Physical Analogue Kolmogorov-Arnold Networks based on Reconfigurable Nonlinear-Processing Units

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The recent emergence of Kolmogorov–Arnold Networks (KANs), where learnable nonlinear functions are placed on network edges rather than fixed activations on nodes [1], opens a natural opportunity for physical analogue computing, where nonlinear device characteristics can directly embody these edge functions. We present a physical analogue implementation of KANs in which univariate functions are directly learnt *in-materia* using Reconfigurable Nonlinear Processing Units (RNPUs) [2]. These multiterminal silicon devices exhibit tunable nonlinear I–V characteristics that serve as hardware-native KAN edge functions. By combining multiple RNPUs into edge-processing blocks and integrating mixed-signal interfacing, we built a system-level analogue KAN (aKAN) architecture capable of regression and classification with fully programmable nonlinear transformations [3].

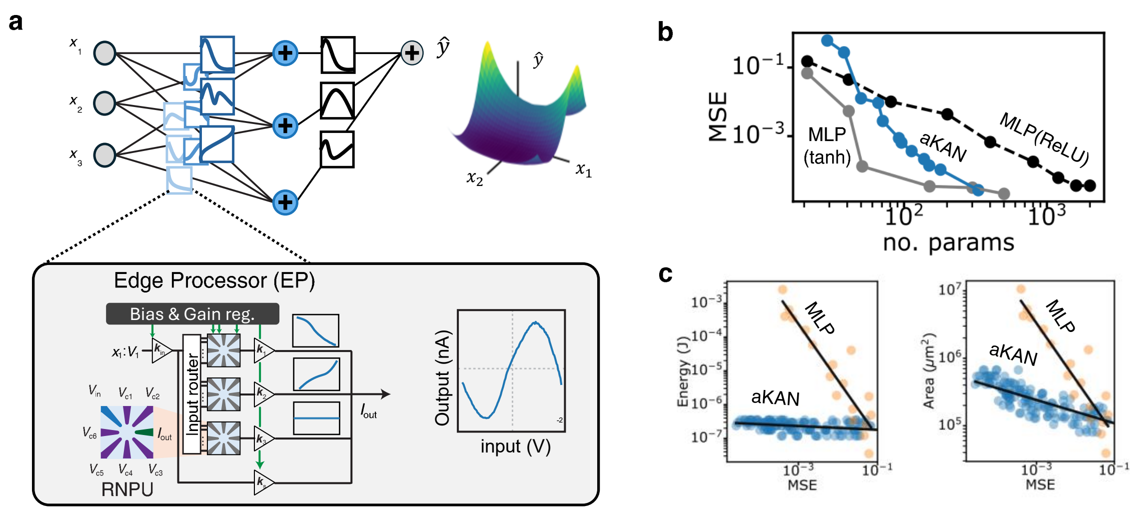

Figure 1: (a) KAN approach and RNPU-based edge processor. (b) Scalability of aKANs vs. MLPs, and (c) energy and area comparison, evaluated on the same function-approximation example.

Using experimentally calibrated device models and hardware measurements, we demonstrate accurate function approximation across tasks of increasing complexity while requiring fewer or comparable trainable parameters than Multi-Layer Perceptrons (MLPs). As part of a full inference pipeline, aKAN achieves up to two to three orders of magnitude lower energy and up to $\sim$10× lower area than a comparable digital fixed-point MLP. These results establish RNPUs as effective physical primitives for analogue nonlinear computation, and demonstrate that the KAN framework provides a natural and powerful abstraction for harnessing the intrinsic nonlinear richness of reconfigurable analogue devices.

[1] Z. Liu et al., arXiv, arXiv:2404.19756, 2024.

[2] T. Chen et al., Nature, 577 (7790), 341-345, 2020.

[3] M. Escudero et al., arXiv, arXiv:2602.07518, 2026.