FUZDEMA: A PORTABLE FUZZY-BASED DECISION-MAKING TOOL FOR RELIABLE COMMUNICATION IN WIRELESS UNDERGROUND SENSOR NETWORKS

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Abstract *– The deployment and the exploitation of a Wireless Underground Sensor Network (WUSN) remain challenging because of signal attenuation in the soil and the limited battery that powers the sensor nodes. Due to the attenuation of the signal in the ground, the reception or loss of the sent data depends on the ground conditions, which can change dynamically. However, in existing WUSNs, each node sends the data collected in each round regardless of the signal attenuation. It is well demonstrated that sensor nodes consume the most energy during transmission. Obviously, transmission without receiving any data significantly reduces the lifetime of a sensor node useless. This paper presents a novel fuzzy-based decision-making solution called FuzDeMa that reduces energy consumption by anticipating data losses before transmission. To do so, FuzDeMa assesses in real time the loss or the reception of a packet according to the in-situ node's environments before its transmission and decides whether to send or not the packet based on the computed reliability. To validate the proposed approach, we embed it into a dedicated underground node called the MoleNet and realized real experimentations firstly with an existing dataset and secondly, with precision-measuring equipment to estimate the energy consumption. The results revealed the possibility of prolonging the lifetime of the sensor node by saving up to* $81.7876\mu J$ *in a single round. Additionally, FuzDeMa shows the ability to save energy for up to* 46 *of additional revolutions, thus extending the life of the sensor node to* 32.85% *for* 140 *real transmission cycles. An analytical generalization of FuzDeMa is provided regardless of a specific dataset or sensor node. Thus, we provided the conditions for a random dataset to save the energy with any sensor node that implements FuzDeMa during transmissions.*

Keywords – Decision-making, embedded systems, energy efficiency, fuzzy inference system, signal loss, wireless underground sensor network (WUSN)

1. INTRODUCTION

Contrary to conventional Wireless Sensor Networks (WSNs), in which nodes are located above the ground, a Wireless Underground Sensor Network (WUSN) consists of sensor nodes buried in the ground. Despite the increase in its popularity, deploying and operating a WUSN is very challenging [1]. In addition to the limited resources (computation, storage, energy, communication) of sensor nodes, a WUSN has to face several additional challenges. First, the attenuation of Electromagnetic waves (EMs) in soil widely affects the link quality during each transmission [2]. In WUSN, changes in link quality depend on soil properties, which can vary over time due to weather conditions [3] and transmitted data at a bad instant can be easily lost due to signal attenuation and not received by either an intermediate node or the final destination.

A real time assessment of the reception/loss of data transmitted by a sensor node could be a good solution to avoid energy wastage. Nevertheless, because using a low power micro-controller and low bandwidth, sensor nodes cannot efficiently execute locally, or via the cloud, well-known Machine Learning (ML) solutions for learning/predictions purposes [4] are used. ML solutions in WSN have fundamental limitations on their applications, and the accuracy of the prediction can be affected by the data quality. Unsupervised ML, such as clustering , is widely used to prolong the lifetime of the sensor network by organising the communication within the network [5, 6]. The main idea is to reduce the amount of data to send to save the sensor nodes' energy without impacting the data quality. A recent application of ML to avoid energy wastage in WSN for precision agriculture consists in reducing the amount of transmitted data to the sink [7]. This solution helps reduce energy consumption and bandwidth while maintaining good accuracy by trying locally to "guess" another value and send it only when the guessing is wrong. Although this work applies light ML techniques in smart agriculture applications and demonstrates its feasibility, it differs from our approach since it only focuses on data and does not consider network conditions. On the other hand, recent lightweight computational intelligence solutions such as fuzzy logic have been used in several applications as a decision-making tool adapted to embedded systems [8, 9, 10], but to the best of our knowledge, none of them has ever been applied to sending decisions.

This paper introduces a novel fuzzy logic-based approach applied to network conditions to save energy related to transmission in WUSN called FuzDeMa. It is known that the sensor node's largest energy consumption source occurs during wireless data transmission by the transceiver. For that, this latter evaluates the reception probability of sending the data based on its environment parameters. If the reception probability is low, the node keeps the data locally and avoids a useless transmission, thus saving energy. The results show that FuzDeMa can save up to $81.7876\mu J$ per round in a real and dedicated underground sensor node called the MoleNet. Furthermore, the energy evaluation through a real dataset reveals that FuzDeMa can extend the lifetime of the sensor to up to 32.85% without losing information at the sink (for 140 different measurements. The main contributions of this paper are as follows:

- A new lightweight decision-making approach based on Sugeno's fuzzy inference system that accurately estimates packet loss before transmission.
- The evaluation of the performance of the proposed FuzDeMa according to a real dataset. FuzDeMa has been compared to a recent and accurate path loss model.
- The implementation of FuzDeMa on a real and dedicated sensor node used for underground applications such as precision agricultural and ecological monitoring.
- The evaluation of the energy behaviour of FuzDeMa when operating within real sensor nodes according to different scenarios.
- The energy consumption of FuzDeMa was intensively evaluated using precision-measuring equipment.
- The analytical generalization of FuzDeMa is performed in order to give the energy break-even point of the proposal regardless of the sensor node used.

The rest of this paper is organised as follows: Background and related work are presented in Section 2; Section 3 presents the main motivation of this work and states the problem of the paper. The fuzzy-based solution for decision-making during transmission is described in Section 4; Section 5 presents the performance evaluation of FuzDeMa on a real dataset. Integration of our proposal within a real sensor node is given in Section 6 and Section 7 describes the experimental setup used for the evaluation of the energy consumption. The energy consumption of FuzDeMa within the MoleNet is discussed in Section 8 and Section 9 extends the validation of FuzDeMa by providing a generalization with an analytical approach regardless of the sensor node. The paper ends with a conclusion in Section 10.

2. BACKGROUND AND RELATED WORK

In this section, we firstly present the existing path loss models in WUSN. The most relevant applications based on the fuzzy logic for decision-making are described thereafter.

2.1 Path loss models of EM waves in WUSN

The characteristics of the wireless underground channel differ to the conventional free space wireless communication channel. These differences are caused by the wave propagation mechanism in the underground channel. In this section, we present the main existing path loss models designed for the prediction of EM loss in the soil. According to the communication types in WUSN, we classified the existing approaches into full underground and mixing path loss models.

2.1.1 Full underground path loss models

These models are designed to evaluate the EM loss when the transmitter and the receiver are both under the ground (underground to underground communications).

One famous path loss model in the literature is called modified Friis proposed by Li et *al.* [11]. This model is based on the Friis transmission equations initially designed for free space communication. The authors obtained the total loss L_{tot} of an EM crossing the ground by taking into account the loss due to wave attenuation in soil *(1)-(3)*.

$$L_{tot} = 6.4 + 20log(d) + 20log\left(\beta\right) + 8.69\alpha d \qquad (1)$$

$$\alpha = 2\pi f\sqrt{\frac{\mu_0\mu_r\epsilon_0\epsilon^{'}}{2}\left(\sqrt{1+\left(\frac{\epsilon^{''}}{\epsilon^{'}}\right)^2}-1\right)} \qquad (2)$$

$$\beta = 2\pi f\sqrt{\frac{\mu_0\mu_r\epsilon_0\epsilon^{'}}{2}\left(\sqrt{1+\left(\frac{\epsilon^{''}}{\epsilon^{'}}\right)^2}+1\right)} \qquad (3)$$

The constants α and β are the key elements of the modified Friis model and constitute the real and the imaginary parts of the complex propagation constant γ ($\gamma = \alpha + i\beta$). The permeability in vacuum μ_0 and the permittivity in free space ϵ_0 are related to the light velocity in vacuum by $\epsilon_0\mu_0c^2 = 1$. For non-ferrous soils, the magnetic permeability can be neglected ($\mu_r = 1$).

