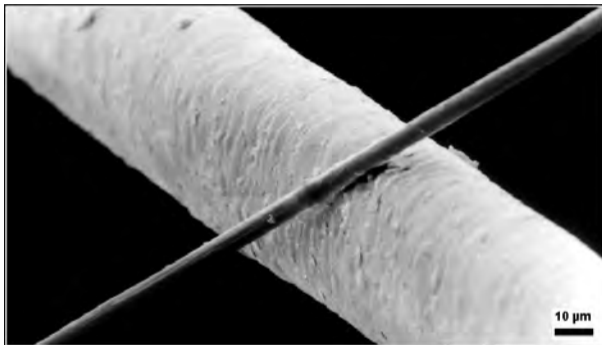


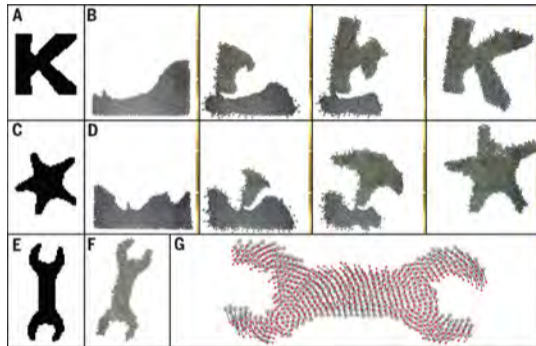
“

In-body imaging tech achieves 100microns resolution.
Leaky blood vessel inroads are only a few in diameter. [6]

”



src: Wikipedia [3]



src: Science, 2014 [7]

Really Dense Networks of Things

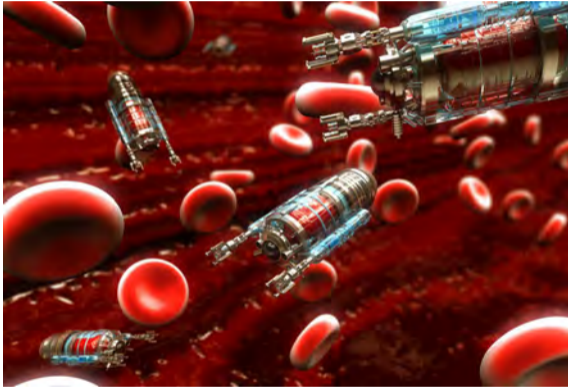
Georgios Exarchakos, ECO, TU/e
Assistant professor, Smart Networks

Credits: Tim v.d. Lee, ECO, TU/e
PhD Candidate, Smart Network Resourcing



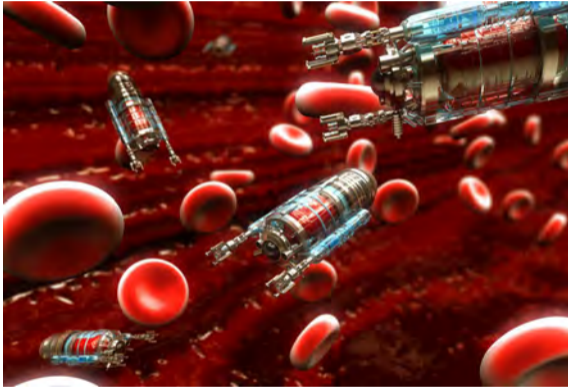
3

October 10, 2018



src:Boston Children's Hospital, Harvard Medical School [2]

- ▶ Miniaturization
- ▶ Communication microrobot-to-x
- ▶ Continuous coordination
- ▶ Navigation
- ▶ Privacy
- ▶ Info/robot retrieval
- ▶ Single-task operation



src:Boston Children's Hospital, Harvard Medical School [2]

- ▶ Miniaturization
- ▶ Communication microrobot-to- x
- ▶ Continuous coordination
- ▶ Navigation
- ▶ Privacy
- ▶ Info/robot retrieval
- ▶ Single-task operation

Challenges

- ▶ microrobot-to-x
- ▶ Continuous coordination
- ▶ Privacy
- ▶ Info/robot retrieval
- ▶ Single-task operation

Requirements

- ▶ Really dense $> 10^5/m^3$
- ▶ THz communications
- ▶ Small power budget
- ▶ Collective intelligence
- ▶ Simple processing
- ▶ One-off microrobot-to-I

Resources

- ▶ time
- ▶ frequency
- ▶ wavelength
- ▶ transmit power
- ▶ links
- ▶ energy
- ▶ computation
- ▶ memory
- ▶ ...

