Leveraging Spiking Neural Networks for Solar Energy Prediction in Agriculture

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Brain-Inspired Systems at UC Santa Cruz

Introduction

❖ **Motivation: Powering Cellular Base Stations w/ PV Panels**
- Solar-powered base stations (BS) offer a solution to the lack of power infrastructure by leveraging in-situ energy power generation.

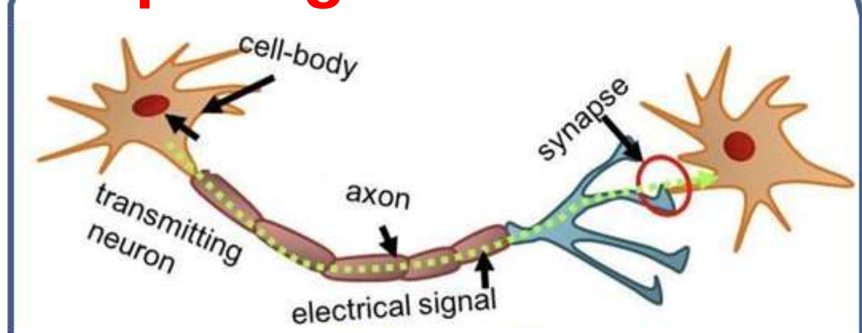
❖ **How can a system be optimized?**
- Future power output can assist in optimization
- Predictions of solar power generation are valuable for appropriate provisioning of photovoltaic (PV) panels and batteries, which can **reduce the cost** and use of environmentally harmful materials.
- The predictions can also influence network distribution models to balance user experience, BS power consumption, and battery preservation.

❖ **Solar energy provides clean** and **efficient** electricity, but its variability due to changing weather conditions poses challenges for integration into agricultural energy systems.

To achieve both accuracy and efficiency, we propose a Spiking Neural Network-based model that leverages weather forecast data to predict next-day hourly solar irradiance for agricultural applications.

