

## Design and Performance Analysis of a Neuromodulable Spiking Recurrent Cell in the Context of Supervised Learning

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**Summary: Design and Performance Analysis of a  
Neuromodulable Spiking Recurrent Cell in the  
Context of Supervised Learning**

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MASTER THESIS COMPLETED FOR THE PURPOSE OF OBTAINING THE MASTER'S DEGREE IN  
ELECTRICAL ENGINEERING BY  
BERNARD Aurélien

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## Abstract

From the desire to understand how neurons work and how we learn, neuroscientists from early 1900 to the 1950s proposed increasingly more complex neuron models. However, no learning rule seemed to have a satisfactory performance until the invention of back-propagation which uses optimisation and calculus to optimise the performance at a certain task. This new learning rule required neural networks to steer away from highly non-linear biological neuron models to ones with continuous properties that allow them to work. Machine Learning researchers favoured this new technique and have obtained increasingly better results with increasingly larger networks, large amounts of data, more computing power necessary to use them, and inevitably, higher power requirements. In an attempt to solve the shortcomings of modern artificial neural networks, the machine learning community is looking again into bio-inspired spiking neural networks and new learning rules that would perform as well as backpropagation. To this date, these attempts have had varying levels of success but have all fallen short of the modern standards of machine learning. However, a recent contribution has proposed a new way of creating and training spiking neural networks by re-designing classical recurrent neural network cells to force them to exhibit spiking behaviour. This allows the use of backpropagation without the need for approximations or adaptations as other spiking neural network training methods have proposed in the past. In this work, we analyse the proposed spiking recurrent cell from a nonlinear systems dynamics perspective and observe some of its shortcomings. Then, we propose two new cells that extend and reduce some of the previously observed issues. Namely, we extend the cell by introducing neuromodulation capabilities to have 3 distinct types of excitability through the addition of a single parameter, and with the second proposed cell, we extend further its capabilities by introducing bursting behaviour. Finally, we perform tests on small neural networks composed of 42 neurons based on the former cell on the MNIST benchmark coded in spikes through latency, and rate coding. In the experiments, we first modulate the neurons to fixed firing types and analyse the performance and behaviour of the network on the 2 tasks. We then randomly initialise the modulation through the network and set it as a learnable parameter for the same tasks. In these tests, we have achieved 91% accuracy which is close to state-of-the-art performance on SNNs that contain more than 100 times the number of neurons. Furthermore, we have observed that in the current setup, the network does not use a heterogeneity of firing types in the network to obtain the best results. Instead, it converges to one of the newly introduced firing types.

Concisely, the main goal of this work is to introduce neuromodulation to a spiking neural network cell that learns through direct backpropagation, and show that modulation can also be learned through this same learning algorithm to obtain satisfactory results.

