Neuron-Inspired Communications for Energy Efficient Internet of Things Networks

Paweł Kryszkiewicz
Chair of Wireless Communications
Poznan University of Technology
Poznan, Poland
pawel.kryszkiewicz@put.poznan.pl

***Abstract*—Internet of Things devices are becoming a pervasive technology of the contemporary world. As the transceivers are typically battery-powered, their energy efficiency is crucial. This has to consider not only the spectral efficiency of the utilized modulation but also the energy consumption for reception, signal processing and keeping radio ON. The paradigms observed in human brains for communications between millions of closely distanced neurons can be utilized in wireless networks to improve communications energy efficiency. The paper presents the main features of brain communications and maps them to the closest solution in wireless communications technology. Multi-hop, low power, on-off keying transmission with diversity and sleep mode is proposed, as a neuron-inspired scheme. Its advantage is shown in numerical terms.**

***Index Terms*—Internet of Things, Wireless Sensor Network, Energy Efficiency, Brain Inspiration**

I. Introduction

Internet of Things (IoT) is becoming a pervasive technology of today's world, ranging from the industrial environment to agriculture and private people. By 2022 there will be on average 1.8 IoT connections for each member of the global population [1]. The density of IoT devices will be significant, requiring a significant reduction in setup cost and time, e.g., by changing fixed connections to wireless connections. In addition, to be cable-free, the devices must be battery powered. This requires the wireless communications to be highly energy-efficient in order to allow for long battery lifetime. The technologies that are typically highly spectrally efficient, e.g., Orthogonal Frequency Division Multiplexing, turbo codes, Massive MIMO, require relatively high energy for signal processing, transmission and reception. Therefore, these are not the optimal solutions for battery-powered IoT devices. It has been shown in [2] that these technologies are energy-efficient (energy efficiency is defined as a ratio of the achieved rate to the total power consumption) only for relatively long transmission distances. In the case of a dense IoT network, *simpler* modulations are considered, e.g., Pulse Position Modulation (PPM), On-Off keying (OOK) or Frequency Shift Keying (FSK) [3], [4]. From the point of view of spectrum access, Time Division Multiple Access (TDMA) is considered, in which long sleep time in between access allows for energy consumption reduction [5]. However, these approaches lack a holistic approach to network energy consumption.

This work has been funded by National Science Centre in Poland within the "BioNets" project (no. 2016/23/B/ST7/03937) of the OPUS programme.

A new trend in wireless systems design is to follow the rules used in nature as a result of years of evolution. One of the examples is to copy the behavior of bumblebees to design wireless communications in Vehicle-to-Vehicle connections [6]. From the perspective of dense, energy efficient networks, it is interesting to have a closer look at the human brain. It is a structure composed of around 10^{11} neurons that are interconnected, and can operate over a long period of time with relatively low power consumption. One of the first approaches to this problem is [7], where microglia activity is copied to a wireless sensor network in order to increase fault tolerance.

In this paper, the electro-chemical activity of a single neuron will be analyzed in order to provide some design rules for a dense, energy efficient IoT network. First, a simplified description of a single neuron operation will be presented in Sec. II. Next, a neuron-inspired IoT communication protocol will be presented in Sec. III. Its initial performance evaluation will be presented in Sec. IV. Future work and conclusions will be presented in Sec. V.

II. Paradigms of Neuron Communications

Neurons utilize electro-chemical reactions to convey information [8]. First, an input signal arrives to the dendrites using their endings called synapses. The synapses obtain the signal from the previous neurons using either an electrical signal (through gap junction) or, more commonly, using neurotransmitters (chemical substances that are typically synthesized from amino acids). A given neuron may receive signals from many connected neurons. These signals are summed electrically at the axon hillock, creating some initial membrane potential. The summation is done both over many input neurons (spatial summation) and over time (temporal summation). As visible in Fig. 1, the resting potential of a neuron with no input signal equals about -70 mV. When the summated input signals exceed the threshold of about -55 mV, an action potential is launched, causing depolarization to a voltage of 40 mV. This impulse has constant amplitude, no matter how significantly the input signal exceeds the threshold potential. This behavior is called a *one-or-none* event. Such an electrical signal travels across the axon to its end, where it is passed to another neuron using synapses. An important neuron feature is a refractory period, i.e., a period of time over which the neuron that has just released an impulse is unable to release another impulse. First, during depolarization and while the voltage drops to the resting potential, an absolute refractory period is observed even when a very strong input signal cannot make the neuron fire another impulse. Afterwards, a relative refractory period is observed, during which the membrane potential is lower than the resting potential (denoted as *Refractory period* in Fig. 1). This requires the input signal to increase the membrane potential more, to reach -55 mV, in order to fire another impulse.

