A Fuzzy Framework for Self-Aware Wireless Sensor Networks

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Abstract

Abstract: We have developed a fuzzy logic framework to simulate self-awareness in wireless sensor networks (WSNs) that envisages data transmission losses due to abnormalities in the operating environment. Fuzzy logic is selected to model the awareness, because it requires less data to encode, and occupies less memory, making it suitable for sensor nodes with limited resources. We view WSN as a multi-layered infrastructure, where a central-server in the top-layer manages the gateways in the intermediate-layer, and the gateways are aggregating the raw sensed data from the bottom layer's sensors. The self-awareness is simulated using Mamdani Fuzzy inference system (FIS) that utilizes a custom-defined membership functions of the selected parameters, such as temperature, humidity, wind speed, and battery residual-level to guide WSN through its data transmissions. The input and output parameters are defined with three linguistic variables (low, medium and high) and a predetermined set of rules is applied to the selected FIS to determine the impact level. The impact is mapped into packet error rate and the gateway then decides whether to carry out the data transmissions while being aware of the selected uncertainties and their impact. The experimental results on a multivariate dataset integrating real-time meteorological data with randomly generated battery voltage revealed that the proposed FIS framework demonstrated 38% energy savings by non-executing unworthy communications against normal transmissions.

Keywords: fuzzy framework; self-aware; layered architecture; Mamdani fuzzy inference system; environmental uncertainties; transmission efficiency.

1. INTRODUCTION

Self-awareness provides the capability to sensors for understanding their own behaviors and the surrounding environment. A certain level of self-awareness is required for autonomous and sustainable operation; at a higher-end, it may aid in trustworthy decision-makings, which are obligatory in today's applications. Furthermore, providing a minimal notion of self-awareness may facilitate the conscious of sensor's task and the operating environment than the typical sensor.

In this paper, we have developed a self-aware framework to simulate the awareness of internal and external uncertainties to the sensors' deployed for outdoor monitoring. The wireless sensor network architecture is viewed as a three layered network, where the data transmission to the central-server at the top-layer is decided by the gateway based on the awareness of selected uncertainties; the gateway conserves sensors' energy by terminating the impaired transmissions. We have selected the battery residual (internal) and wind speed, temperature, and humidity (external) parameters, the sensor to be aware of. Mamdani Fuzzy Inference System is selected to study the impact, as it is widely used in interpretable decision support applications and it has output membership functions (Kansal and Kaur, 2013). The output membership function represents the impact-level in a scale of 0 to 1 and the estimated impact-level is then mapped into packet error rate (PER) ranging from 0 to 60% (maximum). The transmissions with 60% and above PER are aborted by the gateways.

Using the custom-defined functions, the amount of attenuation caused by the selected environmental parameters on the transmitted signal is estimated, and a four-dimensional plot is generated to demonstrate the impact on a [0, 1] scale. The experiment results on a multivariate dataset demonstrated that the proposed self-aware FIS framework is energy efficient by cancelling 38% of impaired transmissions when compared to normal transmission.

In our prior works on self-awareness and self-redesign (Habib and Marimuthu, 2016, 2017, 2019; Boudriga et al., 2019) the sensing nodes were pre-assumed to possess a built-in self-awareness notion. In this work, we have derived the notion of self-awareness through the developed fuzzy framework, because it is easy to implement as a simple function or as a lookup table within the resource-constrained sensing nodes. By examining a sample meteorological dataset (*Accuweather*, 2022) containing particular weather extremes, such as haze, dust storm, and fog, a set of meteorological parameters is chosen, and the associated custom-defined membership functions are developed. Further, the fuzzy logic aids to generate a more comprehensive subclasses, such as low, medium and high by assigning different grade values of combined membership functions.

The main contribution of the work is of fourfold. First, we have analyzed the meteorological dataset to select the environmental parameters to be aware of while transmitting the data. Second, we have derived a mathematical model, describing the impact of selected parameters on the transmitted signal and presented it as a four-dimensional plot. Third, we have derived custom membership functions to define the real-time behavior of the selected input uncertainties, where a set of functions is used to define the sub-classes of the selected parameter. Fourth, we have quantified the impact in terms of packet error rate and mapped the error into transmission efficiency.

