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# Numerical exploration of spiking neuron circuits in organic pOTFT technology

Laurie E. Calvet<sup>1</sup>, Paoline Coulson<sup>1</sup>, B. Iniguez<sup>2</sup>, K. Romanjek<sup>3</sup>

<sup>1</sup>Center for Nanoscience and Nanotechnology, CNRS-Université Paris-Saclay, Palaiseau, France

<sup>2</sup>Department of Electronic, Electrical and Automatic Control Engineering, University Rovira i Virgili, Tarragona, Spain

<sup>3</sup>CEA-LITEN, 38000 Grenoble, France

e-mail: laurie.calvet@c2n.upsaclay.fr; phone: +33 (0) 170 27 04 77

**Abstract**— Spike-based neural networks have the potential to significantly increase the computational power of information technologies compared to other architectures. While many different types of sensors and conventional circuits have been implemented using flexible Thin Organic Large Area Electronics, TOLAE, processes, explorations of artificially spiking neuron circuits are much rarer. Here we numerically investigate neuron circuits in gravure printed scalable OTFT technology and consider how the circuits change with variability. Finally, we discuss how the intrinsic variability from processing can be used to advantage for classification tasks. These circuits constitute a promising low cost way to integrate neuromorphic hardware with sensors fabricated using the same methods.

**Keywords**—organic electronics, spiking neuron circuits, classification circuits

Increases in computing performance have led to significant advances in computing systems, ranging from handheld devices to supercomputers, and have enabled rapid advances in Artificial Intelligence (AI). This progress is closely linked to the continued shrinking of the complementary metal-oxide-semiconductor (CMOS) technology feature size, which has now reached fundamental barriers. To improve capabilities of future AI systems, researchers are exploring new computational paradigms, which can exploit the specific needs of a set of applications and the interactions between hardware, software and algorithms in a computing system. Simultaneous to the interest in approximate computation is the explosion of research in printed electronics, which use either organic or oxide based semiconductor materials, for a growing number real-world applications[1]. Flexible Thin Organic Large Area Electronics (TOLAE) processes enable **lower cost, energy and environmental footprint** for sensor systems and can provide excellent compatibility with biological objects through their chemistry and intrinsic flexibility[2], [3]. In addition to consuming less energy during fabrication, at the end of use the electronic materials on flexible substrates can be easily removed and the substrates can be recycled. Nevertheless, organic technology poses large challenges when used for commercial applications. They are slower and although the technology is starting to mature compared to

CMOS, they are much less reliable.

Here we consider how to realize hardware for classification of sensors using organic electronics. We first consider numerically the implementation of a spiking neuron circuit in organic electronics. Next we consider the

impact of variability on its functionality. Finally, we consider how to exploit this variability using a carefully chosen classification.

## I. SPIKING NEURON CIRCUIT SIMULATIONS

Our neuron circuit simulations are based on the characteristics of 210 OTFT devices with 19 different width/length dimensions. [4] The circuit operates in the deep sub-threshold regime, where device characteristics can be modeled as [5]:

$$I = I_0 \exp\left(\frac{-\ln 10}{S}(V_{sg} - V_0)\right) \left(1 - \exp\left(\frac{V_{sd}}{k_B T}\right)\right) \quad (1)$$

where  $S$  is the subthreshold slope,  $I_0$  and  $V_0$  are respectively the current and voltage when the subthreshold current turns on above the background leakage. Note that while  $V_t$  could also be used, the use of the turn on current and voltage ensures that the extracted parameters are obtained closer to the circuit operation in the deep threshold. Using an automatic fitting program, we extracted the parameters from all the available devices, where channel widths were fixed at 1 mm and lengths varied from 10 to 600  $\mu\text{m}$ . The fitting involved 1) obtaining first a fit to the leakage current, 2) identifying  $I_0$  and  $V_0$  in the leakage current as the points just prior to the large increase in current, and 3) fitting to equation (1) between  $I_0$  and  $I = 5 \times 10^{-9}$  A, the expected maximum of our circuit, to obtain the subthreshold swing  $S$ . An example of the fitting is shown in Fig. 1.

