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LOCAL RESOURCE EXPLOITATION

Using fuzzy logic for reliable communication in a wireless underground sensor network for precision agriculture

Utilisation de la logique floue pour une communication fiable dans un réseau de capteurs souterrains sans fil pour l'agriculture de précision

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ABSTRACT:

Nowadays, the Wireless Underground Sensor Networks (WUSNs) face the loss problem of Wireless Underground Communication (WUC) due to soil properties. This problem affects the reliability of a WUSN during wireless communication. Indeed, the prediction of packet loss/reception becomes very challenging due to the use of soil as the communication medium. In this paper, we proposed a reliable communication scheme for WUSNs based on Fuzzy Logic. To achieve it, we designed a Fuzzy Inference System (FIS) based on the famous Sugeno FIS. The proposed inference system consists of 4 inputs and one output. The inputs are made up of fuzzy sets that give information on a sensor node. These informations are the burial depth of the transmitter and receiver nodes, the distance between them and the soil moisture portion in percent. The resulting output of the proposed approach gives the probability of a packet sent to be received by a receiver node. To evaluate the proposed approach, intensive experimentations have been conducted with real sensor node devices deployed within a real agricultural field. To validate our approach, several performance assessors have been used. The obtained results show that the proposed approach is very accurate for predicting the reception or loss of packets in WUSN applications with fewer computations.

Keywords: Wireless Underground Sensor Network, Wireless Underground Communication, Reliable communication, Fuzzy Inference System, Computational Intelligence.

RÉSUMÉ :

De nos jours, les réseaux sans fil avec capteurs souterrains (WUSN) sont confrontés au problème de pertes de communication souterraine causées des propriétés du sol. Ce problème affecte la fiabilité d'un WUSN pendant les communications sans fil. En effet, la prédiction de la perte/réception de paquets devient très difficile en raison de l'utilisation du sol comme support de communication. Dans cet article, nous proposons un schéma de communication fiable pour les WUSNs basé sur la logique floue. Pour ce faire, nous avons conçu un système d'inférence floue (SIF) basé sur le célèbre SIF Sugeno ou TSK. Le système d'inférence proposé se compose de 4 entrées et d'une sortie. Les entrées sont constituées d'ensembles flous qui donnent des informations sur un nœud capteur. Ces informations sont la profondeur d'enfouissement des nœuds émetteur et récepteur la distance entre ces nœuds et le taux d'humidité du sol (en pourcentage). La sortie résultante de l'approche proposée donne la probabilité qu'un paquet envoyé soit reçu par un nœud récepteur. Pour évaluer l'approche proposée, des expérimentations intensives ont été menées avec des nœuds de capteurs réels déployés dans un champ agricole réel. Pour valider notre approche, plusieurs indicateurs de performance ont été utilisés. Les résultats obtenus montrent que l'approche proposée est très précise pour prédire la réception ou la perte de paquets dans les applications WUSN avec moins de calculs.

Mots clés : Réseaux sans fil avec capteurs souterrains, Communications sans fil souterraines, Communication fiable, Système d'inférence floue, Intelligence computationnelle.

1. INTRODUCTION

The research interest on the Internet Of Underground Things (IOUT) widely increase during recent decades especially for Wireless Underground Sensor Network (WUSN) field due to the large amount and the variety of applications (Salam et al., 2019 et Vuran et al., 2018). In WUSN, sensor nodes must communicate with each other through Wireless Underground Communications (WUC). However, since certain soil conditions (temperature, humidity, particle size, density, etc.) significantly affect the propagation of electromagnetic (EM) waves, the reliability of WUC has become a key issue in this research area. Furthermore, when the soil moisture increases, the data delivery rate will considerably decrease or even be null. In the latter case, the transmitter wastes energy unnecessarily by sending a packet that will never reach the receiver due to the attenuation of EM waves in the ground. Since a node consumes more energy during transmission and reception mode, sending a package, when necessary, will result an improved sensor lifetime (Yenke et al., 2016). Many advanced researches have been conducted during the few years for designing path loss models in WUSN (Bogena et al., 2009 et Wohwe Sambo et al., 2020). However, despite the prediction of signal attenuation in the soil of these path loss approaches, their execution needs high computational and memory resources. Moreover, for real-time applications in WUSN, the path loss model should be computed by each node in order to estimate its maximum communication range according to *in-situ* parameters. Meanwhile, the sensor nodes are cheap and very resources limited due to their small size. Thus, the real-time prediction of communication range by the computation of path loss models is a key issue due to the resource restriction of networks.

