Leveraging Spiking Neural Networks for Solar Energy Prediction in Agriculture

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Abstract

Can the efficiency of biological neurons revolutionize solar energy prediction in agriculture? Unlike traditional neural networks, Spiking Neural Networks (SNNs) mimic the sparse, event-driven nature of biological neurons, offering superior temporal model capacity and energy efficiency. We propose a deep learning model leveraging weather forecasting data from the National Renewable Energy Laboratory (NREL), eliminating the need for costly solar irradiance meters. Our SNN-based model matches the accuracy of Long Short-Term Memory (LSTM) networks while consuming only 4.3% of the energy. This significant reduction makes SNNs ideal for resource-constrained agricultural deployments. This study shows that brain-inspired computing can lead to more sustainable and efficient energy management in agriculture, transforming renewable energy integration in farming operations.

1 Introduction and Related Work

Renewable energy sources, especially solar energy, are becoming increasingly important for sustainable agriculture [1, 5, 6]. Solar energy [9] provides clean and efficient electricity, but its variability due to changing weather conditions poses challenges for integration into agricultural energy systems. Systems that minimize this unpredictability would help the technology's appeal by allowing farmers to make better-informed decisions on incorporating solar energy infrastructure. This study introduces the application of *Spiking Neural Networks (SNNs)*, a novel approach inspired by biological neurons, to predict photovoltaic (PV) power generation.

SNNs have the potential to improve prediction accuracy compared to traditional stateful models like *Long Short-Term Memory (LSTM)* [8] networks and the *Markov Decision Process* [10]. By encoding information into neuronal spike timing and/or firing rates, SNNs process information through precisely timed spikes, making them sensitive to temporal patterns and sequences in the input data. This enables SNNs to better capture temporal dynamics and non-linear relationships in weather and solar irradiance data. Their event-driven, sparse nature has the potential to also lead to better computational efficiency than traditional models, allowing for broader use in power-conscious systems such as embedded agricultural de‘ployments. Integrating weather forecast data aims to achieve high accuracy in forecasting next-day hourly solar irradiance, enabling better planning and utilization of PV panels and batteries in agriculture to reduce costs and environmental impact.

2 Methodology

Spiking Neural Networks resemble biological neurons [2–4] in their functionality, enabling sparse asynchronous computations and temporally regulated neural activity. Neuroscientists have devised various spiking neuron models to accurately represent the dynamics between the input and output signals of biological neurons. Among these, the Leaky Integrate-and-Fire (LIF) model [4] is commonly

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Table 1: 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

used for its simplicity and effectiveness within SNNs. The LIF model is mathematically expressed as:

$$\frac{dV(t)}{dt} = -\frac{V(t) - V_{\text{reset}}}{\tau} + X(t), \tag{1}$$

where $V(t)$ denotes the membrane potential of the neuron at time t, $X(t)$ is the input to the neuron at time t, τ is the membrane time constant, and V_{rest} represents the resting potential of the neuron. When the membrane potential $V(t)$ exceeds a predetermined threshold V_{th} at time t_f, the neuron fires a spike, subsequently resetting the membrane potential $V(t)$ to a lower reset value $V_{\text{reset}} < V_{\text{th}}$. This model strikes a balance between computational efficiency and biological fidelity. We use the LIF neuron model in all our simulations.

3 Results

We first train a simple LSTM network with a single layer of size 50 to use as a comparison to the SNN. We use *mean absolute error (MAE)* as our loss function. A batch size of 72 is used with the Adam optimizer. The dataset and the processing methods used are described in detail in Appendix A.1. To improve the model, we added output scaling to normalize the data to reasonable values with the results being shown Figure 1. Quantitative results in Table 1 show that SNNs perform comparably to LSTMs, with the advantage of energy efficiency.

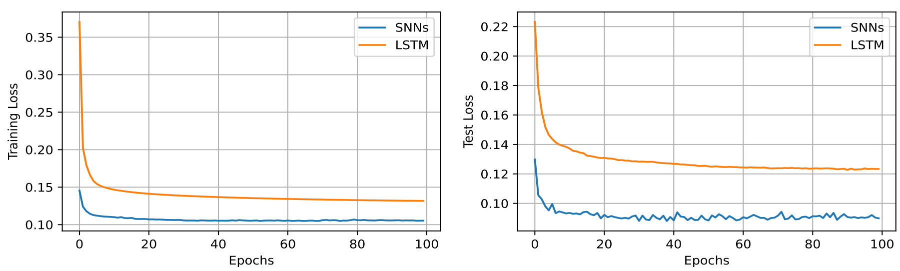

Figure 1: Performance metrics of training **(left)** and test loss **(right)**. It can be clearly seen that SNNs have lower test and training loss.

Energy Efficiency Comparison. To compare the energy efficiency of SNNs and LSTMs, we calculated the theoretical energy consumption for each model. Table 2 presents the results, demonstrating that SNNs consume significantly less energy than LSTMs. Detailed calculations can be found in the Appendix A.2.