The rest of the paper is organized into six sections. Section 2 details the related work, and Section 3 describes the network model. Section 4 discusses the selection of self-aware parameters and the fuzzy characterization, and Section 5 presents the proposed methodology. Section 6 discusses the outcomes of the experiments and Section 7 concludes the paper.

2. RELATED WORK

Wireless sensor networks (WSN) are deployed in many outdoor applications that are inaccessible due to extreme weather conditions (Luomala and Hakala, 2015) or are deployed at elevated spots (Yu et al., 2020). Such WSNs need to be self-aware in order to transmit the data without error. The term self-aware started appearing more than three decades ago, when researchers were trying to define the self-aware hypothesis from a human perspective (Keromnes et al., 2019). Further, it is categorized as a subjective and objective phenomenon (Duval and Wicklund, 1972) and then, as private and public self-awareness (Chen et al., 2014). Our literature survey revealed that self-awareness was considered as a preliminary requirement in building secure and optimized systems (Gelenbe et al., 2020), fog and mist computing systems (Preden et al., 2015), self-adaptive and trustworthy computing systems (Habib and Marimuthu, 2020), and healthcare IoT (Karmani et al., 2019). In this work, we have derived a self-aware model, which would be aware of the defined uncertainties and their impacts on WSN data transmission.

Our extensive sensor communication research survey revealed that there were few works dealing with the study of environmental uncertainties causing transmission losses at 2.4 GHz (Abuhdima and Saleh, 2010). Many studies focused on path losses around 40 GHz (Srivastava and Vishwakarma, 2014) with only a few focusing on RF transmission losses in at 2.4 GHz. Rama Rao et al. (2012) analyzed the received signal strength at 868, 916, and 2400 MHz in forest, and mango and guava vegetation environments, whereas Mujlid and Kostanic (2016) carried out an empirical study on transmission losses due to dust storms at RF frequencies at 2.4 GHz.

To the best of our knowledge, few works have focused on developing frameworks that combine self-awareness and fuzzy-logic; moreover, many of these frameworks are primarily focused on applications in the healthcare industry. Arguedas et al. (2016) proposed a fuzzy classifier to identify the emotional states of students registered for online learning platform. Liu et al. (2014) developed a fuzzy logic based Parkinson’s disease risk predictor from the player’s real-time behavioral data on a tablet game platform. Bahreini et al. (2019) discussed a software developed using fuzzy logic to provide real-time facial emotions of learners in an e-learning environment. Mehmood et al. (2020) developed a trust-based energy-efficient communication scheme for wireless body area networks, where they utilized a fuzzy logic based ranking system for performance evaluation. In another work on designing energy-efficient data transmissions in WSN, Razzaq and Shin (2019) utilized fuzzy-logic to assign weights to the links to select the cluster-head possessing high resources. In a recent research work, Gotzinger et al. (2022) proposed a fuzzy logic based early warning system for providing self-awareness of health status, whereas, Forooghifar et al. (2018) introduced a self-aware wearable system to improve the seizure detection capabilities. In this work, we applied fuzzy logic to simulate self-awareness within the sensors, where we defined custom membership functions to represent the external and internal entities causing data loss in the data transmission from the gateway in a layered architecture.

3. NETWORK MODEL

We have considered a three-layered architecture as illustrated in Figure 1, where there are C clusters in layer-1; N data sensors (DS) and M ($M << N$) monitoring sensors (MS) are distributed uniformly among the clusters. A set of gateways, collecting raw data and environmental information from layer-1 sensors (DS and MS), is distributed in layer-2, and a central-server managing the gateways is present in layer-3.