With the advancement of Computational Intelligence (CI) and Machine Learning (ML), recent solutions take into account the limited resources of sensor nodes that have been widely proposed (Wohwe Sambo et al., 2019 et Gui et al., 2016). Between these CI and ML approaches, we can mention Neural Network, Genetic Algorithm, Swarm Intelligence or Fuzzy Logic (FL). The latter is widely used due to its performance and its lightness during implementation.

In this paper, we extend our previous work, in which we proposed the Wireless Underground Sensor Network Path Loss Model (WUSN-PLM) (Wohwe Sambo et al., 2020 et Wohwe Sambo et al., 2019). Due to relevant issues like input parameters or resources needed for executing the path loss prediction, we propose a lightweight approach for *in-situ* reliable communications in WUSN based on FL. To achieve it, we design a fuzzy inference model based on the famous TSK fuzzy system. The proposed FIS is made up of 4 fuzzy sets as inputs and one output fuzzy set. They are the burial depth of transmitter and receiver, the soil moisture proportion, the linear distance between nodes and the reliability that gives a receiver the probability of successfully get a packet sent by a transmitter. In order to evaluate our proposed FIS, intensive measurements in the real experimental field at the botanic garden of the University Cheikh Anta Diop of Dakar in Senegal have been conducted. The evaluation process of our proposed FIS considers several metrics. Over the 140 observations performed, our proposed model made a total of 128 good predictions (93TP and 35TN), then 91.43% accuracy. Moreover, we have shown that according to some scenarios regarding the node locations or the distance between nodes that the number of rules initially used (36) to predict the delivery reliability can be reduced to only one rule.

The rest of this paper is organized as follows: The WUSN-PLM is presented in Section 2; Some related works on FL applications are presented in Section 3; Section 4 presents our fuzzy model for the reliable communication in WUSN; In order to validate our proposed approach, intensive experimentation and comparisons are conducted in Section 5; The conclusion and future works are presented in Section 6.

2. THE WUSN-PLM AND MOTIVATION

The WUSN-PLM is a model designed to predict the signal attenuation in soil for WUSN applications like precision agriculture or ecological monitoring. In order to improve its accuracy, it is based on the accurate Mineralogy-Based Soil Dielectric Model (MBSDM) to predict the values (real and imaginary parts) of the Complex Dielectric Constant (CDC) (Mironov et al., 2009). The MBSDM is preferred to other CDC predictions because it shows a better accuracy with a lesser number of inputs (Wohwe Sambo et al., 2019). It considers the presence of free and bound water in moist soils in order to predict the value of CDC with higher precision. The proposed WUSN-PLM is designed for the 3 types of Wireless Underground Communications (WUC): Underground-to-Underground, Underground-to-Aboveground and Aboveground-to-Underground. This is because, in practice, despite buried sensor nodes communicate with each other (UG2UG), the sensed information must be analyzed at the surface (UG2AG). The above ground Base Station can send an instruction to a buried node in order to collect data (AG2UG). Due to underground phenomena like the reflection or the refraction of the wave, that occur at different depths, the proposed WUSN-PLM is based on topsoil region (first 30 cm) (1) and subsoil region (after 30 cm) (1). For subsoil region, the loss due to reflection is neglected whereas, for topsoil depths, it is added to the general path loss. Moreover, for AG2UG communication, the wave attenuation due to refraction proposed by Dong et *al*. (2013) is added to (1) and (2) for top and sub depths respectively.