Bogena et *al.* [12] proposed the semi-empirical model called CRIM-Fresnel by combining the Complex Refractive Index Model (CRIM) and Fresnel equations. They showed that the signal attenuation in soils A_{tot} given in *(4)-(6)* depends on the soil attenuation constant α, the reflection coefficient of the wave and the distance d between the transmitter and the receiver.

$$A_{tot} = \alpha d + R_c \qquad (4)$$

$$\alpha = 8.68\frac{60\pi(2\pi f\epsilon_0\epsilon^{''} + \sigma_b)}{\sqrt{\frac{\epsilon^{'}}{2}\left\{1+\sqrt{1+\left[\left(\epsilon^{''}+\frac{\sigma_b}{2\pi f\epsilon_0}\right)\right)/\epsilon^{'}\right]^2}\right\}}} \qquad (5)$$

$$R_c = 10\log\left(\frac{2R}{1+R}\right); \quad R = \left(\frac{1-\sqrt{\epsilon^{'}}}{1+\sqrt{\epsilon^{'}}}\right)^2 \qquad (6)$$

Where f is the frequency in hertz of the EM wave, ϵ_0[1] is the dielectric permittivity in free space, σ_b is the bulk density, $\epsilon^{'}$ and $\epsilon^{''}$ the real (Dielectric Constant (DC)) and imaginary (Loss Factor (LF)) parts of the mixing model respectively.

Another semi-empirical path loss model has been proposed by Chaamwe et *al.* in [13]. This model combines modified Friis and CRIM-Fresnel path loss models. Moreover, the proposed path loss model adds signal attenuation due to the refraction phenomenon of an EM in the soil. The resulting path loss L_{tot} given in *(7)* depends on the refractive attenuation factor K *(8)* of the EM. Here ϕ_1 and ϕ_2 are respectively the incidence and the refraction angles of the wave.

$$L_{tot} = 6.4 + 20\log\left(d\beta K\sqrt{\frac{2R}{1+R}}\right) + 8.68\alpha d \qquad (7)$$

$$K = 20\log\left(\sqrt{\frac{\epsilon_1\cos(\phi_1)}{\epsilon_2\cos(\phi_2)}}\right) \qquad (8)$$

Other path loss models are also based on the modified Friis; however, these latter ones are interested in the prediction of DC and LF. The *in situ* path loss model proposed by Sadeghioon et *al.* in [14] uses a real Time Domain Reflectometry (TDR) to predict in real time the values of DC and LF. The main challenge of this approach remains the expensive cost of the TDR. Another similar approach is proposed by Wohwe S. et *al.* in [15] by using a new model called Mineralogy-Based Soil Dielectric Model (MBSDM) to predict with lesser inputs the values of DC and LF.

2.1.2 Mixing path loss models

In contrast to path loss models designed only for underground communications, further research is being carried out to assess the attenuation of a wave as it passes through different communication media (air-to-ground or ground-to-air).

By adding loss in free space path loss L_{fs} *(9)* to the loss due to underground communication L_{tot} *(1)*, Sun et *al.* proposed in [16] a path loss model for communications between the air and the ground (Air-to-Underground $A2U$ and Underground-to-Air $U2A$). Similar to [13], the Sun et *al.* adds to their model, the loss due to refraction. The two resulting loss estimations are given in *(10)* and *(11)*.

$$L_{fs} = -147.55 + 20\log(d) + 20\log(f) \qquad (9)$$

$$L_{AG2U} = L_{tot} + L_{fs} + 10\log\left(\frac{\left(cos\phi_1\sqrt{\epsilon^{'} - sin^2\phi_1}\right)^2}{4cos\phi_1\sqrt{\epsilon^{'} - sin^2\phi_1}}\right) \qquad (10)$$

[1] $\epsilon_0 = 8.85 * 10^{-12} F.m^{-1}$

$$L_{U2A} = L_{tot} + L_{fs} + 10\log\left(\frac{\left(\sqrt{\epsilon^{'}}+1\right)^2}{4\sqrt{\epsilon^{'}}}\right) \qquad (11)$$

Dong et *al.* present in [17] a mixing path loss model similar to [16]. However, the proposed model neglects the loss due to refraction for U2A communications and assumes that the incidence angle is null. Thus, the obtained EM attenuations during A2U and U2A communications are summarised in *(12)* and *(13)* below.

$$L_{AG2U} = L_{tot} + L_{fs} \qquad (12)$$

$$L_{U2A} = L_{tot} + L_{fs} + 20\log\left(\frac{\sqrt{\frac{\sqrt{(\epsilon^{'})^2+(\epsilon^{''})^2}+\epsilon^{'}}{2}}+1}{4}\right) \qquad (13)$$

2.1.3 Complete path loss models

Only a few path loss models are designed to estimate the EM attenuations in the soil for the three different types of communication (U2U, A2U, and U2A) that can occur in WUSN. The most famous is the Wireless Underground Sensor Network - Path Loss Model (WUSN-PLM) designed for agricultural or ecological applications proposed in [3]. In addition to the communication type, the WUSN-PLM is able to consider the burial depth of the sensor nodes (transmitter and/or receiver) and to adjust the different losses due to the reflection or refraction of the EM wave. The depth of the proposed model is subdivided into two regions: topsoil (first 30cm after the ground surface) and subsoil (after the 30cm) regions. Furthermore, the proposed approach uses the MBSDM as in [15] to predict the values of DC and LF. The overall path loss according to the burial depth of the transmitter is given in *(14)* and *(14)* for topsoil and subsoil regions respectively.

$$L_1 = -288.8 + 20\log\left(d_1 d_2 d_{ug}\beta f^2\sqrt{\frac{2R}{1+R}}\right) + 8.69\alpha d_{ug} \qquad (14)$$

$$L_2 = -288.8 + 20\log\left(d_1 d_2 d_{ug}\beta f^2\right) + 8.69\alpha d_{ug} \qquad (15)$$

Where d_1 and d_2 are travelled distance in the air by the wave; d_{ug} denotes the underground distance. For the communication between two buried nodes, d_1 and d_2 are the distance travelled by the signal inside the waterproof box. However, for a smaller distance (less than 1 m), the signal loss in free space can be neglected [12]. In the case of A2U communication, d_1 will represent the distance between the above-ground node and the soil surface. For U2A communication, d_2 is the height of the buried node relative to the ground surface.

We observe that the existing path loss models are mainly based on the dielectric parameters of the soil summarized into the Constant Dielectric Complex CDC (made up of the dielectric constant ϵ' as the real part and the loss factor ϵ'' as the imaginary part). In addition to parameters such as the volumetric water content and the distance be- tween the transmitter and the receiver, other studies have shown that wave frequency and burial depth affect signal attenuation in the soil [18, 19].

The performance comparison of some existing path loss models is provided in Table 1 below.