Our goal was to realize a biophysical artificial neuron circuit that could realize many of the behaviours exhibited by biological neurons. We modified a Morris-Lecar inspired neuron [6] to accommodate only pOTFT transistors, as shown in Fig. 2. The model neuron gives rise to a spike train due to the opening and closing of ‘K’ and ‘Na’ ion channels and their relative timing. Using Python and the parameters obtained from the real devices, we then implemented circuit simulations. As a starting point for exploring spiking neurons in organic electronics, we used the mean values from the real devices, and then explored how the variation in these parameters effects the circuit performance.

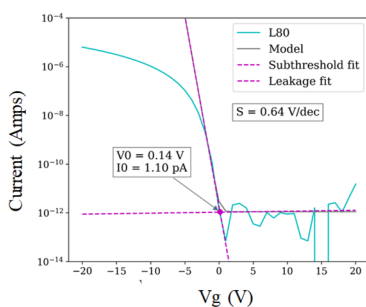


Fig. 1 Example of transistor characteristics and fitting procedure to obtain parameters for the compact model in equation 1.

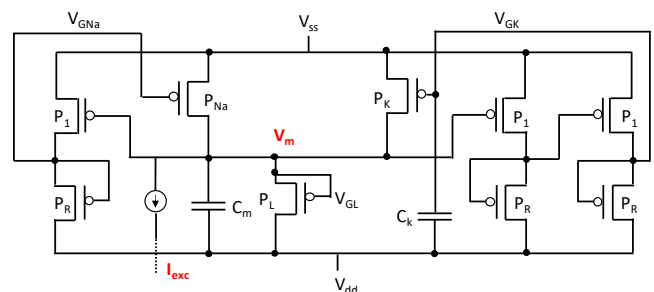


Fig. 2 Circuit diagram of a Morris-Lecar inspired spiking neuron circuit simulated with Python using parameters from organic OTFT transistors. Note that the  $P_{Na}$  and the  $P_K$  transistors are meant to be analogous to the ‘Na’ and the ‘K’ ion channels in a Morris-Lecar model. The excitatory current is the input and the output is the membrane voltage  $V_m$ .

## II. RESULTS

Fig. 3 shows an example of the spike trains resulting from the numerical simulations. This circuit functions differently from the CMOS version [6]. Without an excitation current  $I_{exc}$ , the  $P_{Na}$  transistor is turned on and the  $P_L$  and  $P_K$  transistors are in the off state. As  $I_{exc}$  increases, the membrane capacitance  $C_m$  is charged but there are just small changes in  $V_m$ . Once  $I_{exc}$  is large enough to switch the inverter, however,  $V_m$  exhibits a sharp rise, the  $P_{Na}$  transistor will turn off and the  $P_K$  will turn on.  $C_m$  will discharge through  $P_L$ , which will return  $V_m$  back to its resting potential and the cycle will start again. However, at large  $I_{exc}$ , the leak transistor, will remain on and the action of the  $P_{Na}$  transistor will be reduced, and thus the spike trains will be lost. The neuron circuit in Fig. 2 thus has the interesting property of exhibiting a relatively small spike range, that can be used to great advantage for sensor applications to limit the impact of larger fluctuations that might occur for instance to unwanted noise.

We examined the effect of variability by running a series of Monte Carlo simulations, where the parameters of the compact model for each transistor varied up to a percentage. This allows us to estimate how the spike range of the circuit would change for a given variation in the processing. An example of these results is shown in Fig. 4, where random variations of 20% in these parameters still allow for robustly spiking circuits despite large changes in the output characteristics.