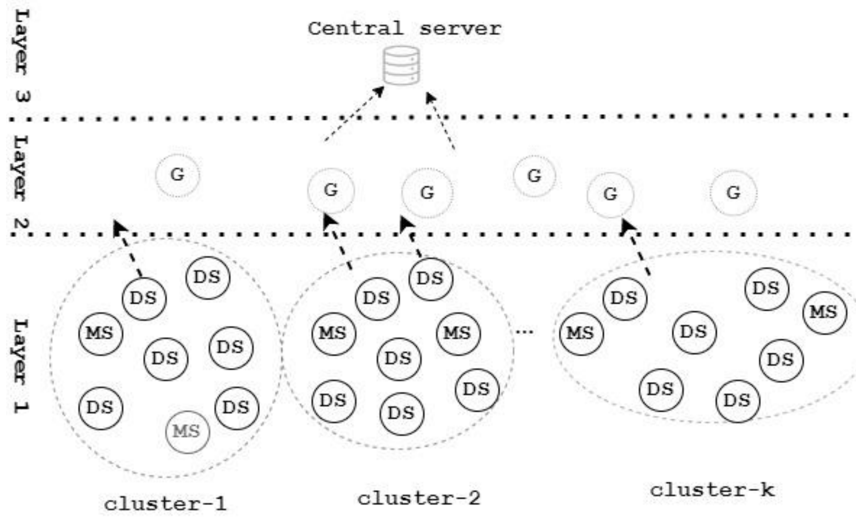


Figure 1. WSN network model.

A data sensor $i,(i \in N)$ in a cluster $j,(j \in C)$ should be self-aware of the surrounding transmission environment by a simple processing of received environmental data $\{e_1, e_2, e_3, ..., e_n\}$ from an adjacent MS within the cluster j. The data sensors are periodically programmed to deliver the acquired data to the gateway. The sensing data is relayed to a nearby gateway in layer-2, where fuzzy intelligence is used to simulate self-awareness of the external environment and the level of resources that are currently accessible before transmission to the central-server.

4 FUZZY CHARACTERIZATION OF SELF_AWARE PARAMETERS

4.1 Effect of weather and residual energy on data transmission

In a WSN operating outside, environmental uncertainties are unavoidable; the signal broadcast by a sensor node is susceptible to attenuation owing to various weather extremes, such as dusty, Haze, fog, and rain. The attenuated transmitted signal causes data errors that require retransmissions and drains the battery. Additionally, a rise in temperature or humidity above the typical working range may undoubtedly result in a non-linear change of rated current, which in turn shortens the battery's life and, as a result, reduces the sensor's performance.

4.2 Selection of self-aware parameters

We selected four self-aware parameters, based on their significant impact on data transmission at 2.4 GHz: temperature, wind speed and humidity, as the three external parameters and battery residual as the internal parameter. Additionally, the selected self-aware parameters help the gateways to some extent identify the cause of transmission failures.

4.2.1. Weather Index

As shown in Equation (1), the weather index (WI) is the result of combining the meteorological parameters temperature, wind speed, and humidity into one term. The range of selected factors, including humidity (0-100%), temperature (0-60°C), and wind speed (0-40 km/h), was obtained after a period of analysis of the meteorological dataset (*Accuweather*, 2022). Figure 2 displays a four-dimensional plot that illustrates the individual and combined effects of the three meteorological conditions on the transmitted signal strength. A color bar with a 0 to 1 scale is used to depict the level of impact. An impact of 0.78 was produced by a very strong wind speed, medium temperature, and low humidity (40, 35, 40), whereas a high on all three parameters produced a maximum equal to $0.99 \approx 1$. We derived the formula in Equation (1) to cap the impact *I(WI)* at 1, where, the subscript *a* stands for the actual data and the subscript *N* for normal range of each parameter.

$$I(WI) = \begin{cases} \frac{H_a}{H_N} + \frac{T_a}{T_N} + \frac{W_a}{W_N} & \text{if one parameter} > Normal \\ \left(\frac{H_a}{H_N} + \frac{T_a}{T_N} + \frac{W_a}{W_N}\right)/2 & \text{if any two} > Normal \\ \left(\left(\frac{H_a}{H_N} + \frac{T_a}{T_N} + \frac{W_a}{W_N}\right)/3\right) & \text{if all} > Normal \end{cases} \quad (1)$$