2.2 Applications of fuzzy logic for decision-making

In this section, we present several pieces of work and approaches based on fuzzy logic for decision-making. Each of the presented pieces of work are based on the Mamdani [20] Fuzzy Inference System (FIS) or the Sugeno FIS [21]. Jassbi et *al.* [22] proposed a space fault detection model based on fuzzy logic. To find the best performance for a gyroscope fault detection, the authors designed two FIS based on Mamdani and Sugeno with 73 rules. The comparisons of the two existing FIS show that despite the good results and the simple structure of Mamdani, the Sugeno FIS provides better results with the three different tests.

For evaluating the quality of experience of Hapto-Audio-Visual Environments (HAVEs), Hamam et *al.* [23] proposed a decision-making model based on fuzzy logic. To achieve this, the authors designed and compared their approach based on Mamdani and Sugeno FIS. This is similar to Jassbi et *al.* [22]. The output set describes the satisfaction and the benefit gained from the application and is made up of five membership functions. From the experimentations and comparisons, the authors show that the Sugeno FIS gives better results than Mamdani in their application.

Like the previous proposals, SinglaSingla2015 uses the two existing FIS to design a decision-making tool for diabetes diagnosis. As input data, the author considers 11 parameters needed to diagnose different types of diabetes. The output of his proposal consists of four variables corresponding to the different types of diabetes. To validate the tool, the author considered a dataset consisting of 150 different cases of diagnosed patients and compared the results obtained with Mamdani and Sugeno FIS. The best result was observed with the Sugeno FIS which achieved 146 good predictions on the 150 cases (i.e. 97.33% accuracy).

Another fuzzy logic-based application based on Sugeno FIS is proposed by Cavallaro [24] to find the suitable sustainability index of the biomass. The four inputs (energy output, energy ration, fertilizers and pesticides levels) of the proposed decision-making tool help in giving information about chemical pressure caused by crop cultivation and contaminant impacts due to the use of fertilizers and pesticides. From these inputs, the resulting index of the biomass consists of five fuzzy variables that represent the sustainability level of the particular crop according to the energy use. To validate its model, the author compared it with real data from five different crops. Dhimish et *al.* [25] proposed a fault detection approach for Photovoltaic (PV) systems based on artificial neural networks and fuzzy logic. The fuzzy logic is used to find the maximum power point tracking thanks to the Mamdani and Sugeno FIS. The output of the proposed solution is made up of the 10 different types of fault that can occur in a PV system. Based on their experiments, the authors conclude that the Mamdani or Sugeno FIS can be used for fault detection of PV. Chaudhary [8] compared Mamdani and Sugeno FIS for the detection of packet dropping attack in mobile ad-hoc networks. The resulting sytem uses as inputs the ratio of forwarded packets and the average rate of dropped packets. The results show a similar performance of the two FIS, however, due to the simplified defuzzification process of Sugeno, this latter is a better choice than Mamdani for the detection of packet attacks.

Almadi et *al.* [26] proposed a novel framework based on the fuzzy logic to identify the behaviour of drivers. The resulting approach is based on the Mamdani FIS and the authors considered as inputs speed limits, the weather and road conditions. The different possible behaviours of the drivers are considered as output set. To validate the decision-making approach, the authors considered a dataset made up of 100 people grouped in five different age categories.

The fuzzy logic is also used for Non-deterministic Polynomial (NP) hard optimization problem in wireless sensor networks. These optimization problems include the clustering that is widely used in several approaches based either on Mamdani or Sugeno FIS [27, 5, 28, 29]. Bayrakdar [9] proposed a fuzzy-based solution for loss-less data transmission in WUSN. This proposal efficiently selects the collector station of each underground sensor node to improve the throughput, the average delay, the packet loss ratio and the node's lifetime. The fuzzy inference system consists of the burial depth of the node, the residual energy and the node's density. Only one-hop underground-to-aboveground communications between buried nodes and the base station are considered. The output of the FIS gives the distance of a gathered node with the collector station. However, this study does not consider real parameters such as the soil moisture level, the locations of the transmitter/receiver and the distance between nodes which widely affect the link quality in WUSN. Furthermore, a typical WUSN must deal with the three communication types of WUSN (underground-to-aboveground, aboveground-to-underground and underground-to-underground) described in [1, 3].

Despite a large number of applications of fuzzy logic in decision-making and to the best of our knowledge, there is no previous study or research on reliable communication in WUNS based on fuzzy logic that takes into account dynamic changes in the environment of sensor nodes before transmission.

Table 1 – Performance's comparison of some path loss approaches

	Balanced accuracy	Matthew Correlation Coefficient	Area Under the ROC curve
Modified Friis* [11]	75.77%	0.52	0.83
NC Modified Friis* [13]	72.03%	0.35	0.87
ZS PLM [16]**	50%	/	/
XD PLM [17]**	50%	/	/
WUSN-PLM [3]	81.06%	0.64	0.92

** Path loss models designed for Underground to Underground (U2U) communications*

*** Path loss models designed for Underground to Aboveground (U2A) and Aboveground to Underground (A2U) communications*

3. MOTIVATION AND PROBLEM STATEMENT

In this section, the main motivation of this work is presented. Furthermore, the problem and the differents assumptions of the proposed work are stated.

3.1 Motivation

The proposition of new and accurate path loss models in the literature allows researchers to predict if a sent packet can be received or not according to the link budget equation and the signal attenuation in the soil (Section 2.1). However, the problem of real time prediction by the sensor node itself still needs to be solved. Thus, a decision-making tool that can be integrated into a node becomes the most adequate solution for this problem. Meanwhile, the trade-off between performance, computational cost, and energy consumption is challenging to get, especially for WUSN. From the existing machine learning and computational intelligence-based approaches, fuzzy logic is considered to be a good candidate. Indeed, as we seen in Section 2.2, the fuzzy logic shows good performance results while reducing the computational cost in decision-making for resource-constrained systems such as sensor nodes. These results are possible because of its simplicity, which allows its rapid conception, adaptability to the uncertainty of incomplete information and the small dataset required for its implementation. Furthermore, as shown in [30], the computational cost for fuzzy-based systems can be constant, thus, no additional computation is needed regardless of the number of inputs. The present paper improve our previous work [30] that discussed the possible use of fuzzy logic for reliable wireless underground communications.

However, the validation of this type of solution needs more experimentations and must be integrated in real devices to verify its feasibility. In addition, the computational cost (energy consumption) should be carried out to verify its applicability in real applications. Thus, by addressing these issues, the present study is a novel contribution in the fields of wireless underground communications and fuzzy logic for WUSN.

3.2 Problem statement and assumption

Nowadays, extending the lifetime of a sensor remains a real challenge, especially in WUSN. Furthermore, knowing that a node drains most of its battery during transmission, the energy can be wasted especially when the link is broken, thus no information is received. To reduce these energy losses, we propose a new lightweight decision-making solution for reliable transmission described in the following sections. We assume that the deployment of nodes in a typical WUSN is mainly deterministic, thus the position of each of them is well-known. Furthermore, we assume that the burial depth of a node is considered to be a known parameter by the latter.

4. THE FUZZY-BASED APPROACH TO REDUCE TRANSMISSION WASTAGE

In this section, we briefly describe the functioning of an FIS and then the proposed approach is described in detail.

4.1 Overview of a fuzzy inference system

As we can see from Fig. 1, a typical Fuzzy Inference System (FIS) consists of 3 steps : i) fuzzification, ii) application of the inference rules and iii) defuzzification. During the fuzzification process, the real input variables are converted into linguistic fuzzy variables. Thereafter, the membership degree of the inputs is computed based on the membership functions before applying operations (AND, OR, NOT) according to the fuzzy rules defined in the inference system. During the defuzzification process, the output of the FIS is a fuzzy set that represents the degree of membership of the input variables.

