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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 the 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 uselessly. 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 MoleNet and realised 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 μ 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 generalisation of FuzDeMa is provided regardless of a specific dataset or sensor node. Thus, we provided the needed conditions for a random dataset to save the energy with any sensor node that implements FuzDeMa during transmissions.

Keywords – Wireless Underground Sensor Network (WUSN), Energy-Efficiency, Decision-Making, Signal loss, Embedded systems, Fuzzy Inference System

NOTE: Title, abstract and keywords must be identical to the ones submitted electronically in EDAS – Editor's Assistant. Use the command `\ITUnote` to achieve the appropriate formatting.

1. INTRODUCTION

Contrary to conventional Wireless Sensor Networks (WSN), in which nodes are located above the ground, a Wireless Underground Sensor Network (WUSNs) consists of sensor nodes buried in the ground. Despite the increase in its popularity, deploying and operating a WUSN are 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 (EM) 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 this energy wastage. Nevertheless, because using low power micro-controller and low bandwidth, sensor nodes cannot efficiently execute locally, or via Cloud,

well-known Machine Learning (ML) solutions for learning/predictions purposes [4]. 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 whether 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. Knowing 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 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 a real sensor nodes according to different scenarios.
- The energy consumption of FuzDeMa was intensively evaluated using precision measuring equipment.
- The analytical generalisation 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 the related works 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. In integration of our proposal within a real sensor node is given in Section 6; 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; Section 9 extends the validation of FuzDeMa by providing a generalisation with an analytical approach regardless of the sensor node. The paper ends with a conclusion in Section 10.

2. BACKGROUND AND RELATED WORKS

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

2.1 Path loss models of EM waves in WUSN

The characteristics of the wireless underground channel are much different as compared 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).

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

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

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

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 $\epsilon_0 \mu_0 c^2 = 1$. 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.

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

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

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

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, ϵ' and ϵ'' 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.

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

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

Other path loss models are also based on the modified Friis, however, these latter 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.

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

The two resulting loss estimations are given in (10) and (11).

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

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

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

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.

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

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

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.

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

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

Where d_1 and d_2 are traveled 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 traveled by the signal inside the waterproof box. However, for a smaller distance (less than 1 m), the

214 signal loss in free space can be neglected [12]. In the case
215 of A2U communication, d_1 will represent the distance
216 between the above-ground node and the soil surface. For
217 U2A communication, d_2 is the height of the buried node
218 relative to the ground surface.
219

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

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

231 2.2 Applications of fuzzy logic for decision 232 making

233 In this section, we present several works and approaches
234 based on fuzzy logic for decision making. Each of the pre-
235 sented works is based on the Mamdani [20] fuzzy infer-
236 ence system (FIS) or the Sugeno FIS [21].

237 Jassbi *et al.* [22] proposed a space fault detection model
238 based on fuzzy logic. To find the best performance for a
239 gyroscope fault-detection, the authors designed two FIS
240 based on Mamdani and Sugeno with 73 rules. The com-
241 parisons of the two existing FIS show that despite the
242 good results and the simple structure of Mamdani, the
243 Sugeno FIS provides better results with the three differ-
244 ent tests.

245 For evaluating the quality of experience of Hapto-Audio-
246 Visual environments (HAVE), Hamam *et al.* [23] pro-
247 posed a decision-making model based on the fuzzy logic.
248 To achieve it, the authors designed and compared their
249 approach based on Mamdani and Sugeno FIS. Similar to
250 Jassbi *et al.* [22]. The output set describes the satisfaction
251 and the benefit gained from the application and is made
252 up of 5 membership functions. From the experimenta-
253 tions and comparisons, the authors show that the Sugeno
254 FIS gives better results than Mamdani in their application.
255 Like the previous proposals, SinglaSingla2015 uses the
256 two existing FIS to design a decision-making tool for dia-
257 betes diagnosis. As input data, the author considers 11 pa-
258 rameters needed to diagnose different types of diabetes.
259 The output of his proposal consists of 4 variables corre-
260 sponding to the different types of diabetes. To validate
261 the tool, the author considered a dataset consisting of 150
262 different cases of diagnosed patients and compared the
263 results obtained with Mamdani and Sugeno FIS. The best
264 result was observed with the Sugeno FIS which achieved
265 146 good predictions on the 150 cases (i.e. 97.33% accu-
266 racy).

267 Another fuzzy logic based application based on Sugeno

268 FIS is proposed by Cavallaro [24] to find the suitable sus-
269 tainability index of the biomass. The 4 inputs (Energy
270 output, Energy ration, Fertilizers and Pesticides levels) of
271 the proposed decision-making tool help in giving infor-
272 mation about chemical pressure caused by crop cultiva-
273 tion and contaminant impacts due to the use of fertilizers
274 and pesticides. From these inputs, the resulting index of
275 the biomass consists of 5 fuzzy variables that represent
276 the sustainability level of the particular crop according to
277 the energy use. To validate its model, the author com-
278 pared it with real data from 5 different crops.

279 Dhimish *et al.* [25] proposed a fault detection approach
280 for PhotoVoltaic (PV) systems based on artificial neural
281 network and fuzzy logic. The fuzzy logic is used to find the
282 maximum power point tracking thanks to the Mamdani
283 and Sugeno FIS. The output of the proposed solution is
284 made up of the 10 different types of fault that can occur
285 in a PV system. Based on their experiments, the authors
286 conclude that the Mamdani or Sugeno FIS can be used for
287 fault detection of PV.

