Adapting Sensor Network Protocols to Environmental Changes through Machine Learning

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***Abstract*—Wireless sensor networks often suffer from severely changing environmental conditions, which affect their communication quality. Changing temperatures, humidity levels, soil moisture levels, and many other parameters are hard to model or predict. In this abstract, we propose to learn their effects on communication quality and to develop a set of networking protocols to cater for these changes and, if necessary, to switch off communication completely, until conditions improve again. We explore this idea on the basis of an example from underground sensor networks and soil moisture levels.**

***Index Terms*—underground sensor networks, machine learning, environmental changes, soil moisture, MoleNet**

I. Introduction

Wireless sensor networks (WSN) have become an important tool to measure and deliver various environmental properties [3]. However, researchers have clearly showed that wireless communication quality depends on that same environment the sensor network is monitoring. For example, underground wireless communications depend on the soil moisture and soil consistency [4], and LoRa communications have been shown to depend on temperature [1].

In this abstract, we propose to learn these conditions as opposed to model or predict them and to adapt to them with a combination of machine learning and fuzzy systems. We motivate and sketch our proposal based on an example from underground sensor networks and soil moisture.

II. Application scenario and observations

In our own on-going research on underground wireless sensor networks (WUSN) for agricultural applications in sub-Saharan Africa [9] we have observed quite of an extreme case of dependency, where very high soil moisture during rainy periods break all underground wireless communications. An example of this case is given in Figure1. In this experiment, we have two underground nodes and one aboveground node. All nodes are MoleNet nodes, a 433MHz based hardware solution, developed by us earlier [9]. With increasing volumetric water content (VWC) at the underground nodes, communication between the two underground nodes breaks (the red line), while the communication between the underground and the aboveground nodes is still possible. Looking carefully at the VWC data, it looks like there is a threshold of the VWC, above which underground communication is hindered. However, this exact value depends also on the distance between the nodes and on the soil consistency, and not solely on soil moisture.

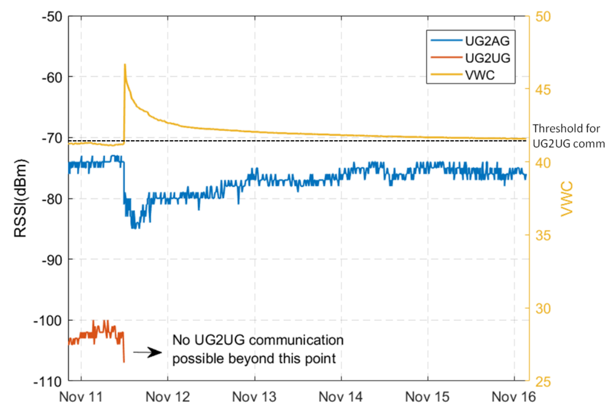

Fig. 1. With increasing volumetric water content (VWC), the communication underground breaks for a prolonged period of time. Real-world experiments with two underground and one aboveground MoleNet nodes [9].

III. Proposed approach

Current research addresses this problem by modelling the path loss in terms of the soil moisture and predicting the success of the communication, for example in the work of Dong and Vuran [2]. Sophisticated path loss models for WUSN already exist and show very good results when compared with real experiments [7]. However, such approaches require lots of additional information, which is not necessarily available for all WUSN applications, such as distances between any pair of nodes, soil consistency and corresponding path loss exponents for different places in the field, etc. Especially the path loss exponent measurement is an almost impossible task for real deployments, as it fluctuates massively throughout natural fields due to stones, soil variations and trapped underground water. It also changes with time. On the other hand, soil moisture is usually part of the deployment requirements for underground WSNs anyway.

The current approach to the problem and our proposed one are depicted in Figure 2 with a black and green line, respectively. Our proposal is to observe the behaviour of the system depending on the measured VWC and to learn when to send data and when not. Not sending data at all during down times of the wireless links can save a lot of energy for better times. Compared to the traditional approach of modelling and computing the path loss, our new approach takes a much more direct way to the solution of the problem (see Figure 2) and does not require distance, position or path loss exponent measurements.

