# Neuron-like Signal Propagation for OWC Nanonetworks

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***Abstract*— Neuron-inspired signal propagation is proposed for communication in networks of nanodevices. Nanodevices should be able to interpret and forward signals inside the network in order to transport the information between two endpoints. Applications at the nano level demand processing systems that are very power efficient and simple. To achieve that, a brain inspired spiking neural network with pattern recognition and relaying capabilities is presented. The neural network learns the desired features using STDP, a power efficient and biologically plausible learning method. Finally, several nanonetworks are simulated, communicating using OWC. The results obtained show that signal similarity between the emitted and received signal highly depends on the design space of the neurons. It is possible to create networks with NDs capable of transporting information between two endpoints.**

***Keywords—Nanotechnology, Nanonetworks, Molecular, communication, SNN, STDP, Relay.***

## I INTRODUCTION

One of the promising topics in technology right now is, without a doubt, the Internet of things (IoT). The IoT consists in giving network connectivity to physical devices and everyday objects by embedding electronics inside them so they can communicate with each other over an established network and allow remote control or monitoring. The range of fields in which IoT can be useful is enormous thus making it an interesting topic of research and development. Electronic devices such as sensors, microcontrollers and antennas are currently deployed in many devices and places including domestic appliances, hospitals, public parks, vehicles, etc. The number of devices is increasing exponentially, for instance, in 2015 there were already 83 million smart devices in people's homes. This number is expected to grow to 193 million by 2020. As the number of devices s continues to increase we see reduction in their size, volume and cost [1]. By means of economy of scale, future IoT devices will have a much smaller footprint, lower power consumption, longer operation lifespan and will be deployed in even larger numbers than nowadays. In order to realize these envisioned IoT devices, nanotechnology plays a central role. Nanotechnology is the construction and use of functional complex structures based on molecular (atomic) manufacturing scale. They exhibit novel physical, chemical and biological properties, phenomena, and processes because of their nanometer size [2]. At the nanometer scale, a nanomachine (NM) is defined as the most basic functional unit, integrated by nano-components and able to perform simple tasks such as sensing or actuation. Deploying NMs in objects and interacting with them through the internet opens up a new and exciting field of research on the information transmission, i.e., the Internet of nano-things (IoNT). Nano-scale devices impose a new set of challenges posed by the physical characteristics of NMs, which needs investigating [3] including: (*i*) dimension, where size reduction sets new constraints, e.g., power limitations, which include independent energy harvesting and low power consumption; (*ii*) scarce computational resources, where microprocessors/controllers may not be suitable, thus the need for computationally efficient architectures; and (*iii*) nanoscale communications with low power and less complexity and with compliant protocols.

Nanonetworks (nanoscale network) will enable a new and unlimited number of applications that will revolutionize the world we live in. There are a growing number of research activities worldwide in developing products at the nanoscale, some of them already being used while others are just a vision for the future. Some application of nanonetworks include biomedical (immune system support, implants, intelligent drug delivery, health monitoring), environment (bio-degradation, air pollution control and animal control), industry (food and water quality control, functionalized materials and fabrics) and military (functionalized equipment) [4].

In this paper, we propose a novel wireless communication architecture for nanodevices (NDs) based on neural networks, with relaying and pattern recognition capabilities. Different NMs communicate wirelessly exploiting the optical spectrum. We have created a simple and efficient network composed of NDs which can propagate information between two endpoints. After that, we calculated the similarity between the emitted and received signal for different parameters and noise levels.

The rest of the paper is organized as follows: Section II introduces the multiscale nano-device communication. The optical nanonetwork system architecture is explained in Section III. Section IV presents the simulation set up and the achieved results. Finally, Section V concludes the paper.

## II MULTISCALE NANO-DEVICE COMMUNICATION

By their nature, NDs have an extremely small workspace and can only act locally, i.e., can sense their surrounding and/or actuate upon it. Also, because of their simple architectures and limited resources, the range of things that they can do individually is very limited. Therefore, exploring NMs-to-NMs communications will considerably expand their capabilities and applications by allowing them to execute distributed and cooperative tasks to pursue a common objective as well as expand their coverage areas [5]. For NMs-to-NMs network, there are several communications paradigms. The most popular ones are Molecular Communications (MC), Terahertz (THz) Band RF Communications and Optical Communications.

