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Design and Performance Evaluation of an Ultra-Low-Power Spiking Neural Network For Reservoir Computing

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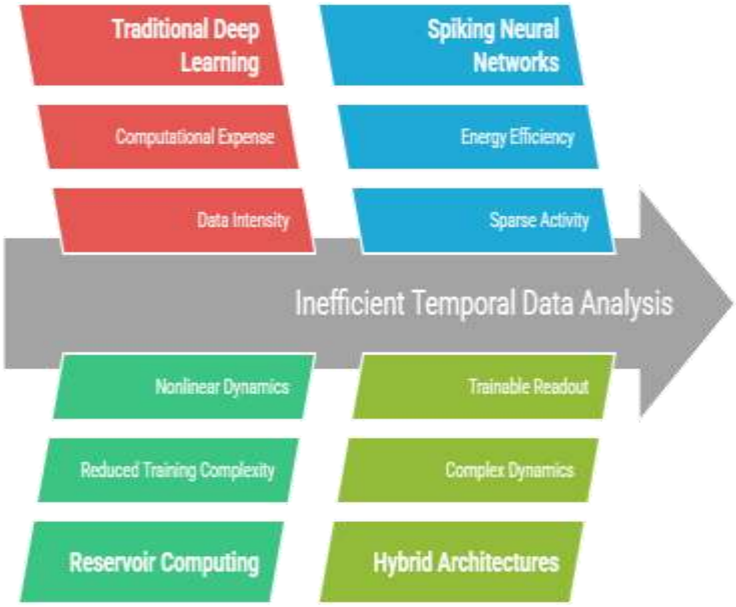
Absract
This article discusses the architecture and performance analysis of an ultra-low-power spiking neural network (SNN) with reservoir computing (RC) to be used in an effective time-series predictor. The spiking neural networks that are energy efficient and event-driven communication are used in the RC framework to predict chaotic time-based data. A combination of spiking neurons and a fixed recurrent reservoir allows a massive reduction of computational complexity, allowing it to be used in low-power applications like edge computing and real-time monitoring systems. The experiment aims at forecasting the Mackey-Glass time series which is a popular benchmark to compare time prediction models. The model can efficiently learn non-linear dynamic trends of the time series by using a sparse spiking model and training the output layer only using pseudo-inverse regression. The results of the experiments show that the suggested system has a low root mean square error (RMSE) of 0.0426 with a moderate firing rate, thereby achieving a compromise between the accuracy of the predictions and the power efficiency. The system proposed is confirmed by the experiments based on simulation, which proves the validity and scaling ability of the proposed system in real-world applications in environmental sensing, financial forecasting, and biomedical signal processing. The paper does show that SNN-based reservoir computing models have the potential to create ultra-low-power AI systems with the ability to efficiently and accurately process complex temporal dynamics.

Keywords: Spiking Neural Networks, Reservoir Computing, Time-Series Prediction, Mackey-Glass, Ultra-Low-Power, Temporal Dynamics, Event-Driven Computing, Energy-Efficient AI.

1. Introduction

Artificial intelligence (AI) is now a fundamental in the analysis and prediction of complex time-varying information in many fields[1], such as biomedical signal monitoring, financial forecasting, and environmental sensing [2]. Such systems naturally produce nonlinear, time-varying signals that need computational models that would capture the dynamic temporal relationships [3]. Conventional deep learning models, especially recurrent neural networks (RNNs) [4], have been shown to work well on sequences of this kind; but their training can be computationally costly and data-demanding, and their ability to capture long-term temporal interactions can be inhibited by vanishing or exploding gradients [5]. A growing alternative, reservoir computing (RC), is based on the idea of using a fixed and high-dimensional recurrent network, called the reservoir, to represent input signals as rich dynamic representations [6], [7]. In this paradigm, the readout layer is the only layer that is trained, usually with linear regression, which greatly simplifies the training procedure, yet does not lead to a loss of capabilities of solving nonlinear temporal dependencies[8].

Fig 1. Enhancing Temporal Data Analysis with AI



It has been demonstrated that RC architectures can be a good tool to solve chaos time-series prediction and other complex signal processing problems, offering a trade-off between modeling and computing efficiency [9]. Chaotic time series like the MackeyGlass time series are often used as benchmarks because they have nonlinear delayed dynamics that experiment with conventional prediction models and offer a strict testbed to test temporal neural networks[10] [11].