The methodology we propose is a combination of machine learning, such as Q-Learning, with fuzzy decision techniques [5]. The Q-Learning needs to learn the VWC threshold for individual neighbours at each sensor node. The fuzzy decision techniques is required to stabilise the decisions and to avoid switching on and off the communication close to the learnt threshold. An advantage of our proposal is that it can easily incorporate further environmental or internal parameters, such as temperature, buffer state or battery level. In fact, the methodology does not depend at all on VWC, but can be applied to any single parameter or set of parameters which influence the transmission. The resulting decision can also range from increasing or decreasing the transmission power to switching off the communication completely.

Another advantage of the proposed approach with Q-Learning is that it takes into account also non-modelled parameters and adapts to them. This is due to the nature of Q-Learning of being non-model based reinforcement learning technique. This is very useful for sensor networks, where any fluctuations in the environment, such as closing/opening windows, further influence the communication quality, but are very hard to model. Moreover, if the distances between nodes change, the model will also be adapted.

Our approach will not only enable sensor networks (underground or aboveground) to avoid wasting resources in case of communication outage, but will also help optimising resources in any deployment.

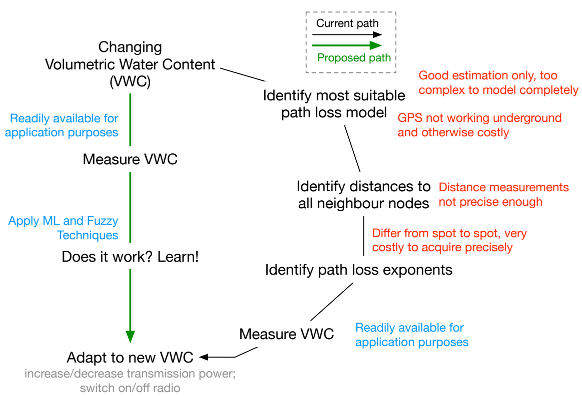

Fig. 2. Our proposed approach is much more direct and leads to the desired result faster and with less additional information than the existing one.

However, several new challenges arise. When each node learns for each of its neighbours when to send data and when not, any existing MAC or routing protocols would fail. Thus, new protocols need to be designed at all networking stack levels. The main challenge is to cooperatively decide on new transmission powers or on switching off and on the communication al-together. Another challenge is to make sure that local buffers do not overflow in times of no communication.

IV. Future work

We have started already designing a MAC protocol, which learns the VWC threshold and decides on switching on/off the communication. First results with a one-hop simulation scenario show very good results [8]. We have developed a sophisticated simulation environment[1], based on OMNeT++ and Castalia to enable VWC simulation with changes per time. Figure 3 shows an excerpt of these results, where we compare the energy consumption of our approach with a non-adaptive approach (does not consider the VWC at all, but sleeps when no data transmission is required) and against B-MAC [6]. We can see from the figure, that the adaptive approach is better than the non-adaptive one. An interesting observation is that B-MAC consumes much more energy than the non-adaptive approach, which is due to its broadcast behaviour.

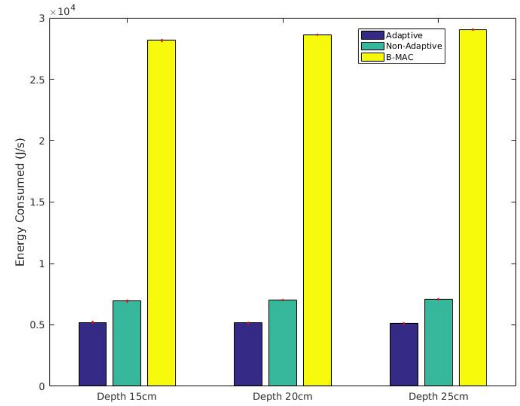

Fig. 3. Initial results of one-hop VWC-based adaptive communication in terms of energy consumption, compared to a non-adaptive approach and B-MAC.

In the immediate future we plan to extend this one-hop approach to a fully fledged MAC protocol with unicast and broadcast modes, before we proceed with a routing protocol.

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