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# Distributed Artificial Intelligence Integrated Circuits For Ultra-Low-Power Smart Sensors

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**Abstract**—Wireless sensor networks (WSN) could be defined as networks of autonomous devices that can sense and/or act on a physical or environmental conditions cooperatively. To make these sensors smarter, Artificial Intelligence (AI) is used to process sensed data but also to solve challenges such as security, energy aware routing, ect. This paper present a solution of using AI in the case of distributed sensors networks that aims to tackle these challenges

**Index Terms**—Wireless Sensor Network, Graph Neural Network, Distributed Intelligence, Smart Sensors, On-edge Computing

## I. INTRODUCTION

Wireless sensor networks (WSN) could be defined as networks of autonomous devices that can sense and/or act on a physical or environmental conditions cooperatively [1]. They are used in many fields such as health monitoring, smart cities, etc. Usually, the sensors broadcast wirelessly the data to an aggregator. Then, they process the data using Artificial Intelligence (AI) paradigms or send it to the cloud to be processed later [2]. However, as shown in [3], this centralized structure has three main drawbacks. First, the aggregator has to be able to process a potentially enormous amount of data in real time. This leads to a compromise to do between the energy consumption and the computing capabilities of the system. Another problem that can hurt the battery lifetime is transmitting the whole raw data. Finally, transmitting the acquired data does not guarantee the information privacy in case of interception by a malicious individual.

To reduce the impact of the first two drawbacks, “on-edge” computing allows to pre-process the data at the sensor level with AI and therefore reduce the amount of data to broadcast to the aggregator. In this decentralized architecture, it is possible to use distributed AI models for processing. In [3], Larras *et al* present a Clique-Based Neural Network (CBNN). In CBNNs, only the activated node index is transmitted. Thus, if the transmission is intercepted, it is impossible to retrieve the original data. Moreover, the amount of transmitted data is very low compared to a system exchanging raw data. However, CBNN rely on a specific architecture because of the cliques that are defined *a priori*. A more general and flexible approach of distributed AI is the Graph Neural Networks (GNN) model. Graphs are interesting because each node represents a sensor or an actuator. The edges between each pair of node (modeling their relation) will create the graph  $G$  of our network as shown

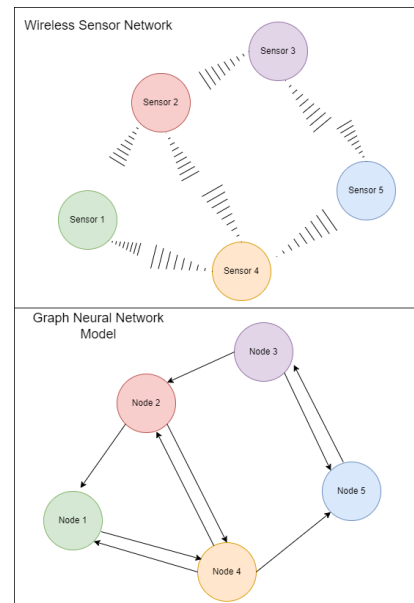


Fig. 1. Modeling a sensor network into a directed Graph Neural Network

in Figure 1. The idea is that each node exchanges data only with its neighbors and then converges to a correct classification of its environment. Finally, GNN are also interesting because they are able to converge even in a heterogeneous network [7]. GNN are mainly used on software or in post-processing applications and literature does not provide examples of GNN implemented directly into the sensor network.

In Section II, we present how and why we use graph theory and GNN to model our WSN, then we compare our solution to the state of the art. In Section III we present our ambitions with this model.