288 Chaudhary [8] compared Mamdani and Sugeno FIS for the
289 detection of packet dropping attack in mobile ad-hoc net-
290 works. The resulting system uses as inputs the ratio of
291 forwarded packets and the average rate of dropped pack-
292 ets. The results show a similar performance of the 2 FIS,
293 however, due to the simplified defuzzification process of
294 Sugeno, this latter is a better choice than Mamdani for the
295 detection of packet attacks.

296 Almadi *et al.* [26] proposed a novel framework based on
297 the fuzzy logic to identify the behaviour of drivers. The
298 resulting approach is based on the Mamdani FIS and the
299 authors considered as inputs speed limits, the weather
300 and road conditions. The different possible behaviours of
301 the drivers are considered as output set. To validate the
302 decision-making approach, the authors considered a data
303 set made up of 100 people grouped in 5 different age cat-
304 egories.

305 The fuzzy logic is also used for Non-deterministic Polyno-
306 mial (NP) hard optimization problem in wireless sensor
307 networks. These optimisation problems include the clus-
308 tering that is widely used in several approaches based ei-
309 ther on Mamdani or Sugeno FIS [27, 5, 28, 29].

310 Bayrakdar [9] proposed a fuzzy-based solution for loss-
311 less data transmission in WUSN. This proposal efficiently
312 selects the collector station of each underground sen-
313 sor node to improve the throughput, the average de-
314 lay, the packet loss ratio and the node's lifetime. The
315 fuzzy inference system consists of the burial depth of
316 the node, the residual energy and the node's density.
317 Only one-hop underground-to-aboveground communica-
318 tions between buried nodes and the base station are con-
319 sidered. The output of the FIS gives the distance of a
320 gathered node with the collector station. However, this
321 study does not consider real parameters such as the soil
322 moisture level, the locations of the transmitter/receiver
323 and the distance between nodes which widely affect
324 the link quality in WUSN. Furthermore, a typical
325 WUSN must deal with the three communication types

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

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 WUSN based on fuzzy logic that takes into account dynamic changes in the environment of sensor nodes before transmission.

3. MOTIVATION AND PROBLEM STATEMENT

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

3.1 Motivation

The proposition of new and accurate path loss models in the literature allow 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 the 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 data set required for its implementation. Furthermore, as we shown in [30], the computation 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 works [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 a 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.

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

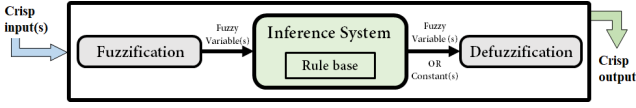


Fig. 1 – Different parts of a Fuzzy Inference System

Sugeno FIS is the weighted average of each rule inside the inference system (16).

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

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 4 inputs and 36 ($2 \times 3 \times 3 \times 2$) 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:

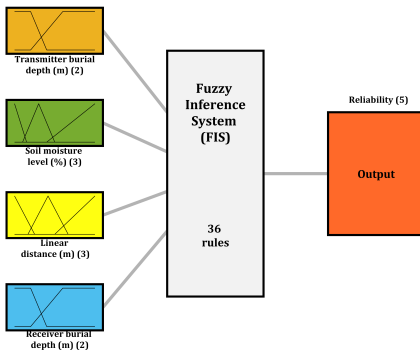


Fig. 2 – Overview of the proposed FIS

- **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 behavior of the EM is slightly the same when the burial depth is lesser than 50cm but depends only if the node is fully buried or not [31].

- **The average soil moisture proportion (MST):** It 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):** It consists of 3 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 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	<i>close</i>	$\begin{cases} 1 & 0 \leq x \leq 0.1 \\ 2 - 10x & 0.1 < x \leq 0.2 \\ 0 & \text{else} \end{cases}$
	<i>far</i>	$\begin{cases} 0 & 0 \leq x \leq 0.1 \\ 5x - 1/2 & 0.1 < x \leq 0.3 \\ 1 & \text{else} \end{cases}$
MST	<i>low</i>	$\begin{cases} 1 - x/15 & 0 \leq x \leq 15 \\ 0 & \text{else} \end{cases}$
	<i>average</i>	$\begin{cases} x/20 - 1/2 & 10 \leq x \leq 15 \\ 5/2 - x/20 & 30 < x \leq 50 \\ 0 & \text{else} \end{cases}$
	<i>high</i>	$\begin{cases} x/15 - 2/3 & 40 \leq x \leq 100 \\ 0 & \text{else} \end{cases}$
LD	<i>close</i>	$\begin{cases} 1 - 2x/15 & 0 \leq x \leq 7.5 \\ 0 & \text{else} \end{cases}$
	<i>medium</i>	$\begin{cases} x/5 - 1 & 5 \leq x \leq 10 \\ 3 - x/5 & 10 < x \leq 15 \\ 0 & \text{else} \end{cases}$
	<i>far</i>	$\begin{cases} x/20 - 0.5 & 10 \leq x \leq 30 \\ 0 & \text{else} \end{cases}$

During the fuzzification process, the membership degree of each input parameter x of the proposed FIS is evaluated

