Adaptive multi-radio quality of service model using neural network approach for robust wireless sensor network transmission in multipath fading environment

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ABSTRACT

Wireless sensor network loss in wireless data transmission is one of the problems that needs attention. Interference, fading, congestion, and delay are some factors that cause loss in wireless data transmission. This paper used an adaptive multi-radio model to enhance the wireless data transmission to be more robust to disturbance in a multipath fading environment. A neural network approach was used to generate the adaptive model. If we use 433 MHz as our carrier frequency with 250 kHz bandwidth and 12 spreading factors, we can get signal noise ratio (SNR) for 20 meters at about -9.8 dB. Thus, we can use the adaptive model to enhance the WSN wireless data transmission's SNR to 9 dB, automatically changing the radio configuration to 797.1 MHz frequency, with 378.1 bandwidth and 7.111 for spreading factor. Based on the result, the wireless data transmission link has been successfully enhanced using the proposed adaptive model for wireless sensor networks (WSN) in a multipath fading environment.

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1. INTRODUCTION

International Telecommunication Union–Telecommunication Standardization Sector (ITU-T) designated wireless sensor networks (WSN) as the next generation in 2010 [1]. This network can support the internet of things since it observes its surroundings and transmits the data it collects to the server [2]. This data then will undergo extra processing to yield more information that the user will find helpful. Wireless communication between each WSN node is used to transmit the observation data. The observation data will then be transferred from node to node utilizing the ad-hoc network concept, starting at the farthest node and ending at the nearest node (with the server) [3]. One of the fundamental ideas of WSN is that this network was less expensive [4] compared to constructing fixed telecommunications infrastructure, such as towers, and any other structures like mobile cellular communication networks. WSN has many benefits, but it also has many problems with data transmission, like interference [5], delay [6], packet loss [7], and others [8].

The main problem in WSN's forest environment was that its wireless communication for data transmission suffered from additional loss caused by the forest's unique environment. This additional loss is caused by the forest's unique environment, which creates multipath fading that causes the signal to vary when it is finally received by the receiver [9]. This phenomenon decreases the signal quality, making wireless data transmission harder in the forest environment.

This problem in WSN has been attention by many researchers in the last decade. To enhance the quality of service in wireless data transmission in Wireless Sensor Networks, several researchers have added new methods such as adaptive transmission [10], routing [11], [12], mobile data collectors [13], [14], clustering [15] and others [16], [17]. Adaptive transmission is one of the most promising methods for making wireless data transmission robust. Adaptive transmission WSN means that the transmission will be using a resource-limited WSN node, with a selection of optimum configuration so it can enhance quality of service (QoS) with limited resources [18], [19]. The novelty of this research work lies in the new models of the SOWSN that are built based on our measurement data in a forest environment that simulates a real-world wireless sensor network application. This computationally intelligent SOWSN was developed using measurement data in a forest environment to create an adaptive and dynamic multi-radio model to enhance QoS and make wireless transmission robust in a multipath fading environment.

2. METHOD AND EQUIPMENT

2.1. Field measurement equipment

Long range (LoRa) radio transceivers were used for measurements in both transmitter and receiver pairs. The LoRa radio was configured using a microcontroller by changing its parameters manually. The LoRa radio configuration is presented in Table 1.

A microcontroller was installed to control data transmission and preprocessing for the transmitter and the receiver. The microcontroller on the transmitter side was configured to command the LoRa transceiver to broadcast packet data every 100 microseconds. The microcontroller on the receiving end was configured to command the LoRa transceiver to receive incoming packet data, extract the received signal strength indicator (RSSI) value, and send it straight to our recording device. Measurement was done every five meters from 5 to 100 meters. The pair of LoRa transceivers were placed on top of the ground with an antenna height of less than 30 cm. The measurement equipment block diagram can be seen in Figure 1.