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

$$-288.8 + 20\log\left(d_1 . d_2 . d_{ug} . \beta . f^2\right) + 8.69\alpha . d_{ug} \tag{2}$$

Where f is the wave frequency; 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 (Bogena et al., 2009). α and β are the attenuation due to material absorption and the phase shifting respectively. They are based on the

CDC gives by the MBSDM (Mironov, 2009). The reflection factor R depends on the dielectric constant and its value can be found in (Chaamwe et al., 2010).

The WUSN-PLM is evaluated within a real agricultural field with real sensor nodes based on ARDUINO boards. The experimental field was the botanical garden of the University Cheikh Anta Diop of Dakar in Senegal. A total of 140 measurements have been conducted in dry and moist sandy clay soil. To validate the model two types of transceivers have been used: LoRa SX1278 and the cheap nRF905 transceivers. According to the type of transceivers used, gap indicators (SX1278) and confusion matrices (nRF905) are used to evaluate its performance. The Proposed WUSN-PLM outperforms the other existing path loss models on each type of WUC with 81.06% Balanced accuracy and 87.129% Precision. The Matthews Correlation Coefficient shows that the correlation between the prediction and the observation of the proposed WUSN-PLM is 0.64.

Despite the higher performance of the WUSN-PLM, its implementation remains a key issue for real-time application in WUSN. The prediction of the CDC by the MBSDM needs computational resources that sensor nodes do not have. Thus, the prediction *in-situ* of the path loss remains highly challenging.

3. APPLICATIONS OF FUZZY INFERENCE SYSTEMS

For evaluating the quality of experience of Hapto-Audio-Visual environments (HAVE), Hamam et *al.* (2008) used FL. They used 5 inputs sets and one output set with 36 rules defined inside the FIS. The output set describes the satisfaction and the benefit gained from the application and is made up of 5 membership functions. From the experimentations and comparisons, the authors show that the Sugeno inference system gives better results than Mamdani in their application.

Another application of FL is presented by Bagis and Konar (2015) for an application of a microstrip antenna considered as a complex or non-linear system. Their approach consists of optimizing the number of inputs necessary for the FIS by using the Artificial Bee Colony (ABC). The results have shown that the use of ABC in order to find accurate inputs for Mamdani and Sugeno is feasible and can be considered as an alternative for non-linear problems.

Cavallaro (2015) proposed a FIS based on TSK (Sugeno-type) for a sustainability index of the biomass called Fuzzy Sustainable Biomass Index (FSBI). To achieve it, he used as inputs 4 fuzzy sets (Energy output, Energy ration, Fertilizers and Pesticides) with a total of 12 fuzzy variables. These inputs give information about chemical pressure caused by crop cultivation and contaminant impacts due to the use of fertilizers and pesticides. The output set FSBI consists of 5 fuzzy variables that represent the sustainability level of the particular crop according to the energy use. Its proposed FIS is based on 81 rules for the computation of the FSBI output. In order to validate its model, the author compared it with real data from 5 different crops.

Dhimish et *al.* (2018) proposed a fault detection model for PhotoVoltaic (PV) based on Artificial Neural Network (ANN) and FL. Its goal was to detect possible faults in PV using radial basis function (RBF). The authors used the FL for the maximum power point tracking based on Mamdani and Sugeno. 2 fuzzy sets with 10 fuzzy variables each are used as inputs for describing the voltage and the power ration of the PV. The output set gives the different type of fault classified into 10 variables values. Experiments conducted by authors shown that the use of Mamdani or Sugeno FIS for PV fault detection is possible.

Chaudhary (2018) compared Mamdani and Sugeno FIS for the detection of packet dropping attack in Mobile Ad Hoc Networks (MANET). The author used 2 inputs fuzzy sets: the data packet forwarded ratio and the average data packet dropped rate. The overall number of membership functions designed as inputs are 6. The results show that both designed FIS have slightly the same performance, however, due to the simplified defuzzification process of Sugeno, it can be a better choice than Mamdani for the detection of packet attacks.

The FL is also widely used for Non-deterministic Polynomial (NP) hard optimization problem like the clustering in several approach either based on Mamdani or Sugeno FIS (Wohwe Sambo et al., 2019 et Hamzah et al., 2019).

