A Deep-Learning Approach to Modeling Nanowire Single-Photon Avalanche Detectors

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***Abstract*—Single-photon avalanche detectors (SPADs) are critical for many applications, such as quantum communication and light detection and ranging (LiDAR). Traditional planar structure-based SPADs suffer from a serious trade-off of high dark count rates and limited photon detection efficiency. III-V compound semiconductor nanowire (NW) single-photon avalanche detectors have shown promising performance, but their design and fabrication are complicated, expensive and time-consuming. Thus, predicting key device performance metrics for different nanowire structures before actual experiments is critical. We introduce a deep learning-based modeling framework, named NW-SPAD-Net, that predicts SPAD performance for given nanowire configurations. NW-SPAD-Net predicts key metrics, including photon detection efficiency and dark count rate, with computational time reduced from hours (by conventional modeling methods) to seconds (by this work). NW-SPAD-Net consists of two artificial neural networks: an electric field and a quantum efficiency prediction sub-networks, both of which achieved superior training mean squared errors ($< 9\times10^{-4}$). Our approach accelerates the prototyping and iterative design process, providing an efficient model for designing next-generation high-performance nanowire single-photon detectors.**

I. Introduction

Single-photon avalanche detectors (SPADs) are crucial in cutting-edge applications such as quantum communications and light detection and ranging (LiDAR) [1]. These devices harness the avalanche effect, where a single photon hitting the detector and generating an electron-hole pair sets off a chain reaction of electron multiplication. The avalanche process amplifies the signal to a level large enough to be registered by the external electronics.

Traditional near-infrared single-photon avalanche detectors often rely on planar InGaAs/InP and Ge-on-Si structures, for which mitigating the performance trade-off between dark count rate and photon detection efficiency remains a challenging issue. Recent advancements have highlighted the potential of employing III-V compound semiconductor nanowires for single-photon avalanche detectors to minimise the trade-off between photon detection efficiency and dark count rate [3]. However, nanowires' complicated material growth and device fabrication processes require precise predictive modeling to optimize designs before experiments begin. Traditionally, SPAD modeling has been a slow and resource-intensive process. It relies on methods such as Monte-Carlo simulations or steady-state drift-diffusion models, where the former often require extensive random trials to accurately predict outcomes, and the latter constantly struggles with numerical convergence beyond avalanche breakdown [3].

This paper introduces a deep learning-based model that substantially speeds up SPAD modeling, reducing computation time from hours to seconds. Using advanced artificial neural network architectures, our model efficiently predicts key performance metrics such as photon detection efficiency (PDE), dark count rate (DCR), avalanche triggering probability (ATP) and quantum efficiency (QE). With the proposed workflow, users can generate a detailed mapping between the nanowire's properties (e.g., nanowire lengths and doping) and PDE and DCR; coupled with general optimization algorithms, one can easily find a group of optimal candidate structures with minimized performance trade-offs. These short-listed candidate structures will significantly accelerate the time-consuming material growth and device fabrication cycles.

II. Methodology

The proposed deep-learning-based framework is named nanowire single-photon avalanche detector prediction net (NW-SPAD-Net), based on a full-connection network, where artificial neurons between each layer are fully connected. NW-SPAD-Net consists of two sub-networks: i) the electric field prediction network is specifically tailored to accurately predict the electric field within the nanowires, a critical parameter that can be used to calculate photon detection efficiency and dark count rate, and ii) the quantum efficiency prediction network is used to predict the intrinsic light absorption efficiency within a nanowire. These networks are designed to handle the experimentally accessible input parameters that characterize a nanowire's physical and electrical properties. This includes the length of each segment, doping concentrations, and applied voltage. The NW-SPAD-Net is constructed assuming that nanowires have the most common axial p-i-n device structure grown by the metal-organic chemical-vapor deposition (MOCVD) technique [2]. The model has seven input parameters, including p-/i-/n-region lengths, doping concentrations for each region, and the applied voltage. The electric field prediction network takes all parameters, while the quantum efficiency prediction network works without the applied voltage.

The development of two separate sub-networks is to ensure that different physics models involved in predicting electric fields and quantum efficiency can be learned by the neural networks more accurately. NW-SPAD-Net operates as follows: 1) given a vector of seven nanowire parameters, the electric field prediction sub-network calculates a spatial distribution of electric field within a nanowire, which is then used to determine the avalanche triggering probability (ATP); 2) the quantum efficiency prediction sub-network also generates a spatial quantum efficiency distribution; 3) photon detection efficiency can be computed based on ATP and quantum efficiency; 4) extra information on nanowire's bulk/interface defect densities, together with ATP, can be used to compute dark count rate.