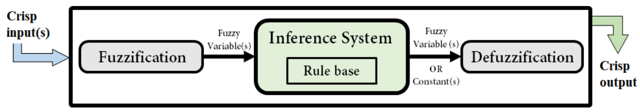


Fig. 1 – Different parts of a Fuzzy Inference System.

From the two famous FIS in the literature and from Section 2.2, the Sugeno-type is more suitable for low-power and automated decision-making system due to his simple defuzzification process [30].

Indeed, the output z^* in Sugeno FIS is the weighted average of each rule inside the inference system *(16)*.

$$Z^* = \frac{\sum_{i=1}^{n} \alpha_i z_i}{\sum_{i=1}^{n} \alpha_i} \tag{16}$$

n is the number of rules inside the inference system, and α_i denotes the aggregated membership degree of each rule obtained by applying *min* or *max* operators. z_i represents the linear output of rule i.

4.2 The fuzzy-based approach for reliable transmission

Energy reduction during transmission in WUSN must be performed in real time by each node, predicting whether or not the data to be sent can be received before transmission. However, sensor nodes are high resources restricted, and the use of a traditional ML approach should not be considered. We use a portable, easily integrated and lightweight fuzzy-based approach for decision-making before transmission in a WUSN. The proposal consists of four inputs and 36 ($2\times3\times3\times2$) rules inside the inference system. The crisp output is the probability (or degree) that checks if it will have a reception or data loss according to input data. The input parameters give an overview of the environment between the transmitter and the data receiver. According to [3], these parameters are the key factors that affect wireless underground communication. In order to make it as easy as possible to calculate the membership degrees of the different inputs, we have used simple membership functions (trapezoidal and triangular). The inputs are:

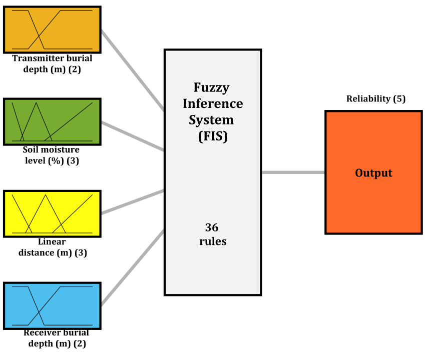


Fig. 2 – Overview of the proposed FIS.

- *The burial depth of the transmitter* **(BD)** and *the burial depth of the receiver* **(NBD)**: They give the distance between the ground surface (zero meters) to the node's location. Knowing that the soil can be subdivided into two regions (topsoil and subsoil), the BD and NBD each consist of two trapezoidal membership functions *close* and *far* (Fig. 3a). The membership functions are trapezoidal because the behaviour of the EM is slightly similar when the burial depth is less than 50cm but depends on if the node is fully buried or not [31].

- *The average soil moisture proportion* **(MST)**: This represents the water level in the soil. Contrary to the previous parameters, the moisture level in the soil is evaluated through three triangular membership functions: *low*, *average* and *high* (Fig. 3b). We chose triangular functions here because of the direct impact of the soil moisture in the quality of underground communications. Based on calibration measurements carried out using the dataset [31], we observe that the impact of soil moisture on communication becomes more significant at 40% moisture regardless of the location of the nodes. The soil moisture varies from dry soil (nearly 0% moisture) to free water (close to 100% moisture).

- *The distance between the transmitter and receiver* **(LD)**: This consists of three triangular membership functions: *close*, *medium* and *far* (Fig. 3c). Similar to the soil moisture, the direct distance between the transmitter and the receiver has a direct impact on the communication quality. For example, we have observed that when the linear distance between nodes is small (less than 7m), underground communications are reliable with very few lost packets. The range value of the distance between the transmitter and receiver (up to 30m) depends on our previous results [3, 30] and the dataset [31].

Table 2 – Computation of the membership degrees.

Fuzzy sets	Variables	Membership degree
BD / NBD	*close*	$\begin{cases} 1 & 0 \le x \le 0.1 \\ 2 - 10x & 0.1 < x \le 0.2 \\ 0 & \text{else} \end{cases}$
	far	$\begin{cases} 0 & 0 \le x \le 0.1 \\ 5x - 1/2 & 0.1 < x \le 0.3 \\ 1 & \text{else} \end{cases}$
MST	*low*	$\begin{cases} 1 - x/15 & 0 \le x \le 15 \\ 0 & \text{else} \end{cases}$
	average	$\begin{cases} x/20 - 1/2 & 10 \le x \le 15 \\ 5/2 - x/20 & 30 < x \le 50 \\ 0 & \text{else} \end{cases}$
	high	$\begin{cases} x/15 - 2/3 & 40 \le x \le 100 \\ 0 & \text{else} \end{cases}$
LD	*close*	$\begin{cases} 1 - 2x/15 & 0 \le x \le 7.5 \\ 0 & \text{else} \end{cases}$
	medium	$\begin{cases} x/5 - 1 & 5 \le x \le 10 \\ 3 - x/5 & 10 < x \le 15 \\ 0 & \text{else} \end{cases}$
	far	$\begin{cases} x/20 - 0.5 & 10 \le x \le 30 \\ 0 & \text{else} \end{cases}$

During the fuzzification process, the membership degree of each input parameter x of the proposed FIS is evaluated according to Table 2. The probability used for decision-making (defuzzification) in the fuzzy-based approach is the average weight of the 36 rules of the inference system given in *(16)*. Having only two classes (reception or not reception), our proposed decision-making system divides the probability of reception into two equal parts. Thus,

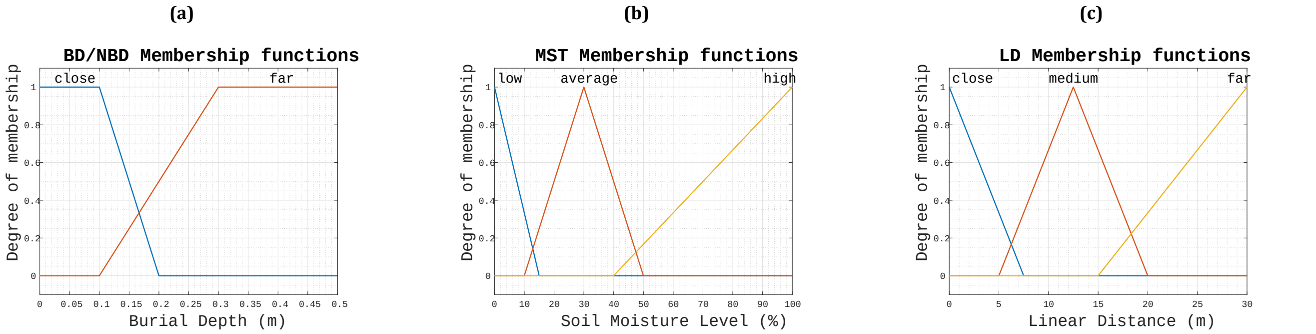


Fig. 3 – (a) Membership functions of the transmitter (BD) and receiver (NBD) burial depths. (b) Membership functions of the soil moisture level (MST). (c) Membership functions of the distance between the transmitter and the receiver (LD).

when the calculated probability is less than or equal to 0.5, we assume that the packet to be sent will be received (reception), otherwise the packet will be lost, so the transmission can be avoided. In addition, as it is shown in [30], the crisp output can easily be obtained by merging several *If-then* rules without any computation, thus obtaining a constant complexity ($\mathcal{O}(1)$).