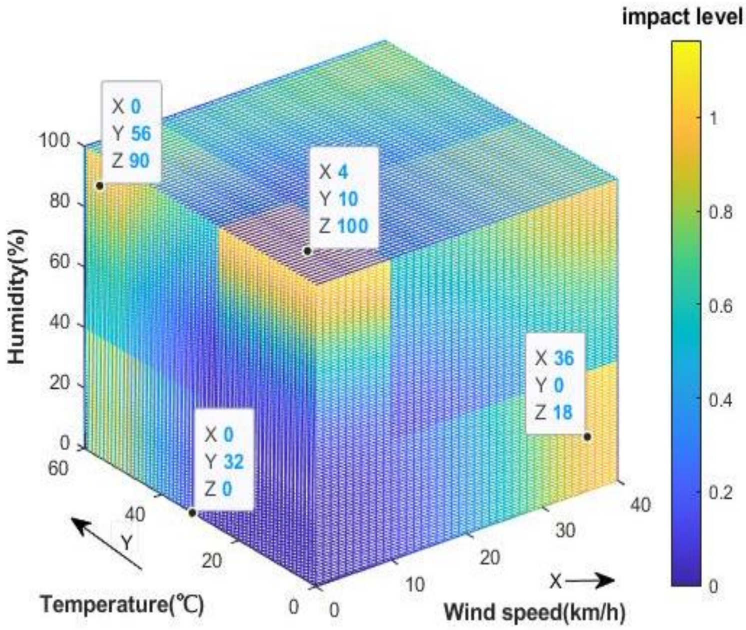


Figure 2. Impact of weather on transmitted sensor signal.

4.2.2. Battery residual

Alkaline batteries with a maximum voltage of 3V are used in the wireless sensor node, and the amount of battery left over depends on how quickly the current is depleted. The sensor functions properly until the remaining voltage is maintained above 1.8 V, according to (Guo et al., 2013; Silva et al., 2012). Uncertain weather circumstances, particularly extremely high temperatures and humidity, could cause the present discharge rate to exceed the rated value $\left(\frac{\partial i}{\partial t}\right)$; moreover, the occasioning of increased retransmissions in bad weather also depleted the battery capacity. Thus, the residual battery capacity at a time t can be formulated as in Equation 2, where the first part represents the increased rated current under high temperatures. The term δ_1 is estimated by dividing the difference in temperature between actual Te_{act} and normal Te_{nor} by *d*. Here, the term d has been set to ten to show that every $10^{\circ}C$ raise in temperature significantly affect the battery discharge. The second part of Equation 2 illustrates how more retransmissions(N_{Rt}) brought on by dusty and foggy weather over the chosen time period t lead to an increased loss of battery energy.

$$BR(t) = \left(BR(t-1) - BR(t-1) * \frac{\partial(i_r + i_{\delta_1})}{\partial t}\right) + \left(BR(t-1) - BR(t-1) * \frac{\partial i}{\partial t} * N_{Rt}\right) \qquad (2)$$

Where, $\delta_1 = \frac{Te_{act} - Te_{nor}}{d}$

4.2.3. Combined Effect of Battery Residual and Weather Index

We have analyzed the impact of temperature variations and combined battery residual on the packet error rate. The battery residual is represented as a function of rated current. The temperature has a linear and negative impact on transmitted signals and it is prominent; however, the high humidity has a marginal impact on signal strength at low temperatures, according to (Luomala and Hakala, 2015). In order to analyze the influence of temperature, we have taken into account temperature variations at 20°C, 30°C, 40°C, and 50°C. Following the research in (Shao, 1999), we created a Gaussian fit of the interpolated dataset to determine how temperature affects packet error rate at different battery levels.

4.3 Fuzzy characterization

We have utilized fuzzy logic to simulate the awareness, as the weather and battery residual need a smooth transition boundary of values to represent them than using a crisp set of values. Moreover, it is also evident from the meteorological records that the weather impact exists significantly after a time lag, which needs to be represented using changeover borders.