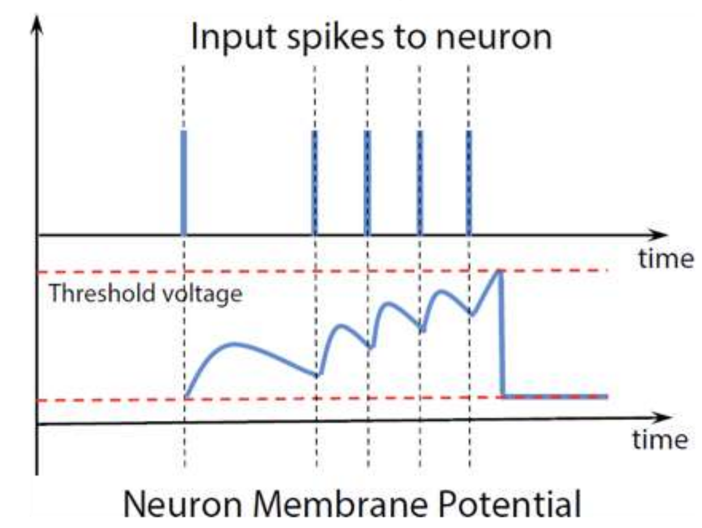
Method

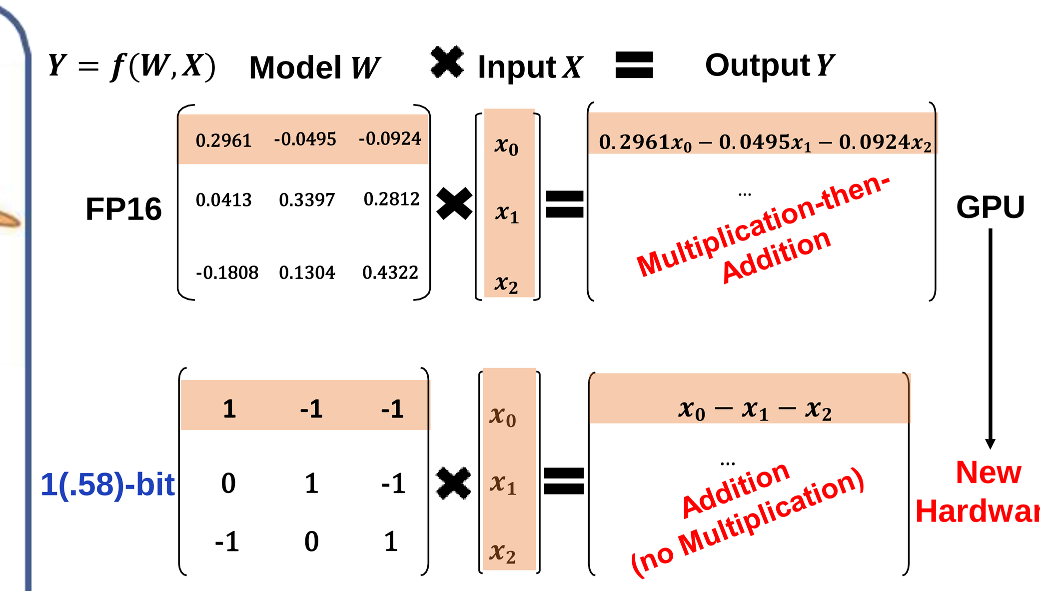
Spiking Neuron



LIF Equation:

$$C\frac{dV}{dt} = -\frac{V}{R} + \sum_j w_j I_{post,j}$$





Pure Addition

Integer	
Add	
8 bit	0.03pJ
32 bit	0.1pJ
Mult	
8 bit	0.2pJ
32 bit	3.1pJ

FP	
FAdd	
16 bit	0.4pJ
32 bit	0.9pJ
FMult	
16 bit	1.1pJ
32 bit	3.7pJ

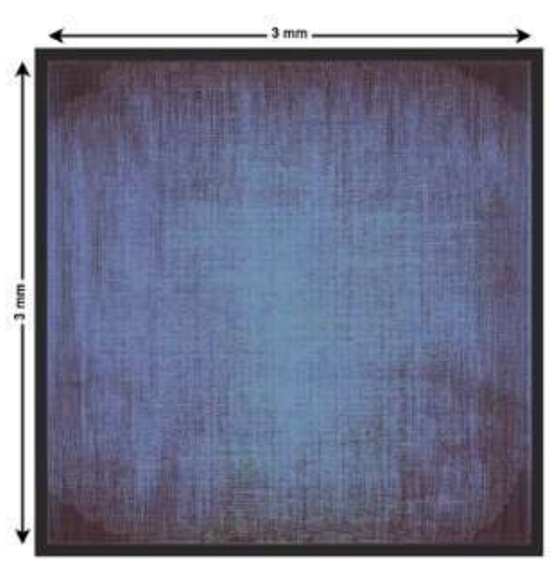
Memory	
Cache	(64bit)
8KB	10pJ
32KB	20pJ
1MB	100pJ
DRAM	1.3-2.6nJ

Leaky Integrate-and-fire Model
Simplest and most efficient

Benefits of using SNNs

1. Power Efficiency!

- More power for TX/RX



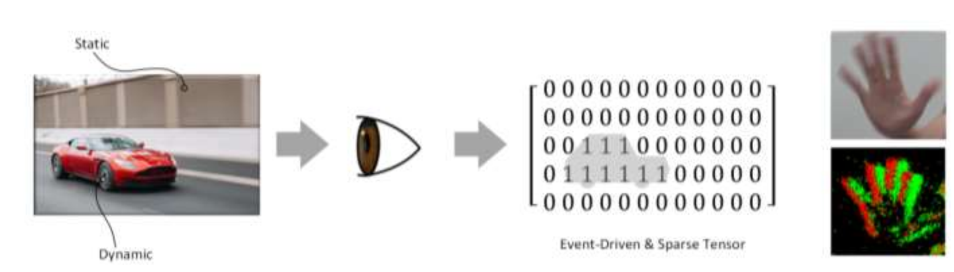
Generic Solar Panel
1000 W generation

Nvidia RTX 4090
450 W Consumption
(nearly half our power budget!)