In MC molecules are used as the carrier signal to encode, transmit and receive information [6] and provides means for NMs (biological or artificial) to communicate with each other

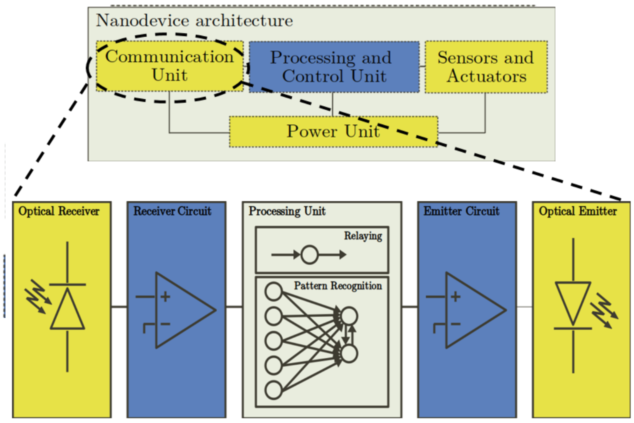


Fig. 1: Proposed architecture of the communication module in a nanodevice

[4]. In THz band RF Communications, the frequency band with the range of 0.1-10 THz is used for ND-to-ND communications [7]. Finally, Optical Communications use the range of frequencies roughly between 450 and 750 THz [16-17].

## III Optical Nano Network system Architecture

A ND is constructed using nano-scale component with a specific task at the nano-level [9]. The tasks performed, which are very simple and are restricted to its neighborhood environment due to its limited capabilities and a small size, include computation, sensing, actuation, communication and energy harvesting. NDs can be both artificial nano-machines as well as naturally created ones found in biological systems. The system architecture for a ND-based communication is illustrated in Fig. 1, which includes processing and control unit, communication unit, power unit, sensors and actuators.

### *3.1 ND architecture*

The communication module, see Fig. 1, is composed by an optical receiver (Rx), an optical emitter and signal conditioning circuits. The foreseen optical transceivers for NDs are plasmonic devices like nano-antennas or spasers. The processing unit composed of spiking neural networks (SNN) with relaying and pattern recognition capabilities is used for interpreting the information received from the network and forwarding it to other points in the network. In the proposed work, NDs communicate by exchanging spike-encoded information. The usage of SNNs takes inspiration from the human brain which consumes no more than 20 W of power and can do rather complex tasks for traditional computers like facial recognition and natural language processing [17].

### *3.1.1 Relaying*

A neuron will produce a spike at its output when its membrane voltage level reaches a threshold. In addition, a neuron can have a spike output with higher energy for each received spike, making it a natural spike regenerator and a relay node. However, neurons have specific dynamics, set by time constants, which define how fast they can accumulate and fire. This leads to a bandwidth limitation, which sets the maximum relaying speed. In order to model the neuron dynamics, the leaky integrate-and-fire (LIF) model has been used [11, eq. (1) and (2)].

For a neuron with $n$ synapses, each pre-synaptic spike $S_{it}$ increases the membrane potential $P$ by a value influenced by the synaptic weight $W_i$ and the neuron's time constant $\tau$ . The membrane potential is also decreasing by a constant value $D$ at each time instant. If $P$ surpasses the threshold value $P_{\text{thr}}$ the

$$P(t) = \begin{cases} P(t-1) + \frac{1}{\tau}\left(\sum_{i=1}^{n} W_i S_{it} - D\right) & if\ P_{\text{rest}} < P(t-1) < P_{thr} \\ P_{\text{refract}} & if\ P(t-1) \geq P_{\text{thr}} \\ P_{\text{rest}} & if\ P(t-1) \leq P_{\text{rest}} \end{cases} \quad (1)$$

$$O(t) = \begin{cases} V_{\text{spike}} & if\ P(t) \geq P_{\text{thr}} \\ 0 & else \end{cases} \quad (2)$$

neuron outputs a spike and enters in a refractory state. The refractory state is defined as the membrane potential being reset to $P_{\text{refract}}$ and the neuron being insensible to its inputs during a refractory period $T_{\text{refract}}$. With no received stimuli, the neuron membrane potential remains at a fixed level $P_{\text{rest}}$. The LIF model enables creation of neurons with different working speeds and thresholds.