In fuzzy set theory, the fuzzy set (S) is defined as in Equation 3, where, X is a set of self-aware parameters, and x is the element of the set.

$$S = \{[x, \mu_s(X)] \mid x \in X\}, \qquad (3)$$

By investigating the meteorological statistics (*Accuweather*, 2022) over a period of time, we formulated the mathematical equations of the selected membership functions and the range of input uncertainties is set as follows: temperature (x_1; 0-50℃), humidity (x_2; 30%-100%), wind speed (x_3; $0 - 40\, ms^{-1}$), and battery residual (x_4; 1 – 3 V). We derived four custom membership functions, as shown in Equations 4 to 7, to define the selected input uncertainties.

$$\mu_s(x_1) = \begin{cases} 0 & x_1 < 28℃ \\ 0.9 * \exp(x_1/50) - 1.5 & 28 \leq x_1 \leq 50℃ \\ 1 & x_1 > 50\, V \end{cases} \tag{4}$$

$$\mu_s(x_2) = \left\{\exp(-\left(\frac{x_2 - 102.3}{39.2}\right)^2)\right\} \qquad 0 \geq x_2 \geq 100 \tag{5}$$

$$\mu_s(x_3) = \begin{cases} 0 & x_3 \leq 10\, km/h \\ \log\left(1 + 0.67 * (x_3 - 10)\right) & 10 < x_3 < 35\, km/h \\ 1 & x_3 \geq 35\, km/h \end{cases} \tag{6}$$

$$\mu_s(x_4) = \begin{cases} 0 & x_4 \leq 1.5\, V \\ -2.208 * x_4 + 4.42 & 1.5 < x_4 < 2\, V \\ 1 & x_4 \geq 2\, V \end{cases} \tag{7}$$

The output membership function is defined to reflect the packet error rate against the input uncertainites. The output membership function is defined using negative exponential distribution as stated in Equation (8), where the term x_i represents the value of weather impact against varying battery residual.

$$\mu_s(O) = \left\{\exp(-\left(\frac{x_i - 0.0448}{0.7701}\right)^2)\right\} \qquad 0 \geq x_i \geq 1 \tag{8}$$

5 PROPOSED METHODOLOGY

The proposed fuzzy logic framework is demonstrated as in Figure 3, where fuzzification block converts the crisp set of self-aware inputs into fuzzy inputs using custom-defined membership functions that are combined according to custom fuzzy rules with multiple conjunctive antecedents (A), and single consequent (B), as in Equation (9).

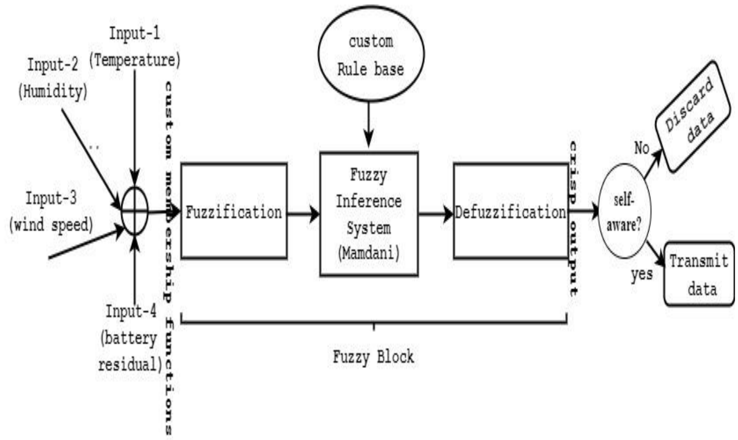


Figure 3. Self-aware framework using fuzzy-logic inference.

In fuzzy logic design, the assignment of appropriate labels, selection of membership functions, and machinery of fuzzy rules are found to be challenging since the membership functions are custom-defined.

$$\begin{aligned} &A = A_1 \cap A_2 \cap \ldots A_L \\ &\textit{if } \mathrm{x}_1 \text{ is in } \mathrm{A}_1 \text{ and } \mathrm{x}_2 \text{ is in } \mathrm{A}_2 \ldots \text{and } \mathrm{x}_\mathrm{L} \text{ is in } \mathrm{A}_\mathrm{L} \text{ then y is in B} \\ &\mu_A(x) = \min(\mu_{A_1}(x), \mu_{A_2}(x), ,\ldots, \mu_{A_3}(x)) \end{aligned} \tag{9}$$