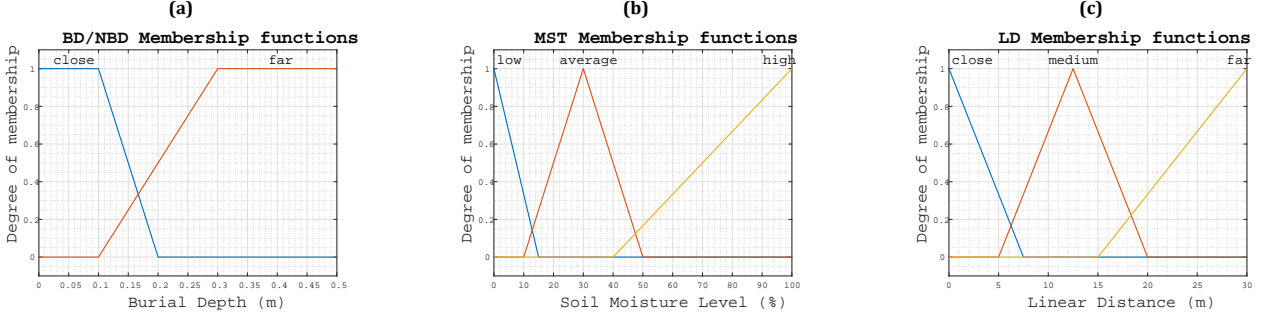


Fig. 3 – (a) Membership functions of the transmitter (BD) and receiver (NBD) burial depths. (b) Membership functions of the soil moisture level (MST). (c) Membership functions of the distance between the transmitter and the receiver (LD)

474 according to Table 2. The probability used for decision-
 475 making (defuzzification) in the fuzzy-based approach is
 476 the average weight of the 36 rules of the inference system
 477 given in (16). Having only two classes (reception or not
 478 reception), our proposed decision-making system divides
 479 the probability of reception into two equal parts. Thus,
 480 when the calculated probability is less or equal to 0.5, we
 481 assume that the packet to be sent will be received (recep-
 482 tion), otherwise the packet will be lost, so the transmis-
 483 sion can be avoided. In addition, as it is shown in [30], the
 484 crisp output can easily be obtained by merging several *If-
 485 then* rules without any computation, thus obtaining a con-
 486 stant complexity ($\mathcal{O}(1)$).

487 5. PERFORMANCE EVALUATION OF FUZDEMA

488 To evaluate the performance of the proposed FuzDeMa,
 489 we consider the dataset of [31] also used to design and
 490 validate our previous works [3]. From this dataset, 140
 491 different scenarios were evaluated in 2 different configu-
 492 rations of the soil: dry and moist.
 493 For each scenario, we evaluate the performance of the
 494 FuzDeMa by considering the following metrics (17) - (21)
 495 that depend on the values of True Positive (TP); True Neg-
 496 ative (TN), False Positive (FP) and False Negative:

- 498 • The *Threat Score* (TS): also known as the *critical suc-
 499 cess index* (CSI) and given in (17) is a performance
 500 metric used to measure the success of an initiative
 501 (reception or loss of a packet).
- 502 • The *Fowlkes-Mallows index* (FMI): is an index used
 503 to determine the similarity between two different
 504 classes (reception or not reception). Its formula is
 505 defined in (18).
- 506 • The *Matthews correlation coefficient* (MCC): also
 507 known as *Phi-coefficient* applied in two classes helps
 508 to measure the correlation differences between the
 509 real observation and the predicted values (19).
- 510 • The *Balanced Accuracy* (bACC) : It is a metric use
 511 when to evaluate how good a binary classifier is
 512 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) : It 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 dataset.

$$TS = \frac{TP}{TP + FN + FP} \quad (17)$$

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

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

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

$$F1 - Score = \frac{2TP}{2TP + FP + FN} \quad (21)$$

$$RMSD = \sqrt{\frac{FP + FN}{TP + FP + TN + FN}} \quad (22)$$

5.1 Dry soil configurations

The 80 measurements of the dry configuration occurred
 when the soil moisture was close to 0%. From the exper-
 imental 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.

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

Table 3 – Confusion matrix for dry soil configurations

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

5.2 Moist soil configurations

When the soil moisture level is different 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 data set 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.

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

To validate the performance of FuzDeMa in predicting of 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 summarises 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.

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

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.

Evaluation of FuzDeMa performances (ROC Curve / AUC)

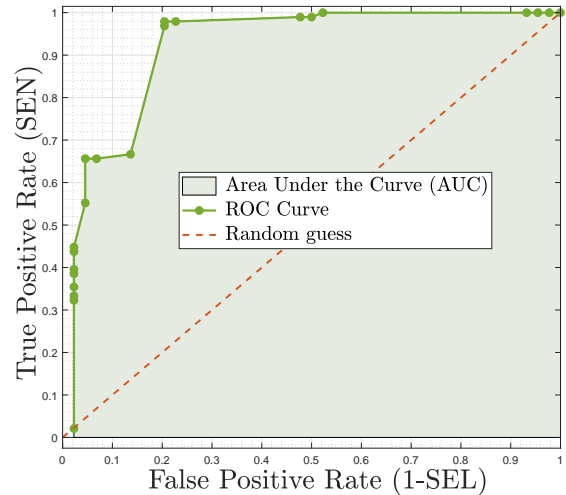


Fig. 4 – Overall ROC curve evaluation of FuzDeMa with an AUC = 0.92

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 MoleNet² [32] is a sensor node specially designed for ecological and agricultural monitoring. However, it can be used also in any other underground monitoring purposes. The MoleNet is based on the Wattuino Pro Mini board powered by Atmega328p microcontroller. The Wireless Underground Communications are achieved by the RFM69CW transceiver at 433MHz 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 summarises the different steps performed by the MoleNet is illustrated in Fig. 5. To save its