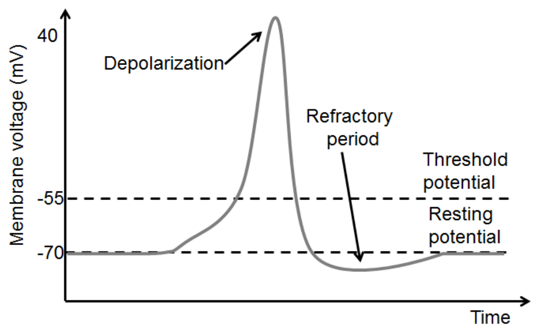

Fig. 1. Voltage in time at a neuron conveying information.

III. Proposed Neuron-Inspired IoT Communications Protocol

A. Digital modulation: ON-OFF Keying

The above-presented basics of inter-neuron communications can be viewed as a digital communication system. This observation comes from the *one-or-none* neuron behavior, resulting in the generation of an impulse of constant parameters (duration, amplitude) if the input signal exceeds a given threshold. If this threshold is not exceeded, no impulse is emitted. This resembles the ON-OFF Keying (OOK) transmission. The potential of this modulation has been proved mathematically for dense networks. It has been shown in [2] that coding is not energy-efficient for short-range communications, because of the energy required for computations. Similarly, advanced multicarrier modulations, e.g., Orthogonal Frequency Division Multiplexing, provide a significant computation energy burden for short-range communications. Single carrier modulations, namely, Frequency Shift Keying (FSK), Pulse Position Modulation (PPM) and OOK, have been compared for wireless sensor networks in [3], [4]. While PPM outperforms FSK in terms of energy efficiency for short-range communications [4], it is outperformed by OOK in the same scenario [3]. OOK is a simple modulation scheme that requires, in the simplest approach, a transmitter being a local oscillator (LO) connected to an antenna (for low-power transmission). The LO is powered only while bit 1 is transmitted and can be turned off for bit 0 [9]. This can significantly reduce transmitter energy consumption. The required low-power OOK transceivers have already been designed, e.g., for wake-up radios [9]. The wake-up radio is a low-power, low-rate radio working in parallel to a main, high-rate radio. It is to detect a wake-up signal (typically OOK) directed to a given transceiver, and activate the main radio. However, these designs can potentially work as stand-alone radios, as suggested by the neuron's nature.

B. Transmitter diversity

A neuron sums many incoming signals from many neurons. This can be mapped to a transmitter diversity technique, i.e., signals from many previous transmitters, transmitting the same signal, add up at the receiver antenna. The advantage of this approach is the additional power of the wanted signal at the receiver, increasing the signal-to-noise ratio (SNR). Moreover, the deep shadowing of a channel from one transmitter is rare to occur at the other links. To present a diversity gain, two transmit nodes can be considered, each transmitting identical symbol d of mean power 1, scaled by $\sqrt{P}$ to obtain transmit power P. Assuming each channel is described by a single, complex coefficient, i.e., h_1 and h_2, the received signal, after the addition of noise sample n, equals

$$y = (h_1 + h_2)\sqrt{P}d + n. \tag{1}$$

As channel coefficients are typically random variables (e.g., Rayleigh or Rice distributed), the mean SNR Γ can be calculated, assuming that h_1 and h_2 are uncorrelated, i.e., $E[h_1 h_2^*] = 0$, giving

$$\begin{aligned}\Gamma &= \frac{E[|d|^2]PE\left[|h_1|^2 + h_1^* h_2 + h_1 h_2^* + |h_2|^2\right]}{E[|n|^2]} \\ &= \frac{PE\left[|h_1|^2\right]}{E[|n|^2]} + \frac{PE\left[|h_2|^2\right]}{E[|n|^2]} = \Gamma_1 + \Gamma_2.\end{aligned} \tag{2}$$

It is visible that the mean SNR is a sum of mean SNRs from each link, i.e., Γ_1 and Γ_2 for reception from the first and second transmitters, respectively. The mean SNR is always higher than in the case of no diversity.