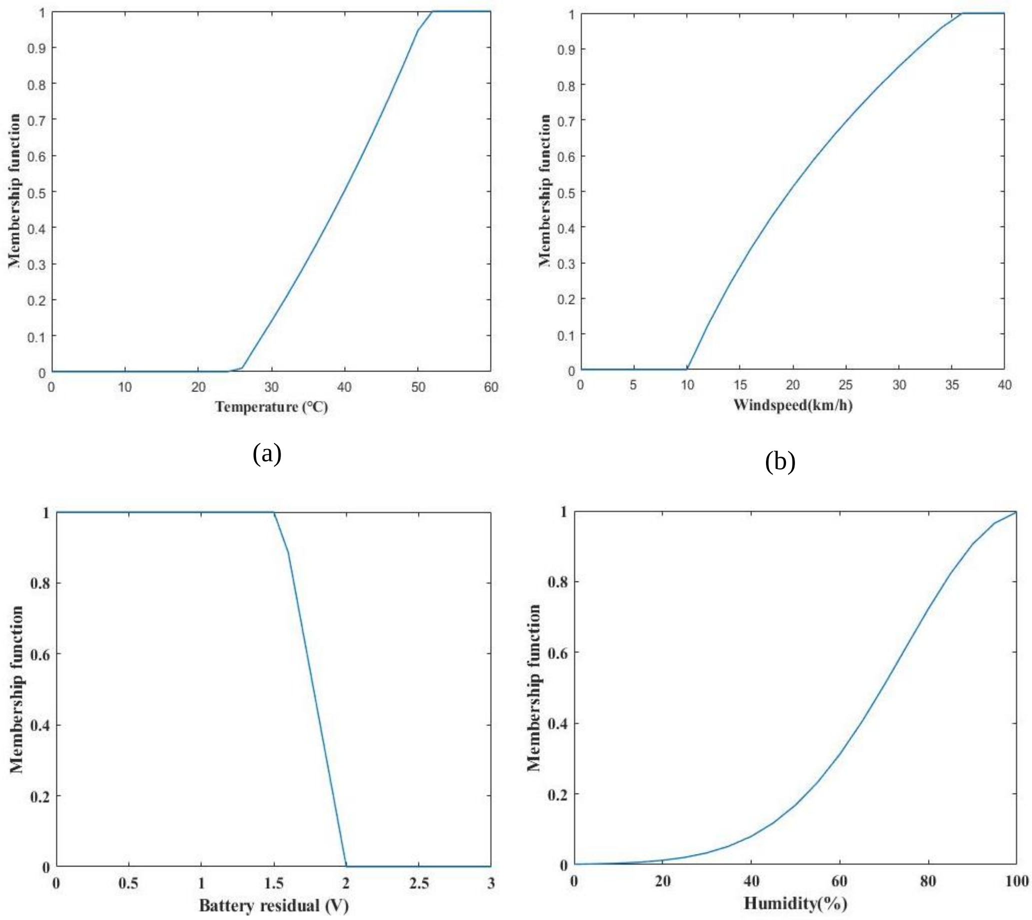
6 RESULTS AND DISCUSSIONS

A three-layered WSN network with five clusters in Layer 1 and 10 data sensors (DS) and 4 monitoring sensors (=50% of DS per cluster) per cluster has been taken into consideration. Five gateways (G) (10% of the total DS) in layer 2 were responsible for initiating the proper data transmission to the central-server. The sensors start with full battery power (3 V), and it is anticipated that normal transmission will use 0.2% of the residual energy. Additionally, it is anticipated that each retransmission due to bad weather will use 0.1% extra battery power. Based on our investigation, we defined normal operating circumstances as temperatures between 0 and 27℃, wind speeds between 0 and 10 km/h, humidity up to 70%, and battery residuals between 2.1 and 3V. Under typical operating circumstances, the packet error rate is thought to be zero and the received signal strength is at its highest level during a pre-scheduled regular transmission. In contrast to the IEEE 802.15.4 standard, which uses a signal with 0% error vector magnitude (EVM) to test ZigBee receiver sensitivity, the signal's actual EVM could be up to 35% (Farahani, 2008). Data loss resulted from an increase in packet errors caused by the worsening weather and declining battery residual. We made the assumption that a 10% increase (35%+10%) in EVM might result in data errors that could be fixed with a few retransmissions, however a 20% to 25% increase from 35% (around 60%) might cause data loss. Thus, data that has a packet error loss of 60% or more should thus be ignored.