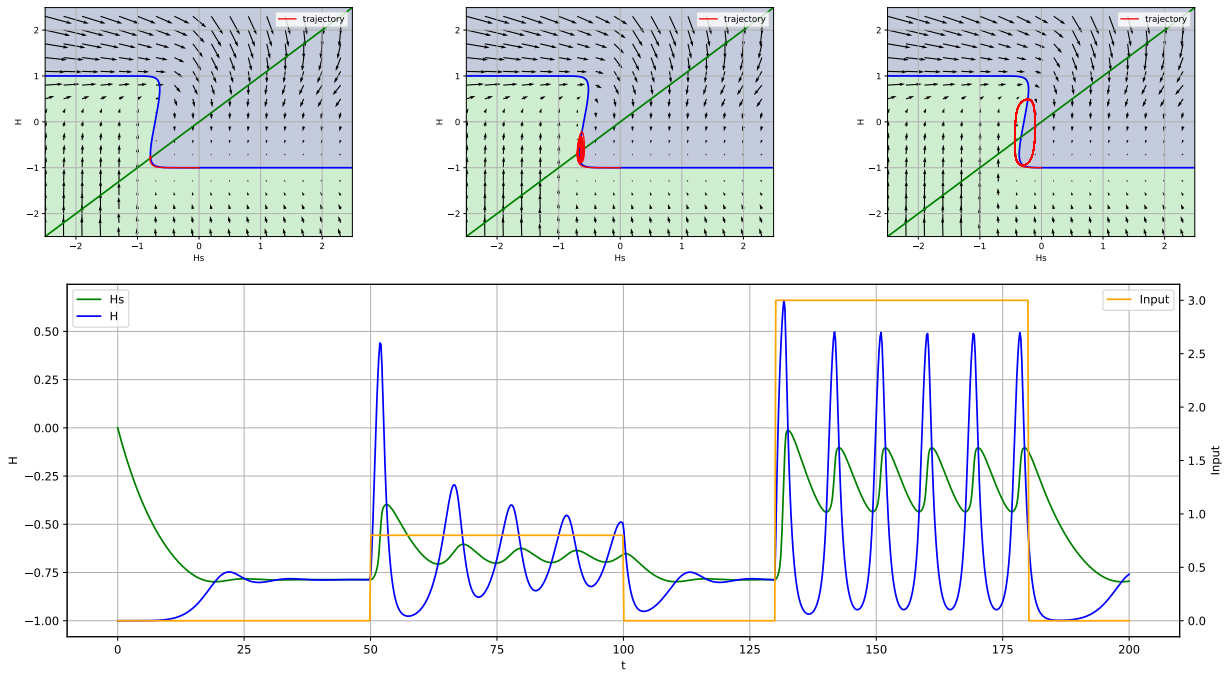


Figure 1: Phase portraits and voltage trace of the SRC cell at  $I_{app} = 0, 0.85$ , and  $3$  respectively.

