Energy-Efficient Dynamic and Spatiotemporal Spectrum Access via Spiking Reservoir Computing

Nima Mohammadi, Lingjia Liu, Yifei Song, Yang Yi

Abstract

- Neuromorphic computing-based energy-efficient reinforcement learning for spectrum access
- Spiking neural networks (SNNs), liquid state machines, are adopted for energy efficiency
- Homeostatic regulation maintains near-chaotic reservoir dynamics for robustness.
- Numerical results show superior performance over existing models in throughput and power consumption.

Motivation

- Energy and compute constraints of IoT devices makes it difficult to deploy conventional DRL (DQN/DRQN/DEQN) strategies.
- Goal: energy-efficient opportunistic access in partially observable wireless environments

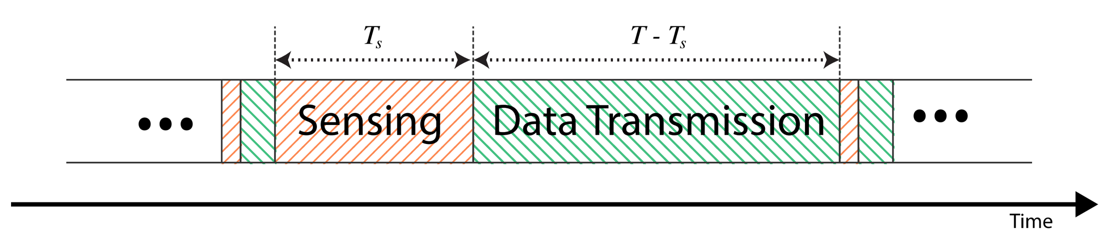
Key Contributions

- SNRPG: fully-spiking reservoir policy-gradient RL for spectrum access
- Liquid state machine (LSM) reservoir with small-world topology plus P-CRITICAL homeostasis for near-critical dynamics
- Outperforms DRQN/DEQN on PU/SU throughput;
- ~60x lower inference energy vs ANN baseline.

Method: SNRPG

- Architecture: LSM reservoir of spiking neurons → feed-forward spiking readout
- Reservoir: Small-world connectivity (high clustering, short paths) for rich fading memory
- Homeostasis: P-CRITICAL nudges mean branching factor $\bar{\eta} \lesssim 1$ (near-chaotic regime)
- Training: Surrogate-gradient on readout; event-driven sparse spiking for energy savings.

RL Formulation



For SU (agent) i we have:

State: $s^u[n] = (E^u[n], C^u[n])$

Action: $a^u[n] = (p^u[n], o^u[n])$

DSA: $o^u[n] \in \{\text{'Idle'}, \text{'Active'}\}$

SSA: $o^u[n] \in \{\text{'Idle'}, p_1, p_2, \ldots, p_K\}$

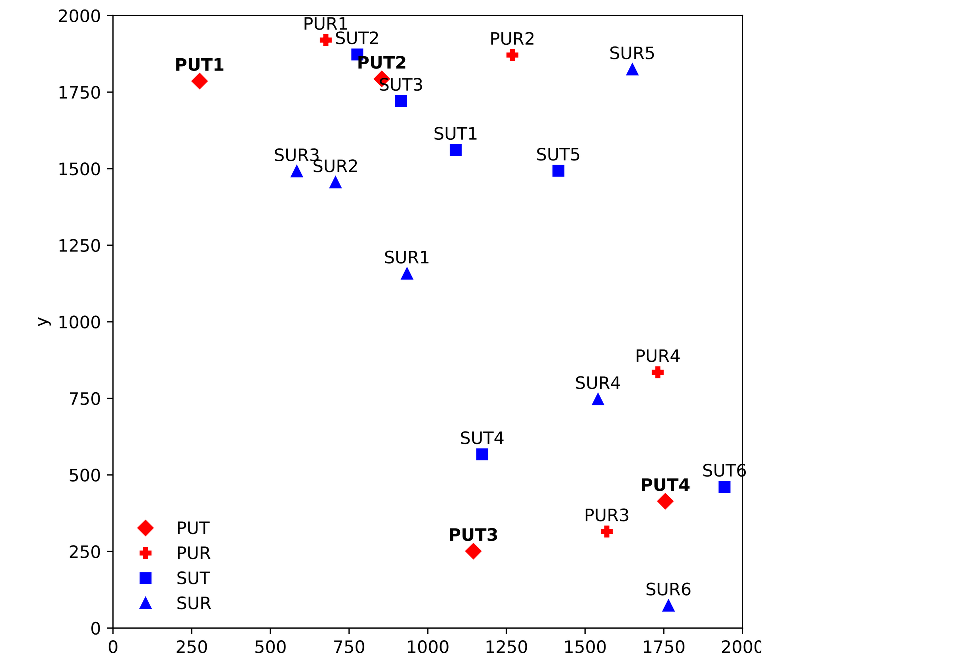
Reward:
$$r^u[n] = \beta_1 1(\eta_m^{PU}[n] < \tau) + \beta_2 1(o^u[n] = \text{' Idle'}) + \beta_3 \min\{\beta_4, \lfloor \eta_u^{SU}[n] \rfloor\} + \beta_4 o^u[n]$$