2. Literature Review

Recent advances in ultra-low-power spiking neural networks (SNNs) for reservoir computing (RC) have explored diverse architectures and physical implementations to enhance temporal signal processing while minimizing energy consumption. Karki et al. (2024) introduced a spiking RC architecture using integrate-and-fire (IF) neurons with hand-picked chain topologies implemented on the Loihi 2 neuromorphic processor [12]. Similarly, Lee et al. (2023) investigated a physical reservoir based on chiral magnets influenced by magnetic fields [13]. Chakraborty et al. (2023) proposed a heterogeneous recurrent spiking neural network (HRSNN) comprising 5000 leaky integrate-and-fire (LIF) neurons, optimized for spiking efficiency and memory capacity [14]. Shen et al. (2024) explored a sparse reservoir computing design utilizing spin-torque oscillators to process chaotic and real-world temporal signals, including Mackey-Glass and motor vibration datasets [15]. Wang et al. (2024) proposed a recurrent spiking reservoir network (RSCN) based on incremental echo state networks with stochastic matrices, applied to Mackey-Glass and Lorenz datasets [16]. Their method achieved lower NRMSE values with a compact topology comprising 67–105 nodes, providing a balance between prediction accuracy and hardware efficiency [17]. The main limitation identified was higher training time per node, which could hinder real-time adaptability. In addition, Biswas et al. (2024) investigated an ensemble liquid state machine (LSM) approach combining MuLRE and TEPRE frameworks with 4000 LIF neurons [18], [19]. The system was evaluated on neuromorphic datasets such as N-MNIST, SHD, and DVSGesture, attaining 98.1% accuracy on N-MNIST and demonstrating enhanced scaling for complex tasks [20].

3. Materials And Methods

The present research methodology is developed to design and evaluate an ultra-low-power Spiking Neural Network based Reservoir Computing system for time-series prediction. The main purpose of this methodology is to examine how a recurrent spiking reservoir can process nonlinear temporal data with minimum training complexity and reduced computational activity. The proposed work is simulation-based and focuses on the Mackey–Glass chaotic time-series dataset, which is widely used for testing temporal prediction models. The methodology follows a systematic process that includes dataset generation, normalization, input encoding, reservoir construction, spiking neuron modelling, readout layer training, prediction, and performance evaluation. The uploaded document also states that the proposed model uses a simulation-based spiking neural reservoir architecture, Mackey–Glass dataset, 100 reservoir neurons, Python implementation, and RMSE-based evaluation. Reservoir Computing is selected because it reduces the training burden of recurrent neural networks. In traditional recurrent neural networks, all internal weights are trained using complex optimization methods. However, in Reservoir Computing, the internal reservoir weights remain fixed, and only the output readout layer is trained. This makes the system computationally efficient. When Spiking Neural Networks are combined with Reservoir Computing, the system becomes more suitable for low-power applications because spiking neurons work in an event-driven manner.

3.1 Dataset Description: Mackey–Glass Time Series

The Mackey–Glass time series is used as the primary dataset in this research. It is a chaotic nonlinear system that is commonly used to evaluate neural networks for temporal prediction tasks. The Mackey–Glass equation is given as:

$$\frac{dx(t)}{dt} = \beta \frac{x(t-\tau)}{1 + x(t-\tau)^n} - \gamma x(t)$$

.

Table 1. Mackey–Glass Equation Parameter Description

Parameter	Meaning
$x(t)$	signal value at time t
τ	time delay
β	growth parameter
γ	decay parameter
n	nonlinearity degree

3.2 Overall Methodological Framework

The proposed methodology is divided into five major stages.