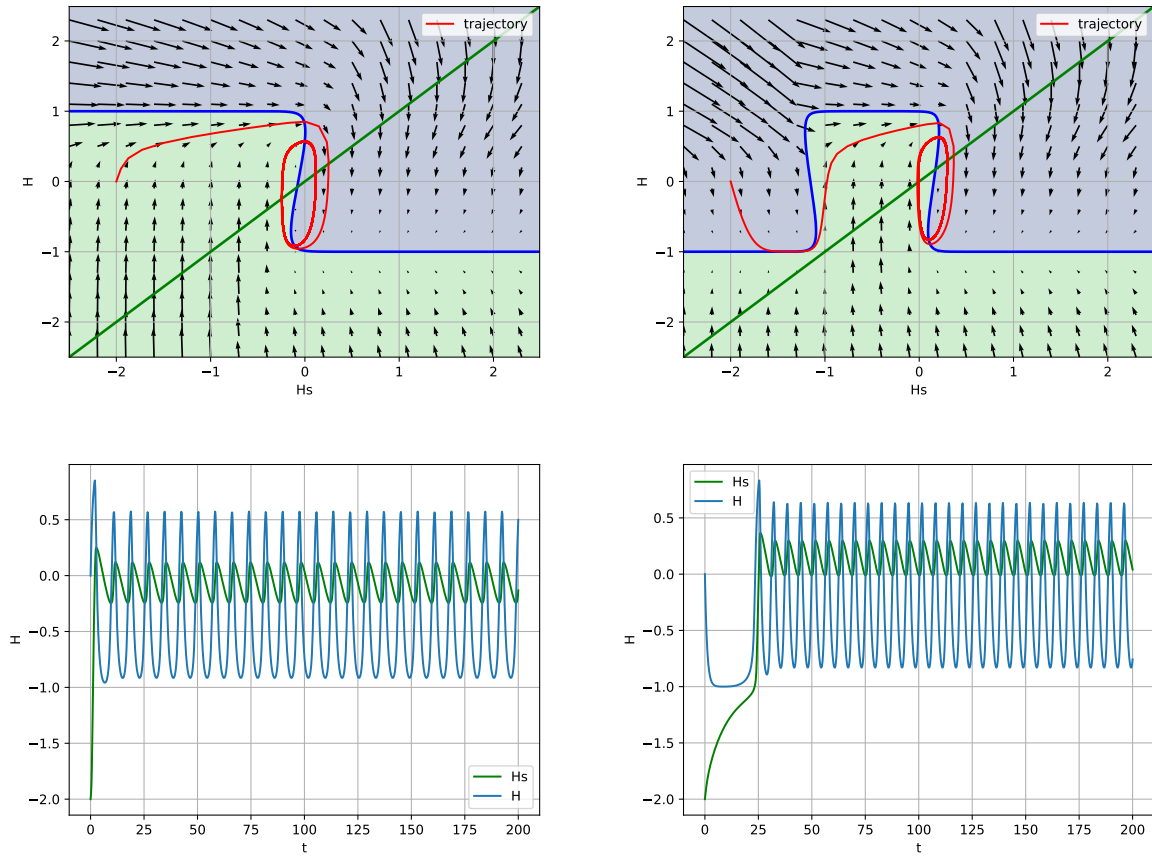


Figure 2: Spiking phase portraits and traces of the SRC model on the left and its extended version on the right.