$$\eta_{i,m}^{PU/SU}[n] = \frac{1}{T - T_s} \sum_{t'=nT+T_s}^{(n+1)T-1} e_m^i[t']$$

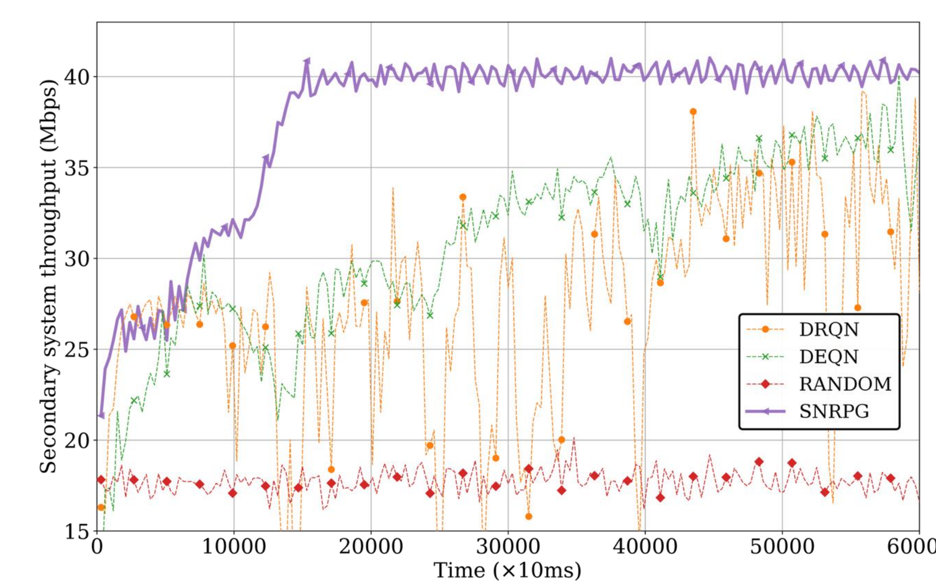
- Reward combines (i) PU protection, (ii) discourage idling, (iii) SU spectral efficiency (capped), and (iv) power penalty
- Training: online with replay

