital energy ε_{Da} , the electron occupation $n_{Da\sigma}$, the Zeeman energy E_{ZDa} , and the Coulomb repulsion U_{Da} . The index a defines the left/right quantum dot. The hybrid Hamiltonian H_S contains the normal state energy ε_A and an induced pairing gap Δ_0 . The tunnel Hamiltonian H_T includes two couplings between the quantum dot and ABS: a spin conserving, t , and a spin flipping process, t_{so} . The spin-orbit interaction determines the ratio of t_{so}/t .

Proximity effects of the semiconductor-superconductor hybrid transform the quantum dot orbitals into YSR states [46–48] and create a new basis of spinless fermions for a Kitaev chain model. The YSR states are a superposition of electron and hole components and in this basis, the Kitaev chain has more generalized effective couplings, describing the interaction between the two YSR states. We can write the effective Hamiltonian describing the interaction between these two states as

$$H_{\text{eff}}^{\text{coupling}} = \sum_{\sigma,\eta=\uparrow,\downarrow} (t_{\sigma\eta} c_{DL\sigma}^\dagger c_{DR\eta} + \Delta_{\sigma\eta} c_{DL\sigma}^\dagger c_{DR\eta}^\dagger) + \text{H.c.}, \quad (\text{B2})$$

where we consider different ECT and CAR amplitudes, $t_{\sigma\eta}$ and $\Delta_{\sigma\eta}$ between electron and hole components of the quantum dots. Note that each site still has an on-site energy and Coulomb interaction as in Eq. (B1). Considering that the YSR states have electron and hole components, the couplings $t_{\sigma\eta}$ and $\Delta_{\sigma\eta}$ have to be generalized. The ground states of a single proximitized quantum dot are a spin singlet and a spin-down state in the even- and odd-parity subspace:

$$\begin{aligned}
 |S\rangle &= u|00\rangle - v|11\rangle, \quad |\downarrow\rangle = |01\rangle, \\
 u^2 &= 1 - v^2 = \frac{1}{2} + \frac{\xi}{2E_0}, \\
 \xi &= \varepsilon + \frac{U}{2}, \quad E_0 = \sqrt{\xi^2 + \Delta_{\text{ind}}^2}. \quad (\text{B3})
 \end{aligned}$$

This allows us to define the YSR state as $|\downarrow\rangle = f_{\text{YSR}}^\dagger |S\rangle$ and the effective coupling of Eq. (B2) written in terms of YSR

states becomes

$$H_{\text{eff}} = \sum_{a=L,R} \delta \varepsilon_a f_a^\dagger f_a + \Gamma_o f_L^\dagger f_R + \Gamma_e f_L^\dagger f_R^\dagger + \text{H.c.}, \quad (\text{B4})$$

where $\delta \varepsilon_a = E_\downarrow - E_S$ is the excitation energy of the YRS state and $\Gamma_{o/e}$ are odd/even generalized effective couplings between the YSR states. The odd coupling is defined as

$$\Gamma_o = \langle S_\downarrow | H_{\text{eff}}^{\text{coupling}} | S_\downarrow \rangle = -t_{\uparrow\uparrow} v_L v_R + t_{\downarrow\downarrow} u_L u_R + \Delta_{\uparrow\downarrow} v_L u_R - \Delta_{\downarrow\uparrow} u_L v_R, \quad (\text{B5})$$

where $|S_\downarrow\rangle$ and $|S_\uparrow\rangle$ are odd parity tensor states and Γ_o is a linear combination of spin-conserving couplings, namely, equal spin ECT and opposite spin CAR processes. The even-parity coupling

$$\Gamma_e = \langle SS | H_{\text{eff}}^{\text{coupling}} | \downarrow\downarrow \rangle = -\Delta_{\uparrow\uparrow} v_L v_R + \Delta_{\downarrow\downarrow} u_L u_R + t_{\uparrow\downarrow} v_L u_R - t_{\downarrow\uparrow} u_L v_R \quad (\text{B6})$$

couple states with total spin zero and one, i.e., breaks spin conservation. These odd- and even-parity couplings can be seen as more generalized effective t and Δ parameter from the Poor Man's Majorana Kitaev chain model [56]. To obtain the differential conductance, we employ the Mahaux-Weidenmuller formula to compute the scattering matrix [50]. For this, we rewrite the derived effective Hamiltonian of Eq. (B4) in the Bogoliubov-de Gennes formalism, solve the corresponding eigenequation, and obtain the W matrix, scattering matrix, and conductance matrix. In this work, we focus on the diagonal elements of the conductance matrix G_{LL} and G_{RR} .

2. Numerical training data

After introducing the theory model, we create the theoretical training data by generating a diverse set of Hamiltonians of Eq. (B1) leading to an effective Hamiltonian in the YSR basis of Eq. (B4), incorporating random variations within of parameters in the model in specified intervals:

- (1) induced Zeeman energy in each quantum dot $E_{ZDa} \in I = [-0.2, 0.2]$
- (2) induced pairing gap $\Delta_0 \in I = [0.2, 0.6]$
- (3) tunneling couplings $t_{L/R} \in I = [0.05, 0.4]$
- (4) t 's and Δ 's $\in I = [0.01, 0.48]$
- $\Gamma_{\text{odd/even}} \in I = [0.01, 0.48]$
- (5) temperature $T \in I = [0.02, 0.03]$
- (6) left/right lead coupling $\Gamma_{L/R} \in I = [0.04, 0.06]$.

While we include a Zeeman energy on the QDs, we do not consider the up state of the QDs. As a result, the Zeeman energy only lowers the energy of the down states. The theoretical data, depicted in Fig. 9(c), closely resemble the experimental conductance data, including, e.g., variations in lead couplings, background noise, and interaction strengths across a broad parameter range spanning from the ECT- to the CAR-dominated region. We illustrate in Fig. 9(a) the training/test loss for the initial training step. The loss function shows the expected behavior, with the test loss consistently higher than the training loss, reaching saturation at around 75 epochs. We have chosen a training set of 6000 samples and trained the CNN with a batch size of 16 for 100 epochs. The fluctuations during the training can be related to the stochastic

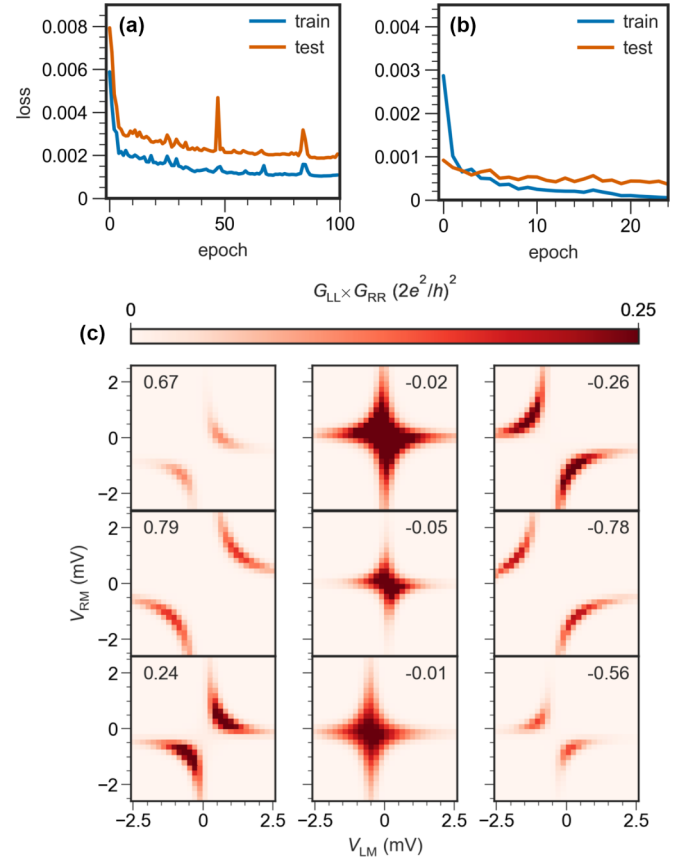


FIG. 9. Training evaluation and numerical training data of the CNN. (a) The train loss and test loss during the initial training of the CNN with the numerical data set [shown in panel (c)]. (b) The train loss and test loss during the retraining of the CNN with labeled experimental data [shown in Figs. 3(a)–3(e)]. (c) Numerical calculations of the product of the left and right differential conductances, $G_{LL} \times G_{RR}$, for varying $(t - \Delta)/(t + \Delta)$, including the ECT-dominated, sweet-spot, and CAR-dominated regimes.

nature of the gradient descent algorithm [69], the small batch size, and randomly chosen training/test data.

3. Experimental training data

We show the training/test loss for the retraining with an experimental training set in Fig. 9(b). The test loss is again consistently higher than the training loss and saturates at around 20 epochs. For the retraining, we only train the CNN for 25 epochs, starting from the already-trained CNN parameters and fine-tuning the parameters to experimental data.