Despite a large number of FL applications and to the best of our knowledge, there is any previous study or research on reliable communication in WUNS based on FL. This presented study is a novel contribution in the fields of WUC and FL.

4. PROPOSED APPROACH

The signal attenuation due to soil properties widely affects the overall reliability of a WUSN, thus the network topology. Despite a large amount of path loss models, the prediction *in-situ* of the reception or the loss of a sent packet by a node remains a key issue. To address this issue, we designed the following approach based on FL for a reliable WUC.

Our proposed approach is based on the famous Sugeno FIS because of the defuzzification process, which is more suitable for a sensor node than in the Mamdani FIS. Our proposed approach is made up of the 4 following inputs:

- The **Burial Depth (BD)**: this fuzzy variable describes the burial depth of the sender node which varies from the ground surface (zero meter) to the maximum depth set at 0.5 meter. Two (2) trapezoidal membership functions have been designed for BD fuzzy variable: *close* for depths near the ground surface in the topsoil region; *far* for subsoil depths up to the maximum depth (**Figure 1a**).
- The **Soil Moisture Level (MST)**: It represents the percentage of water within the soil given by one or more soil moisture sensors. Like it is shown in **Figure 1b**, three (3) triangular membership functions are

designed: *low*, *average* and *high*. They express the level of moisture inside the soil which can vary from 0 % to 100 %.

- The **Linear Distance (LD)**: It is the distance between a transmitter node and a receiver node regardless of their respective burial depths. We also designed 3 triangular membership functions like the fuzzy variable *MST*: *close*, *medium* and *far*. The graphical representation of its membership functions is illustrated in **Figure 1c** in which the real values of *LD* range from 0 to 30 m. The maximum range is set due to our experiments conducted at the experimental field in Senegal.
- The **Neighbour Burial Depth (NBD)**: this fuzzy variable is identical to BD, the membership functions are the same (**Figure 1d**).

According to the fuzzy variables and their corresponding membership functions, the maximum number of rules is 36. However, depending on the location of the transmitter node, the rule number can be reduced.

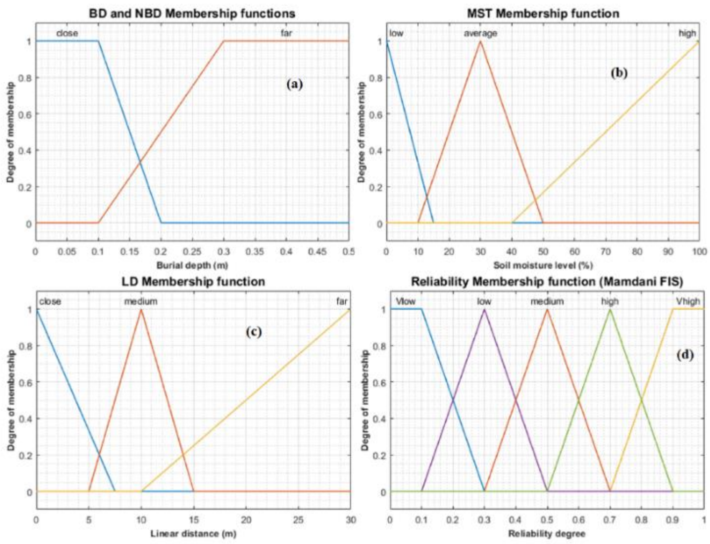

Figure 1: Different membership functions of the FIS. Different membership functions of the FIS. a) BD membership functions of FIS that represent the Burial Depth of Transmitter node. b) MST membership function for the soil moisture which varies from very dry (0 %) to very moist (100 %). c) is the graphical representation of the membership function LD that characterizes the linear distance between transmitter and receiver. d) NDB membership functions of the Burial Depth of Receiver node.

The output fuzzy variable of the proposed approach is the reliability degree that expresses the probability for a packet to be successfully got by a receiver node. This fuzzy variable has 5 constant values. Thus, the reliability degree can be *Vhigh* (very high), *high*, *medium*, *low* or *Vlow* (very low). The probabilities of these degrees are respectively 0.9, 0.7, 0.5, 0.3 and 0.1 for each previous linear membership function.

