Energy-Aware Training of Heterogeneous SNNs with Resonator and Integrator Neurons

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Biologically inspired Spiking Neural Networks (SNNs) have emerged as a compelling paradigm for energy-efficient, real-time signal processing, making them particularly well-suited for the deployment of embedded AI systems [1]-[3]. At the core of most SNN architectures lies the Leaky Integrate and Fire (LIF) spiking neuron model, which has historically dominated the field thanks to its straightforward structure and ease of hardware implementation — both of which contribute to its remarkably low energy footprint [4]-[5]. Despite these practical advantages, LIF neurons fall short in replicating several key neuro-computational properties found in biological neurons [6], and this limitation becomes especially apparent when dealing with complex spatiotemporal processing tasks that require richer neural dynamics [7]. To address these shortcomings, recent research has turned to computationally augmented neuron models. Among them, resonator neurons have demonstrated a notable ability to enhance network performance on such tasks [7]. However, this improvement does not come without a cost, as these more expressive neuron models tend to incur significantly higher energy consumption compared to their LIF counterparts [8]. This creates a fundamental tradeoff between accuracy and efficiency that has yet to be resolved. In this work, we tackle this challenge by investigating heterogeneous SNNs, in which resonator and LIF neurons are deliberately mixed within the same network architecture (see Figure 1). Our central hypothesis is that such a hybrid design can strike an advantageous balance, leveraging the computational richness of resonator neurons where needed, while relying on the efficiency of LIF neurons elsewhere. To guide this balance during training, we introduce an energy-aware regularization strategy (see Figure 1) that actively penalizes neurons with higher energy demands, with consumption estimates grounded in analog circuit implementations. Through extensive experiments on keyword spotting tasks, we demonstrate that our approach improves energy efficiency by a factor of 3, while preserving competitive accuracy — showing that heterogeneous SNNs can indeed make the best of both worlds.

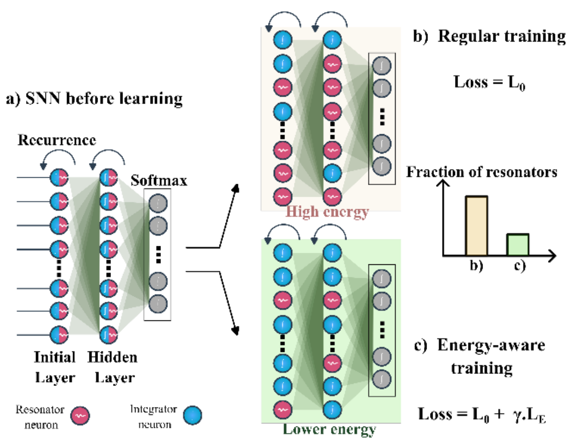

Figure 1: The topology of the neural network used with two types of learning can be used: either standard learning (top right) with a regular loss function, or the proposed energy-aware learning (bottom right) with an additional loss term that penalizes energy consumption by a factor γ.

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