Requirements

- ▶ Really dense $> 10^5/\text{m}^3$
- ▶ Collective intelligence
- ▶ Simple processing
- ▶ One-off device-to-I

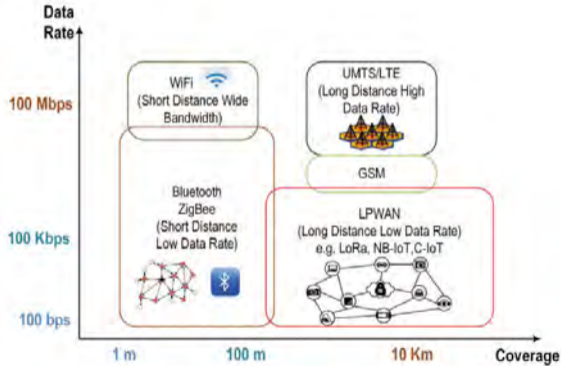
Idea

Wireless Neural Network

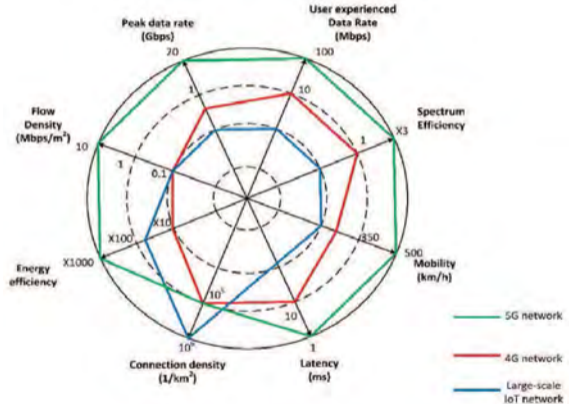
Intuition

- ▶ Attach semantics on links and wireless resources
- ▶ Teach them and build a physical wireless learning machine

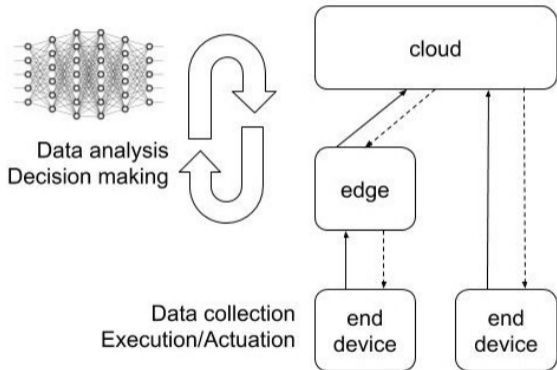
Wireless device density



src: IEEE Access [1]



src: IEEE Access [1]

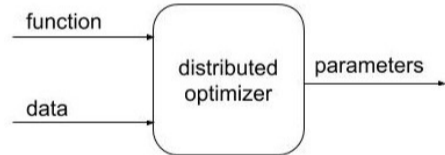


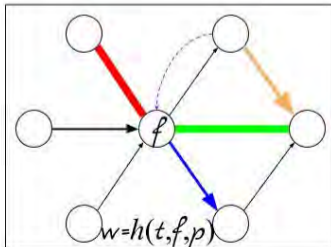
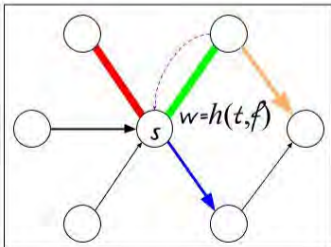
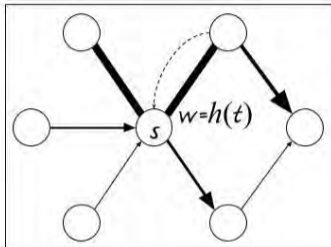
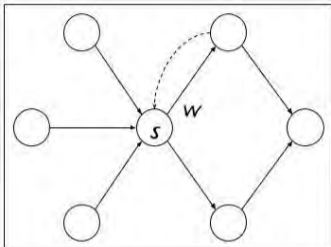
Hierarchical Intelligence

- ▶ ✗ highly dense end devices
- ▶ ✗ device-to-infrastructure
- ▶ ✗ spontaneous intelligence
- ▶ ✗ energy waste
- ▶ ✓ highly intelligent & ultra-low latency