The computation of the membership degree α of a crisp input x for each of these membership functions is presented in **Table 1**.

Table 1. Computation of the membership degrees.

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

5. EXPERIMENTS AND RESULTS

5.1. Experimentations

5.1.1. Experimental Field

To evaluate our model, real experiments are conducted at the botanic garden of the University Cheikh Anta Diop of Dakar in Senegal. The experimental field is an agricultural plantation of onions. The soil is a sandy clay type and due to the high sunlight observed, the young onion seedlings are watered using a drip irrigation system connected to a pool for pisciculture. The experimental field is shown in **Figure 2**.

5.1.2. Sensor Nodes

The nodes are based on ARDUINO boards (**Figure 3d)**. The nodes are powered by a 9 V input. In order to get the physical data from its environment, the nodes are equipped with several sensors. The transmitter (**Figure 3b**) has a sensor LM35DZ to measure the temperature inside the box; a soil humidity sensor YL-69 and a capacitive soil moisture sensor resistant to corrosion; a DHT11 sensor is fixed outside the box to give the temperature and the relative humidity of the soil around the box. Contrary to the transmitter, the receiver node (**Figure 3c**) has only the soil moisture sensor YL-69. Except for the Arduino boards, the transceivers, the batteries and the sensor LM35DZ from the transmitter node, all other components are put outside a plastic box like the MoleNet (Zaman et al., 2016). The wireless communication between the nodes is performed by using pairs of nRF905 transceiver working at low frequency 433MHz.

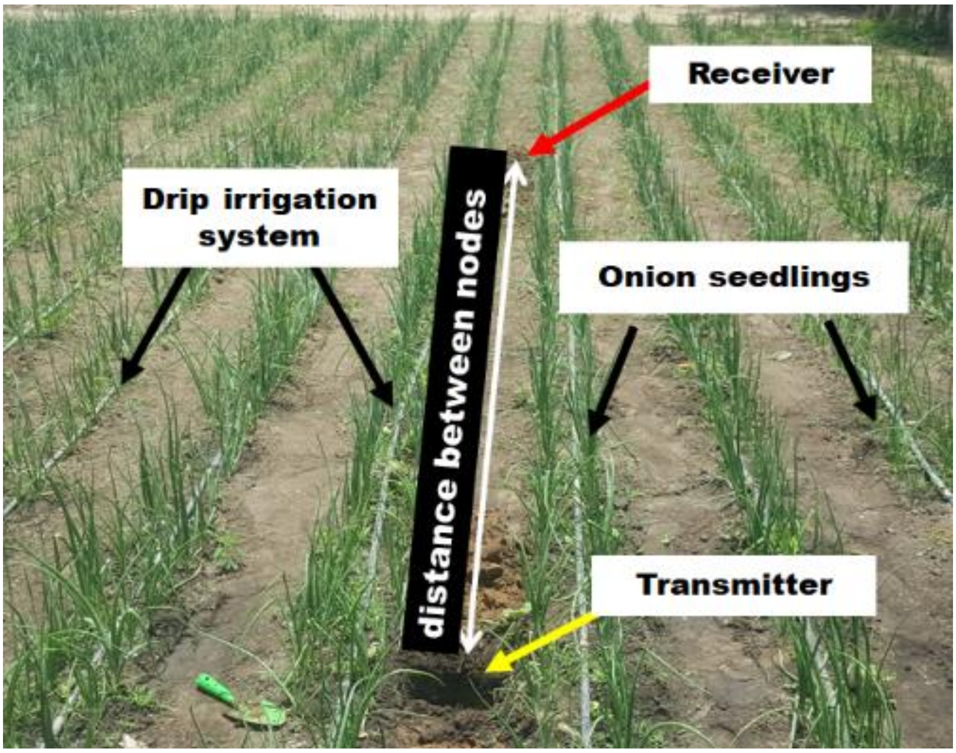

Figure 2: Overview of the experimentation field at the Botanic Garden of the University Cheikh Anta Diop of Dakar in Senegal.