Figure 4 illustrates the custom-defined input uncertainties, where we combined exponential and

Gaussian functions to produce the real-time behavior. As shown in Figure 5, the weather index shows the impact on the output signal against all possible combinations of environmental uncertainties. This function describes the link between battery residual and weather index. The output membership calculations were produced as follows: If the battery value was either high or low, the weather index's impact logically "ANDed" with that number. If it was medium, Equation (10) showed how the impact logically "ORed" with the weather index to forecast the packet error rate against the sent data.

$$
\begin{aligned}
\mu_O(y) &= \mu_{wi}(x) \cap \mu_b(x) \qquad if\ B = H \\
\mu_O(y) &= \mu_{wi}(x) \cap \mu_b(x) \qquad if\ B = L \\
\mu_O(y) &= \min(1, \mu_{wi}(x) \cup \mu_b(x)) \quad if\ B = M
\end{aligned}
\tag{10}
$$



(a) (b) (c) (d)

Figure 4 (a-d). Input membership functions.

6.1. Validation of Proposed Fuzzy Inference System

The Mamdani fuzzy inference system is used to determine how specific uncertainties may affect the sensor's results. For the purpose of validating the created framework, a multivariate dataset made up of environmental characteristics and battery level is established. The battery residual is created at random to include all three ranges, and the environmental parameter values are taken from the meteorological dataset to include all three ranges (low, medium, and high). Table 1 provides a sample calculation of Equation (10)'s criteria to determine the output membership degrees (impact) for a particular input data set (temperature, humidity, wind speed, and battery residual).

Table 1. Calculation of output membership degrees against the input data set.

Input parameter	Input data	μ_L	μ_M	μ_H	Output
Temperature	55	0	0.0	0.98	Max(μ_L , μ_M , μ_H) =1 (No transmission)
Humidity	40	0.08	0.0	0.0	
Wind speed	36	0	0.0	1	
Battery residual	2.6	0.1	0.0	0.0	

The relationship in (Guo et al., 2013) is redrawn and the interpolated values are used to derive the packet error rate in respect to the weather index and the battery residual. The PER is defined to range from 0 to 60%, with the least value signifying clear skies and a fully charged battery, and the maximum value signifying considerable weather uncertainty with nominal or low operational voltage.

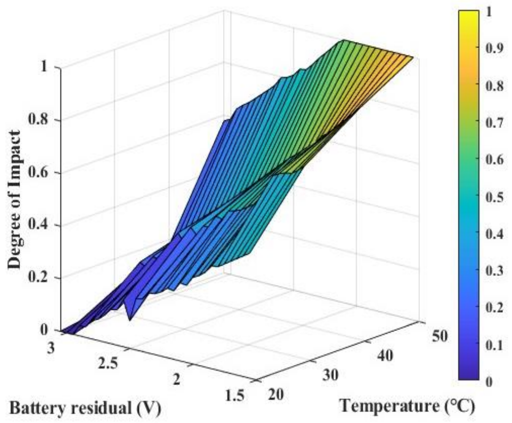


Figure 5. Combined impact on signal.

In the developed FIS, the obtained multivariate dataset is used to estimate the transmission efficiency using the relationship (100 - PER) and to assess self-awareness in terms of estimated PER. A battery residual of 2.5 V, a wind speed of 36 km/h, a temperature of 55 °C, and a humidity of 42% produced an impact value of 0.8896, which, when communicated, results in a

58% packet error rate, which is represented by the first data point in Figure 6 (a-f). As shown in Figure 7, the self-aware transmission at the gateway was initiated when the transmission efficiency values were more than 60%. When compared to the typical transmission, 18 out of the 29 observations were successful transmissions, while the other eleven were not. Thus, the energy is saved by 38% by non-executing the less efficient transmission against normal transmission, as shown in Figure 7.