In Figs. 3(a) and 3(b), we compare the CNN predictions for the experimental dataset. In Fig. 3(a), we show the predictions of the initial theory-only CNN. The predictions show a constant gradient for increasing V_{ABS} capturing the experimental values overall with good accuracy. However, the theory-only CNN does not predict the sweet spot region around $V_{\text{ABS}} = -622$ mV well, which possibly can lead to convergence problems when approaching the sweet spot with the gradient descent algorithm. Figure 3(b) shows the prediction of the retrained CNN for the experimental test data. In this case, the CNN captures the sweet spot region well. The gradient toward

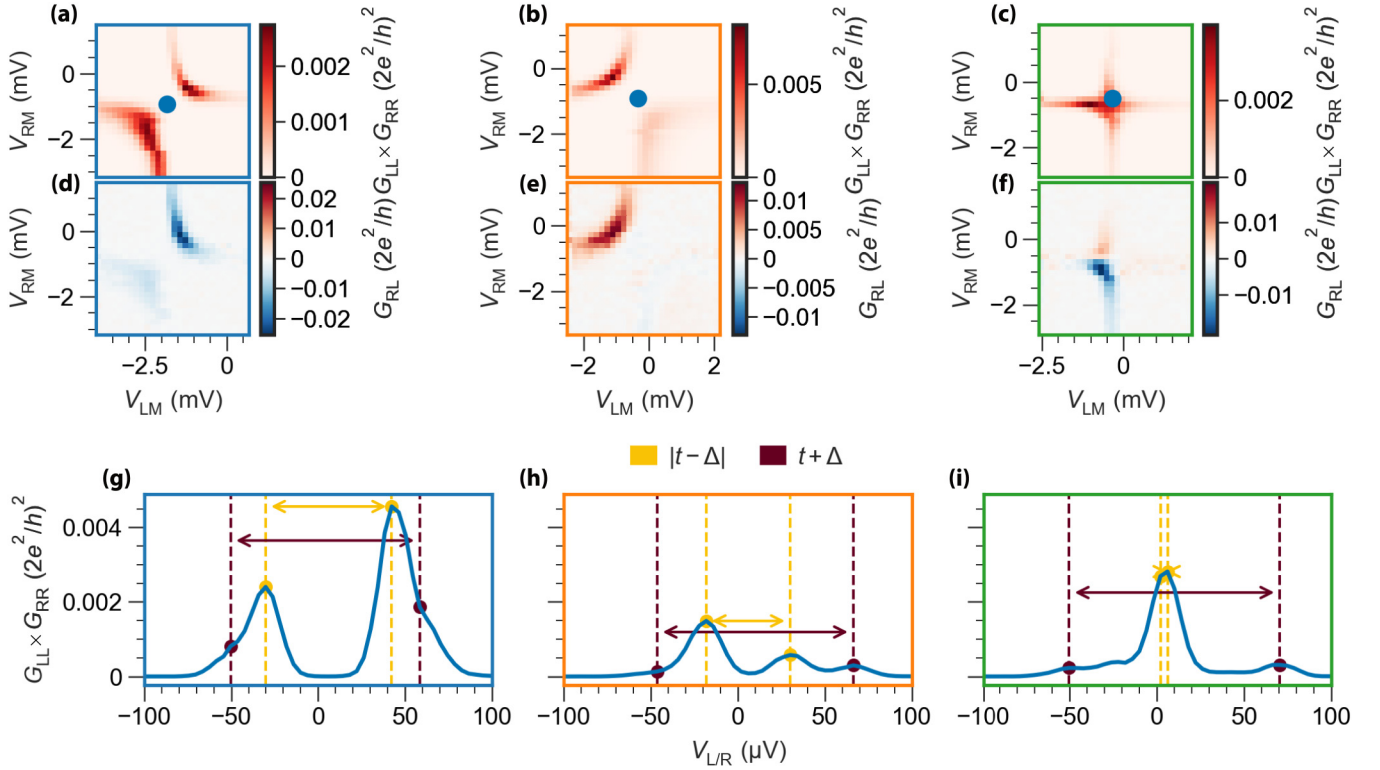


FIG. 10. Extraction of labels using tunnel spectroscopy. (a)–(c) The product of the left and right differential conductance, $G_{LL} \times G_{RR}$, for varying V_{LM} and V_{RM} . The measurements were performed at V_{ABS} values of 85, 104, and 115 mV, respectively. (d)–(f) Nonlocal conductance, $G_{RL} = dI_R/dV_L$, for varying V_{LM} and V_{RM} . The data were measured simultaneously with panels (a)–(c). (g)–(i) $G_{LL} \times G_{RR}$ for varying left/right lead bias, $V_{L/R}$, measured at the V_{LM} and V_{RM} values indicated by the blue marker in panels (a)–(c). The purple, dashed lines indicate the outer peaks. The yellow, dashed lines indicate the inner peaks.

the sweet spot coincides well with the labeled data, which is one of the most important factors for CNN-tuning algorithm. In Figs. 3(c)–3(e), we show three conductance measurements for the ECT, CAR, and sweet-spot regime taken at specific V_{ABS} from above.

APPENDIX C: DATA LABELING PROCEDURE

Figures 10(a) and 10(c) show the charge stability diagrams as presented in Figs. 3(a)–3(c). We use Python code to interpolate the center of the avoided crossings, which is indicated by the blue markers. At the V_{LM} and V_{RM} values corresponding to these markers, we measure G_{LL} for varying V_L , and G_{RR} for varying V_R , and show the resulting $G_{LL} \times G_{RR}$ in Figs. 10(g)–10(i). Each spectrum consists of two inner peaks separated by $|t - \Delta|$ and two outer peaks separated by $t + \Delta$ (see methods section of Ref. [53] for details on the model). These are indicated by the yellow and purple arrows in panels (g)–(i). We label the $V_{L/R}$ values corresponding to the peaks manually, since $G_{LL} \times G_{RR}$ can be too low for a peak-finding algorithm to work. Because the inner peaks do not provide information on the sign of $t - \Delta$, we extract it from the nonlocal conductance. When $t > \Delta$, elastic cotunneling dominates over crossed-Andreev reflection, and the sign of nonlocal conductance will be negative [28]. Likewise, G_{RL} will be predominantly positive for $t < \Delta$, so we extract the

sign from

$$\text{sgn}(t - \Delta) = \begin{cases} 1, & -\min(G_{RL}) > \max(G_{RL}), \\ -1, & \max(G_{RL}) > -\min(G_{RL}). \end{cases}$$

We combine the sign found from the nonlocal conductance measurements with the inner and outer peak spacing to calculate $(t - \Delta)/(t + \Delta)$ for each V_{ABS} value in Fig. 3(f).

We note that directly relating the peak spacings to the CAR and ECT rates is only justified in the infinite Zeeman limit. At zero magnetic field, in limit of large charging energy on the QDs, the sweet spot condition becomes $t = \sqrt{2}\Delta$ as a result of the larger Hamiltonian basis that now includes both spin species [49]. At this sweet spot, there is still a peak at the Fermi level and two peaks that indicate the gap. While the distance between the outer peaks is then no longer $t + \Delta$, we continue to use this form of labeling for the CNN. The direct relation with the CAR and ECT rates is then severed. This means that we are not training the CNN on transport rates, but rather on peak spacings. For our purposes, this is not problematic, as minimizing $(t - \Delta)/(t + \Delta)$ will still correspond to finding the sweet spot. We note that there can be additional excited states in spectroscopy at zero field [51]. These are only visible at one bias polarity. As we look for particle-hole symmetric peaks in $G_{LL} \times G_{RR}$, we filter out these low-Zeeman excited states.

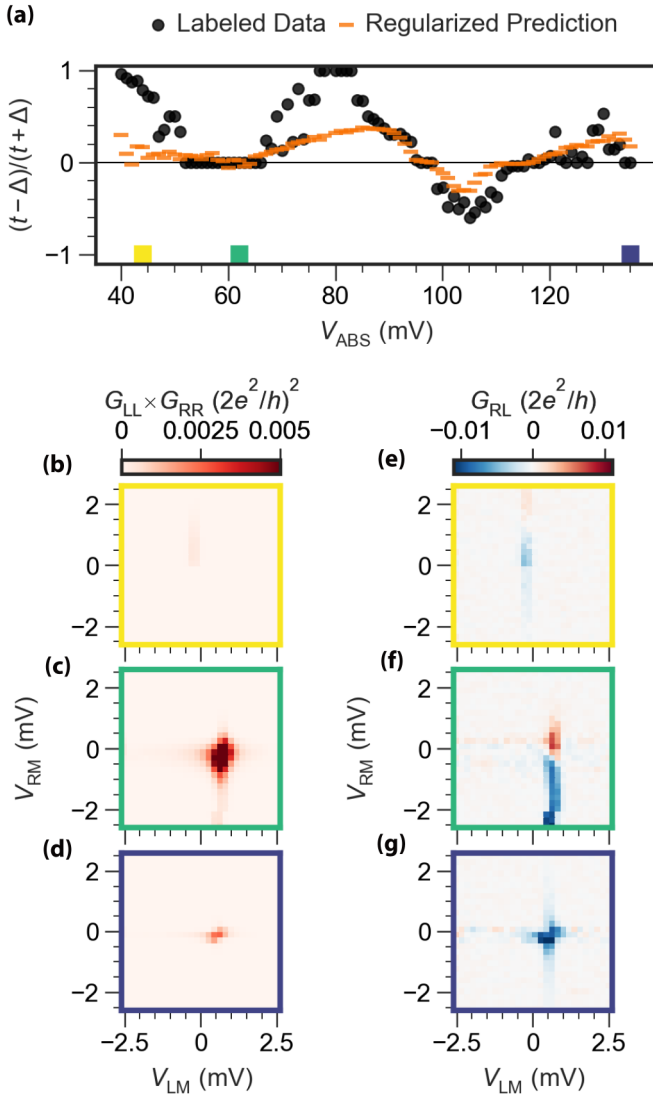


FIG. 11. Selected charge stability diagrams. (a) $(t - \Delta)/(t + \Delta)$ for varying V_{ABS} for Device A. The black markers indicate experimentally labeled data and the orange markers are the retrained and regularized CNN predictions. (b)–(d) The product of the left and right differential conductance, $G_{\text{LL}} \times G_{\text{RR}}$, for varying V_{LM} and V_{RM} . The measurements were performed at V_{ABS} values of 44, 62, and 135 mV, respectively. (e)–(g) Nonlocal conductance, $G_{\text{RL}} = dI_{\text{R}}/dV_{\text{L}}$ for varying V_{LM} and V_{RM} . The data were measured simultaneously with panels (b)–(d).

