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Position Paper: LoRa Mesh Networks for Enabling Distributed Intelligence on Tiny IoT Nodes

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Abstract. LoRaWAN is a widely used solution in today's Internet of Things (IoT) applications to connect remote sensor nodes to the Internet. At the same time, microcontroller-based sensor nodes with increased processing capacities are increasingly becoming smart nodes applied for performing machine learning tasks. We argue that LoRaWAN has important connectivity limitations to truly unleash the potential of these smart tiny nodes. We position to apply LoRa mesh networks as a communication substrate to enable novel networking capacities for the new scenario of distributed smart IoT nodes.

Keywords. IoT, embedded learning, LoRa, mesh networks

1. Introduction

Machine learning (ML) applications are nowadays run on ever smaller computing devices. Microcontroller boards with integrated sensors do the signal processing and perform the machine learning tasks directly on the device [1]. This tendency is enabled by the increased microcontroller computing capacities and the growing availability of frameworks for developers that facilitate the machine learning pipeline from model definition to deployment [2].

There are many sectors in which ML has become part of IoT applications. For precision agriculture, the survey in [3] reviews a large number of applications fields where ML has been used, such as soil prediction, pest detection and produce analysis. Classification tasks through computer vision, for instance, to determine the status of crops, have become established means to automatize decisions in agriculture production processes based on machine learning information [4]. Related fields such as biodiversity analysis with IoT devices have also applied ML solutions [5]. An issue is, however, at what layer of the application stack the decisions are taken, and as such, where the ML is performed, whether at the cloud, at the edge, or at the tiny IoT nodes.

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LoRa is widely used to transmit data from remote IoT nodes over gateways to Internet-hosted applications [6]. A LoRa link between two nodes can cover several kilometers of distance, which enables a geographical spread of a sensor node deployment in IoT applications. LoRa is meant for low data rate communication and in many countries, its duty cycle is limited to 1%. A LoRa packet can have a size of up to 256B. Therefore, LoRa is often used for applications with remote nodes which only from time to time send small amounts of sensor data. A feature of LoRa compared to other Low Power Wide Area Network (LPWAN) technologies is that operating a LoRa network does not require a license, thus it can be deployed without any liaison with a network operator.

The LoRaWAN architecture [7] is a popular solution to materialize LoRa-based IoT applicationd. The architecture defines a star topology among the IoT devices such that a sensor node connects over a single hop with a gateway. The gateway has Internet connectivity and forwards the data received through the LoRa packets to higher layers in the cloud, where the data is processed and the decisions are taken.

The LoRaWAN architecture does not directly interconnect the sensor end nodes between themselves since the logical connection of each end node is with the gateway. This impedes in LoRaWAN the scenario of sensor nodes communicating with each other. With regards to communication link usage, in LoRaWAN the connection and bandwidth capacity between a sensor node and the gateway is not symmetric. The uplink is often the only one used and for transmitting sensor data to the gateway. While there is a downlink as well, it is not often part of the application. There is also the fact that after sending an uplink message an end node only listens at specific time slots to any downlink message from the gateway. This limits the possibility to push messages at arbitrary times from the higher layers to the sensor node.

Since IoT nodes are transforming from being mere sensor data providers into smart nodes with decision capacity, we position that an enriched networking capacity beyond LoRaWAN materialized by LoRa mesh networks is needed to enable and exploit this potential.

2. Opportunities of LoRa mesh networks for the IoT

2.1. Applications

Compared to the large number of IoT applications using LoRaWAN, the portfolio of applications using LoRa mesh networks is still very small.

An application case from the maker community is Meshtastic[2]. This application is operated only within a LoRa mesh network without Internet connectivity. The scenario is remote areas that have no cellular network coverage. A user connects through Bluetooth from her smartphone to a portable LoRa equipped IoT node. Among all users, a mobile LoRa mesh network is formed. The Meshtastic application allows users to send small text messages to each other over the LoRa network.

Another work that proposed LoRa for building an interconnected communication substrate is LoRaX [8]. The LoRaX system aims to extend the Internet to underserved regions through devices with LoRa connectivity. The Internet access is achieved through the low data rate LoRa network.

[2] https://meshtastic.org

In [9] a messaging system was implemented in which clients connect to LoRa nodes for reaching other participants either within the LoRa network or, through hubs, on the Internet. The authors suggest the applicability of the used architecture also for other application cases.

The above summarized applications illustrate how LoRa mesh networks are used for applications today. While these are examples of applications that involve humans, the LoRa mesh networking capacity does not exclude being used by applications that involve Machine to Machine (M2M) communication. Indeed, for diverse machine learning applications of the precision agriculture domain [3] that use trained models at the nodes, the LoRa mesh networking capacity could open an opportunity to build locally interconnected decision making systems that are autonomous from cloud-based services.

Training a machine learning model on-device, i.e. on the microcontroller board is an option to make smart adaptive IoT nodes [10]. A model can be trained on such a node in an isolated fashion with its local dataset, therefore without requiring any network interface, or, if a network interface exists, in collaboration with other nodes, applying a distributed learning approach such as federated learning [11]. In federated learning, the machine learning models are trained locally at each node, but periodically exchanged among the nodes, typically by sending them to a centralized aggregator, where the individual models are merged into a new global model. There have been some works which applied federated learning to the IoT, where the challenges include the communication cost of federated learning and the heterogeneity both in IoT devices and training data [12].

In the work of Kopparapu et al. [13] and our work [14], federated learning was performed among tiny microcontroller-based IoT devices. Both works, however, used a wired connectivity to exchange the machine learning model and did not explore the scenario to communicate over low data rate links such as LoRa.