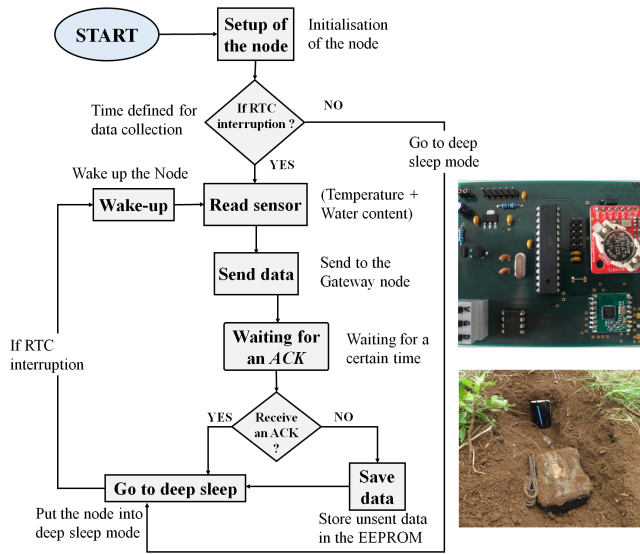


Fig. 5 – Flow chart describing the functioning of the MoleNet. Overview of the PCB and the deployment of the MoleNet at the University of Ngaoundere [32]

energy, the MoleNet sleeps more than 99% of the time. An RTC interruption wakes up MoleNet from deep sleep for sensing and transmission of data to the gateway. After data transmission, the microcontroller waits for an acknowledgement before going to 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.

²molenet.org

The proposed decision-making consists of two equiprobable classes: *reception* (should send) and *no reception* (should not send). From that, 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 case, 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 enough good for transmission. In that case, the gateway will receive the sent packet.

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

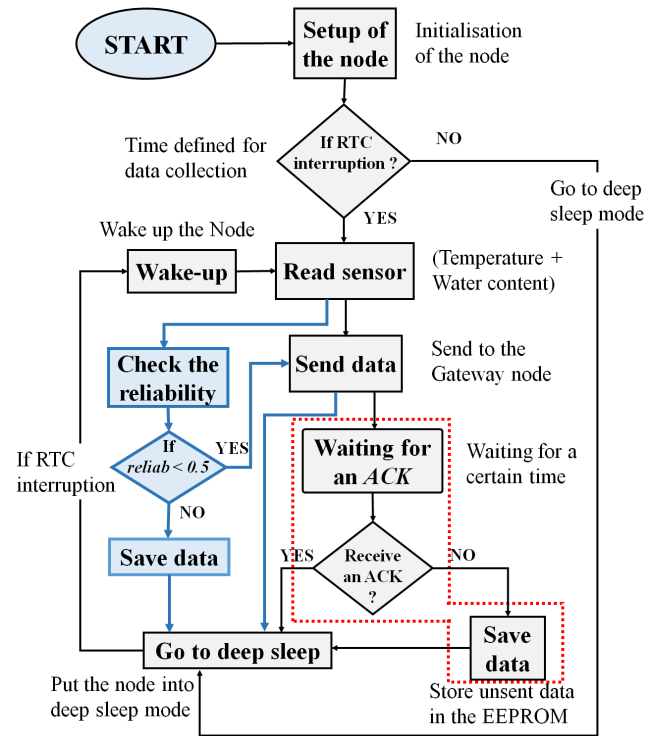


Fig. 6 – Improvement of MoleNet by adding the FuzDeMa module before the transmission of a packet. The blue elements represent the different steps of FuzDeMa according to the MoleNet flowchart. The red section is neglected when implementing FuzDeMa in MoleNet

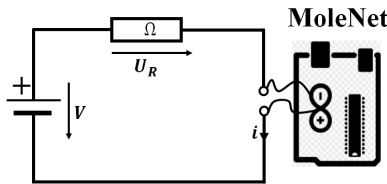
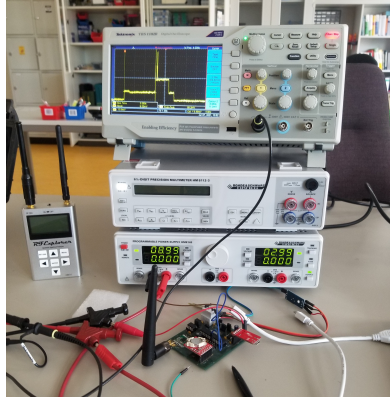
7. EXPERIMENTS AND EVALUATIONS

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

7.1 Measurement setup

To evaluate the energy consumption of the MoleNet, we consider the set-up of Fig. 7. The R&S@HM8143 delivers

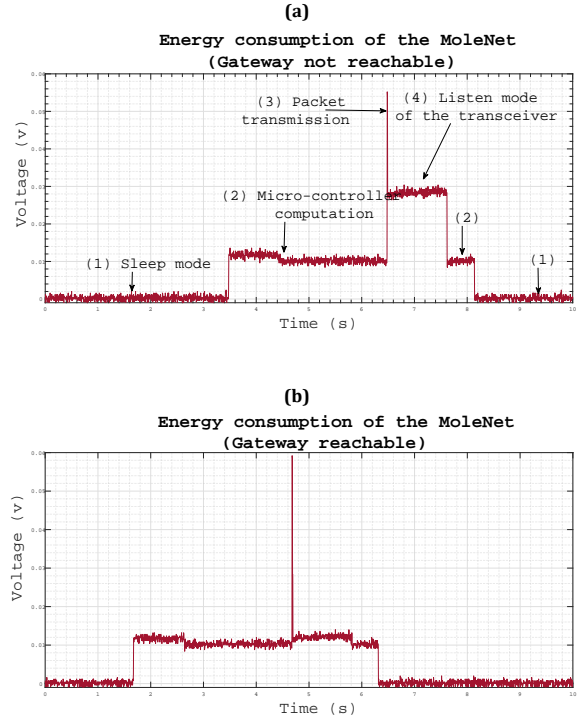
652 to power the MoleNet during the experiment. The preci-
 653 sion multi-meter R&S HM8112-3 is also connected to the
 654 MoleNet to measure the voltage values in real-time and
 655 the current variations. The digital oscilloscope Tektronix
 656 TBS 1102B is also used to visualise the voltage of the
 657 MoleNet. We consider each measurement's output CSV
 658 files for the numerical analysis. To check if the MoleNet
 659 has sent data, we used the digital spectrum analyser RF
 660 Explorer COMBO.