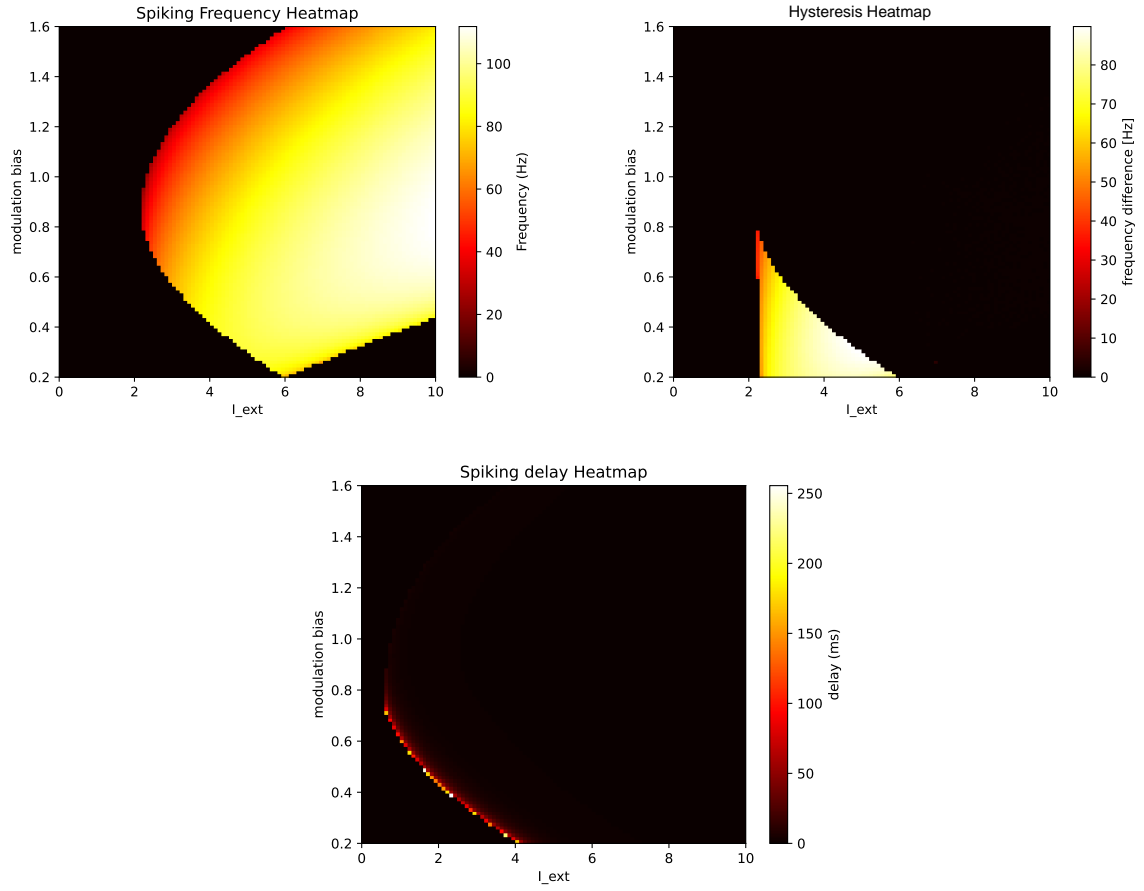


Figure 3: Heatmaps corresponding to the different mSRC  $h_{s0}$  modulation values. On the left, the FI heatmap can be seen showing a decrease in discontinuity of frequencies around  $h_{s0} = 0.9$ . On the right, the spiking delays heatmap shows an increase in delays for lower values of  $h_{s0}$ . At the bottom, we can see the increasing hysteresis range as  $h_{s0}$  decreases.

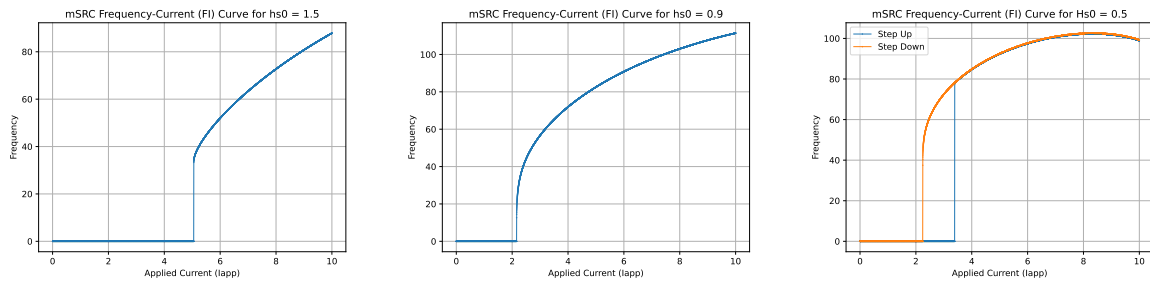


Figure 4: FI curves computed at increasing values of  $h_{s0}$ . From left to right  $h_{s0} = 1.5, 0.9$ , and  $0.5$ . We can see how the discontinuous characteristic decreases with  $h_{s0} = 0.9$  and then increases again with lower values. With  $h_{s0} = 0.5$ , we can see that the step-up FI curve behaves much like type2 while the step-down has a larger frequency range effectively creating hysteresis.