2.2. Technologies to build LoRa mesh networks

There is a certain body of research works in the academic literature on the design and evaluation of LoRa mesh networks. Most works apply simulations and do not have a usable prototype that can easily be deployed in real environments.

In a few works, however, prototypes were built and deployed in real nodes, such as in [15], where the authors present an initial evaluation study of a LoRa mesh network. In their work, the prototype is based on the RadioHead library. The performance of the network is evaluated in field experiments with a very small number of nodes.

In the previously mentioned Meshtastic project, the implementation is available in an open git repository. It is operational and the deployment on real nodes has been shown for ESP32-based T-Beam boards. Meshtastic forms a LoRa mesh network. The message dissemination currently is based on flooding[3]. This solution of flooding avoids complex network management but can lead at a larger scale to congestion if no additional measures are taken.

In our own work we have developed the LoRaMesher library to build LoRa mesh networks [16]. LoRaMesher implements a distance-vector routing protocol for exchanging directed messages among LoRa nodes. For the interaction with the LoRa radio chip,

[3] https://meshtastic.org/docs/developers/Firmware/mesh-alg

LoRaMesher uses RadioLib[4]. The hardware for which LoRaMEsher currently compiles are ESP32-based boards, specifically the T-Beam and ESP32LoRa, with SX1276 LoRa series module. We have started to look at supporting other boards such as the Arduino Portenta [17]. LoRaMesher leverages FreeRTOS[5] to implement task handlers for the packet processing and a packet queue to share packets between tasks. The implementation includes an application-level task for which a demo example is provided, where increasing values of a counter are sent among the nodes. LoRaMesher nodes are self-organizing, i.e., once the device is switched on it becomes part of the LoRaMesher network through receiving and exchanging routing tables with the other nodes of the network.

3. Challenges for using LoRa mesh networks

IoT applications with embedded machine learning on remote nodes and LoRaWAN communication have been shown operational nowadays [18]. For classification and prediction tasks, these smart nodes are used in a 24/7 operation, which is different from the operation mode of traditional sensor nodes. While typical sensor nodes are in sleep mode most of the time to optimize the energy consumption for the longest duration of the battery, smart IoT nodes have to be conceived as permanently operated nodes equipped with batteries that can be recharged, for instance by solar power.

The communication bandwidth of a LoRa link is low. Doing machine learning on the IoT device allows sending a low payload classification result instead of sending a higher amount of raw sensor data for classifying elsewhere, which saves bandwidth of the low capacity LoRa communication link. Given the duty cycle limitations of LoRa, the M2M communication in a LoRa mesh network will need to consider bandwidth saving designs. Another issue of LoRa are the lack of packet delivery guarantees. Federated learning, for instance, will require additional protocols for reliable messaging. Finally, messages in a LoRa mesh network will be delivered with delays, excluding applications that have strict real-time requirements. Therefore, distributed intelligence within a LoRa mesh network may need to identify the tradeoff between using local computation or communication resources.

There will be a need for a network integration of the LoRa mesh layer with the Internet in full-stack IoT applications. Figure 1 depicts a LoRa mesh network where gateways bridge between both networks. A few nodes in the LoRa mesh networks are illustrated as application nodes, while other nodes can operate as routers only. In the current LoRaMesher implementation, all nodes in the LoRa mesh network have 2 byte addresses and are routable. Therefore, gateway nodes, which are at the same time nodes of LoRaMesher, have a routing table that allows any nodes of the LoRa mesh network to be reached from the gateway.

The sending of data messages to specific nodes in both networks can lead to an integration of services and applications that spans over both layers. While in traditional LoRAWAN-based applications, the data flow is mostly unidirectional from sensor to cloud, the gateway in the LoRa mesh network will also enable a bidirectional data flow and forward messages from nodes on the Internet to specific application nodes in the

[4] `https://github.com/jgromes/RadioLib`

[5] `https://www.freertos.org`

LoRa mesh network. This will require to design of a gateway able to handle the different capacities of both networks and types of nodes. Novel kinds of distributed applications will arise for the IoT layer and will require common support services, thus there could be a need for a middleware that provides such a common set of services.

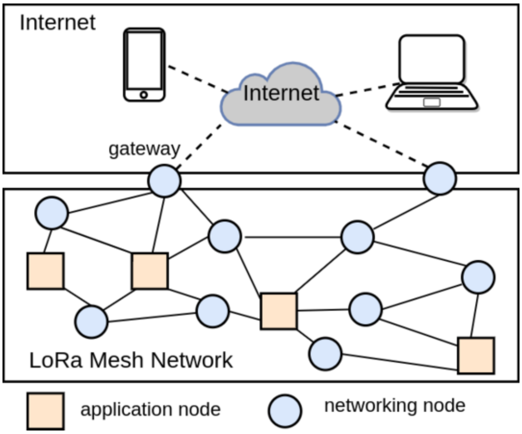

Figure 1. LoRa mesh network and Internet integration over gateways.

4. Conclusions

This paper proposed the use of LoRa mesh networks to enable distributed intelligence in an IoT communication layer. With regards to node-to-node communication, the current LoRaWAN architecture was analyzed and some limitations for these new requirements were identified. A few current applications using LoRa mesh networks were described as well as the technological options to build these networks. With the growing use of machine learning applications on tiny IoT nodes, we argue that LoRa mesh networks could become the communication substrate to build distributed intelligence with tiny edge nodes.

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