OpenSpike
119 mW Consumption
Nothing!

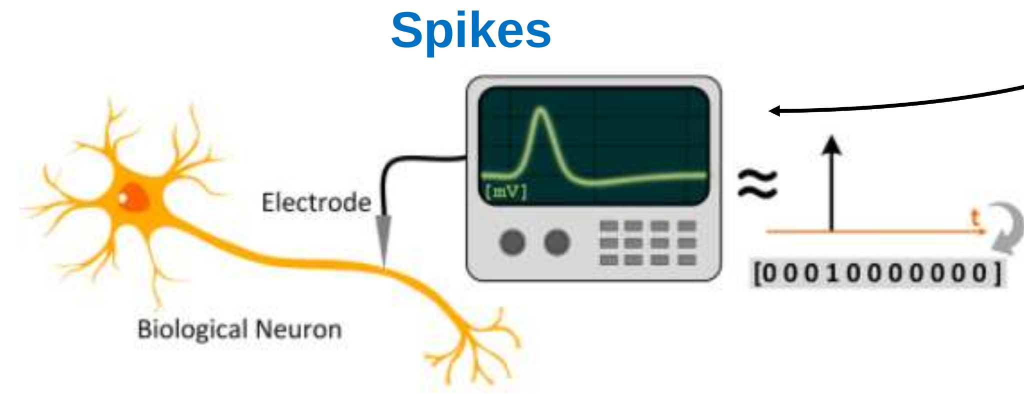
2. Spikes, Sparsity, Static Suppression!

- Biological neurons interact via single-bit spikes
- Biological neurons spend most of their time at rest, setting most activations to zero at any given time
- **Temporal sensitivity** for capturing complex patterns
- **Ideal for modeling weather** and solar dynamics.
- **Low power use** suits **embedded agricultural systems**.



Static Suppression (Event-driven processing)

Spikes



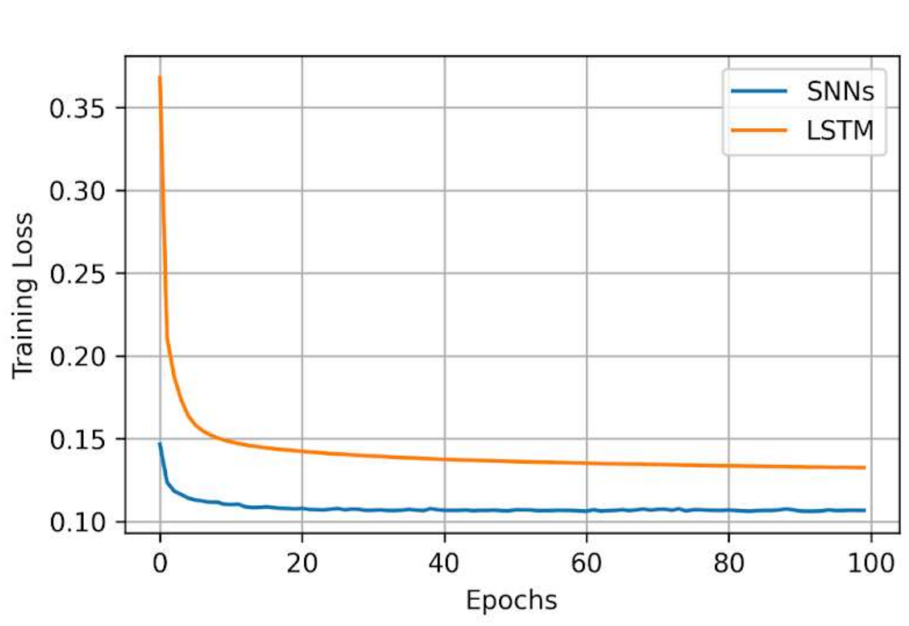
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 7, 0, 0, 0, 0, 0, 0, 0, 0, 0, 5]