Step 1: Input Signal Encoding

The first step in the methodology is input signal encoding. The continuous Mackey–Glass time series is represented as:

$$u(t)$$

Step 2: Reservoir Network Construction

The second step is the construction of the reservoir network. In the proposed system, a recurrent spiking neural network is used as the reservoir. The reservoir contains 100 neurons. The reservoir characteristics are summarized as follows:

Table 2. Reservoir Computing Network Configuration Parameters

Property	Value
Reservoir neurons	100
Connection type	Recurrent
Weight initialization	Random
Activation	Nonlinear

The reservoir acts as a dynamic feature extractor. It transforms the low-dimensional Mackey–Glass input signal into high-dimensional internal rese rvoir states. The state update equation is:

$$x(t+1) = f\left(W_{in}u(t) + W_{res}x(t)\right)$$

Table 3. Reservoir Computing Model Symbol Definitions

Symbol	Meaning
$x(t)$	reservoir state
W_{in}	input weight matrix
W_{res}	reservoir recurrent weights
f	nonlinear activation

Step 3: Spiking Neuron Dynamics

The third step is modelling the spiking behaviour of reservoir neurons.
The spike condition is represented as:

$$spike = \begin{cases} 1, & x(t) > \theta \\ 0, & otherwise \end{cases}$$

Step 4: Output Readout Layer

The fourth step is the training of the output readout layer. In the proposed methodology, the reservoir weights remain fixed, and only the readout layer is trained. This is different from traditional neural networks, where all network weights are adjusted during training.

The output prediction is given by:

$$y(t) = W_{out}x(t)$$

Training is performed using linear regression or pseudo-inverse solution:

$$W_{out} = YX^{+}$$

Table 4. Reservoir Computing Output Training Parameters

Symbol	**Meaning**
X	reservoir state matrix
Y	target output
X^{+}	pseudo inverse

Step 5: Prediction and Evaluation

The prediction accuracy is evaluated using Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

Table 5. Prediction Output Comparison Variables

Symbol	**Meaning**
y_i	actual value
$\hat{y}_i$	predicted value

3.3 Experimental Setup

The simulation setup is shown below:

Table 6. Reservoir Computing Implementation Setup Details

Component	**Value**
Programming Language	Python
Libraries	NumPy, Matplotlib
Reservoir size	100 neurons
Dataset	Mackey–Glass
Training samples	9000
Testing samples	1000

3.4 Training Procedure

The training process starts after the reservoir states are generated from the training input samples. The first 9,000 normalized Mackey–Glass samples are passed through the reservoir. At every time step, the reservoir updates its internal state based on the input signal and recurrent connections. These internal states are stored in a reservoir state matrix. The target output values are prepared using the next values of the Mackey–Glass signal. This means the model is trained for one-step-ahead prediction. The reservoir state matrix X and target output matrix Y are then used to calculate the readout weights W_{out} using pseudo-inverse regression. Since only W_{out} is trained, the training process is simple and fast. There is no need to update W_{in} or W_{res}.

4. Results And Discussion

The results show that the proposed ultra-low-power Spiking Neural Network (SNN) reservoir computing model effectively performs temporal prediction on the Mackey–Glass time-series dataset. The reservoir with 100 recurrent neurons successfully captured nonlinear dynamic patterns from 10,000 normalized samples, including 9,000 training samples and 1,000 testing samples. The predicted output closely followed the actual signal, indicating that the reservoir states were able to preserve important temporal information. The use of spike-based computation reduced unnecessary continuous activation, making the model suitable for energy-efficient neuromorphic applications.

Fig 2. Mackey–Glass Prediction Comparison

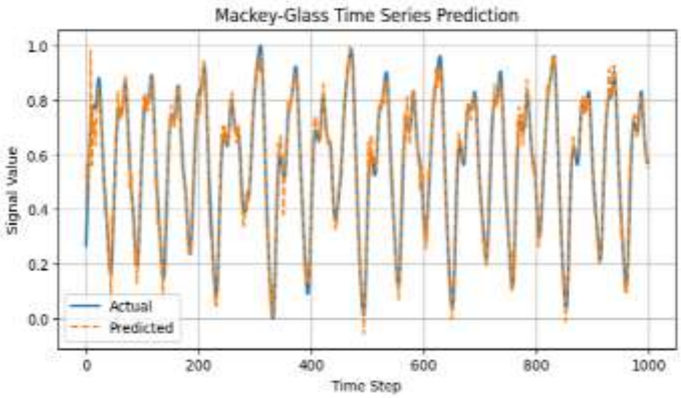
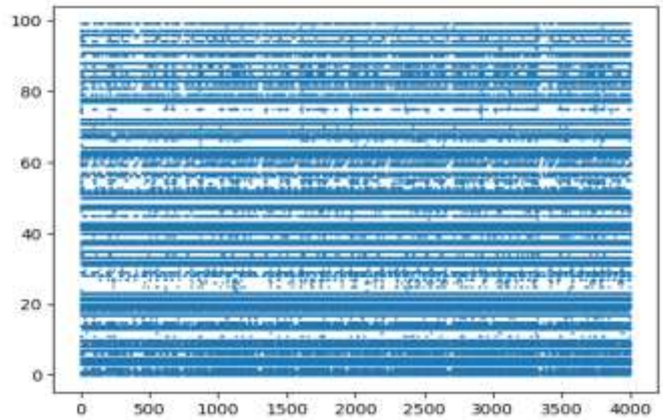