APPENDIX D: CNN PREDICTION LIMITATIONS

As discussed in Appendix B, the CNN was mainly trained on an effective model for the two QDs, which integrates out the ABS coupling them. When the QD-ABS coupling becomes on the order of the ABS energy, this model does not accurately describe the system anymore. In Fig. 11(a), we see that the CNN predicts a sweet spot around $V_{\text{ABS}} = 45$ mV, while the labeled data indicates that $(t - \Delta)/(t + \Delta) \approx 1$. The weighted ratio approaches 1 when $\Delta \rightarrow 0$, as the numerator and denominator will be equal. From the corresponding CSD in Fig. 11(b), we see that the correlated conductance vanishes, which points to weak interaction

between the QDs. However, the corresponding nonlocal conductance in Fig. 11(e) has both signs, which is usually a sign of a sweet spot. The features in panels (b) and (e) depend less on V_{RM} than on V_{LM} , which suggests that the transport is dominated by the left QD. We interpret the presence of positive and negative nonlocal conductance as a sign of direct transport between the left QD and the ABS. From the tunnel spectroscopy in Fig. 1(b), we see that the ABS at the lowest V_{ABS} values comes close to zero energy at its minimum. This is consistent with our interpretation of an increased QD-ABS interaction at low V_{ABS} values.

In Figs. 11(c) and 11(f), we see both signs of nonlocal again, together with a cross in the correlated conductance. The nonlocal features depend mostly on V_{LM} , which suggests strong QD-ABS interaction as in panels (b) and (e). It is hard to tell whether this is an actual sweet spot, and might be related to low Majorana polarization as detailed in Ref. [37]. We note that the CNN predictions and experimentally extracted values of $(t - \Delta)/(t + \Delta)$ agree at this V_{ABS} value.

Finally, we see that the labeled data becomes noisier around $V_{\text{ABS}} = 135$ mV in Fig. 11(a). From panels (d) and (g), we see that the QD-QD interaction is very weak. Accurately labeling the data becomes challenging for low interaction, as the peaks are hard to find due to low conductance. The CNN predictions are greater than the experimental labels here due to the regularization procedure. We conclude that the CNN performs well when the QD-ABS interaction is smaller than the ABS energy. Also, it does not perform well when the conductance becomes low due to weak QD-QD interaction.

APPENDIX E: REGULARIZATION

There are three cases that can lead to a vanishing $(t - \Delta)/(t + \Delta)$ ratio. In the first case, $(t + \Delta)$ becomes very large. The interaction strength is ultimately limited by the ABS energy and the superconducting parent gap. Second, $(t + \Delta)$ is finite, but $t \approx \Delta$, which is the desired sweet spot condition. In the third case, both t and Δ become vanishingly small, but are not equal in size. While this should be mitigated by scaling $t - \Delta$ with $1/(t + \Delta)$, the CNN can incorrectly identify weak QD interaction as a sweet spot. To penalize low interaction, we add a correction to the objective function based on the mean conductance of a measurement. When the QDs have low interaction, the differential conductance will be negligible. First, we compute the average conductance of a charge stability diagram:

$$\langle G \rangle = \frac{1}{N} \sum_{i=1}^N \left(\frac{1}{M} \sum_{j=1}^M G_{\text{LL}} \times G_{\text{RR}}(V_{\text{LM}}^i, V_{\text{RM}}^j) \right).$$

Then, we count the number of pixels of a measurement that have a conductance value greater than $\langle G \rangle$:

$$N_{>} = \sum_{i,j}^{N,M} \Theta[G_{\text{LL}} \times G_{\text{RR}}(V_{\text{LM}}^i, V_{\text{RM}}^j) - \langle G \rangle],$$

where Θ is the Heaviside function. Finally, we offset the objective function based on the ratio of above-average

conductance pixels:

$$f(V_{\text{ABS}}) = \frac{|t - \Delta|}{t + \Delta} + \left(\frac{N}{2N_{>}} \right)^3, \quad (\text{E1})$$

where $N_{>}$ is limited by $0 \leq N_{>} \leq N^2$, assuming $M = N$. As $N_{>} \rightarrow \infty$, this correction disappears. As $N_{>} \rightarrow 0$, the correction becomes very large and a minimum of the objective function cannot be found. We use this regularization procedure for all the automated tuning runs.

APPENDIX F: GRADIENT DESCENT ALGORITHM

As detailed in Eq. (3), we use a gradient descent algorithm to find sweet spots where $t = \Delta$. While most gradient descent algorithms use the slope as a condition for convergence, we use the objective function. The reason is that we cannot compute the gradient at each given point, but need discrete points between which we can approximate the gradient using finite differences:

$$g_i = \frac{f(V_{\text{ABS}})_i - f(V_{\text{ABS}})_{i-1}}{V_{\text{ABS}}^i - V_{\text{ABS}}^{i-1}}.$$

We use a momentum term, k , to update the velocity with the average of the past five gradients in each step:

$$v^{n+1} = kv^n + (1 - k) \langle g \rangle_n.$$

Considering QD-based devices are mesoscopic in nature, predictions of the CNN at the same V_{ABS} can differ. This can result from gate jumps, gate hysteresis, off-centered measurements, etc. The momentum term helps to overcome local maxima of $f(V_{\text{ABS}})$ and find the global minimum. We update V_{ABS} using the velocity scaled by a learning rate, η :

$$V_{\text{ABS}}^{n+1} = V_{\text{ABS}}^n - \eta v^{n+1}.$$

This procedure is repeated until the objective function is below the predefined tolerance, τ :

$$f(V_{\text{ABS}}) = \frac{|t - \Delta|}{t + \Delta} + \left(\frac{N}{2N_{>}} \right)^3 < \tau,$$

where the final term penalizes low QD-QD interaction (see Appendix E for details).

Considering the algorithm directly controls gate voltages on the device, we include some extra constraints. First, the minimal change in V_{ABS} is limited to 60 μV by our digital-analog converter resolution. Second, we limit the maximal change in V_{ABS} to 10 mV. A larger change will shift the Coulomb resonance out of the measurement window. In each iteration, we center the measurements by taking linecuts of V_{LM} and V_{RM} at the extrema of a charge stability diagram, and interpolate their intersection. Furthermore, we limit the algorithm with ± 50 mV from each starting V_{ABS} to confine it to the known region. If the algorithm would propose a V_{ABS} across this boundary, we reverse the sign of the velocity. In the first iteration, we change V_{ABS} by a value drawn from a Gaussian distribution:

$$f(\Delta V_{\text{ABS}}) = \frac{1.2 \text{ mV}}{\sqrt{2\pi}} e^{-\Delta V_{\text{ABS}}^2/2}.$$

While g_i values are generally linear close to the sweet spot, they change sign at the sweet spot. If the CNN identifies a sign

change of $t - \Delta$, we change the sign of the velocity—before updating it with the gradients—and reduce the learning rate by a factor of 2. We also increase the learning rate by 50% every five steps.

1. Choice of learning rate

For a single ABS in the infinite parent gap limit, we can write the elastic cotunneling (t) and crossed-Andreev reflection (Δ) rates as [44]

$$t = \frac{\Gamma^2 I_0 \mu^2}{(\Gamma^2 + \mu^2)^2}, \quad \Delta = \frac{\Gamma^4 I_0}{\Gamma^4 + 2\Gamma^2 \mu^2 + \mu^4},$$

where Γ is the induced gap of the ABS, μ is its electrochemical potential, and I_0 is a proportionality constant. We can then write the sum and differences of t and Δ , as well as their ratio as

$$\begin{aligned} t + \Delta &= \frac{\Gamma^2 I_0}{\Gamma^2 + \mu^2}, \\ t - \Delta &= \frac{\Gamma^2 I_0 (-\Gamma^2 + \mu^2)}{\Gamma^4 + 2\Gamma^2 \mu^2 + \mu^4}, \\ \Lambda &= \frac{t - \Delta}{t + \Delta} = \frac{\mu^2 - \Gamma^2}{\mu^2 + \Gamma^2}. \end{aligned} \quad (\text{F1})$$

At $\mu = \pm\Gamma$, we obtain $t = \Delta$ and calculate the derivative:

$$\frac{d\Lambda}{d\mu} = \frac{4\mu\Gamma^2}{(\mu^2 + \Gamma^2)^2}, \quad \left. \frac{d\Lambda}{d\mu} \right|_{\mu=\pm\Gamma} = \frac{1}{\Gamma}. \quad (\text{F2})$$

In a device, we are tuning μ indirectly using a gate voltage V_{ABS} . We can write the slope in terms of V_{ABS} using

$$\left. \frac{d\Lambda}{dV_{\text{ABS}}} \right|_{\text{sweet spot}} = \left. \frac{d\Lambda}{d\mu} \right|_{\mu=\pm\Gamma} \frac{d\mu}{dV_{\text{ABS}}} \quad (\text{F3})$$

$$= \frac{1}{\Gamma} \frac{d\mu}{dV_{\text{ABS}}} = \frac{\alpha}{\Gamma}, \quad (\text{F4})$$

where α is the lever arm. The authors of Ref. [54] recommend a learning rate that matches the slope at the objective function minimum. Using a lever arm $\alpha = 0.05e$ and an induced gap $\Gamma = 100 \mu\text{eV}$, we obtain $\eta_{\text{opt}} = \Gamma/\alpha = 2 \times 10^{-3} \text{ V}$, which is ten times larger than the learning rate used in the experiments. We lower the learning rate to prevent large changes of V_{ABS} , as cross-capacitance can shift the Coulomb resonances of the QDs.