5.1.3. Methodology

We have considered two scenarios for our measurements: Scenario #A when the soil is dry (**Figure 3a**) and Scenario #B for moist soil (**Figure 3b**). On dry soil, there is no presence of moisture due to the heat released by the sunlight and the wind have dried the soil so that the soil moisture is around 0 %.

For each scenario, the distance between the transmitter and receiver nodes varies between 5 m, 10 m, 15 m and 20 m. On each distance, the buried depth of nodes changes from the ground, 15 cm, 20 cm, 30 cm and 40 cm. Moreover, depths located at the first 30 cm are considered as *top_depth* region and beyond 30 cm, they are considered as *sub_depth*.

Figure 3: Overview of the experimentation field and the wireless sensor nodes. a) presents the agricultural field before the watering system is installed and the young onion plants. b) transmitter node buried under the ground in dry soil configuration. c) Receiver node buried under the ground during moist soil configuration. d) Components of the receiver node equipped with nRF905 transceiver.

During this study conducted, the communication between two sensor nodes (transmitter and receiver) are evaluated according to their burial depths, soil moisture portion and the distance between nodes.

5.1.4. Evaluation metrics

Knowing that the output of a Sugeno FIS is a crisp output (real value), the reliability of WUC is established by the following assumption.

> ***Assumption***: *If the calculated probability for the link quality is less than 0.5, a sent packet by a transmitter will not reach the receiver node: there is a packet loss. However, if the calculated reliability is equal or higher than 0.5 a packet is well received by the receiver: there is a packet reception.*

For the evaluation of the proposed approach, we define the positive class as the reception of a packet (*received*) and the negative class for the not reception of a sent packet (*not received*). We furthermore consider the following parameters:

We evaluate the proposed approach according to the following metrics:

- True Positive (TP), True Negative (TN): when approach successfully predict the positive class and the negative class respectively;
- False Positive (FP), False Negative (FN): The approach does not successfully predict the positive or the negative class respectively.

To evaluate and to compare the reliability of the proposed model to the WUSN-PLM, we use the widely used metrics of (3) to evaluate the performance.

$$\mathrm{SEN} = \frac{\mathrm{TP}}{\mathrm{TP+FN}};\ \mathrm{SEL} = \frac{\mathrm{TN}}{\mathrm{TN+FP}};\ \mathrm{PRE}(\%) = \frac{\mathrm{TP}\times 100}{\mathrm{TP+FP}};\ \mathrm{ACC}(\%) = \frac{(\mathrm{TP+TN})\times 100}{\mathrm{TP+TN+FP+FN}} \qquad (3)$$

Where SEN is the sensitivity and it is the true positive rate and measures the proportion of positive observations that are correctly predicted. The selectivity SEL gives the proportion of negative observations well predicted. The precision PRE stands for the proportion of positive predicted values. The accuracy ACC is the ratio between the good predictions and the overall observations.

5.2. Results and Validation

According to each of the 140 observations performed, we associate $(bd, mst, ld, nbd) \in BD \times MST \times LD \times NBD$ related to the burial depht of the sensor nodes, the average sensed soil moisture and the distance between the nodes. The reliability is computed according to Section 4. Thus, for each scenario, we evaluate the crisp output of the proposed FIS according to the positive and the negative classes.

5.2.1. Dry Soil Configuration

For each linear distance (5m, 10m, 15m and 20m) of dry soil configuration, 24 observations per linear distance are observed. Thus, 80 measurements for dry soil configuration have been conducted within the experimental field. From the 80 tests conducted, the proposed approach obtains a perfect score with 80 good predictions (68TP and 12TN) i.e., 100% accuracy and 0% error.

The comparison of the proposed approach and WUSN-PLM in dry soil configuration is resumed in the confusion matrix of **Table 2**. For dry soil configuration, WUSN-PLM performs 72 good predictions (68TP and 4TN) and 8 bad predictions (0FN and 8FP) over the 80 measurements. With 100% accuracy, the proposed FL approach outperforms the powerful path loss model WUSN-PLM which has 90% accuracy and a prediction error of 10%.