Table 1. LoRa configuration

Parameter	Value
Frequency	433, 868, 920 MHz
Bandwidth	125, 250, 500 kHz
Spreading factor	7-12
Tx-power	20 dBm
Measurement parameter	Signal noise ratio (SNR)

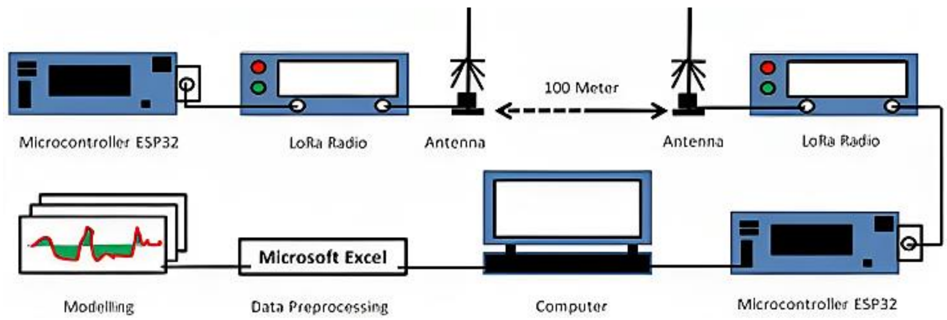


Figure 1. Measurement equipment

2.2. Forest measurement environment

Because of its unique qualities, a rainforest location was selected for the real-time measurement. The forest covers a vast land region with an overgrown flora mass. In between the bigger plants and the trees in this jungle are a variety of flora. There are moments when it is impossible or challenging for people to move in or around a forest due to the highly dense undergrowth. This rainforest location was ideal for measuring the multipath fading channel's effect. This is because large, tall, and small, dense trees will obstruct the radio broadcast. Figure 2 shows the location of the measurement site in the jungle. During the measuring procedure, 72 LoRa radio configurations were employed in this woodland setting. The transmitter and receiver are 15 cm (close to the ground). The GPS coordinates of the forest were -6.358641 and 106.903730 (East Suburban Jakarta).

Figure 2. Measurement environment at jungle site

2.3. Forest measurement environment

Figure 3 shows an example of measuring RSSI in a forest setting using LoRa 433, 868, 920 MHz frequency, 125, 250, 500 kHz bandwidth, and 7, 8, 9, 10, 11, 12 spreading factors. Ten measurements will be taken for each measurement point. Figure 3 illustrates the erratic SNR. The SNR ranged from 5 to 8 dB at its lowest and highest points. Numerous researchers have noted that multipath fading, which occurs in jungle environments where signals are reflected multiple times before reaching a receiver, is the cause of this up-and-down pattern [20]. Others, however, noted that the extremely low height between the transmitter and receiver above the ground was the cause of the Fresnel zone [21]. Using 10 times in SNR measurement data, we average and present its data in Figure 4.

2.4. Neural network method

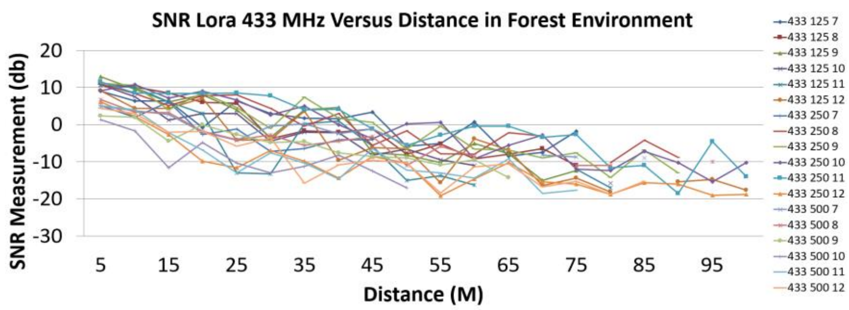
An artificial neural network is a computational intelligence that simulates the behavior of a biological neural network seen in living things. Numerous problems, including control [22], detection [23], [24], and more [25], have been resolved using artificial neural network (ANN) techniques. The technique works by computing and analyzing training data that has already been approved [26]. Artificial neurons, or ANNs, are nodes that simulate the neurons found in the biological brain. Synapses allow each neuron to communicate with other neurons as they do in the brain. Using a synapse attached to it, the receiver neuron processes the signal after receiving it to signal the subsequent neurons. Neurons in ANN act as processing function components. Bias and weights control these neurons that are linked to other neurons. After calculating the signals, an activation function is applied to yield an output [27]. A straightforward equation can be used to represent one layer of an ANN neuron as in (1):