By applying a pulse with maximum amplitude, $V_{max}$, during enough time, we ensure that the neuron spikes as fast as possible. The minimum time between two output spikes depends on the neuron parameters and is given by:

$$T_{\min} = \frac{P_{\text{thr}} - P_{\text{rest}}}{V_{\max} - D} \times \tau + T_{\text{refract}} \quad (3)$$

Note, the maximum firing rate of the relay neuron $FR_{\max}=1/T_{\min}$. We have considered a neuron with the following characteristics: $V_{\max} = 5$ VU (voltage unit), $W_i = [1]$, $P_{\text{thr}} = 40$ VU, $P_{\text{rest}} = 20$ VU, $\tau = 3$ ms, $T_{\text{refract}} = 5$ ms, and $D = 0.5$. Using these parameters, we can obtain through simulation $f_s \geq 666.7$ Hz and $FR_{\max} = 54.5$ Hz. Note, under continuous $V_{\max}$, the neuron firing rate can be determined using (3), which will be the same as above i.e., 54.5 Hz.

Another important experiment consists in changing the input signal to a uniformly distributed random sequence of spikes with amplitudes between [0, $V_{\max}$]. The frequency response obtained for this experiment shows the most probable firing rate of the neuron. Maintaining the parameters for the relay neuron, the most probable firing rate obtained was 28.5 Hz. Applying a uniformly distributed random sequence of spikes with amplitudes between [0, $V_{\max}$] is equivalent to applying a DC signal of value $V_{\max}/2$ because the neuron acts as an integrator. Then, it makes sense that the most probable firing rate obtained is around half of the maximum firing rate.

### *3.1.2 Pattern Recognition*

ND communications are practical provided devices can detect and interpret messages encoded in the spike signals. In ND communications, with messages encoded in spike patterns one can use SNNs' pattern recognition capability for processing of the received spike signals. Spike-time dependent plasticity (STDP), which is a biological process that adjusts the strength of connections between neurons in the brain [11], is considered as an unsupervised learning mechanism used in biological neural systems. Because of its low complexity, it is a more suitable learning technique to use in NDs than more traditional techniques like backpropagation. In STDP, the synaptic weights are adjusted based on the temporal order of pre- and post-synaptic spikes. If a pre-synaptic spike arrives before a post-synaptic spike, the synaptic weight increases (long term potentiation (LTP)), otherwise the synaptic weight decreases (long term depression (LTD)). The learning window (i.e., the modification of the weight $w$ of a synapse connecting a pre- and post- synaptic neurons) for STDP is defined as [11, eq. (4)]:

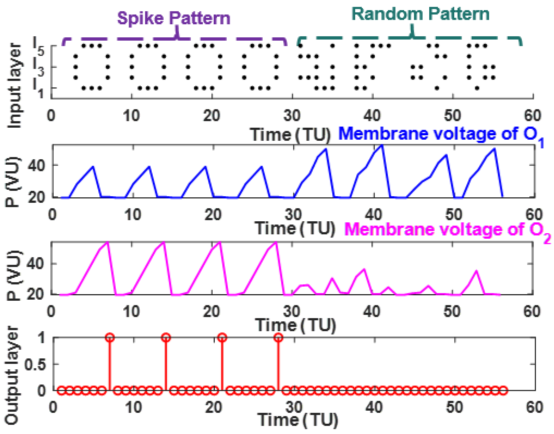


Fig. 2: SNN detecting the target pattern successfully.