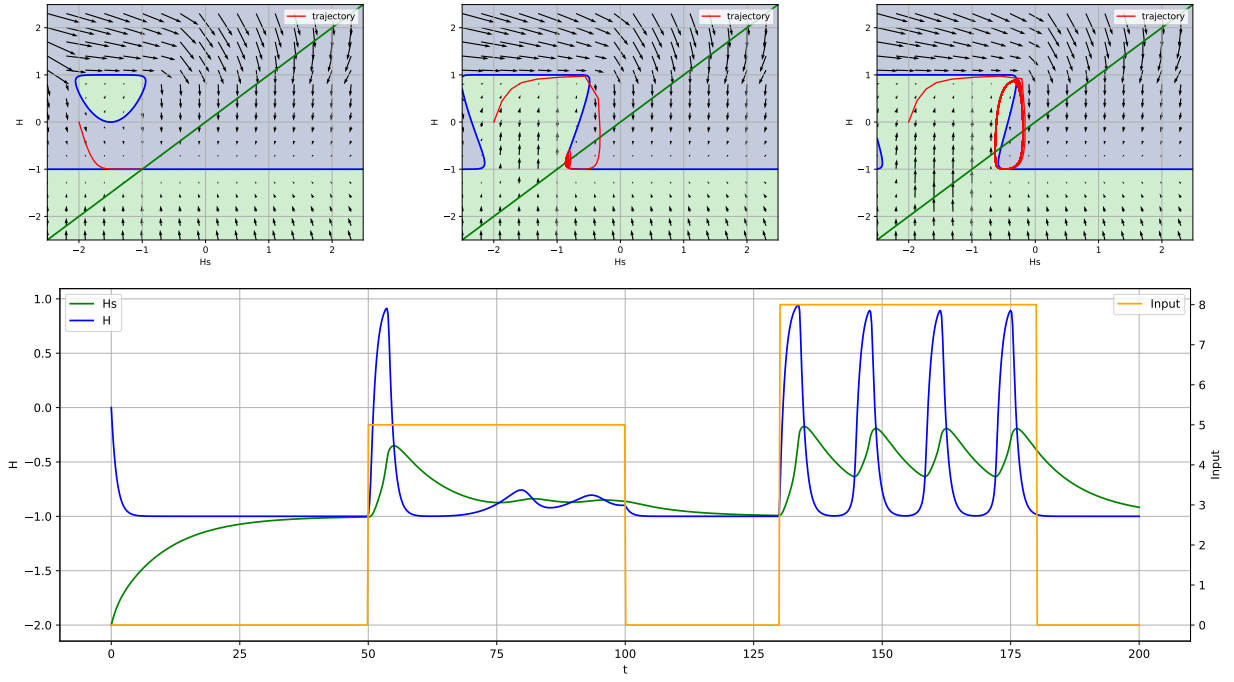


Figure 5: Phase portraits and voltage trace of the mSRC neuron in type 2 regime with  $h_{s0} = 1.5$  at  $I_{ext} = 0, 5$ , and 8 respectively.

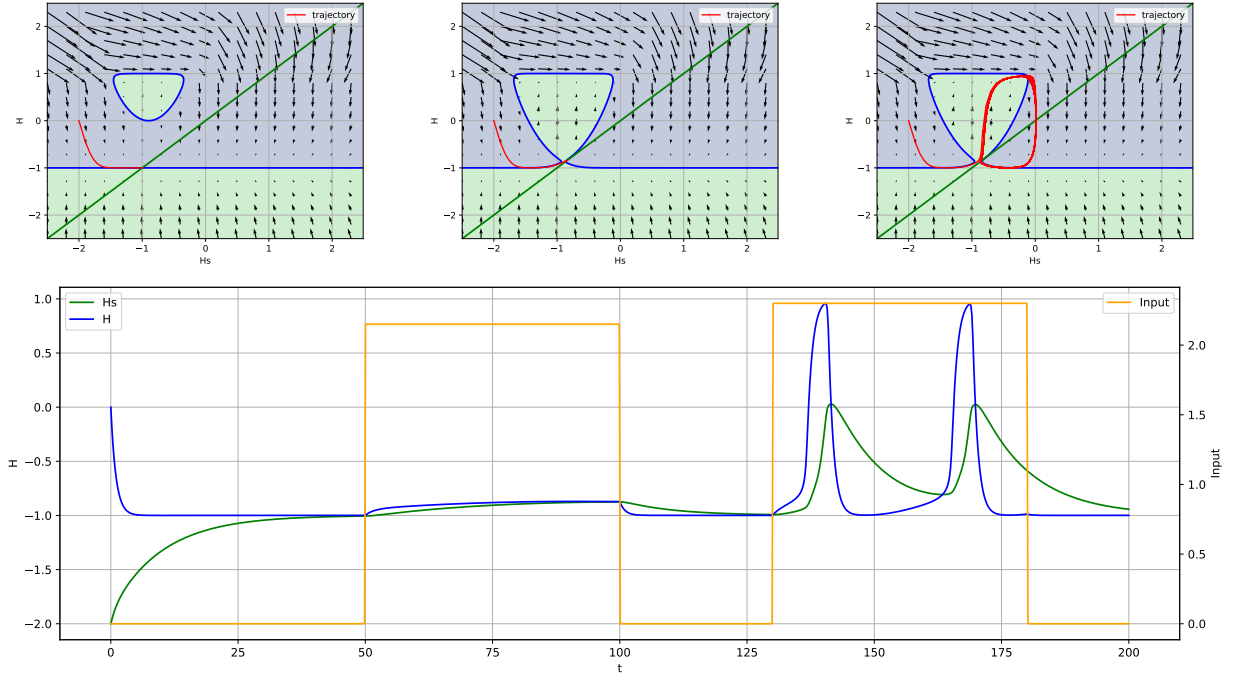


Figure 6: Phase portraits and voltage trace of the mSRC neuron in type 1 regime with  $h_{s0} = 0.9$  at  $I_{ext} = 0, 2.15$ , and 2.3 respectively.