We also note that we chose a relatively low learning rate, η , compared to the optimal value (see Appendix F for details). This η was chosen to prevent large changes in V_{ABS} , which also affects the electrochemical potential of the QDs. The centering of the QD measurements is important for having accurate CNN predictions. This can be improved by using “virtual gates,” which are linear combinations of V_{LM} , V_{RM} , and V_{ABS} that compensate for cross-capacitance (see Appendix B of Ref. [70]). Additionally, the CNN could be trained on more off-centered theory data.

2. Choice of tolerance

At $t = \Delta$, the QD levels intersect perfectly. As t and Δ move away from the sweet spot, an avoided crossing of

magnitude $D = \sqrt{8|t^2 - \Delta^2|}$ opens between the two hyperbolas (see page 4 of the supplementary materials of Ref. [51]). If this magnitude is smaller than the broadening of conductance, an avoided crossing cannot be observed. We can define a tolerance based on broadening and the expected interaction strength $t + \Delta$. First, we rewrite the distance between parabola's as

$$D = 2(t + \Delta)\sqrt{2\frac{|t - \Delta|}{t + \Delta}}.$$

If we demand that the distance is below thermal broadening, $D < 3.5k_B T$, we can write

$$\frac{|t - \Delta|}{t + \Delta} < \frac{1}{8} \left(\frac{3.5k_B T}{t + \Delta} \right)^2 = \tau.$$

Using a temperature of $T = 30$ mK and an interaction strength $t + \Delta = 80$ μ eV, we obtain a tolerance $\tau = 1.6 \times 10^{-3}$. While this quantity is smaller than the value we used in experiments, we note that our conductance broadening is significantly larger than the 9 μ eV we can expect from thermal processes. Substituting the thermal term by a broadening of 20 μ eV yields a tolerance $\tau = 1 \times 10^{-2}$, which is the value we used in the experiments. Therefore, we recommend using a tolerance:

$$\tau = \frac{1}{32} \left(\frac{\gamma}{\Delta^*} \right)^2,$$

where Δ^* is the desired gap at the sweet spot and γ is the linewidth of the Coulomb resonances observed from bias spectroscopy. We note that in principle this allows us to select sweet spots based on their gap by choosing τ . This is seen in Fig. 5(b), where the algorithm converges on the weaker sweet spot at $V_{\text{ABS}} = 99.5$ mV with a higher tolerance than on the stronger one at $V_{\text{ABS}} = 123.5$ mV. Although this implies that we can reject weakly interacting sweet spots, they are still minima of the objective function. A possible improvement of the algorithm could be lowering the tunnel barriers when the objective function does not converge below tolerance, or penalizing the objective function for weak sweet spots, as in Fig. 6.

3. Pseudocode

In Algorithm 1, we show the pseudocode for the automated tuning algorithm.

APPENDIX G: VALIDATION OF POOR MAN'S MAJORANA ZERO MODES IN SWEET SPOTS

The histogram in Fig. 5(b) indicates that a large majority of runs end at $V_{\text{ABS}} \approx 90.5$ mV and $V_{\text{ABS}} \approx 123.5$ mV. Based on the charge stability diagrams in panel (c), the classifier identifies sweet spots at those V_{ABS} values by predicting $\frac{|t - \Delta|}{t + \Delta}$ to fall below a set tolerance. The CSDs here form a cross-shape, which signals a zero-energy state that does not split upon tuning a single QD plunger gate. The nonlocal conductance in Fig. 5(d), having both positive and negative signs, indicates the presence of finite ECT and CAR rates, a condition for the emergence of Poor Man's Majorana zero modes in a two-site Kitaev chain.

ALGORITHM 1. Sweet-spot optimization algorithm.

Require: $V_{\text{ABS_parameter}}, \text{learning_rate}, \text{epochs}, \text{min_step_size}, \text{tolerance}, N, \text{momentum}, \text{damping_term}, \text{max_step_size}, V_{\text{ABS_min}}, V_{\text{ABS_max}}$

- 1: Assert $\text{min_step_size} > 1e - 6$
- 2: **for** $\text{epoch} = 1$ **to** epochs **do**
- 3: **if** $\text{epoch} == 1$ **then**
- 4: $V_{\text{ABS}} \leftarrow \text{handle_first_epoch}(V_{\text{ABS}}, \text{min_step_size})$
- 5: **else**
- 6: **if** $\text{epoch} \bmod 5 == 0$ **then**
- 7: $\text{learning_rate} \leftarrow \text{learning_rate} \times 1.5$
- 8: **end if**
- 9: Compute gradients
- 10: Update V_{ABS} and v using gradients
- 11: **end if**
- 12: Set gate value using $V_{\text{ABS_parameter}}(V_{\text{ABS}})$
- 13: Precenter measurement
- 14: $\text{dbx} \leftarrow \text{measure_func}(\text{measure_func_kwargs})$
- 15: Update $\text{delta_min_t_values}, \text{obj_fun_values}, V_{\text{ABSs}}, \text{dbxs}$
- 16: **if** Overshoot detected **then**
- 17: Reverse v , reduce learning_rate , log overshoot
- 18: **end if**
- 19: **if** $|\text{current_obj_val}| < \text{tolerance}$ **then**
- 20: Log convergence, break
- 21: **end if**
- 22: **end for**
- 23: **if** Nonconvergence after all epochs **then**
- 24: Log nonconvergence details
- 25: **end if**
- 26: Close log **return** $V_{\text{ABSs}}, \text{obj_fun_values}, \text{current_obj_val}, \text{epoch}$

While Figs. 5(c) and 5(d) indicate a sweet spot at which Poor Man's Majorana zero modes emerge, it does not reveal the size of the gap to the first excited state. In Fig. 12(a), we show the local and nonlocal conductance measured on Device A on varying V_{LM} , while the right QD is kept on resonance. We observe a stable zero-energy state, combined with dispersing excited states. Similarly, in panel (b) we show that the sweet spot at 120 mV displays a stable zero-bias peak as well, upon varying V_{RM} , with a gap to excited states. As detailed in Refs. [28,51,53], this is the robustness against local perturbation that defines Poor Man's Majorana zero modes in a two-site Kitaev chain, and can be used to validate sweet spots identified by the automated tuning algorithm.

The gate voltages at which these sweet spots are found differ slightly from the ones in Fig. 5. As these spectroscopic measurements were performed before the automated tuning runs, we attribute the difference to drifts in gate voltage. We identify these as the same sweet spots shown in Fig. 5, as there is only a single ABS in this gate range, as seen from Fig. 1(b), which coincides with two expected sweet spots [53]. In Fig. 13(a), we show a CSD of Device B in the sweet spot used for the training data. We note that this measurement was taken at $V_{\text{ABS}} = -622.2$ mV. This voltage also shows a small difference when compared to the gate voltage, at which $\frac{|t - \Delta|}{t + \Delta} = 0$ in Figs. 3(a) and 3(b). Similarly to the previous