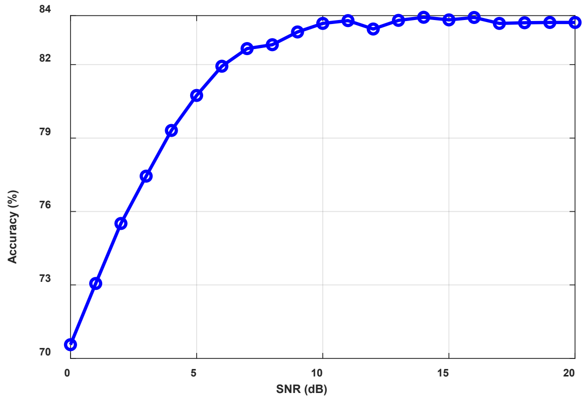


Fig. 3: Network accuracy for different SNR

$$\Delta w = \begin{cases} A_{+}\exp\left(\frac{\Delta t}{\tau_{+}}\right) & if\ t_{\text{pre}} < t_{\text{post}} \\ A_{-}\exp\left(-\frac{\Delta t}{\tau_{-}}\right) & if\ t_{\text{pre}} > t_{\text{post}} \end{cases} \quad (4)$$

where $\Delta t = t_{\text{pre}} - t_{\text{post}}$ is the time difference between the pre- and post-synaptic spikes, $\tau_{+}$ and $\tau_{-}$ correspond to the pre-synaptic and post-synaptic time interval and $A_{+}$ and $A_{-}$ indicate the strengths of potentiation and depression, respectively. The new values for $w$ is given by:

$$w_{new} = \begin{cases} w_{\text{old}} + \sigma\Delta w(w_{\text{max}} - w_{\text{old}}) & if\ \Delta w > 0 \\ w_{\text{old}} + \sigma\Delta w(w_{\text{old}} - w_{\text{min}}) & if\ \Delta w \le 0 \end{cases} \quad (5)$$

where $\sigma$ is the weight adaptation speed. Note, $w_{\min} < w < w_{\max}$ [11, eq. (5)]. This approach allows $w$ profiles to have shapes similar to specific temporal spike patterns that they receive. There is no need for external sources to state if a neuron has received the pattern or not. Because of that, STDP is considered an unsupervised learning mechanism in pattern recognition.

Some type of competitive learning method should be implemented for STDP to ensure correct operation. In neurobiology, lateral inhibition (LI) is a form of competitive learning which defines the capacity of an excited neuron in reducing the activity of its neighbors [13]. LI can be implemented by creating inhibitory connections between the output neurons, so the first neuron to spike will inhibit others from doing the same and consequently preventing activation of STDP in the neurons. A popular form of LI is Winner-take-all (WTA) [14], where the first spiking neuron activates STDP and reinforces the proper synapses while other neurons have their membrane voltages reset to the resting potentials.

By merging STDP and the neuron model, it is possible to create a functional SNN with spike pattern recognition capability. We have created and simulated an SNN setup in MATLAB, which includes 5 input neurons to generate the input spikes and 2 output neurons. Each output neuron is connected via traditional synapses to all the input neurons and to the other output neuron via an inhibitory synapse, which is used for LI in the form of WTA. The output neurons are equipped with STDP that will change $w$ of the 5 input synapses during the learning process. All neurons within SNN are equal with the parameters of $V_{\max}$= 1 VU, $P_{\text{thr}}$ = 40 VU, $P_{\text{rest}}$ = 20 VU, $\tau$ = 1 TU (time unit), $T_{\text{refract}}$ = 3 TU and $D$ = 0.5 VU/TU.

The initial synaptic weights are assigned randomly at the start of simulation, which creates a degree of diversity in determining which neuron is more apt to detect the pattern in the beginning. The pattern recognition task assigned to the network is to detect the spike's pattern. The learning phase consists in feeding the network with random spike sequences at the start and then with the target pattern. If the learning phase is successful, then one of the output neurons should have synapses that are shaped to detect the target pattern effortlessly. Fig. 2 illustrates the phase, where the network is fed with the target pattern and random patterns. Also shown are the membrane potentials for $O_1$ and $O_2$, where $O_2$ is much more sensitive for detecting the target pattern than $O_1$. This results in SNN successfully detecting the pattern when it is present as it can be seen the last graph in Fig. 2.