However, this diversity scheme requires the transmitters to be somehow synchronized, so that inter-symbol interference is limited. In addition, it is important that channel delays from each link are similar in comparison to symbol duration. This can be obtained by increasing the symbol duration (decreasing data rate). On the other hand, the physical nature of the propagation medium allows us to obtain this condition, e.g., according to [10], in the case of indoor propagation, the channel delay spread is the lower the shorter is the link. All these conditions allow the receiver not to implement the equalizer, thus simplifying it and reducing power consumption.

C. Receiver: non-coherent detection

The other kind of summation used during reception in a neuron is summation in time, i.e., incoming signals are integrated in time before the result is compared to the detection threshold (threshold potential). This can be a description of a non-coherent detection of the OOK signal. This detection does not require the channel coefficient to be estimated at the receiver. The receiver can be implemented by a band-pass filter centered at the utilized carrier and an envelope detector. These are elements that are low-energy consuming, as it has been shown in the case of the wake-up radio design [9]. This structure estimates the energy of the symbol at the input, i.e., in a low-noise environment the result should be close to 0 for no impulse transmitted and a value close to the received signal energy when bit 1 has been received.

D. Medium Access Control: multi-hop & sleep

From the Medium Access Control point of view, a neuron-inspired IoT network should naturally utilize a multi-hop protocol. It is a natural way of inter-neuron communication. In the case of wireless transmission, it can allow the transmit power to be limited, reducing the energy consumption at the transmitters and reducing the number of far-away neurons to be interfered. As an example, let us consider a simple, line network topology. The received power can be calculated using the pathloss-exponent pathloss model as

$$P_{RX} = \alpha P d^{-\gamma}, \tag{3}$$

where α is a constant coefficient dependent on antenna gains and frequency, P is the transmission power, d is the distance between the transmitter and receiver, and γ is a pathloss coefficient (varying typically from 2 for Line-of-Sight propagation to 5.5 in highly urban environment). Assuming the network consists of N nodes, each of equal TX power P, the power required for single-hop transmission P^{SH} can be compared with P considering equal RX power in each case, i.e.,

$$\alpha P d^{-\gamma} = \alpha P^{SH} \left(N-1\right)^{-\gamma} d^{-\gamma}. \tag{4}$$

This results in

$$P^{SH} = P \left(N-1\right)^{\gamma}. \tag{5}$$

For fair comparison, the transmission duration has to be taken into account, i.e., one slot for single-hop transmission and $N-1$ slots in multi-hop transmission. As such, the mean power for single-hop transmission $P^{\hat{S}H}$ is related to mean power of multi-hop transmission $\hat{P}$ as

$$P^{\hat{S}H} = \hat{P} \left(N-1\right)^{\gamma-1}. \tag{6}$$

Even in LoS propagation ($\gamma = 2$) the emitted mean power is N-1 times higher in single-hop case than in multi-hop case.

The other problem is interference between adjacent nodes when transmitting different packets. This can be solved by the utilization of the *refractory period* concept used by neurons. A given node deactivates its input while transmitting in a given timeslot and over next M timeslots. As the node is not to transmit neither receive any signal over M slots, it can change its state to *sleep* mode, significantly reducing power consumption. An example of such a network operation is depicted in Fig. 2 for line topology, M=1 and M=2. The color of a given node defines its current state. It is visible that a given node will be in transmit (TX) mode in 1 out of M+2 slots. The same applies to the receiver (RX) activity. While the wanted received power is independent of the utilized M value and equals $S = \alpha P d^{-\gamma}$, the interference is the sum of contributions of other TX nodes on the left and right-hand sides of a given RX. I_i^R and I_i^L can be denoted as the interference power from the ith interfering node ($i \in \{0, 1, ...\}$) on the right-hand and left-hand sides, respectively. They can be calculated as

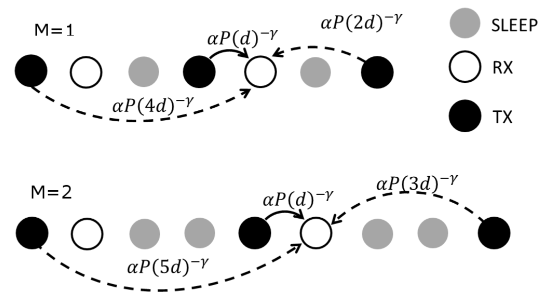

Fig. 2. Neuron-based multihop protocol for M=1 and M=2 sleep slots.