Swarm Intelligence



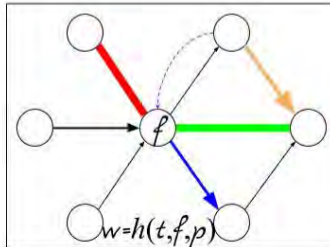
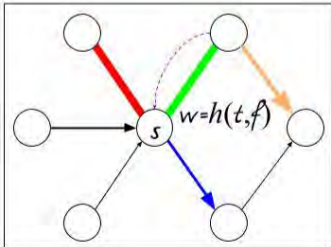
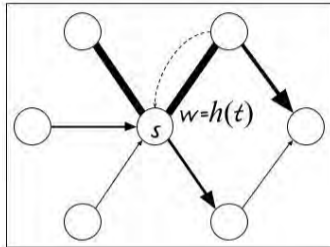
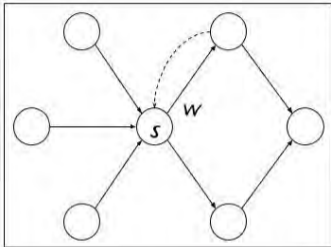


Basics

- ▶ link weight as $f.$ of wireless resources
- ▶ feedback to adapt weights
→ adapt resource allocation function

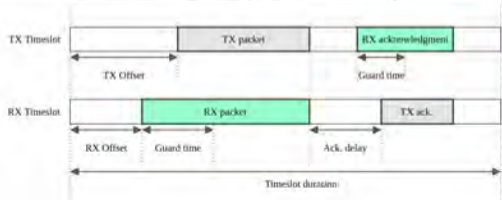
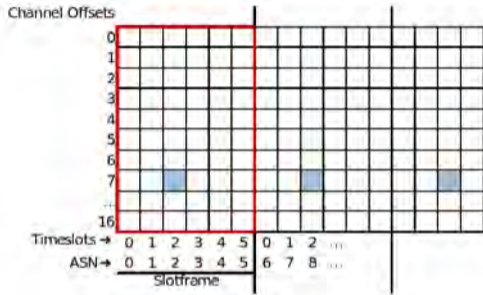
Feedback & Resourcing

- ▶ Delayed delivery at output neuron
- ▶ High local Tx retries with unhappy output neuron
- ▶ ...



Challenges

- ▶ Feedback mechanisms
- ▶ Feedback \rightarrow resources mapping
- ▶ Inherent instability
- ▶ Multi-tenancy applications
- ▶ Deployment

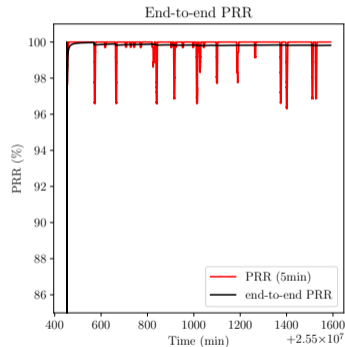
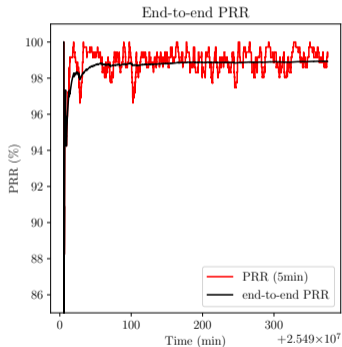
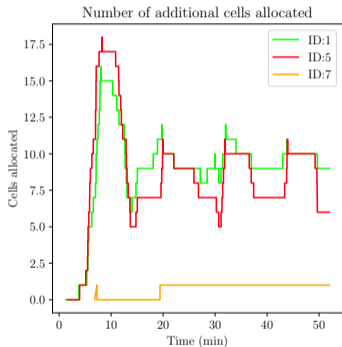


Goal

- ▶ keep reliability high and stable
- ▶ local-only coordination
- ▶ small duty cycle
- ▶ assumed always happy output neuron

Method

- ▶ Continuous swarm coordination & local feedback
- ▶ Time dependent resource release
- ▶ Resource utility based reward