Following the learning of network, its performance can be evaluated for different scenarios. In a real scenario (i.e., with noise), the noise variance after generating the spike signal is computed for a specific signal to noise ratio (SNR) value. We have evaluated the networks accuracy by feeding the it with a random spike signal and noise. Fig. 3 shows the network accuracy as a function of SNRs. For each SNR, the testing dataset contains 100,000 examples for the target pattern and random spike sequences with 50% each. As can be seen, the accuracy reaches the maximum of ~ 84% for a SNR > 13 dB.

### *3.2 Channel*

The total loss of the channel is given by [8, eq. (6)]:

$$L_{\text{tot}}(d) = D_n\left(\frac{\lambda_g}{4\pi d}\right)^2 \times e^{-\mu_{\text{abs}}d} \times e^{-\mu_{\text{sca}}d} \quad (6)$$

where $D_n$ is the directivity of the nanoantenna, $d$ is the distance from the source, $\lambda_g$ is the effective wavelength, $\mu_{abs}$ is the molecular absorption coefficient and $\mu_{\text{sca}}$ is the scattering coefficient [15]. The minimum delay of the channel $\Delta t$ = $(d{\times}n)/c$ where $n$ is the refractive index of the medium and $c$ is the speed of light. Note, in a dense ND network with devices located very close to each other the propagation delay will be very small.

### *3.3 Noise analysis*

The types of noise, which will affect the system performance, are highly dependent on the types of devices and processes within the system. In ND, currently only molecular absorption noise, thermal noise and photon shot noise can be considered since the optical Rx adopted in this scheme is at it development stage, therefore needs more investigation on its noise characteristics. Until now, it has been considered that molecules result in the loss n of optical signals. Note, molecular vibration leads to EM radiation at the same frequency as the incident waves, which is called molecular absorption noise [9, eq. (7)].

The equivalent molecular absorption noise power at the Rx, for a given bandwidth $B$ is:

$$P_{mol} = k_B \int T_0 \varepsilon(f,d)\, df \tag{7}$$

where $k_B$ is the Boltzmann constant, $f$ is the frequency of the EM wave, $T_0$ is the reference temperature and $\varepsilon$ is the emissivity of the channel. The thermal noise power is given by:

$$P_{\text{jn}} = R_L I_{\text{jn}}^2 = 4 k_B T_e B \tag{8}$$

where $R_L$ is an equivalent resistance working at the temperature $T_e$ and $I_{\text{jn}}$ is the generated noise current [16, eq. (8)]. Photon fluctuation noise, also called the photon shot noise is associated with the quantum nature of light itself [16, eq. (9)]. Since the detection of a photon at the Rx is independent from the others, the number of photons counted will suffer fluctuations even for a constant power optical source. These fluctuations of the number of photons detected is the photon shot noise and is described by a Poisson process:

$$P(k \text{ photons in interval}) = \frac{\lambda^k e^{-\lambda}}{k!} \tag{9}$$

where $\lambda$ is the average number of photons per interval and $k$ is the number of occurrences. Photon shot noise is more relevant when the optical power is low, i.e., when the average number of photons is low, variations from the average are more noticeable. The shot noise can be significant in the case of pulse based optical wireless communications, since photodetectors may detect a reduced number of photons.

### *3.4 Network model*

Since NDs have relaying capabilities, the main purpose is to propagate information between two endpoints of the network. Fig. 4 shows the interconnections of 5 devices. The channel information together with the information obtained from the nanodevice model are used to evaluate the optical link between NDs. We can compute the optical link attenuation *att* between two NDs as:

$$att = cos^{m_l}(\theta) \times L_{\text{tot}}(d) \times RA_r \cos(\Psi) \tag{10}$$

where $m$ expresses the Lambert index of a LED light source, $\theta$ represents the angle between the light emission direction and the normal light source, $R$ represents Rx's responsivity, $A_r$ is the active area of the Rx and $\Psi$ is the angle between light emission direction and Rx normal.