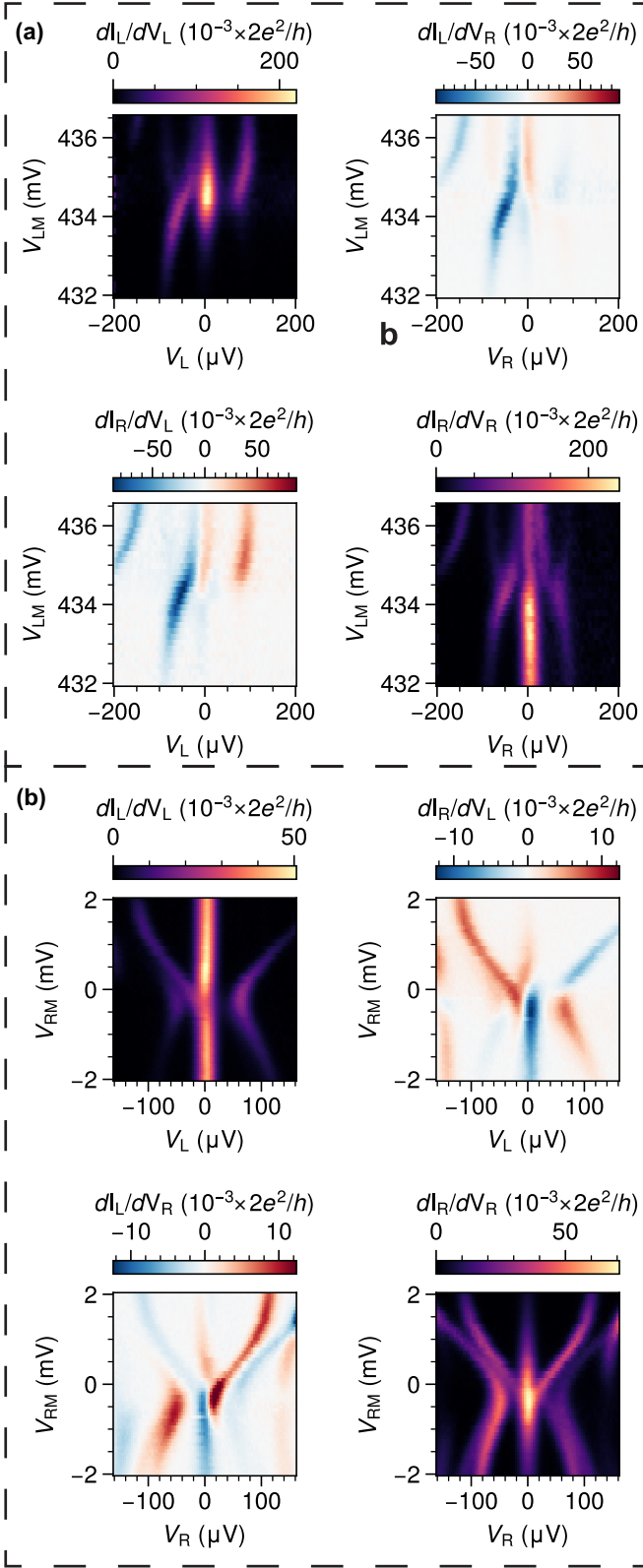


FIG. 12. Zero-energy state stability for Device A at the sweet spots identified in Fig. 5 at zero magnetic field. (a) Full conductance matrix for varying V_{LM} and voltage bias $V_{L/R}$ at $V_{ABS} = 95$ mV. (b) Full conductance matrix for varying V_{RM} and voltage bias $V_{L/R}$ at $V_{ABS} = 120$ mV.

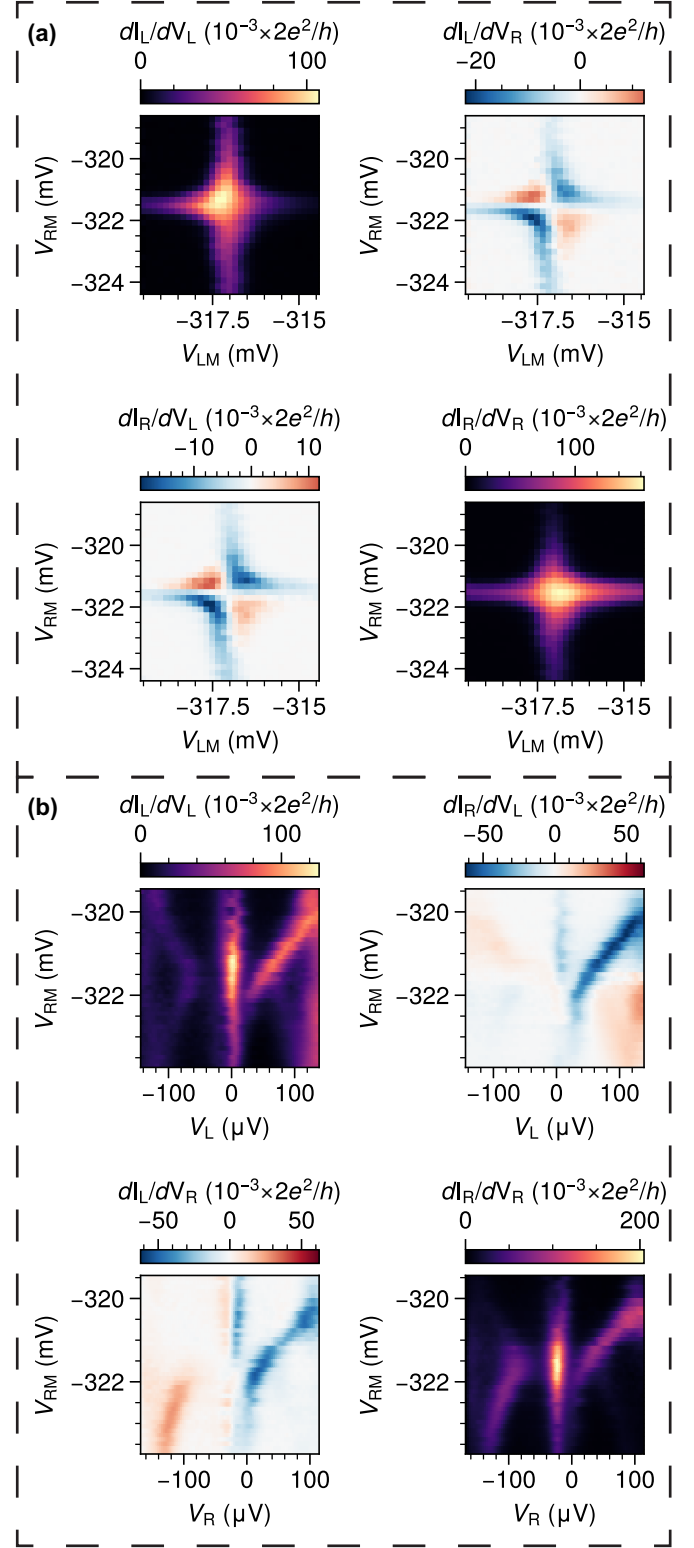


FIG. 13. Zero-energy state stability for Device B at $V_{ABS} = -623.3$ mV at zero magnetic field. (a) Full conductance matrix of a crossing in the CSD, when $t \approx \Delta$, for varying V_{LM} and V_{RM} . (b) Full conductance matrix for varying V_{RM} and voltage bias $V_{L/R}$.

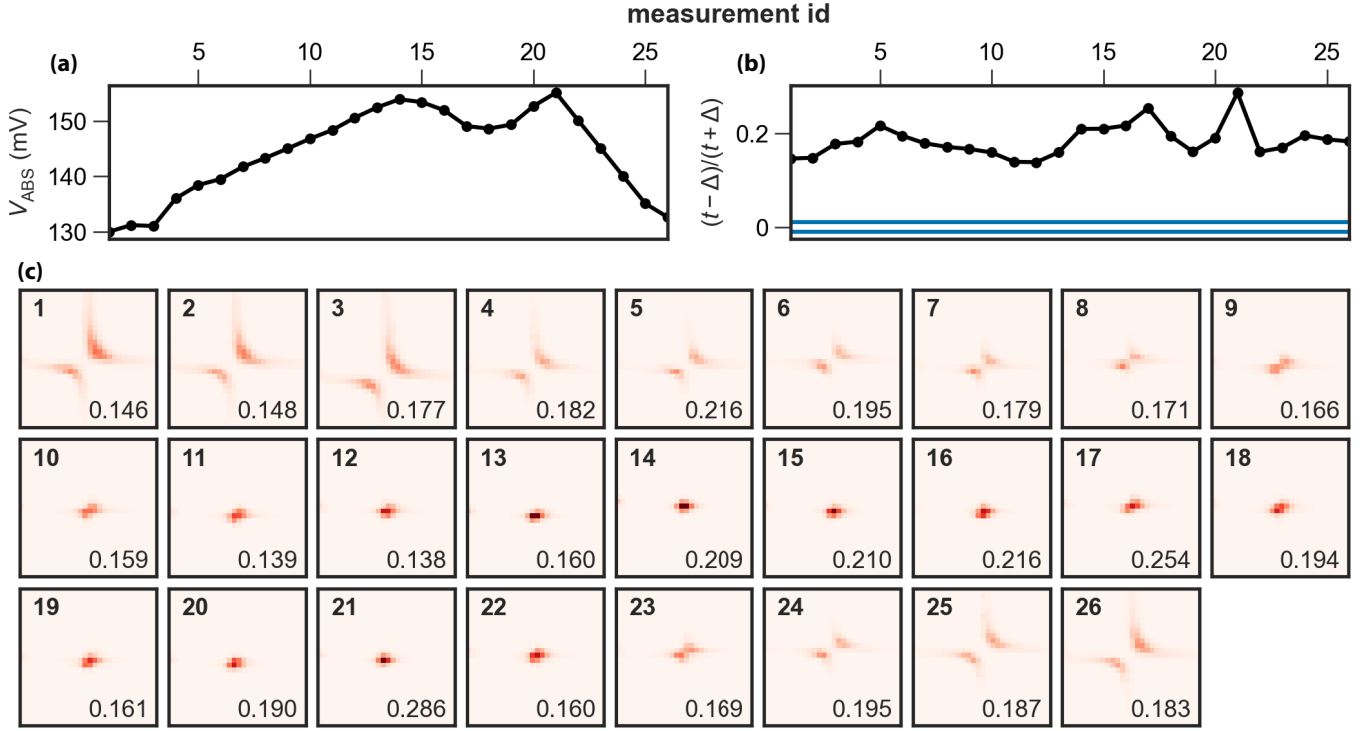


FIG. 14. Example of an unconverged automated tuning run. (a) The hybrid plunger gate voltage, V_{ABS} , for each measurement. (b) Prediction of the weighted ratio of elastic cotunneling and crossed Andreev reflection, $(t - \Delta)/(t + \Delta)$, for each measurement. The horizontal, blue lines indicate the tolerance set before the run. (c) The product of the left and right differential conductances, $G_{LL} \times G_{RR}$, for varying V_{LM} and V_{RM} for subsequent measurements. The measurement IDs are indicated by the bold text in the top left corner. The predicted value of $(t - \Delta)/(t + \Delta)$ is indicated in the bottom right corner.

case, the sweet spot was not characterized at the same time as the collection of the labeled data. As such, we attribute the difference to the drifts in gate voltages. In Fig. 13(b), we show the local and nonlocal conductance measured on device upon varying V_{RM} , while the left QD is kept on resonance. Similar to Device A, we see a stable zero-bias peak with a gap to excited states.