$$a_i = \mathrm{f}_i(IW_i \mathrm{p} + b_i)) \quad (1)$$

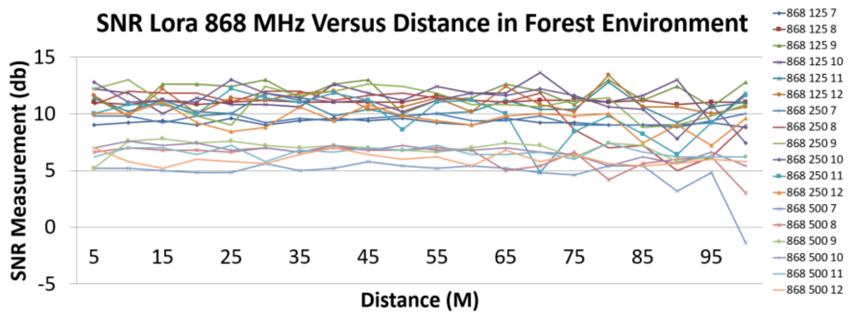
where IW_i= scalar weight, p = scalar input, b_i= scalar bias, and f_i= transfer function

```
10 Meter Measurement
11:31:45.018 -> Received packet hello 0  with SnR 7
11:31:45.391 -> Received packet hello 1  with SnR 7
11:31:45.763 -> Received packet hello 2  with SnR 7
11:31:46.137 -> Received packet hello 3  with SnR 8
11:31:46.506 -> Received packet hello 4  with SnR 8
11:31:46.878 -> Received packet hello 5  with SnR 8
11:31:47.254 -> Received packet hello 6  with SnR 7
11:31:58.831 -> Received packet hello 0  with SnR 7
11:31:59.201 -> Received packet hello 1  with SnR 7
11:31:59.584 -> Received packet hello 2  with SnR 5
11:31:59.956 -> Received packet hello 3  with SnR 5
11:32:00.333 -> Received packet hello 4  with SnR 7
11:32:00.705 -> Received packet hello 5  with SnR 7
11:32:01.077 -> Received packet hello 6  with SnR 7
11:32:01.446 -> Received packet hello 7  with SnR 7
11:32:01.817 -> Received packet hello 8  with SnR 7
11:32:02.223 -> Received packet hello 9  with SnR 7
11:32:02.593 -> Received packet hello 10   with SnR 7
11:32:02.969 -> Received packet hello 11   with SnR 7
11:32:03.340 -> Received packet hello 12   with SnR 8
11:32:03.712 -> Received packet hello 13   with SnR 7
11:32:04.084 -> Received packet hello 14   with SnR 6
11:32:04.456 -> Received packet hello 15   with SnR 6
11:32:04.829 -> Received packet hello 16   with SnR 6
11:32:05.200 -> Received packet hello 17   with SnR 7
11:32:05.572 -> Received packet hello 18   with SnR 6
11:32:05.943 -> Received packet hello 19   with SnR 7
11:32:06.350 -> Received packet hello 20   with SnR 7
```

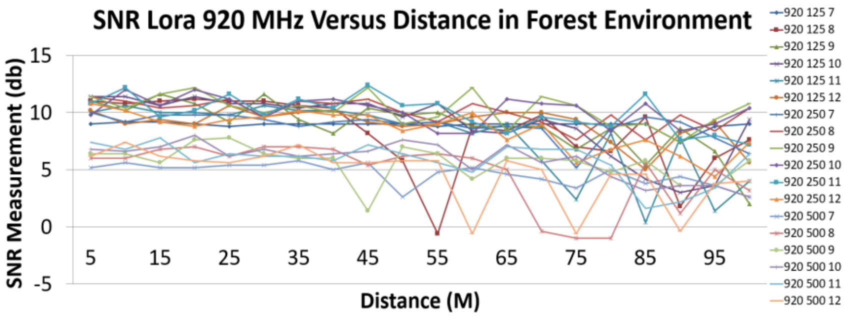
Figure 3. SNR measurement at forest environment in 10 meters



(a)



(b)



(c)

Figure 4. SNR average field measurement data in the forest environment: (a) 433 MHz, (b) 868 MHz, and (c) 920 MHz frequency

3. RESULT AND DISCUSSION

3.1. Adaptive multi radio QoS model

This section will present the model and its evaluation of the SOWSN adaptive multi-radio QoS model. We can write a mathematical model using (1) such as:

$$C_i = tansig(\sum_{i=1}^{ni}(IW_{i,n}p_i + b_i)) \quad (2)$$

Therefore, for the output layer we can write:

$$C_i = purelin\ (IW_{i,n} \sum_{i=1}^{ni}(tansig(\sum_{i=1}^{ni}(IW_{i,n}p_i + b_i))) + b_i)) \quad (3)$$

where: IW_i= scalar weight, p = scalar input such as SNR and distance, b_i= scalar bias, and f_i= scalar output such as frequency, bandwidth, and spreading factor.