Table 2: 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

4 Conclusion

To summarize, we propose an SNN-based model for solar energy prediction in agriculture and demonstrate its effectiveness. The model matches LSTM accuracy while consuming only 4.3% of the energy, highlighting the potential of neuron-inspired computing for efficient energy management. These findings can be further improved upon with the consideration of additional NREL datasets from other regions. Regardless, the results of this study give valuable insight into other applications requiring power efficient models and how the technology can be used for social good.

5 Acknowledgement

We thank Yawen Guo and John Madden from jLab for their help with dataset processing and discussions.

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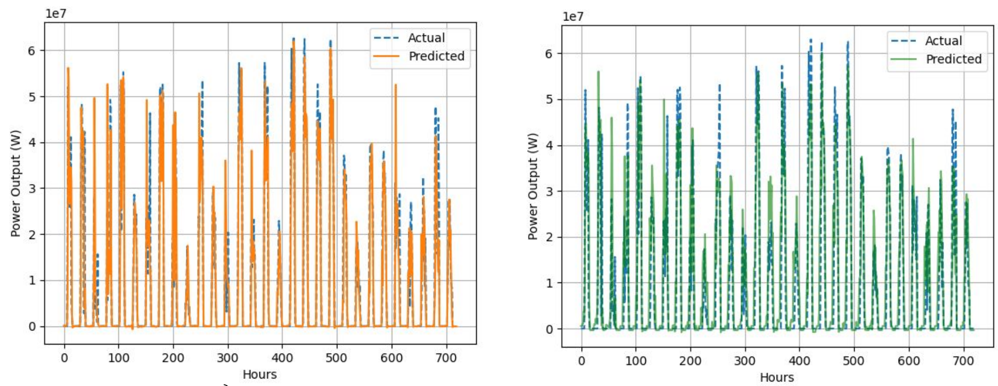
A Appendix

A.1 Training Details

We use 3-layers of leaky integrate-and-fire neurons with size 128. Notably, the last layer has the reset mechanism disabled to give us a single value output of membrane potential rather than the typical output spikes. The input features are passed directly into the network and repeated TIMESTEP=20 times. Figure 2(a) shows the power generation forecasting curve by LSTM and the actual curve, whereas that of by SNNs in 2(b).

Data We are using weather data obtained from the NREL System Advisor Model (SAM) application [7], which outputs .csv data aggregated annually for the specified location. For our initial tests we have selected weather data from a location near Des Moines, Iowa. This weather data is utilized in conjunction with the *nrel-pysam* Python module to model the power produced by a theoretical solar array, serving as a substitute for actual power output data. The nrel-pysam module lacks the capability to forecast power into the future, which is the primary objective of this project.

The dataset is segmented into training, validation, and testing periods, covering 18 years for training, 2 years for validation, and 1 year for testing. Both inputs and outputs are normalized to a standard distribution to facilitate model training. Scaling the input feature to the same distribution assigns them equal weights so that features with high magnitudes do not overpower other features.



a) b)

Figure 2: PV Energy Harvesting Prediction by LSTM **(left)** and SNNs **(right)**. (a) The blue dashed line represents the ground-truth value, while the solid orange lines depict the predictions made by LSTM. (b) The solid green line illustrates the prediction by SNNs.

A.2 Energy Efficiency Comparison

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

$$\mathrm{SOPs}(l) = fr \times T \times \mathrm{FLOPs}(l) \tag{2}$$

where l is the block number, fr is the firing rate, T is the neuron time step, and $\mathrm{FLOPs}(l)$ are the floating-point operations in the block. The SNN's SOPs were calculated to be 109,059 with a 15% firing rate (85% sparsity), while the LSTM's SOPs were 500,100.

Theoretical energy consumption for both SNN and ANN are assuming a chip based on 45 nm technology. Multiply-and-accumulate, or MAC, operations occur in both SNNs and ANNs and have an energy cost of $E_{MAC} = 4.6$ pJ. Spike-based accumulation, or AC, operations occur only in the SNN and have an energy cost of $E_{AC} = 0.9$ pJ. The SNN theoretical energy consumption is modeled as follows:

$$\begin{aligned} E_{SNN} = {} & E_{MAC} \times \mathrm{FLOP}^{1}_{\mathrm{SNN_{Conv}}} \\ & + E_{AC} \times \left(\sum_{n=2}^{N} \mathrm{SOP}^{n}_{\mathrm{SNN_{Conv}}} + \sum_{m=1}^{M} \mathrm{SOP}^{m}_{\mathrm{SNN_{FC}}} \right) \end{aligned} \tag{3}$$

The ANN (LSTM) model's energy consumption was calculated using:

$$E_{ANN} = E_{MAC} \times \mathrm{FLOP}_{\mathrm{ANN}} \tag{4}$$

This difference in energy calculation reflects the fundamental distinction between ANNs and SNNs. ANNs primarily use floating-point operations, particularly MAC operations, for all computations. In contrast, SNNs can leverage binary activations, which allows them to replace many floating-point MAC operations with simpler AC operations, potentially leading to significant energy savings.

The results demonstrate that SNNs consume merely 4.3% of the energy used by LSTMs, underscoring their remarkable energy efficiency. This comparison assumes SNNs are implemented on specialized hardware capable of leveraging their inherent sparsity, while ANNs are used in the same scenario without exploiting sparsity.