The Poor Man's Majorana confirmation step via spectroscopic measurements (Figs. 12 and 13), as shown in this Appendix, can always be performed once a candidate sweet spot is identified by the algorithm.

APPENDIX H: UNCONVERGED RUN EXAMPLE

In Fig. 14(a), we show the V_{ABS} values visited by a run that did not converge. Just as in Fig. 4, the run started from $V_{\text{ABS}} = 130$ mV. For the first 14 measurements, the algorithm visits increasing values of V_{ABS} . We see from Fig. 14(b) that $(t - \Delta)/(t + \Delta)$ does not change significantly in this gate range. From the charge stability diagrams in Fig. 14(c), we see that the interaction between the QDs becomes weaker for increasing V_{ABS} . Eventually, the algorithm reverses direction and returns to the starting $V_{\text{ABS}} = 130$ mV. As we limit the number of measurements per run to 26, the algorithm stops here. This unconverged run highlights that the CNN does not predict $(t - \Delta)/(t + \Delta)$ accurately if $t + \Delta$ is small, as can be seen from the superimposed CNN predictions in the charge stability diagrams. We attribute this to the bias toward strong interaction in our theoretical and experimental training set. We

note that this run ended with a velocity in the right direction and might have converged given more steps.

APPENDIX I: A SPINFUL HAMILTONIAN

Here, we introduce a Hamiltonian that has all the required ingredients to study Majorana-bound states and topological superconductivity. This Hamiltonian describes a spinful quantum dot system including superconductivity, spin-orbit coupling (SOC), and Zeeman splitting and can be written as

$$H = H_0 + H_{\text{SOC}} + H_Z + H_{\text{s-wave}}. \quad (\text{I1})$$

The tight-binding Hamiltonian H_0 describes the movement of electrons in the system that determines the basic electronic band structure. This term is defined as

$$H_0 = \sum_{i,\sigma} \mu_i c_{i\sigma}^\dagger c_{i\sigma} - t \sum_{\langle i,j \rangle, \sigma} (c_{i\sigma}^\dagger c_{j\sigma} + \text{H.c.}), \quad (\text{I2})$$

where μ_i is the onsite chemical potential at site i , t is the hopping amplitude between neighboring sites $\langle i, j \rangle$, and $c_{i\sigma}^\dagger$ and $c_{i\sigma}$ are the electron creation and annihilation operators at site i with spin σ . The Rashba SOC Hamiltonian H_{SOC} is given as

$$H_{\text{SOC}} = i\lambda_R \sum_{\langle i,j \rangle} (c_{i\uparrow}^\dagger c_{j\downarrow} - c_{i\downarrow}^\dagger c_{j\uparrow}) + \text{H.c.}, \quad (\text{I3})$$

where λ_R is the Rashba SOC strength. This term breaks the spin degeneracy and allows spin flips during hopping. The

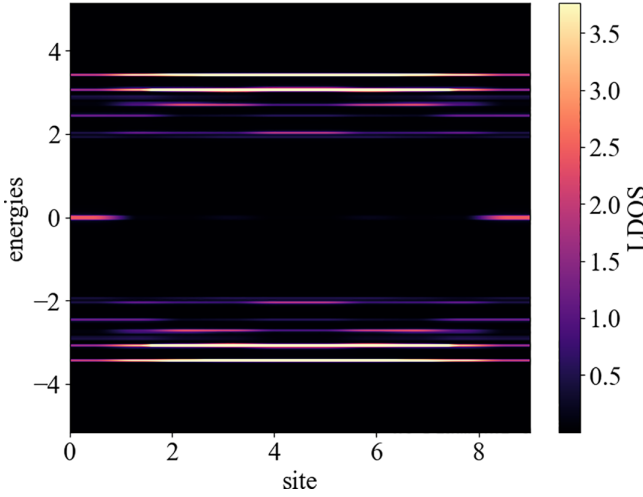


FIG. 15. Example of the LDOS of a ten-site chain that shows zero-energy edge modes.

Zeeman term H_Z ,

$$H_Z = B_z \sum_i (c_{i\uparrow}^\dagger c_{i\uparrow} - c_{i\downarrow}^\dagger c_{i\downarrow}), \quad (I4)$$

breaks spin symmetry and induces energy splitting between spin-up and spin-down states. B_z represents the Zeeman energy proportional to the applied magnetic field. This term removes the spin degeneracy and shifts the energy levels of spin-up and spin-down electrons. The superconducting s -wave pairing term $H_{s\text{-wave}}$ is given by

$$H_{s\text{-wave}} = \sum_i \Delta_s (c_{i\uparrow}^\dagger c_{i\downarrow}^\dagger + \text{H.c.}), \quad (I5)$$

where Δ_s is the superconducting pairing. All terms together lead to the full spinful Hamiltonian

$$\begin{aligned} H = & \sum_{i,\sigma} \mu_i c_{i\sigma}^\dagger c_{i\sigma} - t \sum_{\langle i,j \rangle, \sigma} (c_{i\sigma}^\dagger c_{j\sigma} + \text{H.c.}) \\ & + i\lambda_R \sum_{\langle i,j \rangle} (c_{i\uparrow}^\dagger c_{j\downarrow} - c_{i\downarrow}^\dagger c_{j\uparrow}) \\ & + B_z \sum_i (c_{i\uparrow}^\dagger c_{i\uparrow} - c_{i\downarrow}^\dagger c_{i\downarrow}) + \sum_i \Delta_s (c_{i\uparrow}^\dagger c_{i\downarrow}^\dagger + \text{H.c.}). \end{aligned}$$

By adjusting the parameters λ_R , B_z , and Δ_s we can tune the system in regions where the model can host Majorana bound states or Poor Man's Majoranas in the case of a two-dot system. Compared to the Kitaev model, this Hamiltonian explicitly includes the spin degrees of freedom. In the limit of a strong Zeeman field $B_z \gg t, \lambda_R, B_z$, and Δ_s , the spinful

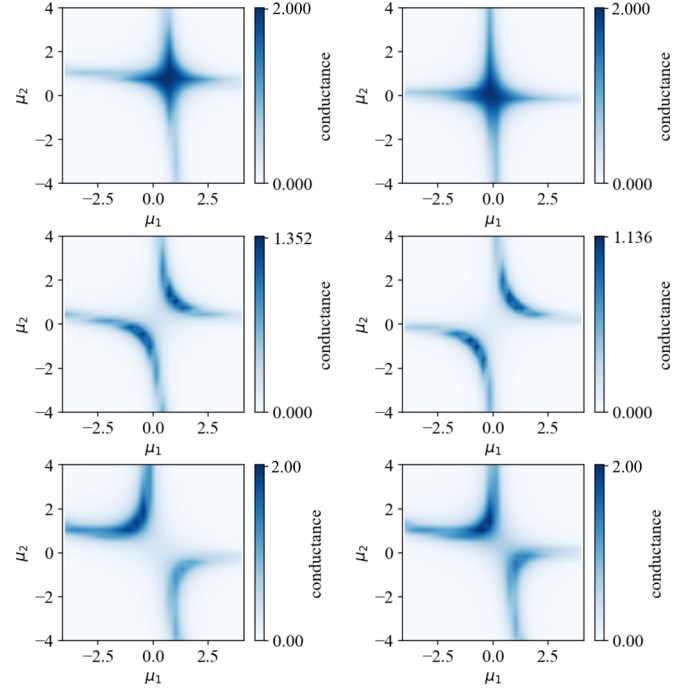


FIG. 16. Simulation of conductance with Hamiltonian from Eq. (I1) and S -matrix formalism using the pyquela library [71].

Hamiltonian approximates the Kitaev model. In Fig. 15, we compute the local density of states (LDOS) to show the appearance of zero-energy edge modes. This model allows us to compute the conductance for different regimes. In Fig. 16, we show that we obtain the same avoided crossings as for the Kitaev model, as well as the features for the Poor Man's Majorana sweet spot.

To train and test a CNN with the spinful model, we create a dataset of 1000 examples and split it into training and testing (80/20). We simulate the data, including the three parameter regimes shown in Fig. 16, namely, the Majorana sweet spot and both avoided crossings (corresponding to the three regimes in the Kitaev chain model). We then train the CNN on these simulations to predict which regime the system is in, based on the avoided crossings of the conductance simulations. On the theory data, the CNN achieved 99.1% accuracy for classification on the test set. Next, we take the 2DEG data [Fig. 3(f)] and use the same CNN to classify between the two regimes of avoided crossings. In this case, we obtain 90.7% (68 out of 75) accuracy on the experimental data, which is in comparison to the CNN prediction of previous work with the Kitaev model for experimental data 92%–94% accuracy [23].

- [1] S. G. Philips, M. T. Madzik, S. V. Amitonov, S. L. de Snoo, M. Russ, N. Kalhor, C. Volk, W. I. Lawrie, D. Brousse, L. Tryputen, *et al.*, Universal control of a six-qubit quantum processor in silicon, *Nature (London)* **609**, 919 (2022).
- [2] Y. Kim, A. Eddins, S. Anand, K. X. Wei, E. Van Den Berg, S. Rosenblatt, H. Nayfeh, Y. Wu, M. Zaletel, K. Temme, *et al.*, Evidence for the utility of quantum computing before fault tolerance, *Nature (London)* **618**, 500 (2023).