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

664 Each transmission of the MoleNet occurs only from the
 665 nodes to the Gateway through a single-hop communica-
 666 tion. After sending a packet, the MoleNet waits for an
 667 acknowledgement sent by the Gateway before going to sleep
 668 mode. Thus, two scenarios are possible:

- 666 • *The Gateway is not reachable:* here, the node sends
 667 a packet, but after the fixed time, it does not re-
 668 ceive an acknowledgement from the Gateway. Dur-
 669 ing this scenario, a communication round of the
 670 MoleNet contains four different stages (Fig. 8a):
 671 1) sleep, 2) micro-controller computation, 3) Trans-
 672 mission, and 4) waiting for an acknowledgement. As
 673 we can see, MoleNet spends additional energy after
 674 the transmission before switching off the transmis-
 675 sion module and going to sleep mode.
- 676 • *The Gateway is reachable:* the node sends a packet
 677 and receives an acknowledgement from the Gateway
 678 node. After the successful transmission, the node
 679 goes into sleep mode (Fig. 8b). Unlike the first sce-
 680 nario, the MoleNet does not go through step 4 and
 681 avoids the energy spent by the communication mod-
 682 ule after a packet transmission.



683 **Fig. 8** – Energy consumption of the MoleNet during a round. (a) Energy
 684 consumed when the Gateway is not reachable. (b) Energy consumed
 685 when the Gateway is reachable

683 7.2 Evaluation

684 To evaluate the energy consumed by the node during a
 685 round is achieved by considering the set-up of Fig. 7. The
 686 value of the energy consumed in Joules (24) is explained
 687 in function of the voltage u (in Volt), time t (in second)
 688 and the resistance R (set to 10Ω for computation conve-
 689 nience). From the output CSV file, more than 2500 mea-
 690 surements (each 4ms) of the time and voltage are pro-
 691 vided by TBS 1102B.

$$E = \frac{u^2 t}{R} \quad (24)$$

692 From the setup of Fig. 7, several shots have been per-
 693 formed and the average values of the energy consumed
 694 by the MoleNet is summarised in Table 7 below.

695 **Table 7** – Energy consumed by the MoleNet in a round

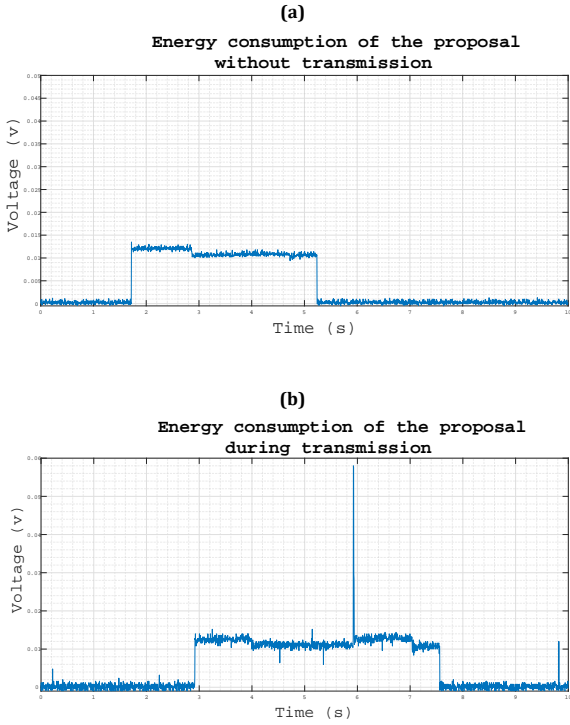
	Gateway not reach.	Gateway reach.
Energy (J)	133.3141 μ J	59.8134 μ J

696 As the table above shows, the power consumption of
 697 the MoleNet doubles when the gateway is not reachable
 698 for about the same running time. This large difference
 699 between these values can be explained by the fact that
 700 the communication module stays in listening mode for
 701 longer. Additionally, It is well known that the commu-
 702 nication module is the most energy-intensive module of
 a sensor node. In other words, the node will consume

703 133.3141 μJ per transmission when the link to the gate-
 704 way (or any other receiver) is broken due to bad ground
 705 conditions.

706 8. EVALUATION OF THE ENERGY CONSUMPTION

708 The evaluation of the energy consumed during the com-
 709 putation of the FuzDeMa is summarised in Fig. 9.



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

710 We observe that the energy consumed by the MoleNet
 711 while performing our proposal during transmission is
 712 similar to the energy consumed during transmission by
 713 the conventional MoleNet (Fig. 9b). Table 8 gives the nu-
 714 merical values of the energy consumed with and without
 715 transmission while running our proposed approach.

Table 8 – Energy consumed by FuzDeMa

	FuzDeMa (no TX)	FuzDeMa (TX)
Energy (J)	51.5264 μJ	68.0133 μJ

716 Despite the short time used to transmit data, we observe
 717 that the MoleNet consumes more than 16 μJ . Thus, by
 718 cancelling a transmission when the environment does not
 719 allow to reach a distant node (here the Gateway), we can
 720 save this energy, thus increasing the lifetime of the sensor
 721 node. The energy consumption of the MoleNet while run-
 722 ning or not our proposed fuzzy-based making-decision
 723 tool is summarised in Fig. 10.