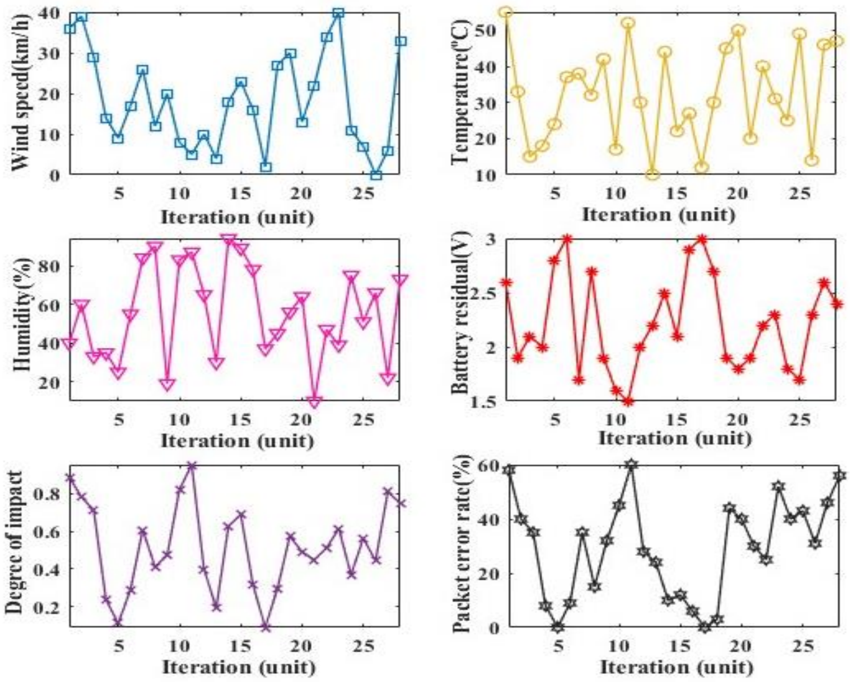


Figure 6(a-f). Packet error rate calculation.

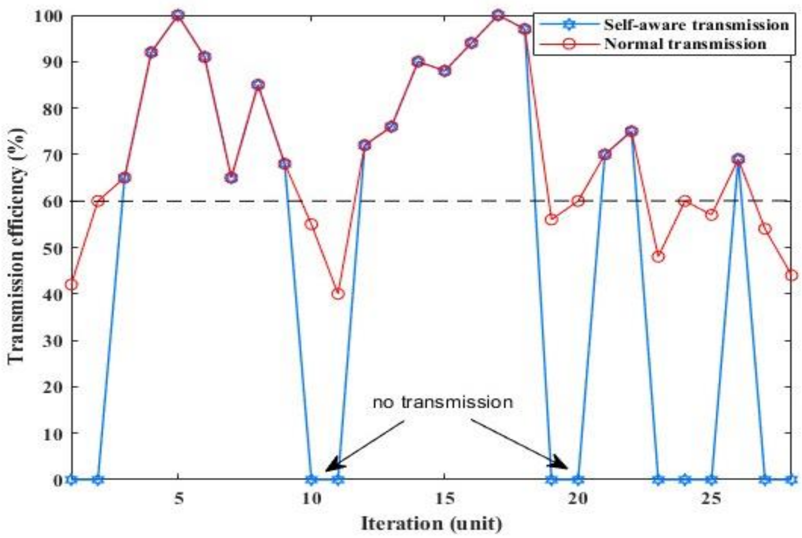


Figure 7. Comparing self-aware (fuzzy) transmission with normal transmission.

7. Conclusion

We developed a fuzzy framework to simulate self-awareness at the gateway within WSN, where estimation of the packet error rate is used as a control parameter to determine whether to send data to the central server. The decision is based on knowledge of how certain uncertainties could impact outdoor sensor transmission. The sensors in the lowest layer relayed the raw data to the gateways in the middle layer of our layered WSN, and the data transfer from the self-aware gateways to the central-server in the top layer is carried out under favorable circumstances. With custom-defined input and output membership functions, the framework employed the Mamdani fuzzy inference system (FIS) to assess the input parameters and to generate the impact values as an output membership function. The framework is validated with a multivariate dataset and in comparison to a standard transmission system, 38% more energy is saved by avoiding unworthy transmissions.

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