## IV Simulation Results

A network composed by 50 NDs randomly deployed in a 6x6 DU (distance unit) plane was created as depicted in Fig. 5. The network consists in a source node (green) the generates and information pulse and sends it to the network until it reaches the sink node (red). The emitted and received signals are illustrated in Fig. 6. In order to evaluate the similarity between the signal at source and sink, a signal similarity metric $S$ was developed (eq. 11).

$$S\big(i(t), o(t)\big) = \frac{nacc\big(i(t), i_d(t)\big)}{nacc\big(i(t), o(t)\big)} \tag{11}$$

where *i(t)* is the signal at source, $i_d(t)$ is a delayed version of *i(t)* and *o(t)* is the signal at sink. The normalized are of the cross correlation *nacc* is given by eq.12.

$$nacc\big(f(t), g(t)\big) = \frac{\int corr\big(f(t), g(t), \tau\big) d\tau}{\max\ corr\big(f(t), g(t), \tau\big)} \tag{12}$$

where *corr* is the correlation between *f(t)* and *g(t)*.

Metric $S$ returns a result between 0 and 1 and the higher the value the stronger is the signal similarity. $C_\epsilon$ is defined as:

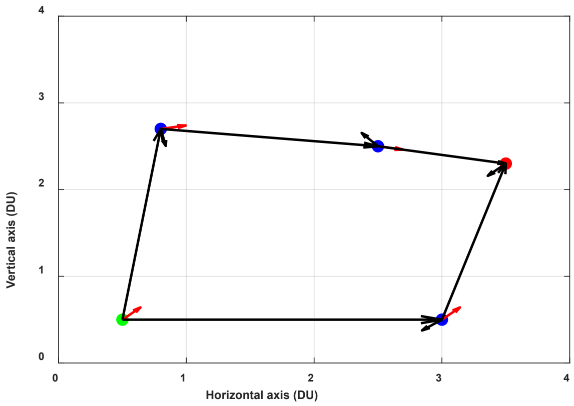


Fig. 4: Simple network example with 5 devices

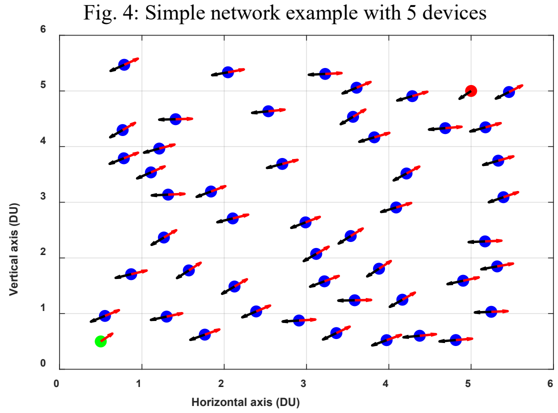


Fig. 5: Nanonetwork with 50 devices deployed randomly

$$C_\epsilon = \{S(i,o) \geq \epsilon \mid \epsilon > 0\} \tag{13}$$

By observing several networks, it was defined that $C_{0.7}$ maintains high signal similarity, i.e. good quality networks.

The set of parameters changed during the results sections are the number of devices in the network and the main neuron parameters: $\tau$, $T_{\text{refract}}$, $P_{\text{thr}}$ and Spike duration. These parameters are the design space of the neuron and changing them results in networks with different relaying capabilities. As it can be seen in Fig. 7, for the same network of Fig. 6, changing the spike duration highly affects the shape of the pulse received.

Fig. 8 was obtained by simulating 3000 networks for each point and calculating the percentage that obtained $C_{0.7}$. It depicts that the optimal number of devices that generates good quality networks is strongly related to the values of the design space. For two different design spaces, the optimal value changes. The orange curve peaked at 30 devices with 50% of networks with $C_{0.7}$. The blue curve peaked at around 55 devices with around 38% of networks with $C_{0.7}$. The blue curve has a set of parameters that creates neurons that are slower and harder to fire in comparison with the orange curve. This results in a higher number of devices needed to propagate the stimulus from source to sink, thus the optimal value appearing for a higher value of devices.

Regarding tests with noise, Fig. 9 illustrates of different signal to noise ratios affect the signal similarity. To obtain this result, 95 networks with $C_{0.7}$ were obtained and, for each of them, the signal similarity for different SNRs was obtained.

As predicted, as the SNR decreases the worse is the signal similarity.