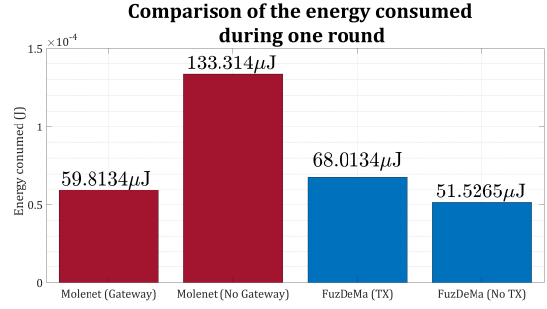


Fig. 10 – Comparison the energy consumption per round

724 Moreover, we evaluate and compare the energy consumed
 725 in two cases: (i) the gateway is reachable; (ii) the gateway
 726 is not reachable.

727 8.1 The gateway is reachable

728 Since the node cannot know by itself perfectly (with prob-
 729 ability 1) when the gateway is reachable or not, we evalu-
 730 ate in this subsection the energy consumed during and
 731 without transmission of our proposal. When the gate-
 732 way is reachable, the conventional MoleNet consumes
 733 around 59.8134 μJ per round, and it is assumed that the
 734 link with the gateway is not broken. When the fuzzy ap-
 735 proach decides to send data (TX) according to the com-
 736 puted reliability (*True Positive*), the node will consume
 737 8.2 μJ more than in the conventional MoleNet (Fig. 11).
 738 In other words, although this case is the worst of our pro-
 739 posal, we see that the additional energy consumed by the
 740 node is minimal and can be neglected.

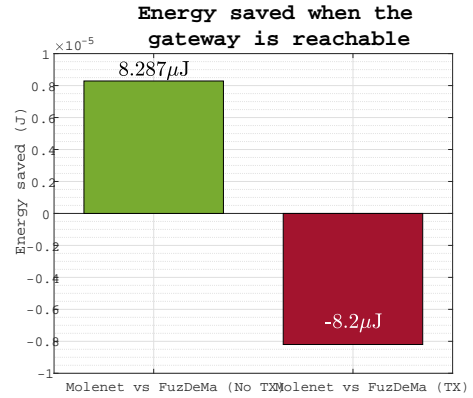


Fig. 11 – Energy saved (and lost) while using FuzDeMa when the gate-
 way is reachable

741 However, if the proposed FuzDeMa does not decide to
 742 allow a transmission (*False Negative*), thus, the energy
 743 saved by FuzDeMa is around 8.287 μJ (Fig. 11). In this
 744 case, the MoleNet sends and receives an acknowledge-
 745 ment from the gateway, and the fuzzy-based control will
 746 not proceed to transmission and thus save 8.287 μJ . The
 747 bad side of the fuzzy-based decision-making tool is that
 748 the gateway will not receive any data from the sensor
 749 node. In short, we summarise in Table 9 the energy saved
 750 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 that case, we notice that the saved energy is slightly 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.

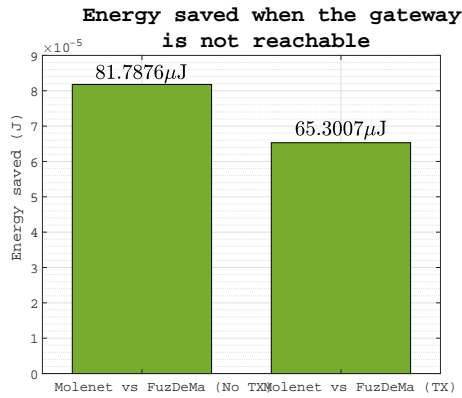


Fig. 12 – Energy saved while using FuzDeMa when the gateway is not reachable

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 GENERALISATION OF FUZDEMA

One key limitation of the MoleNet that we can easily observe occurs when the gateway is not reachable. During that case, the buried node keeps the transceiver in listen 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 deeply the impact of the FuzDeMa for any kind of device.

Let's assume a random sensor field F 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 (none 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 .

$$E_i = mc_{comp} + tx_{cost} \quad (25)$$

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.

$$E'_i = \begin{cases} E_i + fuzz_{cost} & \text{if transmission} \\ E_i + fuzz_{cost} - tx_{cost} & \text{else} \end{cases} \quad (26)$$

As we can observe from Fig. 10, the energy consumed during transmission is higher than the additional calculation of FuzDeMa ($tx_{cost} > fuzz_{cost}$), 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).

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

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

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

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.

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

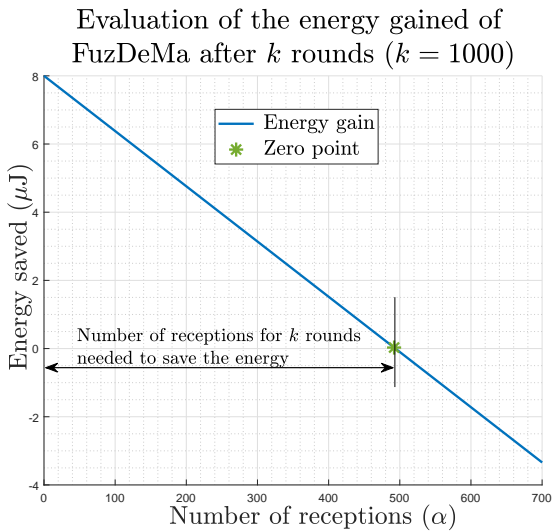


Fig. 13 – Energy saved by FuzDeMa according to the number of receptions

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 to up 32.85%.