- [3] X. Mi, P. Roushan, C. Quintana, S. Mandra, J. Marshall, C. Neill, F. Arute, K. Arya, J. Atalaya, R. Babbush, *et al.*, Information scrambling in quantum circuits, *Science* **374**, 1479 (2021).
- [4] C. J. van Diepen, T.-K. Hsiao, U. Mukhopadhyay, C. Reichl, W. Wegscheider, and L. M. Vandersypen, Quantum simulation of antiferromagnetic Heisenberg chain with gate-defined quantum dots, *Phys. Rev. X* **11**, 041025 (2021).

- [5] E. Rosenberg, T. Andersen, R. Samajdar, A. Petukhov, J. Hoke, D. Abanin, A. Bengtsson, I. Drozdov, C. Erickson, P. Klimov, *et al.*, Dynamics of magnetization at infinite temperature in a Heisenberg spin chain, *Science* **384**, 48 (2024).
- [6] O. Shtanko, D. S. Wang, H. Zhang, N. Harle, A. Seif, R. Movassagh, and Z. Mineev, Uncovering local integrability in quantum many-body dynamics, *Nat. Commun.* **16**, 2552 (2025).
- [7] V. Jouanny, S. Frasca, V. J. Weibel, L. Peyruchat, M. Scigliuzzo, F. Oppliger, F. De Palma, D. Sbroggiò, G. Beaulieu, O. Zilberberg, and P. Scarlino, High kinetic inductance cavity arrays for compact band engineering and topology-based disorder meters, *Nat. Commun.* **16**, 3396 (2025).
- [8] L. J. Splitthoff, M. C. Belo, G. Jin, Y. Liu, E. Grepova, and C. K. Andersen, Gate-tunable phase transition in a resonator-based Su-Schrieffer-Heeger chain, *Phys. Rev. Res.* **6**, 043286 (2024).
- [9] P. V. Klimov, A. Bengtsson, C. Quintana, A. Bourassa, S. Hong, A. Dunsworth, K. J. Satzinger, W. P. Livingston, V. Sivak, M. Y. Niu, *et al.*, Optimizing quantum gates towards the scale of logical qubits, *Nat. Commun.* **15**, 2442 (2024).
- [10] A. Bengtsson, A. Opremcak, M. Khezri, D. Sank, A. Bourassa, K. J. Satzinger, S. Hong, C. Erickson, B. J. Lester, K. C. Miao, *et al.*, Model-based optimization of superconducting qubit readout, *Phys. Rev. Lett.* **132**, 100603 (2024).
- [11] A. Dawid, J. Arnold, B. Requena, A. Gresch, M. Płodzień, K. Donatella, K. A. Nicoli, P. Stornati, R. Koch, M. Büttner, *et al.*, *Machine Learning in Quantum Sciences* (Cambridge University Press, Cambridge, 2025).
- [12] R. Durrer, B. Kratochwil, J. V. Koski, A. J. Landig, C. Reichl, W. Wegscheider, T. Ihn, and E. Grepova, Automated tuning of double quantum dots into specific charge states using neural networks, *Phys. Rev. Appl.* **13**, 054019 (2020).
- [13] J. Schuff, M. J. Carballido, M. Kotzagiannidis, J. C. Calvo, M. Caselli, J. Rawling, D. L. Craig, B. van Straaten, B. Severin, F. Fedele, *et al.*, Fully autonomous tuning of a spin qubit, *Nat. Electron.* **9**, 304 (2026).
- [14] J. P. Zwolak, T. McJunkin, S. S. Kalantire, J. Dodson, E. MacQuarrie, D. Savage, M. Lagally, S. Coppersmith, M. A. Eriksson, and J. M. Taylor, Autotuning of double-dot devices *in situ* with machine learning, *Phys. Rev. Appl.* **13**, 034075 (2020).
- [15] B. Lienhard, A. Vepsäläinen, L. C. Govia, C. R. Hoffer, J. Y. Qiu, D. Ristè, M. Ware, D. Kim, R. Winik, A. Melville, *et al.*, Deep-neural-network discrimination of multiplexed superconducting-qubit states, *Phys. Rev. Appl.* **17**, 014024 (2022).
- [16] C. N. Barrett, A. H. Karamlou, S. E. Muschinske, I. T. Rosen, J. Braumüller, R. Das, D. K. Kim, B. M. Niedzielski, M. Schuldt, K. Serniak, *et al.*, Learning-based calibration of flux crosstalk in transmon qubit arrays, *Phys. Rev. Appl.* **20**, 024070 (2023).
- [17] S. S. Kalantire, J. P. Zwolak, S. Ragole, X. Wu, N. M. Zimmerman, M. Stewart Jr., and J. M. Taylor, Machine learning techniques for state recognition and auto-tuning in quantum dots, *npj Quantum Inf.* **5**, 6 (2019).
- [18] D. T. Lennon, H. Moon, L. C. Camenzind, L. Yu, D. M. Zumbühl, G. A. D. Briggs, M. A. Osborne, E. A. Laird, and N. Ares, Efficiently measuring a quantum device using machine learning, *npj Quantum Inf.* **5**, 79 (2019).
- [19] V. Nguyen, S. Orbell, D. T. Lennon, H. Moon, F. Vigneau, L. C. Camenzind, L. Yu, D. M. Zumbühl, G. A. D. Briggs, M. A. Osborne, *et al.*, Deep reinforcement learning for efficient measurement of quantum devices, *npj Quantum Inf.* **7**, 100 (2021).
- [20] J. Darulová, S. Pauka, N. Wiebe, K. W. Chan, G. Gardener, M. J. Manfra, M. C. Cassidy, and M. Troyer, Autonomous tuning and charge-state detection of gate-defined quantum dots, *Phys. Rev. Appl.* **13**, 054005 (2020).
- [21] S. Czischek, V. Yon, M.-A. Genest, M.-A. Roux, S. Rochette, J. C. Lemyre, M. Moras, M. Pioro-Ladrière, D. Drouin, Y. Beilliard, *et al.*, Miniaturizing neural networks for charge state autotuning in quantum dots, *Mach. Learn.: Sci. Technol.* **3**, 015001 (2022).
- [22] B. Severin, D. T. Lennon, L. C. Camenzind, F. Vigneau, F. Fedele, D. Jirovec, A. Ballabio, D. Chrastina, G. Isella, M. de Kruijf, *et al.*, Cross-architecture tuning of silicon and SiGe-based quantum devices using machine learning, *Sci. Rep.* **14**, 17281 (2024).
- [23] R. Koch, D. Van Driel, A. Bordin, J. L. Lado, and E. Grepova, Adversarial Hamiltonian learning of quantum dots in a minimal Kitaev chain, *Phys. Rev. Appl.* **20**, 044081 (2023).
- [24] J. P. Zwolak and J. M. Taylor, *Colloquium: Advances in automation of quantum dot devices control*, *Rev. Mod. Phys.* **95**, 011006 (2023).
- [25] H. Moon, D. T. Lennon, J. Kirkpatrick, N. M. van Esbroeck, L. C. Camenzind, L. Yu, F. Vigneau, D. M. Zumbühl, G. A. D. Briggs, M. A. Osborne, *et al.*, Machine learning enables completely automatic tuning of a quantum device faster than human experts, *Nat. Commun.* **11**, 4161 (2020).
- [26] J. P. Zwolak, J. M. Taylor, R. W. Andrews, J. Benson, G. W. Bryant, D. Buterakos, A. Chatterjee, S. Das Sarma, M. A. Eriksson, E. Grepová, *et al.*, Data needs and challenges for quantum dot devices automation, *npj Quantum Inf.* **10**, 105 (2024).
- [27] A. Y. Kitaev, Unpaired Majorana fermions in quantum wires, *Phys. Usp.* **44**, 131 (2001).
- [28] T. Dvir, G. Wang, N. van Loo, C.-X. Liu, G. P. Mazur, A. Bordin, S. L. D. ten Haaf, J.-Y. Wang, D. van Driel, F. Zatelli, *et al.*, Realization of a minimal Kitaev chain in coupled quantum dots, *Nature (London)* **614**, 445 (2023).
- [29] J. D. Sau and S. D. Sarma, Realizing a robust practical Majorana chain in a quantum-dot-superconductor linear array, *Nat. Commun.* **3**, 964 (2012).
- [30] C. Beenakker, Search for Majorana fermions in superconductors, *Annu. Rev. Condens. Matter Phys.* **4**, 113 (2013).
- [31] H. Pan and S. Das Sarma, Majorana nanowires, Kitaev chains, and spin models, *Phys. Rev. B* **107**, 035440 (2023).
- [32] C.-X. Liu, A. M. Bozkurt, F. Zatelli, S. L. D. ten Haaf, T. Dvir, and M. Wimmer, Enhancing the excitation gap of a quantum-dot-based Kitaev chain, *Commun. Phys.* **7**, 235 (2024).
- [33] A. Tsintzis, R. S. Souto, and M. Leijnse, Creating and detecting Poor Man's Majorana bound states in interacting quantum dots, *Phys. Rev. B* **106**, L201404 (2022).
- [34] M. Luethi, H. F. Legg, D. Loss, and J. Klinovaja, From perfect to imperfect Poor Man's Majoranas in minimal Kitaev chains, *Phys. Rev. B* **110**, 245412 (2024).
- [35] A. Tsintzis, R. S. Souto, K. Flensberg, J. Danon, and M. Leijnse, Majorana qubits and non-Abelian physics in quantum dot-based minimal Kitaev chains, *PRX Quantum* **5**, 010323 (2024).