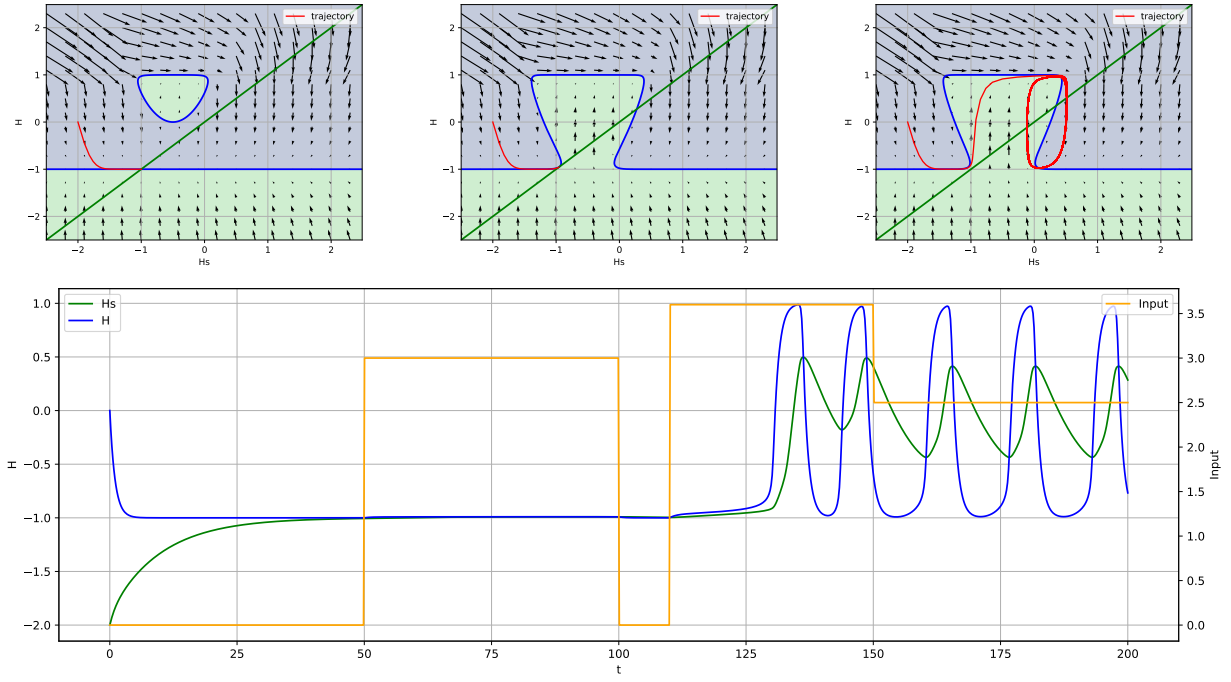


Figure 7: Phase portraits and voltage trace of the mSRC neuron in type 2\* regime with  $h_{s0} = 0.5$  at  $I_{ext} = 0, 3, 3.6$ , and in the voltage trace, 2.5 again. The voltage trace shows the two main characteristics of type2\*, the spiking delay at  $I_{ext} = 3.6$  and the hysteresis as  $I_{ext} = 2.5$  is above the threshold after the onset of the spikes but not from quiescence.