## V Conclusions

The architecture proposed in this work provides NDs with communication capabilities, such as relaying and pattern

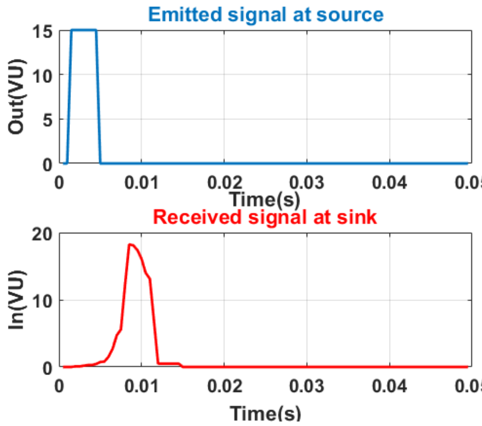


Fig. 6: Received signal at sink node for an emitted pulse of 3.3 ms

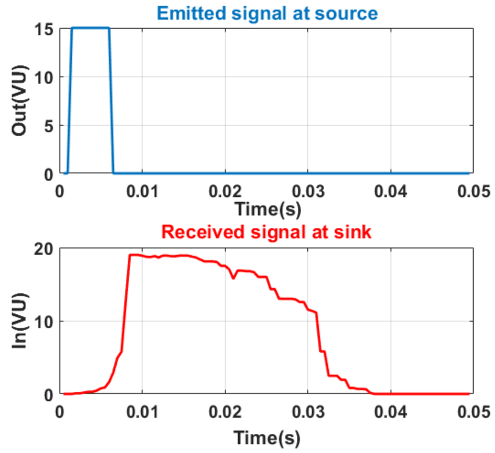


Fig. 7: Received signal at sink node for an emitted pulse of 5 ms

recognition, while using a reduced number of neurons. The results obtained show that signal similarity between the emitted and received signal highly depends on the design space of the neurons as well as the number of devices. It was concluded that given a specific type of relaying neuron, there is an optimal number of devices in order to obtain high quality networks. Different noise levels highly affect the performance of the networks.

Concluding, the results obtained show that it is possible to create networks with NDs and that their relaying capabilities enable the transport of information between two endpoints of the network while maintaining good signal integrity.

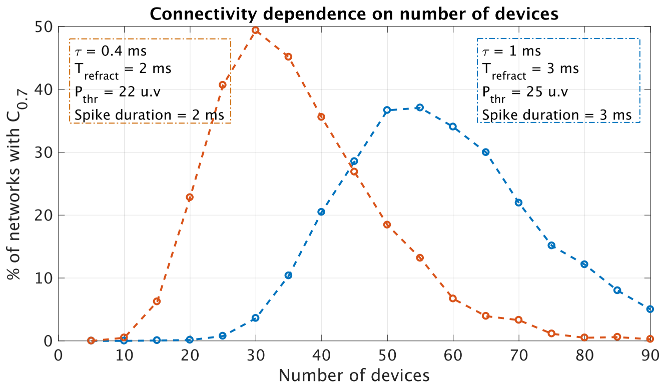


Fig. 8: Connectivity dependence on number of devices for 2 sets of parameters

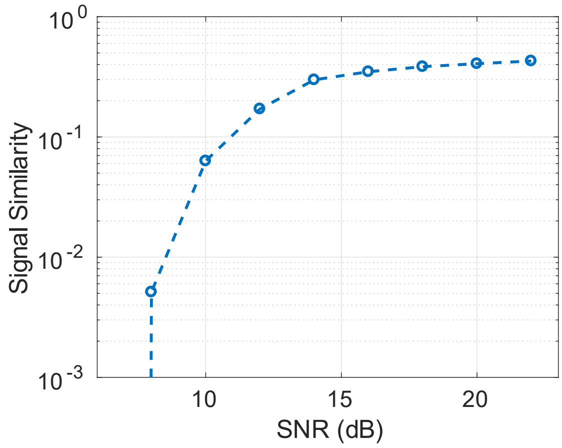


Fig. 9: Dependence of signal similarity with SNR

## ACKNOWLEDGMENTS

This work is supported by H2020/MSCA-ITN funding program under the framework of the European Training Network on Visible Light Based Interoperability and Networking, project (VisIoN) grant agreement no 764461.

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