- [36] W. Samuelson, V. Svensson, and M. Leijnse, Minimal quantum dot based Kitaev chain with only local superconducting proximity effect, *Phys. Rev. B* **109**, 035415 (2024).
- [37] R. S. Souto, A. Tsintzis, M. Leijnse, and J. Danon, Probing Majorana localization in minimal Kitaev chains through a quantum dot, *Phys. Rev. Res.* **5**, 043182 (2023).
- [38] J. Benestad, A. Tsintzis, R. S. Souto, M. Leijnse, E. Van Nieuwenburg, and J. Danon, Machine-learned tuning of artificial Kitaev chains from tunneling spectroscopy measurements, *Phys. Rev. B* **110**, 075402 (2024).
- [39] C.-X. Liu, H. Pan, F. Setiawan, M. Wimmer, and J. D. Sau, Fusion protocol for Majorana modes in coupled quantum dots, *Phys. Rev. B* **108**, 085437 (2023).
- [40] P. Boross and A. Pályi, Braiding-based quantum control of a Majorana qubit built from quantum dots, *Phys. Rev. B* **109**, 125410 (2024).
- [41] S. Heedt, M. Quintero-Pérez, F. Borsoi, A. Fursina, N. van Loo, G. P. Mazur, M. P. Nowak, M. Ammerlaan, K. Li, S. Korneychuk, J. Shen, M. A. Y. van de Poll, G. Badawy, S. Gazibegovic, N. de Jong, P. Aseev, K. van Hoogdalem, E. P. A. M. Bakkers, and L. P. Kouwenhoven, Shadow-wall lithography of ballistic superconductor–semiconductor quantum devices, *Nat. Commun.* **12**, 4914 (2021).
- [42] D. van Driel, G. Wang, A. Bordin, N. van Loo, F. Zatelli, G. P. Mazur, D. Xu, S. Gazibegovic, G. Badawy, E. P. Bakkers, *et al.*, Spin-filtered measurements of Andreev bound states in semiconductor-superconductor nanowire devices, *Nat. Commun.* **14**, 6880 (2023).
- [43] G. Ménard, G. Anselmetti, E. Martinez, D. Puglia, F. Malinowski, J. Lee, S. Choi, M. Pendharkar, C. Palmstrøm, K. Flensberg, *et al.*, Conductance-matrix symmetries of a three-terminal hybrid device, *Phys. Rev. Lett.* **124**, 036802 (2020).
- [44] C.-X. Liu, G. Wang, T. Dvir, and M. Wimmer, Tunable superconducting coupling of quantum dots via Andreev bound states in semiconductor-superconductor nanowires, *Phys. Rev. Lett.* **129**, 267701 (2022).
- [45] A. Jellinggaard, K. Grove-Rasmussen, M. H. Madsen, and J. Nygård, Tuning Yu-Shiba-Rusinov states in a quantum dot, *Phys. Rev. B* **94**, 064520 (2016).
- [46] Y. LUH, Bound state in superconductors with paramagnetic impurities, *Acta Phys. Sin.* **21**, 75 (1965).
- [47] H. Shiba, Classical spins in superconductors, *Prog. Theor. Phys.* **40**, 435 (1968).
- [48] A. Rusinov, Theory of gapless superconductivity in alloys containing paramagnetic impurities, *Zh. Eksp. Teor. Fiz.* **56**, 2047 (1969) [*Sov. Phys. JETP* **29**, 1101 (1969)].
- [49] A. M. Bozkurt, S. Miles, S. L. D. ten Haaf, C.-X. Liu, F. Hassler, and M. Wimmer, Interaction-induced strong zero modes in short quantum dot chains with time-reversal symmetry, *SciPost Phys.* **18**, 206 (2025).
- [50] T. J. Christiansen and M. Zworski, A mathematical formulation of the Mahaux–Weidenmüller formula for the scattering matrix, *J. Phys. A: Math. Theor.* **42**, 415202 (2009).
- [51] S. L. D. ten Haaf, Q. Wang, A. M. Bozkurt, C.-X. Liu, I. Kulesh, P. Kim, D. Xiao, C. Thomas, M. J. Manfra, T. Dvir, M. Wimmer, and S. Goswami, A two-site Kitaev chain in a two-dimensional electron gas, *Nature (London)* **630**, 329 (2024).
- [52] C. M. Möhle, P. K. Rout, N. A. Jainandunsing, D. Kuiri, C. T. Ke, D. Xiao, C. Thomas, M. J. Manfra, M. P. Nowak, and S. Goswami, Controlling Andreev bound states with the magnetic vector potential, *Nano Lett.* **22**, 8601 (2022).
- [53] F. Zatelli, D. van Driel, D. Xu, G. Wang, C.-X. Liu, A. Bordin, B. Roovers, G. P. Mazur, N. van Loo, J. C. Wolff, *et al.*, Robust Poor Man’s Majorana zero modes using Yu-Shiba-Rusinov states, *Nat. Commun.* **15**, 7933 (2024).
- [54] L. Bottou, Stochastic gradient descent tricks, in *Neural Networks: Tricks of the Trade*, 2nd ed., edited by G. Montavon, G. B. Orr, and K.-R. Müller (Springer, Berlin, 2012), pp. 421–436.
- [55] J.-Y. Wang, N. Van Loo, G. P. Mazur, V. Levajac, F. K. Malinowski, M. Lemang, F. Borsoi, G. Badawy, S. Gazibegovic, E. P. Bakkers, *et al.*, Parametric exploration of zero-energy modes in three-terminal InSb-Al nanowire devices, *Phys. Rev. B* **106**, 075306 (2022).
- [56] M. Leijnse and K. Flensberg, Parity qubits and Poor Man’s Majorana bound states in double quantum dots, *Phys. Rev. B* **86**, 134528 (2012).
- [57] H. Pan, S. Das Sarma, and C.-X. Liu, Rabi and Ramsey oscillations of a Majorana qubit in a quantum dot-superconductor array, *Phys. Rev. B* **111**, 075416 (2025).
- [58] I. C. Fulga, A. Haim, A. R. Akhmerov, and Y. Oreg, Adaptive tuning of Majorana fermions in a quantum dot chain, *New J. Phys.* **15**, 045020 (2013).
- [59] C.-X. Liu, S. Miles, A. Bordin, S. L. D. ten Haaf, G. P. Mazur, A. M. Bozkurt, and M. Wimmer, Scaling up a sign-ordered Kitaev chain without magnetic flux control, *Phys. Rev. Res.* **7**, L012045 (2025).
- [60] A. Bordin, C.-X. Liu, T. Dvir, F. Zatelli, S. L. D. ten Haaf, D. van Driel, G. Wang, N. Van Loo, Y. Zhang, J. C. Wolff, *et al.*, Enhanced Majorana stability in a three-site Kitaev chain, *Nat. Nanotechnol.* **20**, 726 (2025).
- [61] S. L. D. ten Haaf, Y. Zhang, Q. Wang, A. Bordin, C.-X. Liu, I. Kulesh, V. P. M. Sietes, C. G. Prosko, D. Xiao, C. Thomas, M. J. Manfra, M. Wimmer, and S. Goswami, Observation of edge and bulk states in a three-site Kitaev chain, *Nature (London)* **641**, 890 (2025).
- [62] W. D. Huisman, S. L. D. ten Haaf, C.-X. Liu, Q. Wang, A. Bordin, F. J. B. Everts, B. Roovers, M. Wimmer, and S. Goswami, Using Andreev bound states and spin to remove domain walls in a Kitaev chain, [arXiv:2601.12891](https://arxiv.org/abs/2601.12891).
- [63] van Driel, D. Cross-Platform Autonomous Control of Minimal Kitaev Chains [Data set]. Zenodo, 2024, <https://doi.org/10.5281/zenodo.10900882>
- [64] <https://gitlab.com/QMAI/papers/crossplatformkitaev>.
- [65] Z. Li, F. Liu, W. Yang, S. Peng, and J. Zhou, A survey of convolutional neural networks: Analysis, applications, and prospects, *IEEE Trans. Neural Netw. Learn. Syst.* **33**, 6999 (2022).
- [66] K. O’Shea and R. Nash, An introduction to convolutional neural networks, [arXiv:1511.08458](https://arxiv.org/abs/1511.08458).
- [67] N. Murray and F. Perronnin, Generalized max pooling, in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (IEEE, Piscataway, NJ, 2014).
- [68] F. Domínguez and A. L. Yeyati, Quantum interference in a Cooper pair splitter: The three sites model, *Physica E* **75**, 322 (2016).

- [69] L. Bottou, Large-scale machine learning with stochastic gradient descent, in *Proceedings of COMPSTAT'2010* (Physica-Verlag, Heidelberg, 2010), pp. 177–186.
- [70] D. Van Driel, B. Roovers, F. Zatelli, A. Bordin, G. Wang, N. Van Loo, J. C. Wolff, G. P. Mazur, S. Gazibegovic, G. Badawy, *et al.*, Charge sensing the parity of an Andreev molecule, *PRX Quantum* **5**, 020301 (2024).
- [71] J. L. Lado, pyqula: Python library to compute quantum-lattice tight-binding models in different dimensionalities, GitHub, 2021, <https://github.com/joselado/pyqula>.