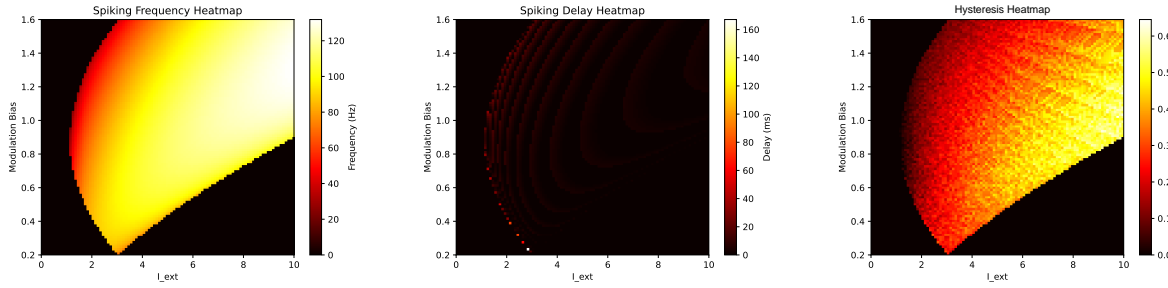


Figure 8: Heatmaps corresponding to the different mSRC  $h_{s0}$  modulation values with an exponential synapse at input with  $\alpha = 0.5$ . We see the FI, spiking delay, and hysteresis amplitude heatmaps from left to right.



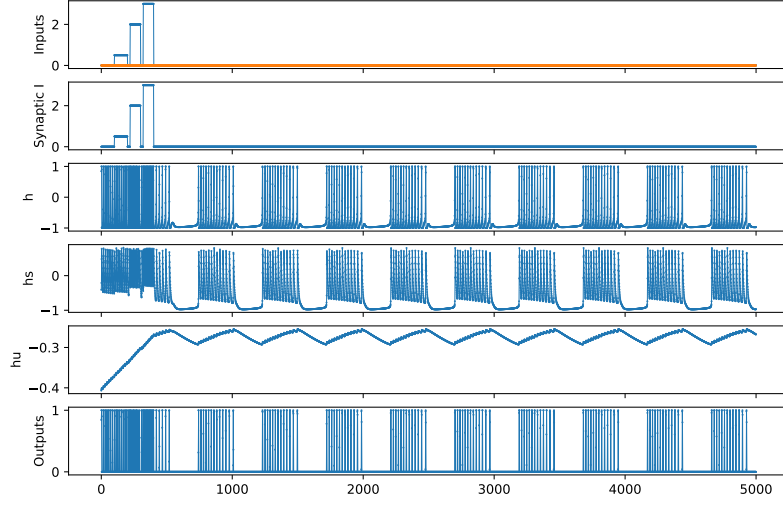


Figure 9: Simulation of a BSRC cell using the PyTorch framework in bursting regime with the following constant values:  $x = 0$ ,  $r = 4$ ,  $r_s = -7$ ,  $r_u = -8.5$ ,  $z = 0$ ,  $z_u = 0.999$ ,  $b = 0$ , and  $h_{s0} = 0.7$ . The simulation also contains an exponential synapse of decay factor  $\alpha = 0.5$ .