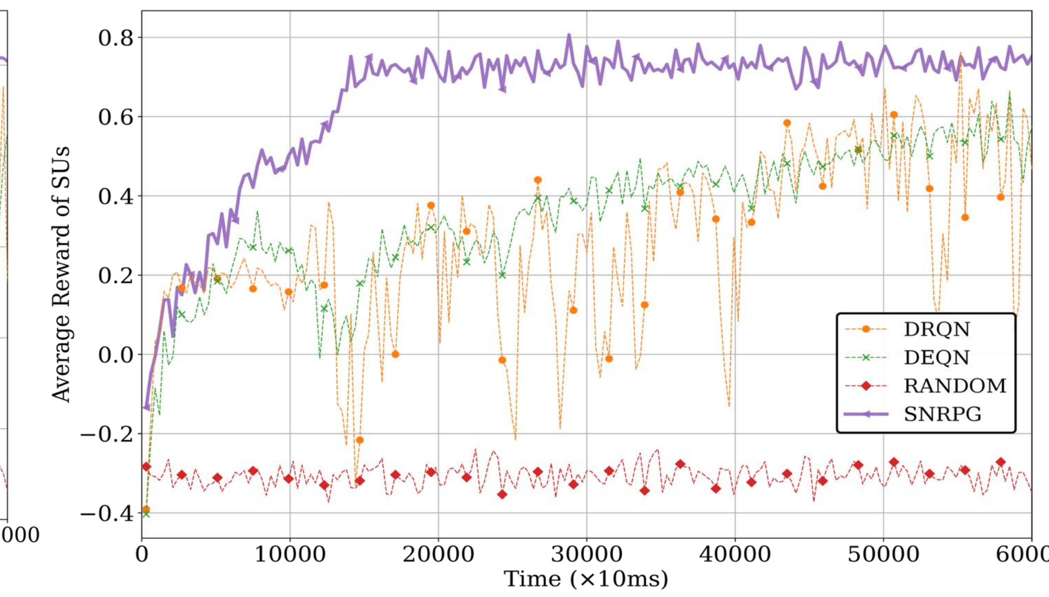
Simulation Results

Parameter	Value
Number of PUs	4
Number of SUs	6
Simulation area	2000m × 2000m
Channel bandwidths	5MHz
Duration of each time slot	1 ms
Sensing duration T_{sen}	2 time slots
PUT/PUR links	4
PUT/SUR interference links	24
PU Tx Power	500 mW
SU Tx Power (DSA)	500 mW
SU Tx Power (SSA)	[50, 500] mW
Variance of Gaussian noise	−157.3 dBm
Sensing/transmission period	10 time slots
PUT/SUT sensing links	24
SUT/SUR links	36
SUT/PUR interference links	24