In Figure 5 the architecture of the adaptive multi radio QoS model is presented. The SOWSN adaptive multi-radio QoS model was developed using 1,080 rows of data training from our measurement using LoRa radio in a forest environment. The input has two variables: SNR and distance. The output has three variables: frequency, bandwidth, and spreading factor. To achieve good performance, the model was trained using 1000 hidden layers. As we can see in (2), the hidden layer is calculated using the summation of activation functions such as Tansig. In (3), the three output neurons will be calculated using the summation of Purelin activation functions to provide the best output [28]. Using that 1000 hidden layer, the neural network adaptive architecture model performance has yielded a mean squared error (MSE) value of 2.85×10^{3}.

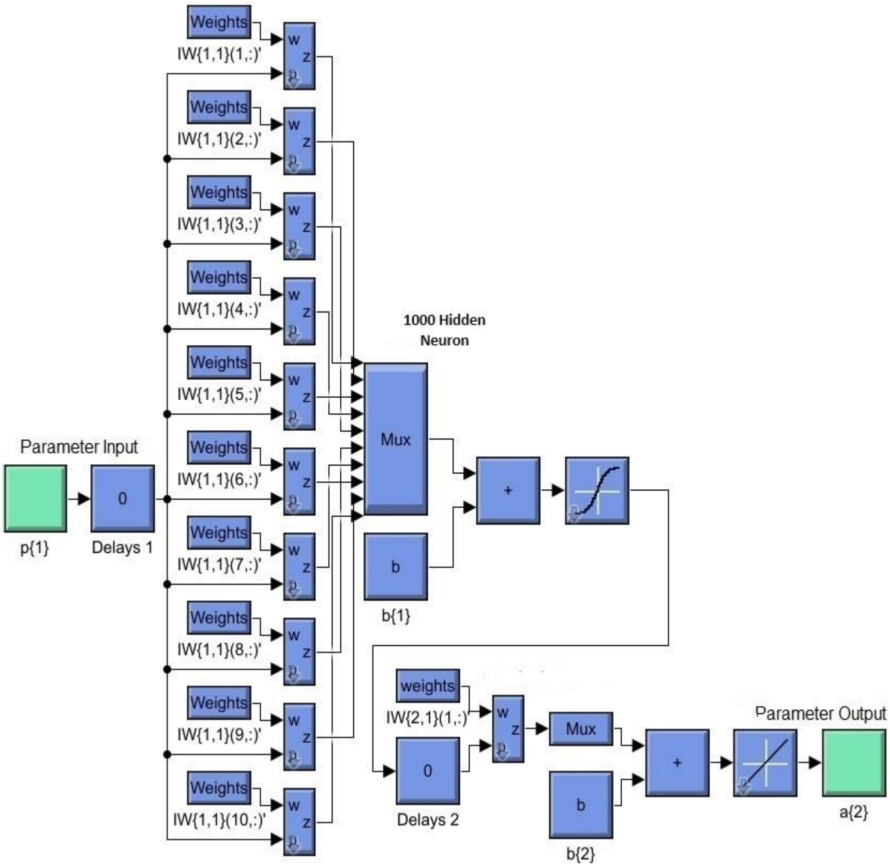


Figure 5. SOWSN adaptive multi radio QoS model

3.2. Model evaluation

This section will present the evaluation of the SOWSN adaptive multi radio QoS model. To make easier comparison, we present before and after the use of neural network method to change the static WSN node to become SOWSN adaptive node. The evaluation before and after the simulation is presented in Table 2.