$$I_i^R = \alpha P \left(\left(1 + M + i(M+2)\right) d\right)^{-\gamma}, \tag{7}$$

$$I_i^L = \alpha P \left(\left(3 + M + i(M+2)\right) d\right)^{-\gamma} \tag{8}$$

giving, for an infinitely long network, a total interference of

$$I = \alpha P d^{-\gamma} \sum_{i=0}^{\infty} \left(3+M+i(M+2)\right)^{-\gamma} + \left(1+M+i(M+2)\right)^{-\gamma}. \tag{9}$$

The infinite sum in the above formula constitutes the reciprocity of the Signal-to-Interference ratio (SIR). This SIR increases with γ and M, starting at about 3.4 dB for $\gamma = 2$ and $M = 1$. As M is a design parameter, SIR in a network can be reduced at the cost of decreased bitrate. Most importantly, this interference power is a *worst case*, as typically the network has a finite number of nodes and the propagation conditions change with distance, i.e., the longer the interference path, the higher the probability of NLoS propagation ($\gamma > 2$), while the wanted signal path has the highest LoS probability ($\gamma = 2$) [11].

The refractory period helps not only to increase SIR. Additionally, the number of multiple receptions of the same packet is decreased. However, to ensure a given node does not transmit a given packet multiple times, a post-reception check of the packet number is proposed (in the digital domain).

IV. Initial Evaluation of Neuron-Inspired Communications Protocol

The proposed neuron-based network has been simulated on a system level. It is assumed that nodes are randomly distributed in a 500m x 500m area. While the transmitter of each node has 10 mW output power, the receiver is characterized by a noise floor of -61 dBm and the required SNR for successful OOK packet reception of 12 dB according to the values measured in [12]. The system operates with 20 kbps bitrate at the carrier frequency of 1.9 GHz. The pathloss is modeled using [10], assuming commercial environment ($\gamma = 2.2$). In order to accurately model the non-coherent diversity, each channel has a random phase. It is assumed that there is only one packet emitted that is transmitted from the random node in the first timeslot.

An example of TX, RX and sleeping nodes location in the 5th timeslot for 5000 nodes is shown in Fig. 3 for the proposed scheme with and without diversity (artificially neglecting at each RX the wanted signals from sources other than the strongest ones). It is visible that diversity allows for faster flooding of the network and a higher transmission range.

This observation is confirmed by the number of timeslots required for a given message to reach a given RX. It is a random variable (dependent on node location and channel coefficients), represented by the Cumulative Density Function (CDF) in Fig. 4 for 2000 (i.e., 0.008 nodes/m^2), 4000 (i.e., 0.016 nodes/m^2) and 10000 (i.e., 0.04 nodes/m^2) nodes. The denser the network, the faster the message distribution. While for 10000 nodes fewer than 5 timeslots are required to distribute a message among half of all nodes, for 4000 nodes it requires about 7 timeslots. For 2000 nodes, this level of message distribution is not achieved even for 40 timeslots. This shows that the sparser the network, the higher the probability of not obtaining a given packet by a given node. This can be solved by increasing TX power or increasing sensitivity. Additionally, the dashed lines in Fig. 4 show the results for systems without diversity. Both the typical time for message reception and the probability of not receiving a given packet (even for infinite waiting time) are increased in this case.

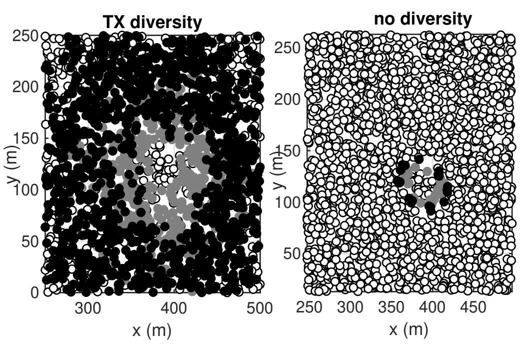

Fig. 3. Comparison of packet propagation with and without diversity for 5000 nodes in the 5th timeslot (node color: white-RX, black-TX, grey-sleep).

