# Physics-informed neural networks for drift–diffusion simulation of silicon solar cells: a current-based formulation and a comparison with finite volumes

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## Abstract

Physics-informed neural networks (PINNs), which solve differential equations by minimizing the residual of the governing physics without a mesh, are increasingly proposed for semiconductor device simulation [1]. However, no PINN has yet computed the current–voltage (J–V) characteristic of an illuminated solar cell, nor been compared on equal terms with a classical solver [4]. We solve the full drift–diffusion system for a one-dimensional $n^+$–p silicon cell (Fig. 1a), with SRH, Auger and radiative recombination, AM1.5G generation and finite surface recombination, against a verified DEVSIM finite-volume reference [2].

The conventional formulation, in which the network outputs the quasi-Fermi levels, overestimates the current by about eight orders of magnitude, because in the heavily doped emitter the required quasi-Fermi-level gradient (~$3\times10^{-8}$ in scaled units) cannot be resolved. We instead let the network output the potential and the electron current, and recover the quasi-Fermi levels from a Slotboom-type integral with exponential fitting [3]; current conservation and the contact conditions are imposed by construction (Fig. 1b).

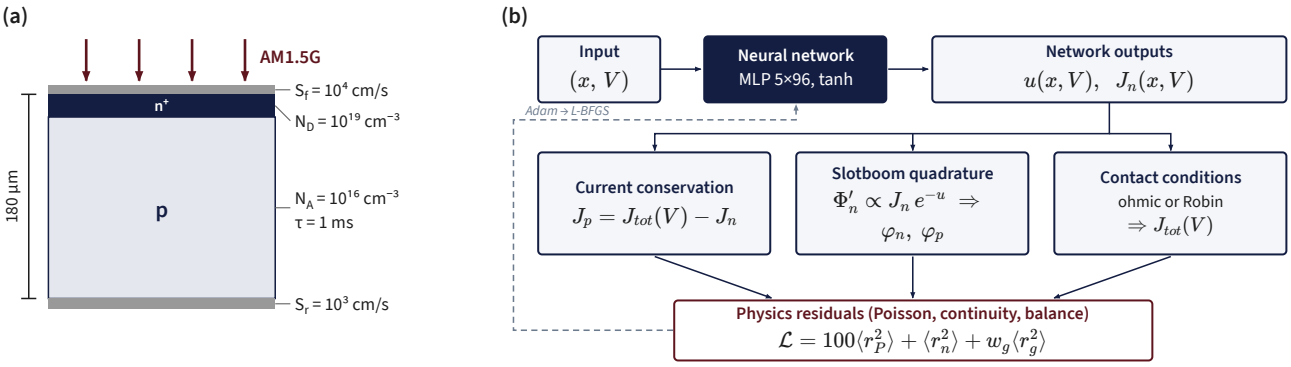


**Figure 1.** (a) One-dimensional $n^+$–p silicon cell studied (not to scale). (b) Current-based PINN formulation: the quasi-Fermi levels are reconstructed from the predicted current instead of being network outputs.

With ohmic contacts, the PINN reproduces the illuminated J–V curve with an efficiency error of 0.19% (median of three seeds; Fig. 2a), and of 1.2% with finite surface recombination. When the full computational cost is counted, however, the PINN was not advantageous: with five varied parameters, a neural network fitted to 64 DEVSIM runs (about 2 min) reaches 0.17%, against 4.1% for the PINN after 103 min of training (Fig. 2b). A current-based, exponentially fitted formulation is thus required for PINNs to work on solar cells, whereas for parametric one-dimensional modelling, classical solvers and data-driven surrogates remain the better choice.

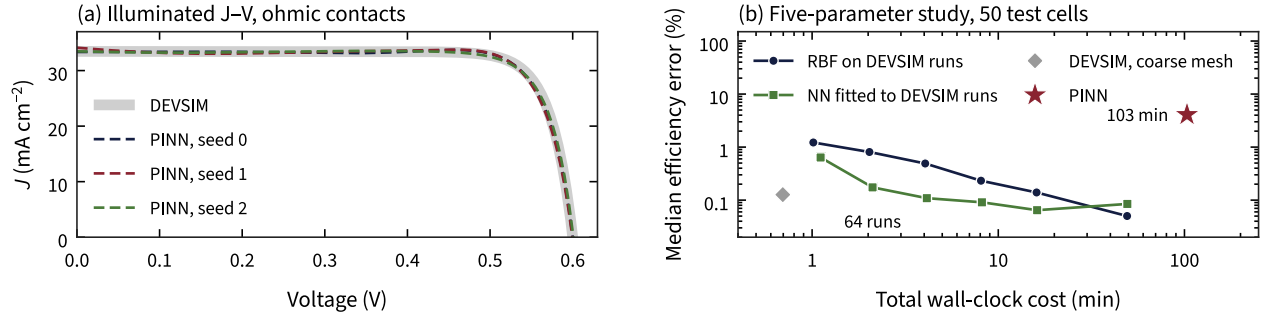


**Figure 2.** (a) J–V characteristic under AM1.5G computed with DEVSIM and with the PINN for three seeds. (b) Median efficiency error against total computational cost when five parameters are varied (τ, $S_f$, $S_r$, $N_A$, $N_D$).

**Keywords:** physics-informed neural networks; drift–diffusion; silicon solar cells; Slotboom variables; device simulation.

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