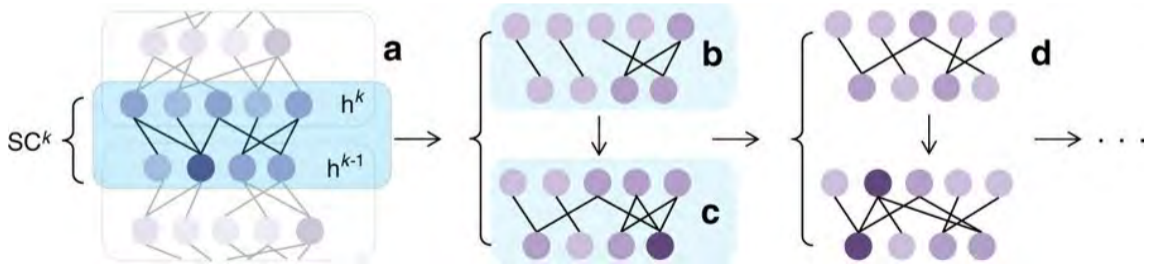


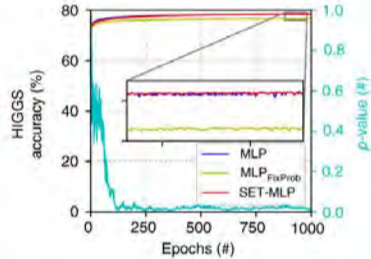
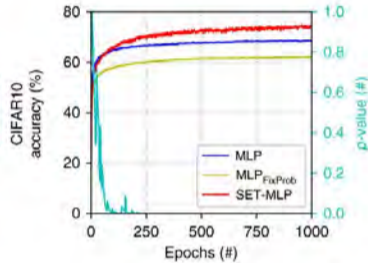
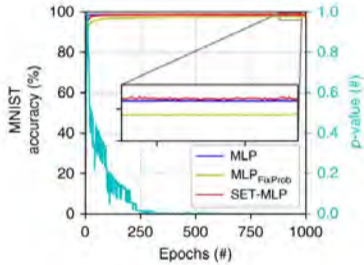
More **predictable links** for more **stable wireless neural networks**

Simple · Distributed · Energy efficient

Dimensionality reduction of ANNs

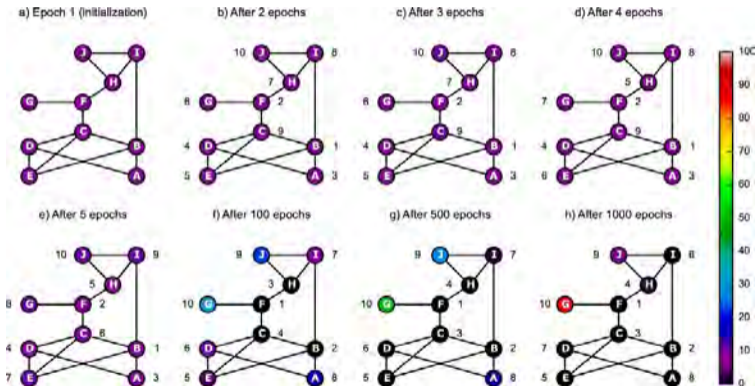
- ▶ Wireless networks are inherently non fully connected
- ▶ ANNs are predominantly fully connected





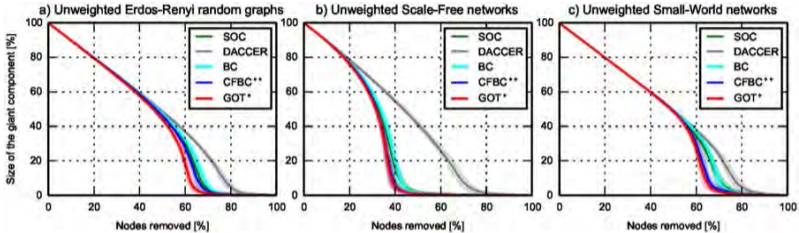
Conclusions

- ▶ Random rewiring could reduce training efforts while maintaining performance
- ▶ Current computation machines unfit for sparse matrix multiplications

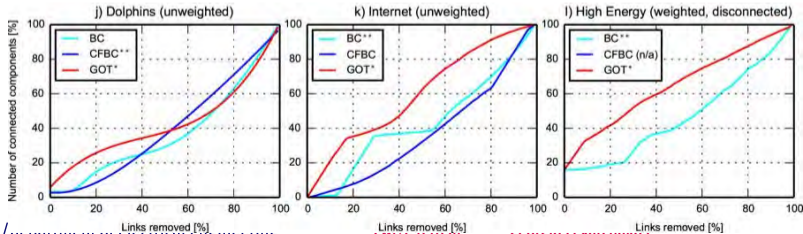


- ▶ One wireless mesh - many WNNs
- ▶ Restrict knowledge leakages
- ▶ Detect influencers
- ▶ Control transmit power
- ▶ Allocate **links** according to needs per WNN

Multi-tenancy of neural networks [4]