III. Results

We conducted the simulations for SPADs based on indium phosphide (InP) nanowires operated at 150 K. For demonstration, only the nanowire's segment length was varied while the nanowire's total length and doping concentrations were fixed. The p-region is fixed at 1 μm, and the i-region length is varied from 600 to 1800 nm, with the n-region length changed correspondingly. The p-/n-region doping is 10^{18} cm^{-3}, and the i-region is slightly n-doped (10^{16} cm^{-3}) due to background doping commonly observed in undoped InP nanowires grown by selective-area MOCVD [2]. The training data was generated by the time-dependent drift-diffusion model [3] with the Semiconductor Module, COMSOL Multiphysics [4]. The electric field prediction sub-network achieved a mean squared error (MSE) of 0.00077 for training, 0.00084 for validation, and 0.00108 for testing. The quantum efficiency prediction sub-network achieved an MSE of 0.00096 for training, 0.00264 for validation, and 0.00466 for testing. The training process was completed in only 1 minute and 37 seconds, allowing for predictions of spatial distributions of electric field and quantum efficiency in less than a second per input nanowire structure.

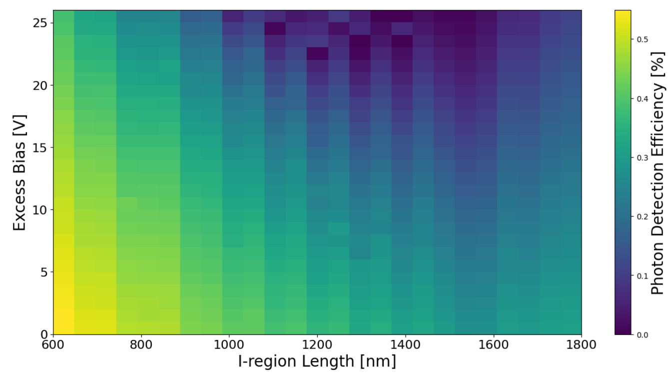

Fig. 1. Photon detection efficiency mapping as a function of the i-region length (from 600 nm to 1800 nm) and applied excess bias (from 0 to 25 V).

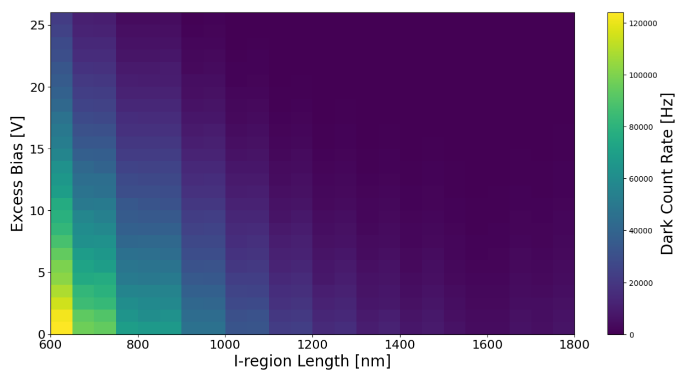

Fig. 2. Dark count rate mapping as a function of the i-region length and excess bias. A defect density of 10^{14} cm^{-3} was used.

Figures 1 and 2 show a mapping of photon detection efficiency and dark count rate, respectively, as a function of the i-region length and excess bias (i.e., the bias above the individual breakdown voltage). The overlap between high PDE and low DCR regions in these two mappings gives the optimal nanowire structures and operating conditions. A bulk defect density of 10^{14} cm^{-3} was used for the dark count rate calculation. Such a density typically indicates poor material-quality nanowires grown by MOCVD. Nevertheless, there is still a large overlap of high PDE and low DCR, featuring larger i-region lengths and higher operating excess biases. Such performance mapping, coupled with any generic optimization algorithms, can assist researchers in locating the optimal device designs with minimal trial-and-error efforts.

IV. Conclusion

We proposed a deep-learning based NW-SPAD-Net that can efficiently predict photon detection efficiency and dark count rate for nanowire single-photon avalanche detectors with high accuracy and minimal computation time. The demonstrated PDE and DCR mappings generated by the NW-SPAD-Net reveal the great potential of nanowire SPADs that can effectively mitigate the trade-offs between key performance metrics. The proposed NW-SPAD-Net greatly advances the high-throughput, highly efficient SPAD design workflow and toolkits.

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References

[1] Xuanyu Qian et al., *"Modeling for single-photon avalanche diodes: State-of-the-art and research challenges."*, Sensors (2023), 23(7), 3412.

[2] Ziyuan Li et al., *"Review on III-V Semiconductor Single Nanowire-Based Room Temperature Infrared Photodetectors."*, Materials (2020), 13, 1400.

[3] Zhe Li et al., *"An efficient modeling workflow for high-performance nanowire single-photon avalanche detector."*, Nanotechnology (2024), 35, 175209.

[4] COMSOL Multiphysics v5.5. www.comsol.com. COMSOL AB, Stockholm, Sweden.