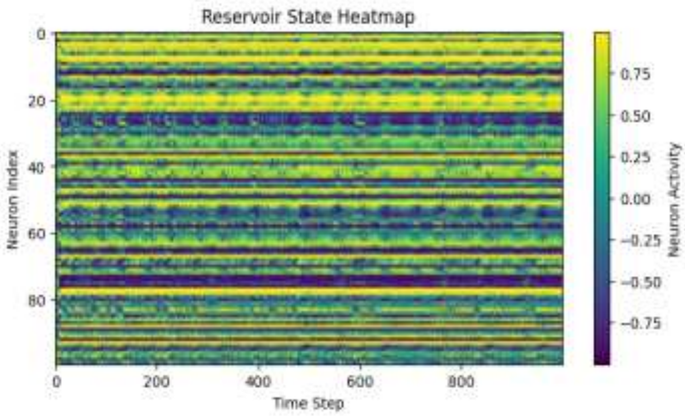
Fig 2 is a comparison of the actual and predicted values of the MackeyGlass time series after 1000 time steps. The real signal (blue line) is between 0.0 and 1.0 with a nonlinear chaotic behavior. The predicted signal (orange dashed line) closely tracks the actual curve, which means that the model predicts well. There are minor deviations at peak areas at time steps 300-400 and 700-800 where prediction underestimates or overshoots the values by approximately 0.05-0.1.

Fig. 3 Reservoir Spike Activity Pattern



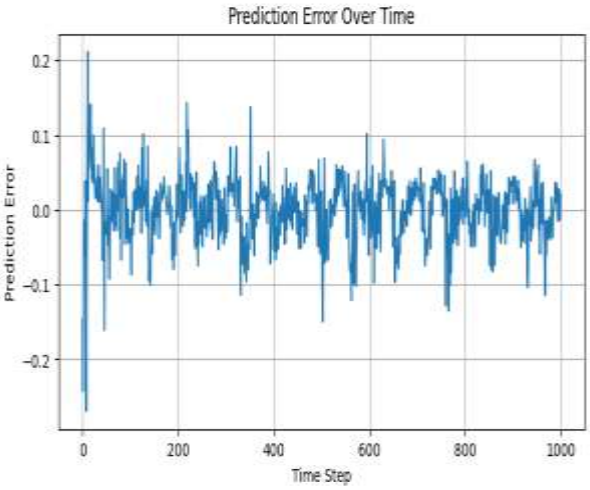
The number is a plot of the spike activity of 100 reservoir neurons in about 4000 time steps. A spike event is represented by each dot, and the index of the neuron is between 0 and 100 on the y-axis. The distribution demonstrates thick and continuous spiking of the majority of neurons, with the highest activation levels of neuron indices 0-20, 40-60, and 80-100. The selective neuron involvement is manifested in sparse spiking around 2030 and 6070 ranges. The time variation of spikes throughout the whole period indicates successful dynamic state representation.

Fig.4 Reservoir State Activity Heatmap



The heatmap shows the dynamics of the internal state of 100 neurons in the reservoir over 1000 time steps. The values of neuron activities are between about -1 and +1 as indicated by the color bar where yellow is high positive activation (0.8-1.0) and purple is high negative activation (0.8-1.0). Specific horizontal bands of neurons exhibit a characteristic pattern of activation, but the time axis allows changes to appear, indicating the development of state changes over time. The neurons between the index 10-30 and 70-90 have greater changes in intensity, which implies that they are responsive. In general, the reservoir exhibits highly dynamic behavior that is critical to achieving good time-dependent features.