Table 2. Confusion matrices of the WUSN-PLM and the proposed approach in dry soil.

		Observ.			
		WUSN-PLM		Proposed FL	
		Rcv.	Not rcv.	Rcv.	Not rcv.
Pred.	Rcv.	68TP	8FP	68TP	0FP
	Not rcv.	0FN	4TN	0FN	12TN

Table 3. Confusion matrices of the WUSN-PLM and the FL approach in moist soil.

		Observ.			
		WUSN-PLM		Proposed FL	
		Rcv.	Not rcv.	Rcv.	Not rcv.
Pred.	Rcv.	20TP	3FP	25TP	9FP
	Not rcv.	8FN	29TN	3FN	23TN

5.2.2. Moist Soil Configuration

The same experiments are conducted in moist soil, Meanwhile, the sensor burial depths vary from the ground surface to 30cm in depth for a practical reason. In each measurement carried out, the sensed soil moisture is taken into consideration as an input. Its value is given by the soil moisture sensors YL-69 equipped in each sensor node. Thus, the average sensed value of the soil moisture between the transmitter and the receiver nodes is considered for the observations. According to the 4 depths (0cm, 15cm, 20cm and

30cm), a total of 60 observations are conducted in moist soil configuration. The comparison of observations in the moist soil of the WUSN-PLM is presented in the confusion matrices presented in **Table 3**. We observe that over the 60 measurements in moist soil both approaches get slightly the same predictions: The WUSN-PLM and the proposed FL approach get 49 (20TP and 29TN) and 48 good predictions (25TP and 23TN) respectively over 60 measurements. Thus, the proposed approach is able to better predict the positive class (reception of data) than the path loss model WUSN-PLM (25TP against 20TP).

The overall measurements conducted for dry and moist soil configuration is 140. The corresponding confusion matrices of the proposed approach and the WUSN-PLM are given in **Table 4**. Over the 140 cases, the proposed FIS outperforms the WUSN-PLM with 128 (93TP and 35TN) and 88 (88TP and 31TN) good predictions respectively.

Table 4. Overall confusion matrices of the WUSN-PLM and the proposed approach.

		Observ.			
		WUSN-PLM		**Proposed FL**	
		Rcv.	Not rcv.	Rcv.	Not rcv.
Pred.	Rcv.	88TP	13FP	93TP	9FP
	Not rcv.	8FN	31TN	3FN	35TN

From **Table 5**, the proposed FL approach outperforms the WUSN-PLM. Indeed, it performs the highest accuracy (91.429%) against 85% observed by the WUSN-PLM. Furthermore, it gets a higher SEN, SEL and PRE than the path loss model WUSN-PLM. However, due to the size inequality of the positive (*Received*) and the negative classes (*Not received*) (96 and 44 respectively), the ACC is not sufficient to evaluate the reliability of prediction models. For such a case, the calculation of the balanced accuracy (bACC) (4) instead of ACC is more suitable to evaluate the performance of a prediction model. From **Table 5**, we observe that despite the size inequality of the measurements, the proposed FIS obtains a higher bACC than the WUSN-PLM (88.21% and 81.061% respectively).

$$\mathrm{bACC}(\%) = \frac{(\mathrm{SEN}+\mathrm{SEL})}{2}; \quad \mathrm{MCC} = \frac{(\mathrm{TP}\times\mathrm{TN}-\mathrm{FP}\times\mathrm{FN})}{\sqrt{(\mathrm{TP}+\mathrm{FP})(\mathrm{TP}+\mathrm{FN})(\mathrm{TN}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})}} \tag{4}$$

Table 5. Evaluation and comparison of the performance of the Proposed FIS and WUSN-PLM.

	PRE	ACC	SEN	SEL	bACC	MCC	AUC
WUSN-PLM	87.13 %	85 %	0.917	0.705	81.06 %	0.643	0.92
Proposed FL	91.18 %	91.43 %	0.969	0.795	88.21 %	0.798	0.92

To evaluate the correlation between the prediction and the observation, the Matthews Correlation Coefficient (4) named MCC is evaluated (**Table 5**). The calculated MCC in the proposed FL approach is better than in the WUSN-PLM (0.643 and 0.785 respectively). In order words, the correlation between the prediction and the observation is higher in the proposed FL than in WUSN-PLM despite the unequal size of the observed classes.