5. PERFORMANCE EVALUATION OF FUZDEMA

To evaluate the performance of the proposed FuzDeMa, we consider the dataset of [31] also used to design and validate our previous work [3]. From this dataset, 140 different scenarios were evaluated in two different configurations of the soil: dry and moist.

For each scenario, we evaluate the performance of the FuzDeMa by considering the following metrics *(17)* - *(21)* that depend on the values of True Positive (TP); True Negative (TN), False Positive (FP) and False Negative:

- The *Threat Score* (TS): This is also known as the *Critical Success Index* (CSI) and given in *(17)* is a performance metric used to measure the success of an initiative (reception or loss of a packet).
- The *Fowlkes-Mallows Index* (FMI): This is an index used to determine the similarity between two different classes (reception or not reception). Its formula is defined in *(18)*.
- The Matthews Correlation Coefficient (MCC): This is also known as the *Phi-coefficient* applied in two classes helps to measure the correlation differences between the real observation and the predicted values *(19)*.
- The *balanced Accuracy* (bACC) : This is a metric used for evaluating how good a binary classifier is when the classes are imbalanced (size of the positive class is higher than the size of the negative class). Its formula is given in *(20)*.
- The F1-Score : This metric is similar to the bACC but is applied when the size of the negative class is higher than the size of the positive class *(21)*.
- *The Root Mean Square Deviation* (RMSD) : This is the square root of errors between the predicted and the observed values *(22)*. It gives the magnitudes of the errors in predictions for varied datasets.

$$TS = \frac{TP}{TP + FN + FP} \tag{17}$$

$$FMI = TP\sqrt{\frac{1}{(TP + FP)(TP + FN)}} \tag{18}$$

$$MCC = \frac{TP\,TN - FP\,FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{19}$$

$$bACC = \frac{TP(TN + FP) + TN(TP + FN)}{2(TP + FN)(TN + FP)} \tag{20}$$

$$F1 - Score = \frac{2TP}{2TP + FP + FN} \tag{21}$$

$$RMSD = \sqrt{\frac{FP + FN}{TP + FP + TN + FN}} \tag{22}$$

5.1 Dry soil configurations

The 80 measurements of the dry configuration occurred when the soil moisture was close to 0%. From the experimental dataset, 68 and 12 observations are obtained for the positive and negative classes (reception ***rcv.*** and loss of packets ***not rcv.***), respectively. The resulting confusion matrix in dry soil configurations is given in Table 3.

Table 3 – Confusion matrix for dry soil configurations.

		Observation	
		rcv.	not rcv.
Prediction	rcv.	68 TP	0 FP
	not rcv.	0 FN	12 TN

We observe that for dry soil, the proposed FuzDeMa achieves perfect predictions ($TS = FMI = MCC = 1$ and $bACC = 100\%$) regardless of the different scenarios of the dataset used (with a 68.57% prevalence).

5.2 Moist soil configurations

When the soil moisture level has a difference of 0%, the soil is assumed to be wet. From the considered dataset, 60 measurements for wet soils are recorded (Table 4). Contrary to the dry configuration, here, the number of negative cases is higher than the number of positive cases (32 and 28, respectively).

Table 4 – Confusion matrix for moist soil configurations

		Observation	
		rcv.	not rcv.
Prediction	rcv.	25 TP	9 FP
	not rcv.	3 FN	23 TN

Furthermore, due to the inequity between the size of the sets, the F1-Score is more suitable than the balanced accuracy. The performance evaluation of FuzDeMa is given in Table 5.

Table 5 – Performance evaluation of FuzDeMa in moist scenarios of the soil

TS	FMI	F1-Score	MCC	RMSD
0.675	0.810	80.675%	0.615	0.447

The results show that FuzDeMa gets a positive correlation between the prediction (reception or loss) and the actual scenarios of the dataset used when the soil is wet. Indeed, the value of the MCC defines a high correlation between the prediction and the observation with an accuracy of 80.675% (F1-Score).

In short, over the 140 measurements of the used dataset [31], the miss-rate (or False Negative Rate *FNR*) probability and the False Discovery Rate (*FDR*) defined in *(23)* of FuzDeMa are 3.125% and 8.824% respectively. These low values demonstrate the high feasibility of FuzDeMa to address the problem of reliable communications in WUSN.

$$FNR = \frac{FN}{FN + TP}; \quad PDR = \frac{FP}{FP + TP} \tag{23}$$

To validate the performance of FuzDeMa in predicting the reception or the loss of packet before transmission, we consider the performance metrics of *(17)* - *(21)*. For each of these parameters, we compare our proposal with WUSN-PLM that obtained the best results compared to the existing path loss models (Table 1). Table 6 summarizes the overall performance comparison of FuzDeMa and WUSN-PLM. We observe that the proposed decision-making tool outperforms WUSN-PLM with higher bACC, MCC, TS and FMI. The comparison table reveals that FuzDeMa has a lower error than WUSN-PLM in the same dataset.
Additionally, to evaluate the proposed approach independently of the fixed threshold (0.50) and the insensibility to class distribution, the Receiver Operating Characteristic (ROC) curve is considered (Fig. 4). Indeed, the ROC curve evaluates graphically the impact of the false positive rate on the sensibility (true positive rate). We observe that the ROC curve is well above the random guess, thus confirming the good accuracy of the proposed approach to differentiate the reception of the loss of a packet before its transmission.

Table 6 – Overall comparison of performances

	bACC	RMSD	MCC	TS	FMI
WUSN-PLM	81.06%	0.39	0.64	0.81	0.89
FuzDeMa	88.21%	0.29	0.80	0.89	0.94

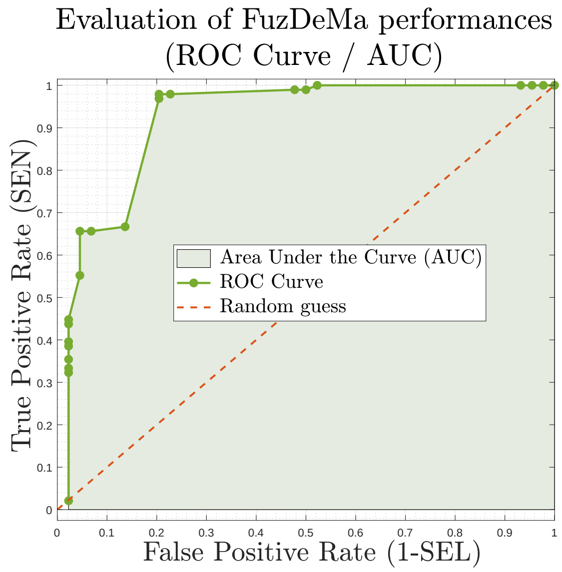


Fig. 4 – Overall ROC curve evaluation of FuzDeMa with an AUC = 0.92.

The numerical evaluation of the ROC curve using the Area Under the Curve (AUC) gives the same value (92%) as that observed for the WUSN-PLM given in Table 1. This value means that FuzDeMa has a 92% chance of making the difference between the two classes (reception and loss of a packet).

6. INTEGRATION OF FUZDEMA WITHIN A REAL DEVICE

Regardless of the good performances of FuzDeMa observed on an existing dataset, in this section, we evaluate our proposal in a real and dedicated sensor node for WUSN.