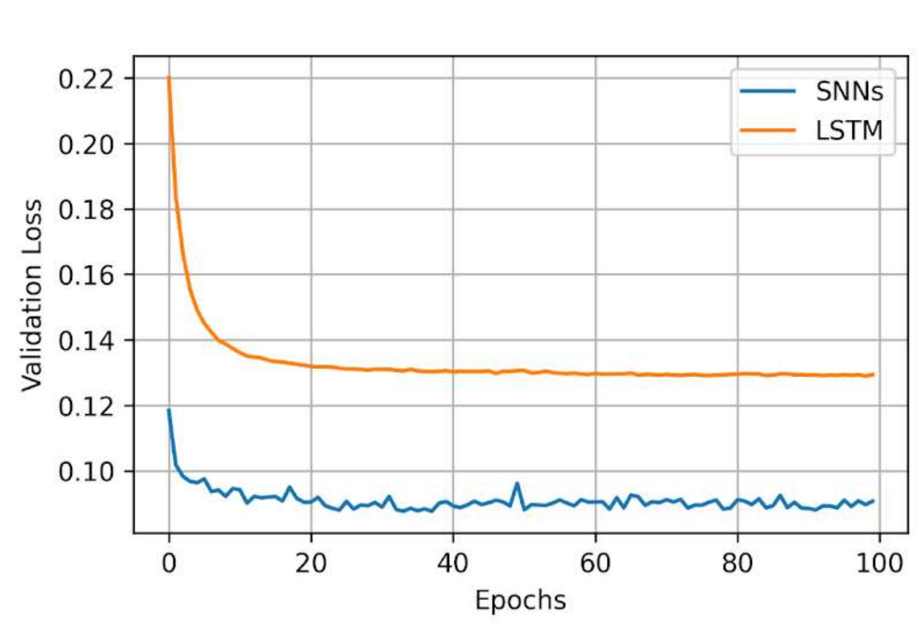
"7 at position 10; 5 at position 20"

Sparsity

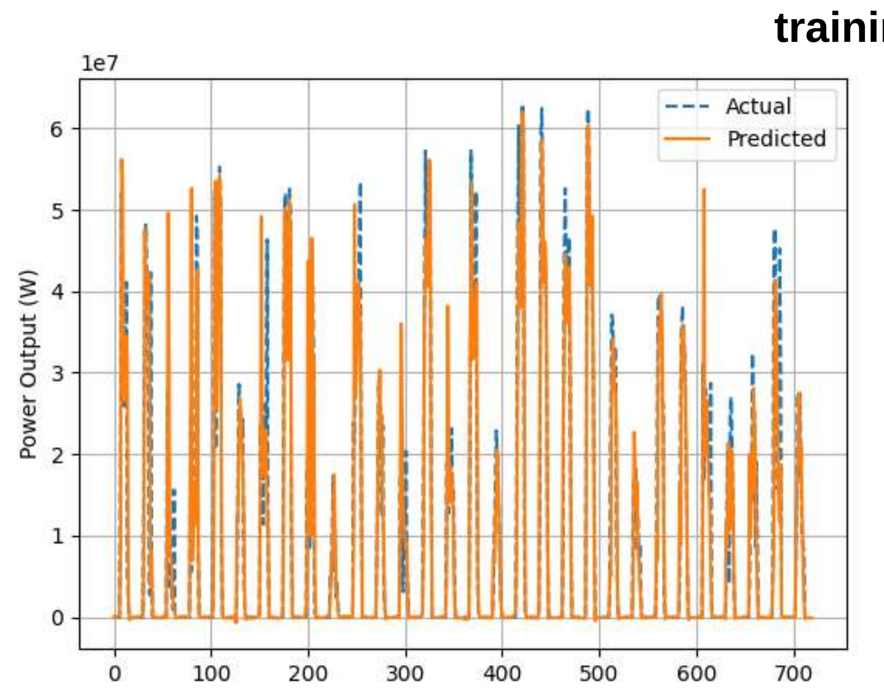
Experiments

❖ **Generalization Performance**
- Comparative analysis reveals that the SNN-based model performs comparably to the Long Short-Term Memory model.