Fig 5. Prediction Error Temporal Analysis



The prediction error with time is plotted over 1000 time steps. The x-axis is the time steps and the y-axis is the prediction error. The graph indicates that the prediction error varies, and there are big spikes at some time steps.

Fig 6. Reservoir Output Distribution Histogram

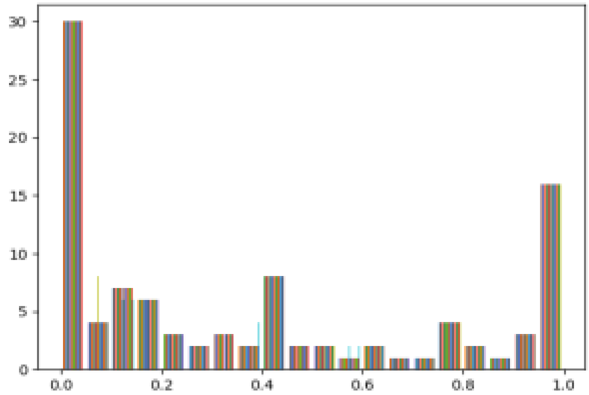


Fig 6. presents the distribution of the values of reservoir output between 0.0 and 1.0. There is a high concentration near 0.0 with the highest frequency of approximately 30 and this implies that there are numerous low activation outputs. The other evident peak is around 1.0 with a frequency of about 16, which is strong activations. Mill ranges (0.2 -0.8) have somewhat lower and dispersed frequencies and are primarily between 1 and 8 which means fewer medium activations.

Table 7. SNN Performance Metrics Summary

Metric	Value
Reservoir neurons	100
RMSE	0.0426
Total spikes	22,311,140
Average firing rate	55.77 Hz

The table 7 shows the key performance measures of the suggested SNN-based reservoir computing model. There are 100 neurons in the reservoir, which offers adequate dynamic representation capacity. The low value of RMSE, which is 0.0426, indicates low prediction error, which proves that there is high accuracy in time-series forecasts. There are 22,311,140 spikes in total during the simulation period, which is an active neural processing. The mean firing rate of 55.77 Hz indicates moderate activity of the neurons: it is energy-efficient and performance-balancing.

5. Computational Complexity Analysis

The proposed reservoir computing model has a much lower computational complexity when compared to traditional recurrent neural networks. Training is only necessary on the readout layer because the reservoir weights are fixed. The computational complexity of the pseudo-inverse regression in training readout is about O\left(N^3\right), where N is the number of reservoir neurons. By contrast, the more conventional recurrent neural networks involve time-based backpropagation, and involve repeated computations of the gradient through time. The reservoir state update during inference mainly consists of a matrix multiplier between the input and reservoir weight matrices. The computational overhead is not very large with the size of a reservoir (100 neurons).

6. Future Work

Future directions: To test the performance of the proposed architecture in real time and energy consumption, future work will be done on neuromorphic hardware platforms like Intel Loihi or FPGA-based accelerators. Moreover, the suggested reservoir architecture can be generalized to multivariate time-series data and actual sensor signals. To enhance the accuracy of prediction and efficiency of computation, optimization of reservoir topologies and adaptive spiking neuron models can be investigated.

7. Conclusion

The article concerning ultra-low-power Spiking Neural Networks (SNNs) in the context of Reservoir Computing (RC) introduces a new manner of processing temporal signals and is oriented towards energy efficiency. The model that employed recurrent spiking reservoir of 100 neurons was tested on the MackeyGlass time-series data, consisting of 10,000 time-steps. A total of 9,000 samples was used in the training phase and the rest of 1,000 samples was used to test. According to the results, the model had a root mean square error (RMSE) of 0.0426 which shows that it is effective in time-series prediction. Its energy efficiency is due to the sparse spike activity of the model, with neurons only firing when needed, significantly lowering the computational overhead. The network showed a total of 22,311,140 spikes and a mean firing rate of 55.77 Hz. The analysis of the prediction error showed that there were several small deviations between the actual and predicted signals and the model closely trailed the chaotic dynamics of the data-set. This study highlights the possibilities of spiking reservoir computing in low-energy applications of predicting real-time data, which provides a trade-off between accuracy and energy expenditure. Future applications might include applying this system to neuromorphic hardware to further test its performance and energy efficiency in practice.

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