6.1 MoleNet: A sensor node for underground monitoring

The MoleNet[2] [32] is a sensor node specially designed for ecological and agricultural monitoring. However, it can be used also for any other underground monitoring purposes. The MoleNet is based on the Wattuino Pro

[2] molenet.org

Mini board powered by the Atmega328p microcontroller. Wireless underground communications are achieved by the RFM69CW transceiver at 433MHz, which is more suitable than 868MHz or the classical 2.4GHz in underground environments. Like most existing sensor nodes, the MoleNet periodically performs the same basic tasks based on events. The flow chart that summarizes the different steps performed by the MoleNet is illustrated in Fig. 5.

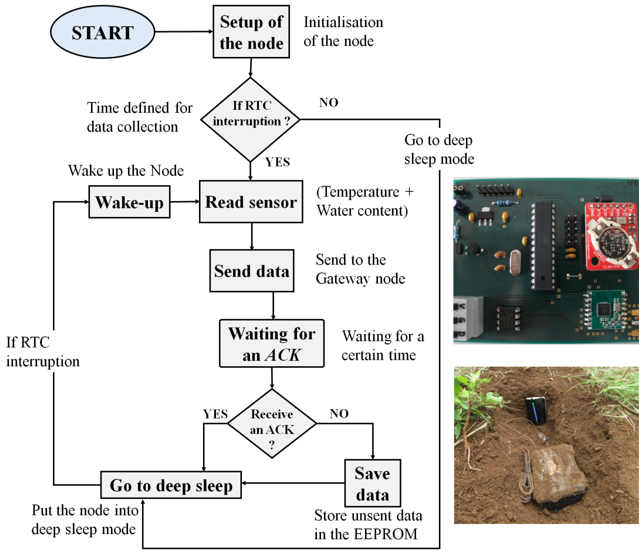


Fig. 5 – Flow chart describing the functioning of the MoleNet. Overview of the PCB and the deployment of the MoleNet at the University of Ngaoundere [32].

To save its energy, the MoleNet sleeps more than 99% of the time. An RTC interruption wakes up the MoleNet from deep sleep for the sensing and transmission of data to the gateway. After data transmission, the microcontroller waits for an acknowledgement before going into deep sleep mode. If it does not receive the acknowledgement before the end of the timer, it saves the sensed data locally in its EEPROM and then goes into sleep mode.

6.2 Integration of FuzDeMa into the MoleNet

The previous fuzzy approach has been implemented and flashed inside the MoleNet to allow decision-making before each transmission. When it wakes up, the node checks the reliability of transmission after reading the sensor. The reliability checking is put after the reading of the sensor because the MoleNet is equipped with a soil moisture sensor, and the sensed value is after that used as a moisture level to evaluate the transmission reliability. The values of the computed reliability vary from 0 to 1. The proposed decision-making consists of two equiprobable classes: *reception* (should send) and *no reception* (should not send). From this, the crisp output is divided into two equal sets for the reception ($[0; 0.5[$) and for the data loss ($[0.5; 1]$).

- If the computed reliability Z^* is low ($Z^* \in [0; 0.5[$) , the MoleNet stops its round and goes into sleep mode because in such cases, it assumes that it cannot reach the gateway (receiver).
- If the reliability Z^* is high ($Z^* \in [0.5; 1]$), the MoleNet presumes that the link quality is good enough for transmission. In this case, the gateway will receive the sent packet.

The flow chart of the integration of the fuzzy-based decision-making for data transmission is summarized by Fig. 6.

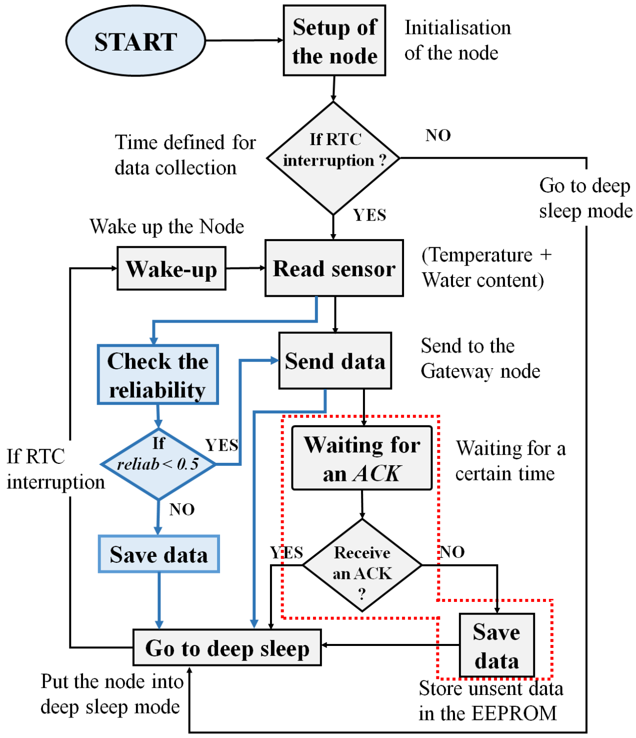


Fig. 6 – Improvement of MoleNet by adding the FuzDeMa module before the transmission of a packet. The blue elements represent the different steps of FuzDeMa according to the MoleNet flowchart. The red section is neglected when implementing FuzDeMa in MoleNet.

7. EXPERIMENTS AND EVALUATIONS

In this section, we describe the experimental setup used to evaluate the energy consumption of the MoleNet in different scenarios. After that the results, discussions and validation are provided.

7.1 Measurement setup

To evaluate the energy consumption of the MoleNet, we consider the setup of Fig. 7. The R&S®HM8143 delivers power to the MoleNet during the experiment. The precision multi-meter R&S HM8112-3 is also connected to the MoleNet to measure the voltage values in real time and the current variations. The digital oscilloscope Tektronix TBS 1102B is also used to visualize the voltage of the MoleNet. We consider each measurement's output CSV files for the numerical analysis. To check if the MoleNet has sent data, we used the digital spectrum analyser RF Explorer COMBO.

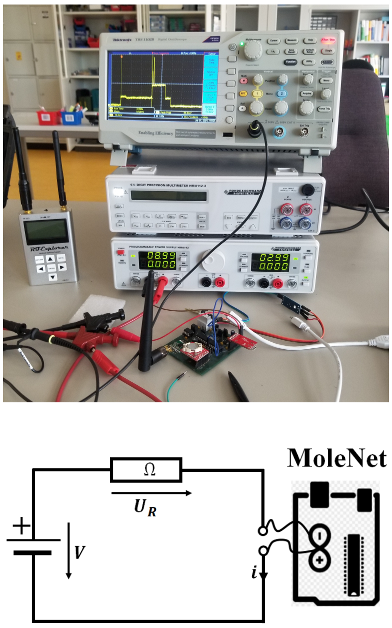


Fig. 7 – Evaluation of the energy consumption during different scenarios of data transmission in the ComNets lab at the University of Bremen, Germany.

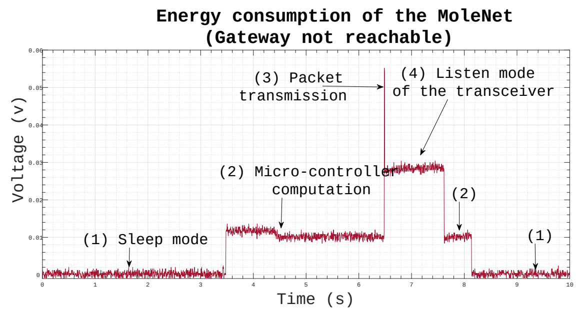
Each transmission of the MoleNet occurs only from the nodes to the gateway through a single-hop communication. After sending a packet, the MoleNet waits for an acknowledgement sent by the gateway before going into sleep mode. Thus, two scenarios are possible:

- *The gateway is not reachable*: here, the node sends a packet, but after the fixed time, it does not receive an acknowledgement from the gateway. During this scenario, a communication round of the MoleNet contains four different stages (Fig. 8a): 1) sleep, 2) microcontroller computation, 3) transmission, and 4) waiting for an acknowledgement. As we can see, the MoleNet spends additional energy after the transmission before switching off the transmission module and going into sleep mode.
- *The gateway is reachable*: the node sends a packet and receives an acknowledgement from the gateway node. After the successful transmission, the node goes into sleep mode (Fig. 8b). Unlike the first scenario, the MoleNet does not go through step 4 and avoids the energy spent by the communication module after a packet transmission.