## II. THE SOLUTION PROPOSED

### A. Use of graph theory for WSN

Presented in 2009 by Scarselli *et al* [4], GNN are based on the concept that nodes  $n$  in a graph  $G$  represent objects or concepts, and edges represent their relationships. Each node  $n$  can have a state  $x_n$ . The state is computed with an aggregation function that will get the neighbors states and process them with the node state. Finally, this combined state is fed into a neural network to create a new state and the process

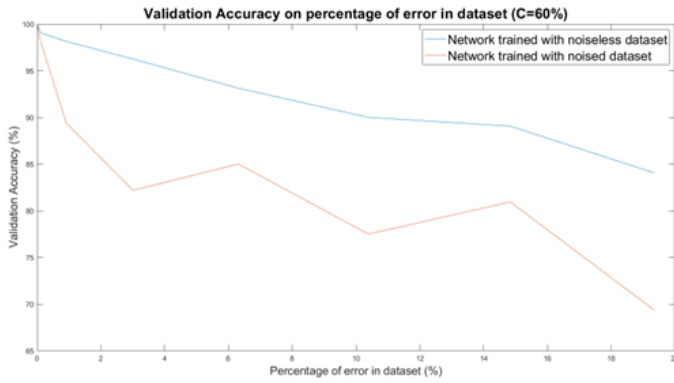


Fig. 2. Validation results after training local networks with a noiseless and the noised dataset for  $C = 60\%$

repeats. This allows a particular node to get information from further and further in the graph. Various kinds of aggregation functions can be used, in [5] Hamilton *et al* present the GraphSAGE model that samples the neighborhood of each node, and then aggregate these samples using a mean aggregator or a LSTM aggregator for example. In 2018, Veličković *et al* present Graph Attention Network (GAT). Following a *self-attention* strategy, the objective is to compute the state of each node in the graph taking into account its relation with its neighbors. This state can be used into another function that will compute an output  $o_n$ . In our model, each node locally implements a neural networks that take the local sensor measurement and the local and the neighbors  $o_n$  as inputs. Our  $o_n$  is a vector that will describe global context without giving any local information. We named it "belief" because it will be more and more precise by after  $K$  iterations (depending of the connectivity in the graph) of exchange with the neighbors. Each node uses a feed forward neural network that will be build with an attention aggregator to adds sensitivity and allow to be more accurate in the local belief. To deal with the heterogeneous environment, the sensors measurements are normalized and quantized as input positions.

To validate our network, we created a global bijective dataset from which we deduce a local dataset for each node. Each node is independently trained with these local datasets. We repeated this on various graph with connectivity  $C$  evolving from  $C = 40\%$  to  $C = 70\%$  to model a distributed network and with different percentage of errors due to noise in datasets. These experiments showed that it is possible to work exchanging only partial information such as belief. They also permit to see that with the normalization and quantification process, training the local network with a dataset without noise gives better accuracy result than training with a noised dataset as in Figure 2.

### B. Comparison with the State of the Art

One of the main constraints in sensor networks would be the geographical constraint. It is sometimes impossible to connect two nodes together even if they are physically near. With the GNN model, belief from one node will get to the other.

Moreover, our current model fits into structural requirements of IEEE 802.15.6 standard such as:

- 1) Nodes should be capable of being removed and added to the network in less than 3 seconds.
- 2) WBANs should be able to operate in a heterogeneous environment where networks of different standards cooperate amongst each other to receive information

Using the GNN also allows to modify the network structure without having to retrain the whole network unlike the CBNN [3] in which we need to recreate the cliques. Only the modified node and its neighborhood will need to be retrain as long as we do not add new belief. Exchanging only beliefs rather than raw datas or state permits to reduce the quantity of data to broadcast and this allows a better security of the system. As said previously, beliefs are auto-sufficient to transmit information and with  $n$  bits it is possible to transmit  $2^n$  different beliefs. Finally, distributed AI models are integrable in hardware directly on the sensor. It reduces considerably the latency that exists in centralized model in which all data are sent to an aggregator and it allows to pre-process the data to determine if they are relevant or not in regard of the targeted application.

### III. CONCLUSION

As shown, we adapted the GNN model for the sensor network field. One of our main goal in the future would be to simulate this model with a surjective context such as smart cities or WBAN . The main difficulty is to extract the local datasets from real datasets but as shown in Section II it could be very interesting. Another objective would be to design an integrated circuit that would implements or accelerate a part of our model and to create a demonstrator.

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