## III. CONCLUSIONS AND PERSPECTIVES

We have shown how OTFTs can be used to realize artificial spiking neuron circuits. Nevertheless, the circuits are slow and are likely to exhibit relatively large variabilities in their behaviour. The speed of the circuits would enable them to be useful for classification circuits in a wide array of sensors that do not require high speed circuits. In previous work we have shown how spiking neurons can be used as a readout circuit for EEG sensors with significantly reduced data transmission [6]. In addition, they are perfectly compatible with sensors realized in organic technologies [3]. Here we argue in addition, that the variability of the circuits can be used to great advantage for realizing classification circuits.

One possibility is to use the spiking neuron circuits in the context of an Extreme Learning Machine (ELM) classification [7]. In such an implementation, sensor data would be fed into an array of spiking neuron circuits where each one would include a variation in its parameters due to

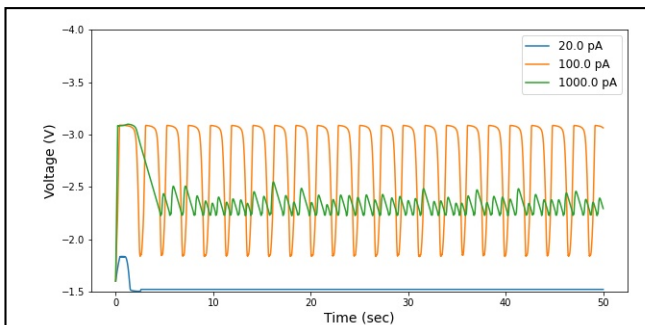


Fig. 3 Output of the simulated circuit from Fig. 2. At small  $I_{exc}$ , the response of the circuit is too weak to exhibit spiking behavior, but and increase in  $I_{exc}$  results in robust spiking. Finally, at large  $I_{exc}$  the spike trains are suppressed.

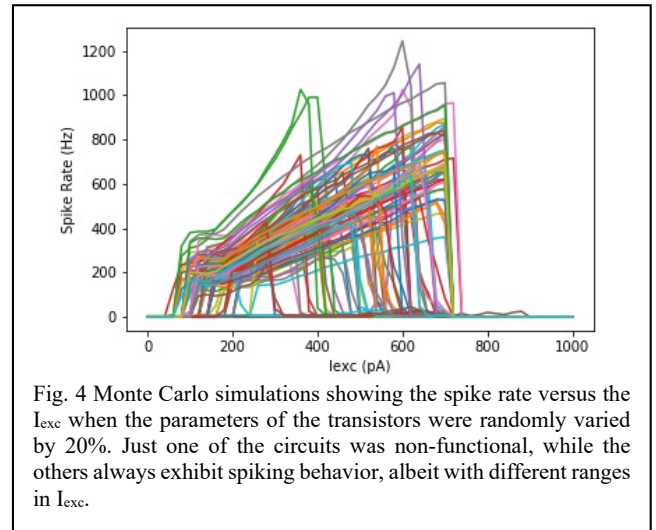


Fig. 4 Monte Carlo simulations showing the spike rate versus the  $I_{exc}$  when the parameters of the transistors were randomly varied by 20%. Just one of the circuits was non-functional, while the others always exhibit spiking behavior, albeit with different ranges in  $I_{exc}$ .

the processing, similar to what is observed in the simulations in Fig. 4. The output of the neurons could be transformed into a non-spiking values via rate encoding, where the number of spikes for a given feature are ‘counted’. Subsequently, these values can serve as the input for an offline classification using a machine learning algorithm or the traditional ELM pseudoinverse solution. (In practice such a classification could be carried out on a small device such as a smart phone.) The natural variability of the fabrication results essentially in the original data being projected onto a higher dimensional space so that the machine learning classification can be much more accurate, as in the ELM algorithm. Note that such an implementation does not necessarily result in an increase in the quantity output data relative to the raw sensor data because the spiking neuron can significantly reduce the quantity of the initial sensor data [6]. One could have in fact the best of two worlds: a projection onto a higher dimensional space and at the same time a reduction in the total amount of data, all the while using processes that are low cost and intrinsically variable.

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