7.2 Evaluation

To evaluate the energy consumed by the node during a round is achieved by considering the setup of Fig. 7. The value of the energy consumed in joules *(24)* is explained in function of the voltage u (in volts), time t (in seconds) and the resistance R (set to 10Ω for computational convenience). From the output CSV file, more than 2500 measurements (each 4ms) of the time and voltage are provided by TBS 1102B.

(a)



(b)

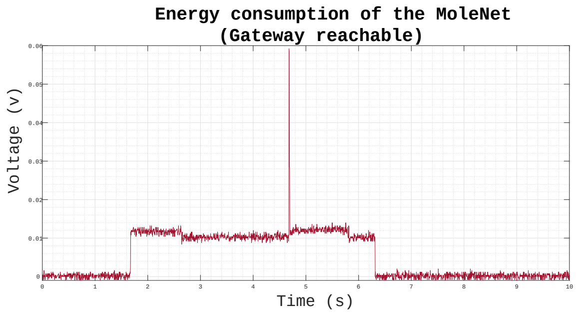


Fig. 8 – Energy consumption of the MoleNet during a round. (a) Energy consumed when the gateway is not reachable. (b) Energy consumed when the gateway is reachable.

$$E = \frac{u^2 t}{R} \tag{24}$$

From the setup of Fig. 7, several shots have been performed and the average values of the energy consumed by the MoleNet is summarized in Table 7 below.

Table 7 – Energy consumed by the MoleNet in a round

	Gateway not reached	**Gateway reached**
Energy (J)	$133.3141\mu J$	$59.8134\mu J$

As the table above shows, the power consumption of the MoleNet doubles when the gateway is not reachable for about the same running time. This large difference between these values can be explained by the fact that the communication module stays in listening mode for longer. Additionally, it is well-known that the communication module is the most energy-intensive module of a sensor node. In other words, the node will consume $133.3141\mu J$ per transmission when the link to the gateway (or any other receiver) is broken due to bad ground conditions.

8. EVALUATION OF THE ENERGY CONSUMPTION

The evaluation of the energy consumed during the computation of the FuzDeMa is summarized in Fig. 9.

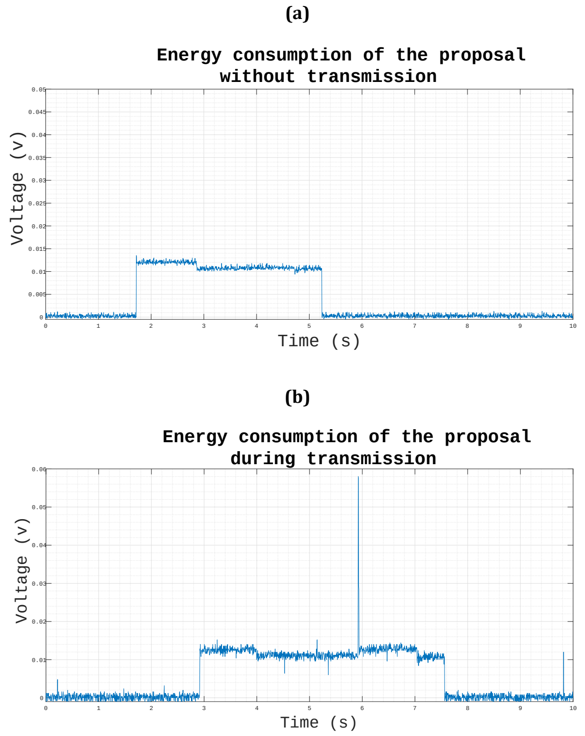


Fig. 9 – Evaluation of the energy drained by the proposed approach. (a) Computation of the proposed FuzDeMa (no TX). (b) Computation of the proposed FuzDeMa (TX).

We observe that the energy consumed by the MoleNet while performing our proposal during transmission is similar to the energy consumed during transmission by the conventional MoleNet (Fig. 9b). Table 8 gives the numerical values of the energy consumed with and without transmission while running our proposed approach.

Table 8 – Energy consumed by FuzDeMa

	FuzDeMa (no TX)	FuzDeMa (TX)
Energy (J)	$51.5264\mu J$	$68.0133\mu J$

Despite the short time used to transmit data, we observe that the MoleNet consumes more than $16\mu J$. Thus, by cancelling a transmission when the environment does not allow it to reach a distant node (here the gateway), we can save this energy, thus increasing the lifetime of the sensor node. The energy consumption of the MoleNet while running, or not, our proposed fuzzy-based decision-making tool is summarized in Fig. 10.
Moreover, we evaluate and compare the energy consumed in two cases: (i) the gateway is reachable; (ii) the gateway is not reachable.

8.1 The gateway is reachable

Since the node cannot know by itself perfectly (with probability 1) when the gateway is reachable or not, we evaluate in this subsection the energy consumed during and without transmission of our proposal. When the

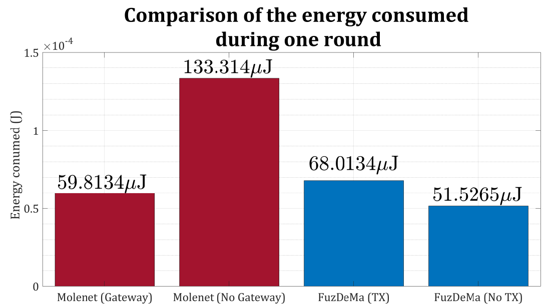


Fig. 10 – Comparison the energy consumption per round.

gateway is reachable, the conventional MoleNet consumes around $59.8134\mu J$ per round, and it is assumed that the link with the gateway is not broken. When the fuzzy approach decides to send data (TX) according to the computed reliability (*True Positive*), the node will consume $8.2\mu J$ more than in the conventional MoleNet (Fig. 11). In other words, although this case is the worst one of our proposal, we see that the additional energy consumed by the node is minimal and can be neglected.

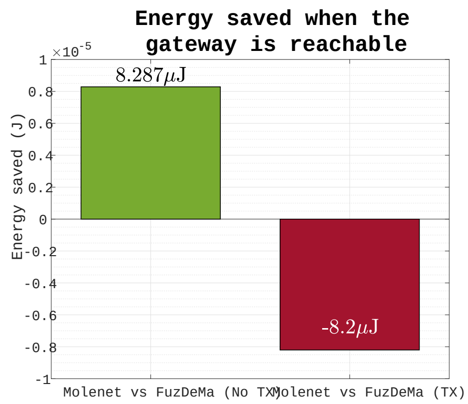


Fig. 11 – Energy saved (and lost) while using FuzDeMa when the gateway is reachable.