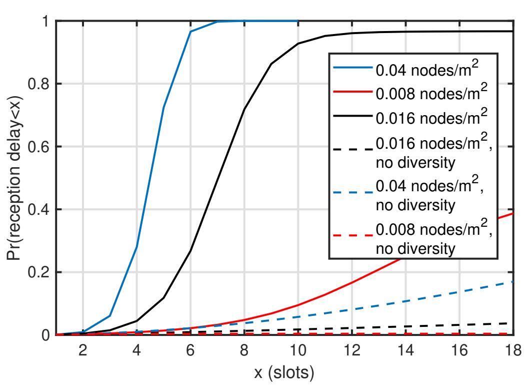

Fig. 4. Cumulative density function of successful packet reception vs. the number of slots required with and without diversity.

The refractory period prevents a given node from repeat reception of a given message, thus reducing RX power consumption. The effectiveness of this mechanism is shown for 10000 nodes in Fig. 5 as the probability of repeat packet reception in the function of node's sleep duration. This probability falls exponentially with the sleep duration. The sleep duration can be adjusted to find a balance between the probability of repeat packet transmission and transmission speed.

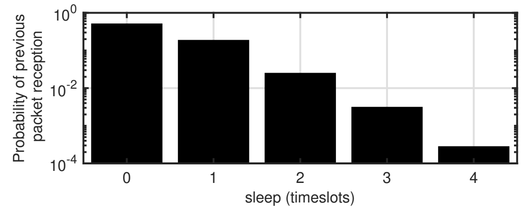

Fig. 5. Probability of repeated reception of a given packet as a function of node sleep duration. 10000 nodes considered

V. Conclusions

A neuron-based network design offers a simple, in terms of hardware and network management, and energy-efficient solution for dense IoT networks. Its analytical and numerical assessment shows a potential that should be further confirmed in a more complex simulation environment in the future.

References

[1] Cisco, "Cisco visual networking index: Forecast and trends, 2017-2022," Tech. Rep., February 2019. [Online]. Available: https://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white-paper-c11-741490.html

[2] A. J. Goldsmith and Soon-Ghee Chua, "Variable-rate variable-power mqam for fading channels," *IEEE Transactions on Communications*, vol. 45, no. 10, pp. 1218–1230, Oct 1997.

[3] F. Qu, L. Yang, and A. Swami, "Battery power efficiency of PPM and OOK in wireless sensor networks," in *2007 IEEE International Conference on Acoustics, Speech and Signal Processing - ICASSP '07*, vol. 3, April 2007, pp. III–525–III–528.

[4] Q. Tang, L. Yang, G. B. Giannakis, and T. Qin, "Battery power efficiency of PPM and FSK in wireless sensor networks," *IEEE Transactions on Wireless Communications*, vol. 6, no. 4, pp. 1308–1319, April 2007.

[5] A. Mezghani and J. A. Nossek, "Power efficiency in communication systems from a circuit perspective," in *2011 IEEE International Symposium of Circuits and Systems (ISCAS)*, May 2011, pp. 1896–1899.

[6] K. S. Gill, B. Aygun, K. N. Heath, R. J. Gegear, E. F. Ryder, and A. M. Wyglinski, "Memory matters: Bumblebee behavioral models for vehicle-to-vehicle communications," *IEEE Access*, vol. 6, pp. 25 437–25 447, 2018.

[7] A. Kliks and L. Kulacz, "Brain inspirations for dense wireless networks: Microglia functionality," in *2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, Sep. 2018, pp. 578–579.

[8] J. Bullock, M. B. Wang, and J. Boyle, *Physiology*, 3rd ed. Philadelphia : Williams & Wilkins, 1995.

[9] R. Piyare, A. L. Murphy, C. Kiraly, P. Tosato, and D. Brunelli, "Ultra low power wake-up radios: A hardware and networking survey," *IEEE Communications Surveys Tutorials*, vol. 19, no. 4, pp. 2117–2157, Fourthquarter 2017.

[10] ITU-R, "P.1238-10: Propagation data and prediction methods for the planning of indoor radiocommunication systems and radio local area networks in the frequency range 300 MHz to 450 GHz," Tech. Rep., 2019.

[11] ——, "M.2135-1: Guidelines for evaluation of radio interface technologies for IMT-Advanced," Tech. Rep., 2009.

[12] N. Pletcher, S. Gambini, and J. Rabaey, "A 65 uw, 1.9 ghz rf to digital baseband wakeup receiver for wireless sensor nodes," in *2007 IEEE Custom Integrated Circuits Conference*, Sep. 2007, pp. 539–542.