- ▶ fast detection of influential nodes
- ▶ fast network fragmentation



density is in the eyes of the beholder

we need in-built intelligence on the pipes, not solely on endpoints

25TH SYMPOSIUM ON COMMUNICATIONS AND VEHICULAR TECHNOLOGY IN THE BENELUX - SCVT 2018



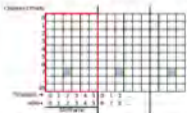
TREE: A Traffic-aware Energy Efficient FTDMA Scheduling Algorithm



Industrial deployments use Wireless Sensor Networks to increase productivity thanks to environment monitoring and actuation at a low cost. A Frequency-Time Division Multiple Access (FTDMA) communication scheme is of particular interest in these dense environments with low data rate. To address the challenges of **energy efficiency**, **reliability** and **scalability** of industrial deployments, **TREE efficiently schedules transmissions** according to traffic load, regardless of the network topology.

FTDMA Communication Scheme

In an FTDMA communication method, such as the IEEE802.15.4-TSCH, time is divided into **timeslots**, and the frequency spectrum is divided into **channels**. Several timeslots compose a slotframe, repeated over time.



Communication resources (timeslots, channels) have to be scheduled in this slotframe to ensure reliable communication. Scheduling interference- and conflict-free is known to be **NP-hard** [1].

TREE Algorithm

The algorithm is fully distributed and relies on two internal variables.

- Ψ_i is updated upon packet exchange and assesses the quality of the allocated resource.
- Φ_i is updated when a packet is scheduled for transmission and assesses the load per neighbor.

These variables periodically decay to mitigate potential errors. The variables' evolutions trigger local scheduling.



Arbitrary diagram of the TREE algorithm.

Centre for Wireless Technology, Research Retreat 2018



A practical comparison of FFNN & GRNN in improving Wi-Fi throughput performance



There is a proliferation of wireless devices today. Such large number of wireless clients can severely affect Wi-Fi throughput performance, especially in dense Wi-Fi settings.



Dense Wi-Fi settings are encountered in densely populated residential areas. Such settings have a large number of wireless clients and APs. Inter AP distance in case of dense Wi-Fi settings is around 6meters, which means that more devices will be serviced per square meter than any other Wi-Fi environment.

Machine Learning

Is advantageous when it comes to establishing

- ✓ Loss optimizers (sparse categorical cross entropy)
- ✓ Learning Decay rates (step, exp.)
- ✓ Epochs (various)
- ✓ Batch sizes (various)

Changes in parameters changes the efficiency and the training time (time taken for training the model)



IOD	Batch Size	Epochs	Accuracy %	Training Time (sec)	Training Time (min)
1	20	800	35	313.53377986	5.225170027
4	25	300	96.45	189.67796025	3.161209443
5	20	800	94.41	296.53464692	4.942320895
7	20	800	79.47	244.4258067	4.073740521
2	10	500	79.5	366.0951117	6.101435252

Generalized Regression Neural Network

Here the output is estimated using weighted average of the outputs of training dataset. The weight is calculated using the



- [1] **M. Chen et al.** “Narrow Band Internet of Things”. In: *IEEE Access* 5 (2017), pp. 20557–20577.
- [2] **Medical millibots for less-invasive surgeries moving out of proof-of-concept studies.** Healthinnovations. **May 28, 2015.**
URL: <https://health-innovations.org> (visited on 10/07/2018).
- [3] **Micrometre.** In: *Wikipedia*. Sept. 30, 2018.
- [4] **Decebal Constantin Mocanu, Georgios Exarchakos, and Antonio Liotta.** “Decentralized dynamic understanding of hidden relations in complex networks”. In: *Scientific Reports* 8.1 (Jan. 25, 2018), p. 1571.
- [5] **Decebal Constantin Mocanu et al.** “Scalable training of artificial neural networks with adaptive sparse connectivity inspired by network science”. In: *Nature Communications* 9.1 (June 19, 2018), p. 2383.
- [6] **Stephen Ornes.** “Inner Workings: Medical microrobots have potential in surgery, therapy, imaging, and diagnostics”. In: *Proceedings of the National Academy of Sciences* 114.47 (Nov. 21, 2017), pp. 12356–12358.
- [7] **Michael Rubenstein, Alejandro Cornejo, and Radhika Nagpal.** “Programmable self-assembly in a thousand-robot swarm”. In: *Science* 345.6198 (Aug. 15, 2014), pp. 795–799.