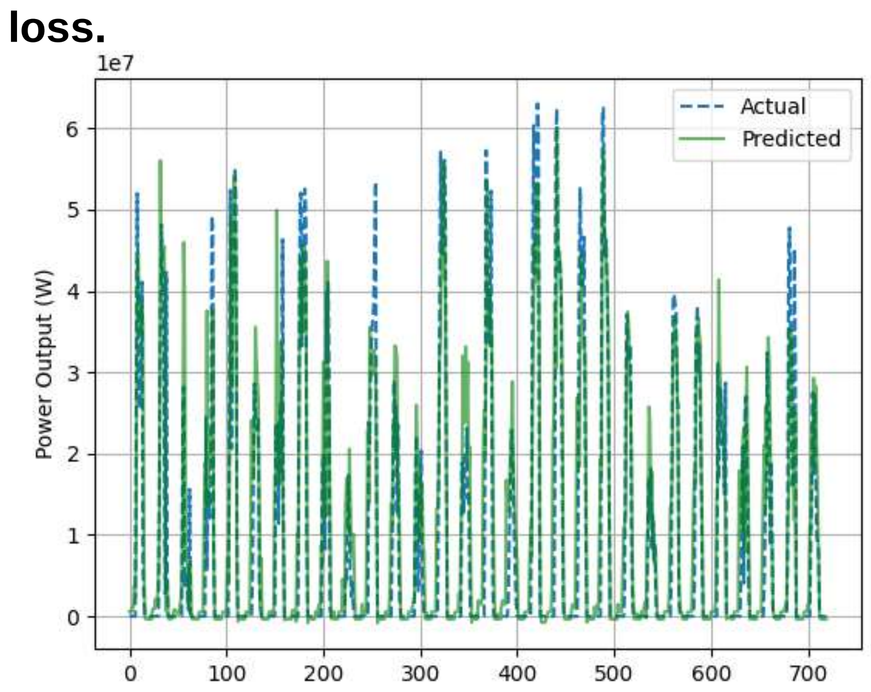




Performance metrics. It can be clearly seen that SNNs have lower validation and training loss.



PV Harvesting Energy Prediction by LSTM



PV Harvesting Energy Prediction by SNNs

❖ **Energy Efficiency for Optimal Performance**
- SNN-based model matches the accuracy of Long Short-Term Memory (LSTM) networks while **consuming only 4.3%** of the energy.

TABLE I
MEAN ABSOLUTE ERROR FOR THE TEST DATASET, DETERMINED BY VARIOUS PREDICTION METHODS. MDP DENOTES THE RESULTS OBTAINED USING THE MARKOV DECISION PROCESS.

Method	LSTM	SNNs	MDP
MAE	0.0509	0.0530	0.2

TABLE II
ENERGY CONSUMPTION COMPARISON BETWEEN LSTM AND SNN MODELS.

Model	Energy Consumption	Ratio to LSTM	SOPs
LSTM	2.30 μJ	1.0	500,100
SNN	0.098 μJ	0.043	109,059

- The energy consumption was calculated using the following methodology: Synaptic operations (SOPs) were determined for each architectural component using the equation:

$$\mathrm{SOPs}(l) = fr \times T \times \mathrm{FLOPs}(l)$$

where l is the block number, fr is the firing rate, T is the neuron time step, and FLOPs(l) are floating-point operations in the block.

- The **SNN's SOPs were calculated to be 109,059** with 15% firing rate (**85% sparsity**), while the LSTM's SOPs were 500,100.

❖ **References**

[1] Eshraghian, J. K., Ward, M., Neftci, E. O., Wang, X., Lenz, G., Dwivedi, G., ... & Lu, W. D. (2023). Training spiking neural networks using lessons from deep learning. Proceedings of the IEEE.
[2] Roy, K., Jaiswal, A., & Panda, P. (2019). Towards spike-based machine intelligence with neuromorphic computing. *Nature, 575(7784)*, 607-617.

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