Table 2 shows us the performance of the proposed model to enhance wireless data transmission for WSN in a multipath fading environment, which is the simulated results versus measurement in Figure 4. In this simulation, 5 test points are selected with distances of 20, 40, 60, 80, and 100 meters. Based on measurement, if we are using 433 MHz as our carrier frequency with 250 kHz bandwidth and 12 spreading factor, we can get SNR for 20 meters at about -9.8 dB, for 40 meters at about -14.4 dB, at 60 meters at about -14.6 dB, and at 80 to 100 meters at about -18.8 dB. This bad SNR was a big problem because if we use the fastest spreading factor of 6 for data transmission, according to the datasheet [29], the minimum SNR result should be -5 dB. However, because of multipath fading and other wireless problems, this configuration has created a poorer SNR value, less than -5 dB. Thus, using an adaptive model, we can enhance the SNR of WSN wireless data transmission to 9 dB. This model for 20 meters changes the radio configuration automatically to become 797.1 MHz frequency, with 378.1 bandwidth and 7.111 spreading factor. This simulation shows that we have successfully enhanced the wireless data transmission for WSN in the multipath fading environment using the proposed adaptive model.

This adaptive model measures the SNR of the transmission link that will be loaded with data at a specific distance. If the SNR is low, this model sets for the first high SNR, which is six, by changing the frequency, bandwidth, and spreading factor on both sides. This scheme will be repeated until the highest SNR value is achieved. After achieving the highest SNR for those transmission links, the transmission will be started. This increased SNR value for data transmission will enhance one QoS parameter, such as reducing packet loss. This can be achieved because this adaptive configuration can reduce interference by changing its frequency carrier and noise or fading by changing the spreading factor and bandwidth. This adaptive configuration is a game changer, compared with a fixed configuration that cannot change its frequency carrier when interference happens or cannot change its spreading factor when noise or fading happens. Although this model has proven to be helpful in enhancing QoS in WSN with a permanent location, this concept also has the potential to be researched to enhance QoS in mobile ad-hoc network (MANET).

Table 2. LoRa configuration before and after

No	Data input	Before (Measurement) Without using an adaptive model				After (Simulation) Using adaptive model			
	Distance (m)	SNR (dB)	Frequency (MHz)	Bandwidth (kHz)	Spreading Factor	SNR (dB)	Frequency (MHz)	Bandwidth (kHz)	Spreading Factor
1	20	-9.8	433	250	12	6	972	444.2	3.811
2	40	-14.4	433	250	12	6	876.4	558.3	15.06
3	60	-14.6	433	250	12	6	972.9	536.9	9.464
4	80	-18.8	433	250	12	6	999.7	251.9	12.19
5	100	-18.8	433	250	12	6	527.1	523.2	9.217
6	20	-9.8	433	250	12	9	797.1	378.1	7.111
7	40	-14.4	433	250	12	9	965.5	99.68	1.043
8	60	-14.6	433	250	12	9	891.1	166.9	7.806
9	80	-18.8	433	250	12	9	899.1	348.9	8.645
10	100	-18.8	433	250	12	9	833.6	54.79	9.567

4. CONCLUSION

In this paper, we would like to present the SOWSN adaptive multi radio QoS model for WSN transmission. This model was used to enhance the quality of service in wireless data transmission for WSN applications. This model takes account of multipath fading phenomena by using data measurement in a forest environment. The data measurement was taken from a forest environment where big trees and vegetation cause multipath fading phenomena. Using the proposed model, the LoRa radio configuration has successfully become adaptive as we designed it in the first place. If we use 433 MHz as our carrier frequency with 250 kHz bandwidth and 12 spreading factor, we can get SNR for 20 meters at about -9.8 dB. Thus, using the adaptive model, we can enhance the WSN wireless data transmission's SNR to 9 dB, which automatically changes the radio configuration to 797.1 MHz frequency, with 378.1 bandwidth and 7.111 for Spreading Factor. The significance of this finding is that it can cause the WSN to have a longer lifetime. This happens because the wireless link has a higher SNR, which causes reliable communication. In the end, this reliable communication caused the data to need 1-time transmission only, compared with unreliable transmission link that needs retransmission data every time data is lost. Hence, there is less power consumption and a longer lifetime for the WSN node. Although this model can impact to longer lifetime for WSN node, more research is needed to understand the model in different terrain such as rocky areas or cities.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Galang Persada Nurani Hakim	✓	✓	✓	✓	✓	✓		✓	✓	✓				
Dian Widi Astuti						✓				✓		✓	✓	
Ahmad Firdausi						✓			✓					
Huda A. Majid					✓				✓	✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The Authors state for data availability that supports the findings of this study are available on request from the corresponding author.

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