However, if the proposed FuzDeMa does not decide to allow a transmission (*False Negative*), the energy saved by FuzDeMa is around $8.287\mu J$ (Fig. 11). In this case, the MoleNet sends and receives an acknowledgement from the gateway, and the fuzzy-based control will not proceed to transmission and thus save $8.287\mu J$. The negative side of the fuzzy-based decision-making tool is that the gateway will not receive any data from the sensor node. In short, we summarize in Table 9 the energy saved and data status when the gateway is reachable.

Table 9 – Evaluation of FuzDeMa (gateway is reachable)

	Energy saved	Data
True Positive	$-8.2\mu J$	send & receive
False Negative	$8.287\mu J$	not send & not receive

8.2 The gateway is not reachable

When the gateway is not reachable, the MoleNet does not receive an acknowledgement, thus, it will consume additional energy (Fig. 8a). In other words, the link between the sensor node and the gateway may be broken. During this scenario, the MoleNet will consume $133.3141\mu J$ per round (Table 7).

If the fuzzy-based control allows a transmission (TX) even if the gateway is not reachable (*False Positive*), the sensor node will consume $65.3007\mu J$ per round lesser than in the conventional MoleNet (Fig. 12). This difference is explained by the fact that the MoleNet stays a few times waiting for the acknowledgement from the gateway and then wastes more energy. In this case, we notice that the saved energy is just about enough for another round of our proposed fuzzy-based decision-making tool ($59.8134\mu J$ or $68.0134\mu J$).

Meanwhile, when our fuzzy controller decides not to allow transmission (no TX), the saved energy increases up to $81.786\mu J$. This case is the best scenario in which the efficiency of our proposed approach (*True Negative*) can be observed. Here, the sensor node will save energy and no data is missed.

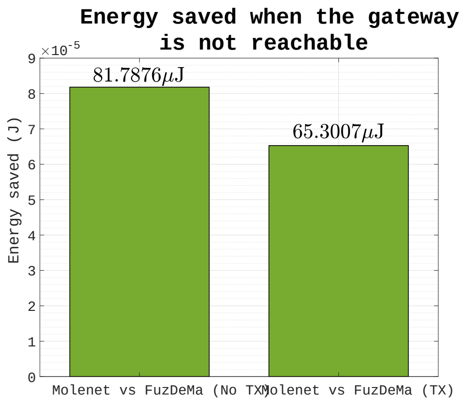


Fig. 12 – Energy saved while using FuzDeMa when the gateway is not reachable.

The overall energy saved when the gateway is not reachable according to the status of the data is shown in Table 10 below.

Table 10 – Evaluation of FuzDeMa (no gateway)

	Energy saved	Data
False Positive	$65.3007\mu J$	send & not receive
True Negative	$81.7876\mu J$	not send & not receive

9. DISCUSSION AND GENERALIZATION OF FUZDEMA

One key limitation of the MoleNet that we can easily observe occurs when the gateway is not reachable. During this case, the buried node keeps the transceiver in listening mode to receive any acknowledgement from the gateway. From Section 7.1, the energy drained by the MoleNet becomes substantial ($\approx 133\mu J$ per round). However, with a different node the presented results may vary. Here, we analyse the impact of the FuzDeMa for any kind of device. Let's assume a random sensor field F is made up of N homogenous nodes. Each sensor node n_i ($i \in [1\ N]$) sends periodically the collected information to the base station. Furthermore, to reduce the energy consumption, there is only one transmission per round in a non-connected way (no acknowledgment is needed from the base station). During a round, a node without the FuzDeMa will consumes E_i *(25)*. mc_{comp} denotes the computation made by the microcontroller and tx_{cost} is the energy consumed by the transceiver during a transmission. Thus, after k rounds, the energy consumed by a sensor node is kE_i.

$$E_i = mc_{comp} + tx_{cost} \tag{25}$$

Meanwhile, when a node integrates the proposed FuzDeMa, the overall energy consumed $E_i^{'}$ per round is given in *(26)*. fuz_{cost} is the additional calculation cost of the FuzDeMa. After k rounds, the overall energy consumed by node n_i depends on the number of data receptions α (with $k \geq \alpha$). This is because the FuzDeMa does not allow a transmission when the conditions are not sufficient for a reception.

$$E_i^{'} = \begin{cases} E_i + fuz_{cost} & \textbf{if } \textit{transmission} \\ E_i + fuz_{cost} - tx_{cost} & \textbf{else} \end{cases} \tag{26}$$

As we can observe from Fig. 10, the energy consumed during transmission is higher than the additional calculation of FuzDeMa ($tx_{cost} > fuz_{cost}$), thus when there is no transmission, $E_i^{'} \leq E_i$. However, after k random rounds, FuzDeMa will save energy when $kE_i \geq kE_i^{'}$. *(27)*.

$$kE_i \geq k(mc_{comp} + fuz_{cost}) + \alpha tx_{cost} \tag{27}$$

In short, the FuzDeMa will improve the lifetime of any sensor node n_i after k rounds when the relation of *(28)* is met.

$$\alpha \leq \left\lfloor \frac{k(tx_{cost} - fuz_{cost})}{tx_{cost}} \right\rfloor \tag{28}$$

When the condition *(28)* is met, the overall energy G_i saved by a node n_i that implements the FuzDeMa after k random rounds with α reception(s) is resumed by *(29)*. Fig. 13 below presents the evolution of the energy saved by FuzDeMa after 1000 rounds.

$$G_i = tx_{cost}(k - \alpha) - kfuz_{cost} \tag{29}$$

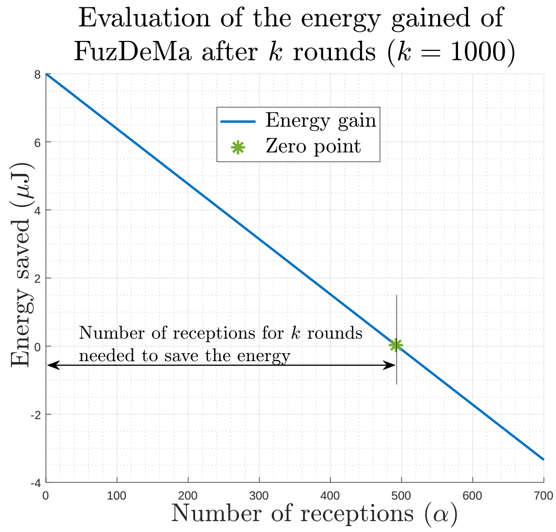


Fig. 13 – Energy saved by FuzDeMa according to the number of receptions.

10. CONCLUSION

In this paper, we proposed and evaluated a novel portable fuzzy-based approach for decision-making during transmission in WUSN to avoid energy waste called FuzDeMa. The main idea of our proposed solution is to allow a sensor node to send data only when it is "sure" of its reception according to a calculated reception probability. The output of the fuzzy inference system used is the reliability of data reception which depends on the soil moisture level, the distance between nodes and the burial depths of the transmitter and receiver. Evaluation of the energy consumed during different scenarios (TN, TN, FP, FN) reveals that the approach can save up to $81.7876\mu J$ per transmission cycle. Moreover, the validation of FuzDeMa is based on a real dataset made up of 140 different measurements in two different configurations (dry and moist soils). The results showed that, the proposed FuzDeMa is able to extend the lifetime of a sensor node by up to 32.85%.

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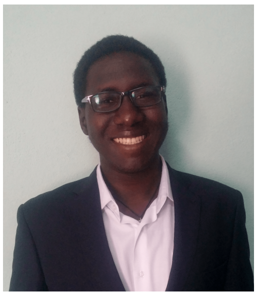

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