Furthermore, in order to evaluate the proposed approach independently of the fixed threshold (0.50) and the insensibility to class distribution, we use the Receiver Operating Characteristic (ROC) curve. The ROC curve evaluates the trade-off between the true and the false positive rate of our proposed approach through a graphical representation. The resulting ROC curve is presented in **Figure 4**. We observe that the ROC Curve is well above the random guess, thus confirms the good accuracy of the proposed approach.

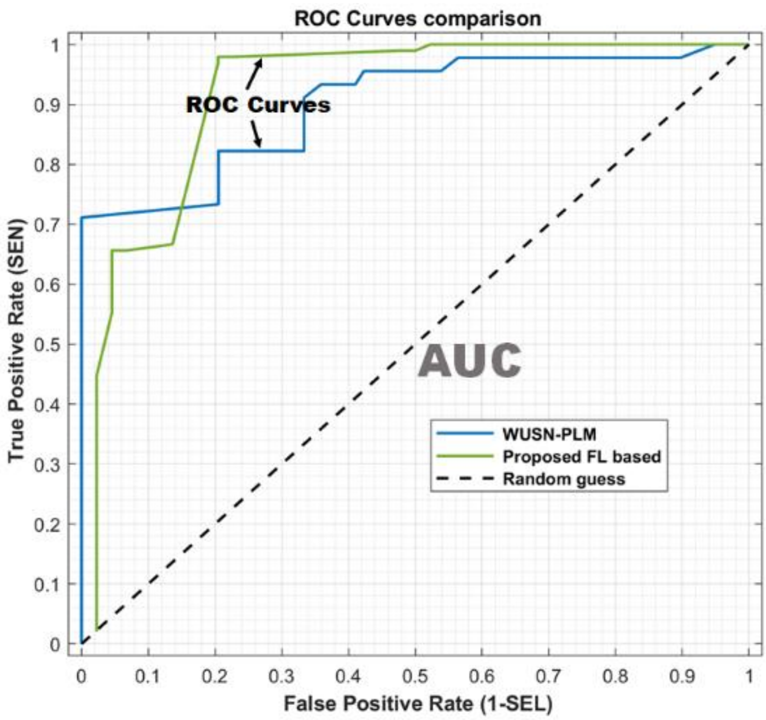

Figure 4: ROC curve and AUC of the proposed FIS

The value of the Area Under Curve (AUC) which quantifies the efficiency of the ROC Curve is calculated according to the trapezoidal rule.

6. CONCLUSION AND FUTURE WORKS

In this paper, we presented an intelligent and reliable WUSN communication based on FL. In order to achieve this, we use the Sugeno FIS due to its simplified defuzzification process. To find the probability of receiving a packet by a node, we considered 4 fuzzy sets as inputs: the transmitter and receiver burial depths, the soil moisture, the linear distance between transmitter and receiver. 4 trapezoidal and 6 triangular membership functions have been designed for the input sets. The output fuzzy set represents the reliability degree of packet delivery classified into 5 constants. In order to evaluate the proposed FL approach, 140 observations from real experiments of our previous works have been considered. The results show that our proposal outperforms the WUSN-PLM with 88.21 % and 81.061 % respectively. Moreover, by comparing the MCC, we observe that obtains a higher correlation between the prediction and the actual case than the WUSNPLM (0.798 and 0.643 respectively). Furthermore, despite the 36 rules defined within our proposed FIS, we showed that, according to some fixed parameters like the burial depth or the linear distance, the rules can be reduced to only one rule. Thus, the energy and the computation time needed are widely reduced.

As future works, the deployment of the proposed FL within a sensor network made up of several nodes is envisaged. Moreover, the evaluation of energy consumption during efficient routing schemes such as clustering is planned.

7. CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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