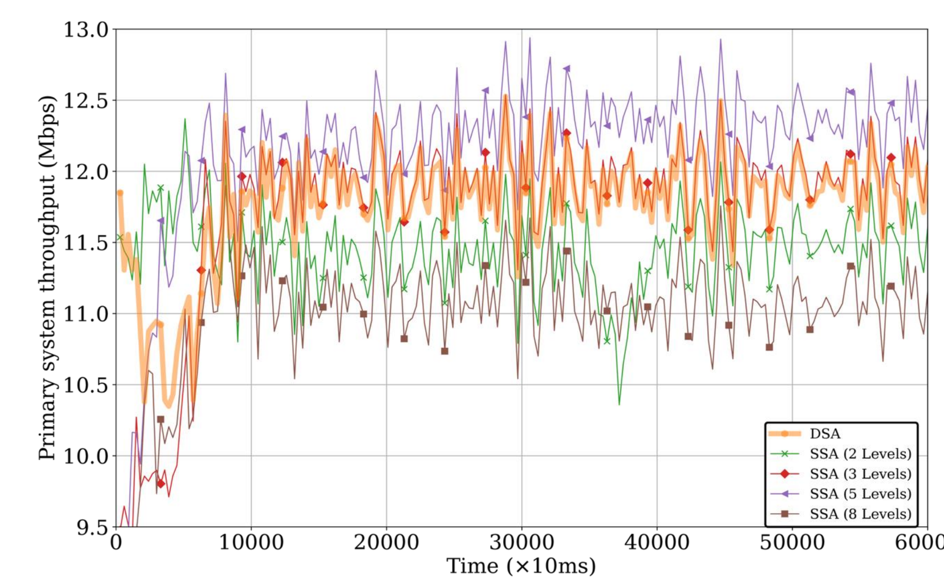


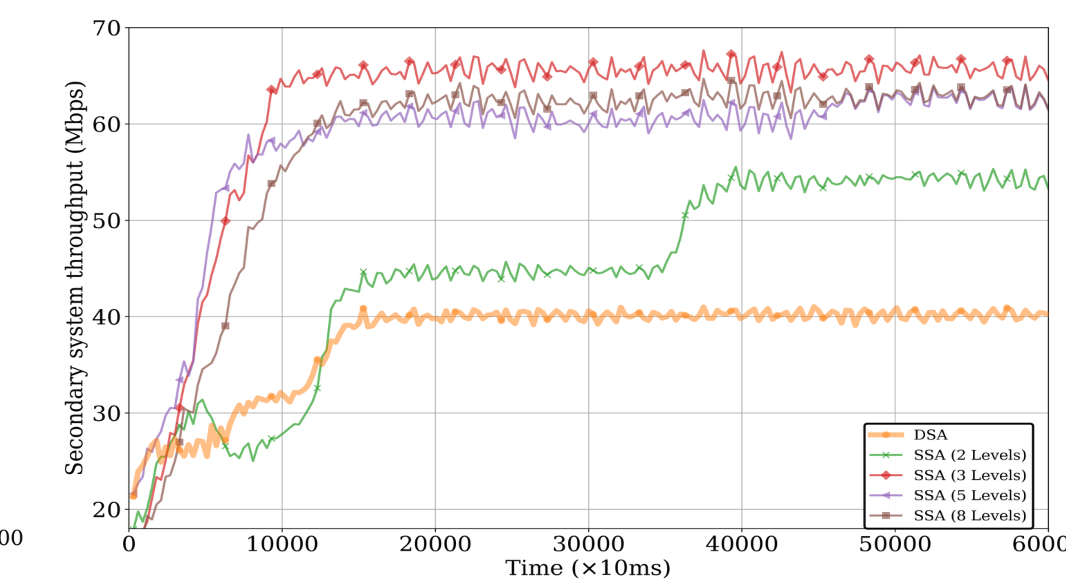
SNRPG vs SOTA: Primary (left) and Secondary (right) system throughputs:



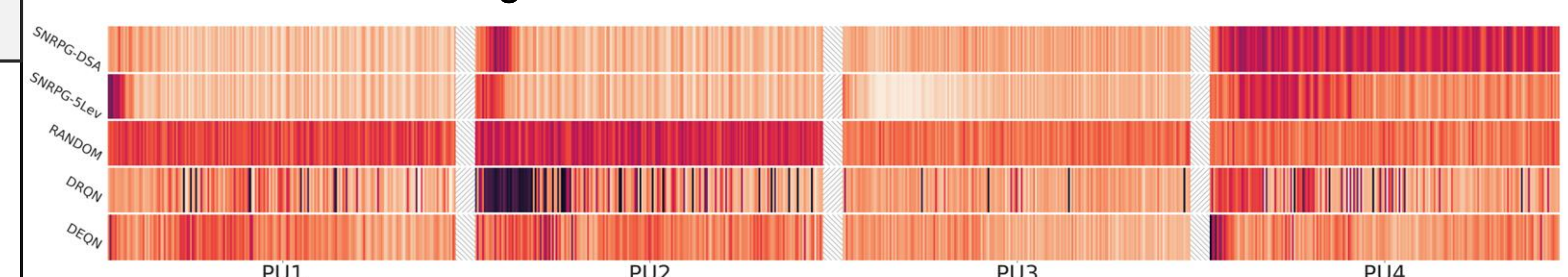


DSA vs SSA: Primary (left) and Secondary (right) system throughputs:





Emitted PU warnings:



- Energy-efficiency: Calculating E_{ANN}/E_{SNN} as $E_{MAC}/(E_{AC} \times A \times T)$ with $T = 10$, $E_{MAC} = 3.2\text{pJ}$ and $E_{AC} = 0.1\text{pJ}$ implies ~60 times improvement.

References

- Chang, H.H., Liu, L. and Yi, Y., 2020. Deep echo state Q-network (DEQN) and its application in dynamic spectrum sharing for 5G and beyond. IEEE Transactions on Neural Networks and Learning Systems.
- Panda P, Aketi SA, Roy K. Toward scalable, efficient, and accurate deep spiking neural networks with backward residual connections, stochastic softmax, and hybridization. Frontiers in Neuroscience. 2020 Jun 30;14:653.