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REFERENCES

- [1] Ian F. Akyildiz and Erich P. Stuntebeck. "Wireless underground sensor networks: Research challenges". In: *Ad Hoc Networks* 4.6 (2006), pp. 669–686. ISSN: 1570-8705. DOI: 10 . 1016 / j . adhoc . 2006 . 04 . 003.
- [2] Kaiqiang Lin and Tong Hao. "Link Quality Analysis of Wireless Sensor Networks for Underground Infrastructure Monitoring: A Non-Backfilled Scenario". In: *IEEE Sensors Journal* 21.5 (2021),

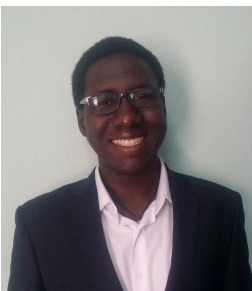
pp. 7006–7014. DOI: 10 . 1109 / JSEN . 2020 . 3041644.

- [3] Damien Wohwe Sambo, Anna Förster, Blaise Omer Yenke, Idrissa Sarr, Bamba Gueye, and Paul Dayang. "Wireless Underground Sensor Networks Path Loss Model for Precision Agriculture (WUSN-PLM)". In: *IEEE Sensors Journal* 20.10 (2020), pp. 5298–5313. DOI: 10 . 1109 / JSEN . 2020 . 2968351.
- [4] G.M. Shafiullah, Adam Thompson, Peter J. Wolfs, and Shawkat Ali. "Reduction of power consumption in sensor network applications using machine learning techniques". In: *TENCON 2008 - 2008 IEEE Region 10 Conference*. 2008, pp. 1–6. DOI: 10 . 1109 / TENCON . 2008 . 4766574.
- [5] Damien Wohwe Sambo, Blaise Omer Yenke, Anna Förster, and Paul Dayang. "Optimized Clustering Algorithms for Large Wireless Sensor Networks: A Review". In: *Sensors* 19.2 (2019), pp. 1–27. ISSN: 1424-8220. DOI: 10 . 3390 / s19020322.
- [6] Monika Malik, Alok Joshi, and Gayatri Sakya. "Network Lifetime Improvement for WSN Using Machine Learning". In: *2021 7th International Conference on Signal Processing and Communication (ICSC)*. 2021, pp. 80–84. DOI: 10 . 1109 / ICSC53193 . 2021 . 9673190.
- [7] Christian Salim and Nathalie Mitton. "Machine Learning Based Data Reduction in WSN for Smart Agriculture". In: *Advanced Information Networking and Applications*. Ed. by Leonard Barolli, Flora Amato, Francesco Moscato, Tomoya Enokido, and Makoto Takizawa. Cham: Springer International Publishing, 2020, pp. 127–138. ISBN: 978-3-030-44041-1.
- [8] Alka Chaudhary. "Mamdani and Sugeno Fuzzy Inference Systems ' Comparison for Detection of Packet Dropping Attack in Mobile Ad Hoc Networks". In: *Emerging Technologies in Data Mining and Information Security. Advances in Intelligent Systems and Computing*. Springer Singapore, 2018, pp. 805–811. ISBN: 9789811315015. DOI: 10 . 1007 / 978 - 981 - 13 - 1501 - 5.
- [9] Muhammed Enes Bayrakdar. "Rule-based collector station selection scheme for lossless data transmission in underground sensor networks". In: *China Communications* 16.12 (2019), pp. 72–83. DOI: 10 . 23919 / JCC . 2019 . 12 . 005.
- [10] Seema Kharb and Anita Singhrova. "Fuzzy based priority aware scheduling technique for dense industrial IoT networks". In: *Journal of Network and Computer Applications* 125 (2019), pp. 17–27. ISSN: 10958592. DOI: 10 . 1016 / j . jnca . 2018 . 10 . 004.