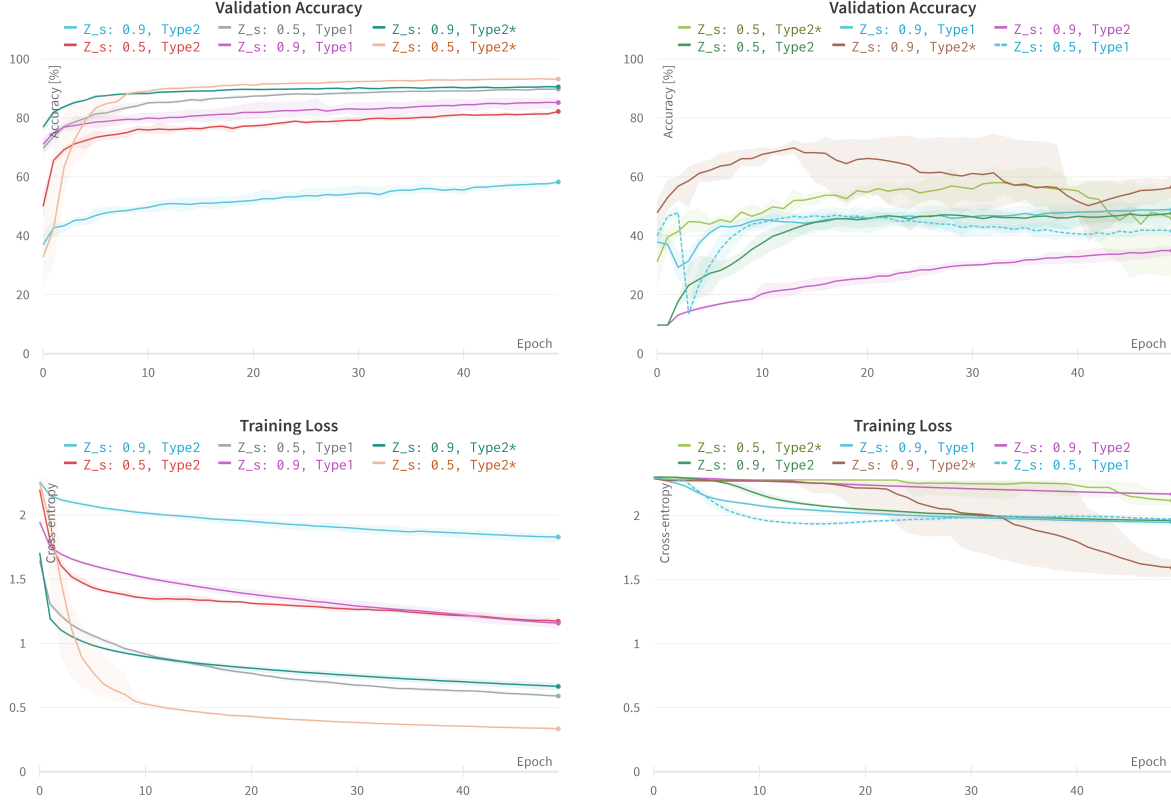


Figure 10: Validation accuracies and training loss for all the trained modulations and values of  $z_s^{hyp}$ . Plots in the left column correspond to the results of the rate-coded task, latency-coded is on the right.

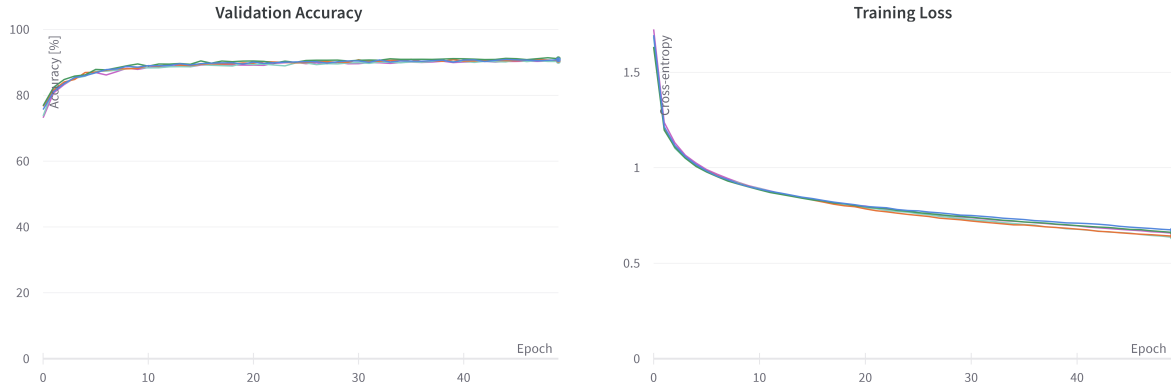


Figure 11: Evolution of validation accuracy and loss during training of 5 small mSRC networks with modulation as a learnable parameter on the rate coded MNIST.