- [11] Li Li, Mehmet Can Vuran, and Ian Fuat Akyildiz. "Characteristics of Underground Channel for Wireless Underground Sensor Networks". In: *The 6th Annual Mediterranean Ad Hoc Networking Workshop*. 2007, pp. 92–99. ISBN: 3143627344. DOI: 10.1038/nature13314. A. arXiv: NIHMS150003.
- [12] H. R. Bogen, J. A. Huisman, H. Meier, U. Rosenbaum, and A. Weuthen. "Hybrid Wireless Underground Sensor Networks: Quantification of Signal Attenuation in Soil". In: *Vadose Zone Journal* 8.3 (2009), pp. 755–761. ISSN: 1539-1663. DOI: 10.2136/vzj2008.0138. URL: <https://www.soils.org/publications/vzj/abstracts/8/3/755>.
- [13] N Chaamwe, W Liu, and H Jiang. "Wave propagation communication models for Wireless Underground Sensor Networks". In: *(ICCT), 2010 12th IEEE International Conference on Communication Technology*. 2010, pp. 9–12. ISBN: 9781424468713. DOI: 10.1136/bmj.a1655.
- [14] Ali M Sadeghioon, David N Chapman, Nicole Metje, and Carl J Anthony. "A New Approach to Estimating the Path Loss in Underground Wireless Sensor Networks". In: *Journal of Sensor and Actuator Networks* 6.3 (2017), p. 18. ISSN: 2224-2708. DOI: 10.3390/jsan6030018.
- [15] Damien Wohwe Sambo, Anna Förster, Blaise Omer Yenke, and Idrissa Sarr. "A New Approach for Path Loss Prediction in Wireless Underground Sensor Networks". In: *2019 IEEE 44th LCN Symposium on Emerging Topics in Networking (LCN Symposium)*. 2019, pp. 50–57. DOI: 10.1109/LCNSymposium47956.2019.9000669.
- [16] Zhi Sun, Ian Fuat Akyildiz, and Gerhard P. Hancke. "Dynamic connectivity in wireless underground sensor networks". In: *IEEE Transactions on Wireless Communications* 10.12 (2011), pp. 4334–4344. ISSN: 15361276. DOI: 10.1109/TWC.2011.093011.110632.
- [17] Xin Dong and Mehmet Can Vuran. "Impacts of soil moisture on cognitive radio underground networks". In: *2013 1st International Black Sea Conference on Communications and Networking, Black-SeaCom 2013* (2013), pp. 222–227. ISSN: 2375-8236. DOI: 10.1109/BlackSeaCom.2013.6623414.
- [18] Xiaoqing Yu, Wenting Han, and Zenglin Zhang. "Path Loss Estimation for Wireless Underground Sensor Network in Agricultural Application". In: *Agricultural Research* 6.1 (2017), pp. 97–102. ISSN: 22497218. DOI: 10.1007/s40003-016-0239-1.
- [19] Erich P. Stuntebeck, Dario Pompili, and Tommaso Melodia. "Wireless underground sensor networks using commodity terrestrial motes". In: *2006 2nd IEEE Workshop on Wireless Mesh Networks*. IEEE, 2006, pp. 112–114. DOI: 10.1109/WIMESH.2006.288625.
- [20] E.H. Mamdani. "Application of fuzzy algorithms for control of simple dynamic plant". In: *Proceedings of the Institution of Electrical Engineers* 121.12 (1974), p. 1585. ISSN: 00203270. DOI: 10.1049/ptee.1974.0328.
- [21] Tomohiro Takagi and Michio Sugeno. "Fuzzy identification of systems and its applications to modeling and control". In: *IEEE Transactions on Systems, Man, and Cybernetics* 15.1 (1985), pp. 116–132. ISSN: 0018-9472.
- [22] J. J. Jassbi, Paulo J. A. Serra, Rita A. Ribeiro, and Alessandro Donati. "A Comparison of Mamdani and Sugeno Inference Systems for a Space Fault Detection Application". In: *2006 World Automation Congress*. 2006, pp. 1–8. DOI: 10.1109/WAC.2006.376033.
- [23] Abdelwahab Hamam and Nicolas D. Georganas. "A comparison of mamdani and sugeno fuzzy inference systems for evaluating the quality of experience of haptic-audio-visual applications". In: *2008 IEEE International Workshop on Haptic Audio Visual Environments and Games (HAVE 2008)*. 2008, pp. 87–92. ISBN: 9781424426690. DOI: 10.1109/HAVE.2008.4685304.
- [24] Fausto Cavallaro. "A Takagi-Sugeno Fuzzy Inference System for Developing a Sustainability Index of Biomass". In: *Sustainability* 7.9 (2015), pp. 12359–12371. DOI: 10.3390/su70912359.
- [25] Mahmoud Dhimish, Violeta Holmes, Bruce Mehrdadi, and Mark Dales. "Comparing Mamdani Sugeno fuzzy logic and RBF ANN network for PV fault detection". In: *Renewable Energy* (2017). ISSN: 0960-1481. DOI: 10.1016/j.renene.2017.10.066.
- [26] Abdulla I. M. Almadi, Rabia Emhamed Al Mamlook, Yahya Almarhabi, Irfan Ullah, Arshad Jamal, and Nishantha Bandara. "A Fuzzy-Logic Approach Based on Driver Decision-Making Behavior Modeling and Simulation". In: *Sustainability* 14.14 (2022). ISSN: 2071-1050. DOI: 10.3390/su14148874.
- [27] Amir Javadpour, Niussha Adelpour, Guojun Wang, and Tao Peng. "Combining Fuzzy Clustering and PSO Algorithms to Optimize Energy Consumption in WSN Networks". In: *2018 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*. IEEE, 2018, pp. 1371–1377. ISBN: 9781538693803. DOI: 10.1109/SmartWorld.2018.00238.

- 1013 [28] Abdulmughni Hamzah, Mohammad Shurman, Omar Al-Jarrah, and Eyad Taqieddin. “Energy-Efficient Fuzzy-Logic-Based Clustering Technique for Hierarchical Routing Protocols in Wireless Sensor Networks”. In: *Sensors (Switzerland)* 19.3 (2019). ISSN: 1424-8220. DOI: 10 . 3390 / s19030561.
- 1020 [29] Paul Dayang, Cyrille Sepele Petsou, and Damien Wohwe Sambo. “Combining Fuzzy Logic and k-Nearest Neighbor Algorithm for Recommendation Systems”. In: *International Journal of Information Technology and Computer Science(IJITCS)* 13.4 (2021), pp. 1–16. ISSN: 2074-9007. DOI: 10. 5815/ ijitcs.2021.04.01.
- 1027 [30] Damien Wohwe Sambo, Blaise Omer Yenke, Anna Forster, Joseph Ndong, Paul Dayang, and Idrissa Sarr. “A New Fuzzy Logic Approach for Reliable Communications in Wireless Underground Sensor Networks.” In: *Wireless Networks* 28.7 (2022), pp. 3275–3292. ISSN: 15728196. DOI: 10 . 1007 / S11276-022-03008-7.
- 1034 [31] Damien Wohwe Sambo. *Dataset for WUSN-PLM*. https://github.com/wsdamieno/Data_WUSN-PLM. Accessed: 2022-10-03. 2019.
- 1037 [32] Idrees Zaman, Martin Gellhaar, Jens Dede, Hartmut Koehler, and Anna Foerster. “Demo: Design and Evaluation of MoleNet for Wireless Underground Sensor Networks”. In: *2016 IEEE 41st Conference on Local Computer Networks Workshops (LCN Workshops)*. 2016, pp. 145–147. DOI: 10 . 1109 / LCN . 2016.040.

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