Predicting Types of Failures in Wireless Sensor Networks Using an Adaptive Neuro-Fuzzy Inference System

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Abstract—In this paper, Adaptive Neuro-Fuzzy Interference System (ANFIS) technique is used to develop models to predict two conditions commonly found in a Wireless Sensor Network's deployment; these conditions are failure due to (i) poorly deployed environment and (ii) human movements. ANFIS models are trained using parameters obtained from actual ZigBee PRO nodes' Neighbour Table experimented under the influence of associated network challenges. These parameters are Mean RSSI, Standard Deviation RSSI, Average Coefficient of Variation RSSI and Neighbour Table Connectivity. The individual and combined effects of parameters are investigated in-depth. Results showed the mean RSSI is a critical parameter and the combination of mean RSSI, ACV RSSI and NTC produced the best prediction results (~92%) for all ANFIS models.

Keywords-ANFIS; Wireless Sensor Network; ZigBee PRO; human movements; poor deployment

I. INTRODUCTION

Wireless Sensor Network's (WSN) network reliability is greatly influenced by the network challenges found in a deployed environment [1, 2]. Particularly in home and building automation applications, poor deployment of nodes (i.e. dense physical obstructions, long distance communication) or any physical change in the environment (i.e. introduction of human movements) are known to degrade the multipath and fading effects [3, 4, 5, 6] between communicating nodes. These phenomenons potentially cause undesired link failures and frequent route changes, leading to higher energy consumption and even early death of battery-powered devices [8]. It is therefore of great interest to study how WSN nodes operate under the influence of these physical network challenges, specifically, poor deployed environment and human movements.

WSN optimisation protocol is often implemented to improve a WSN's network reliability [18]. For instance, a typical routing protocol improves network reliability by selecting links or routes of the highest quality for data delivery [9, 10, 11]. However, the performance of a WSN can be attributed by different associated challenges. Common generalisation of a link performance as good, intermediate or bad does not provide sufficient information for WSN optimisation protocol to execute optimally [12, 25]. For instance, increasing transmit power may improve the delivery reliability of long distance communicating nodes [31]. However, this may not be true for nodes suffering from channel access failure under persistent Wi-Fi interference [13]. In order for WSN optimisation protocol to function optimally, it is highly desirable that the causes of link failures are accurately identified. Failure to identify the cause of link failure may adversely affect the network's performance [1, 12].

Classical logic reasoning is a widely used method to estimate link quality [25]. However, link quality estimation is known to be imprecise due to the complexity of a deployed environment [14, 15, 16, 17]. For example, a link is identified as good only if its Packet Reception Rate (PRR) is greater than a given threshold of 0.95. However, relatively speaking, a link with PRR of 0.94 may not be inferior either. The ambiguity in the evaluation of link quality using classical reasoning can be attributed to the algorithm's ineffectiveness to incorporate and intelligently deal with human knowledge [25]. Hence, the proposed research aims to fill this void using ANFIS.

ANFIS functionally combines the approximate reasoning of fuzzy set theory with the learning and adaptability features of Artificial Neural Networks (ANN). Known for its capability to deal with non-linear and complex control problems, ANFIS is used in this work to break down the uncertainties of WSN into comprehensible knowledge.

The objectives of this paper are twofold. Firstly, the paper aims to develop intelligent models using Adaptive Neuro-Fuzzy System (ANFIS) that accurately predicts if a link failure is due to (i) poor deployed environment or (ii) human movement. Secondly, the paper aims to investigate the individual and combined effects of parameters found in ZigBee PRO node's Neighbour Table (NT) under the influence of associated network challenges.

The contributions of this paper are threefold. First, the ANFIS models are trained and evaluated using parameters obtained from actual nodes in real-world environment rather than from simulations. This is important as research in this area are largely simulation based and may not be extendable to real deployments. These parameters serve as ANFIS models' training inputs leading to realistic and relevant insights. Second, ANFIS model's training inputs are obtained from the different operating layers where the complexity of different network challenges can be understood. Third, ANFIS models are trained using different combinations of parameters. This approach allows comparisons of performance of different parameters and provides meaningful insights to nodes' behaviour.

The remainder of this paper is organised as follows: Section II provides an overview of relevant work in this area including the present practical limitations in WSN deployments. Section III describes the experimental setups, while Section IV introduces the parameters used to train the ANFIS models. Section V explains the basis of ANFIS architecture and also proposes three ANFIS models to be developed. The results of individual ANFIS models are then discussed and summarised in Section VI. Section VII concludes the paper with key points.

II. RELEVANT WORK TO DATE

WSN link failures can be attributed to many causes such as inconsistent radio propagation, hardware dissimilarities, and external interferences. These undesirable operating conditions can lead to unpredictable behaviours [19]. From protocol design standpoint, a node's behaviour may be trivial. However as network size scales up and the deployed environment gets more complex, anticipating the operating behaviour of nodes become increasingly complex and a generic model becomes impractical.

In [19], the authors questioned, "What are the observable causes of packet success and failure in modern platforms, and how can a node detect them?" Knowing the answer to this question would have a significant implication for WSN, possibly leading to accurate link quality estimation and efficient WSN optimisation protocols. To do so, experimentation of node behaviours is necessary. This should be followed by in-depth analysis where underlying patterns are uncovered.

The performance of QoS parameters from physical and application layer of IEEE 802.15.4 nodes are analysed under the influence of WLAN interference in [13]. In addition, a new cross-layer parameter, Packet Reception Rate with Clear Channel Assessment (PRRCCA) is proposed to distinguish persistent WLAN traffic robustly.

The behaviour of the Reception Signal Strength Indicator (RSSI) under the influence of human movements, different antenna orientation, elevation and ground effect are studied in [21]. It is observed that even without human movements, RSSI measurements are inconsistent at different node's orientation and position. Similarly, [20] confirmed the impact of human's physical obstructions on 2.4 GHz wireless signals and showed that RSSI is dependent on the number of people as well as their movement speed. Based on these unique RSSI properties, impacts of human activities on communicating nodes are modeled.

In [22, 23, 30], the impact of building layout and composition of elements on nodes are measured from signal attenuation and communication success rate. Poor deployment of nodes can be predicted from measures of quality of services, capacity, and overall energy consumption. In [24], signal deviation and path loss are found to vary with locations (i.e. different measurements are obtained at different locations). Basic geometry structures such as corridors and walls have inconsistent impact on signal propagation. This shows that there is no basis for a general model especially for complex and vastly different networks. Site-specific solutions are often necessary.

Studies have showed that many existing link quality estimation techniques have limitations under dynamic communication constraints and only few algorithms or protocols have grown out of simulated environment [26]. Successful computation intelligence applications are usually limited to single problem like routing or optimal deployment. In reality, high human intervention is often necessary to overcome incompatibility. This highlights the importance of flexible learning platforms.

In [31], ANFIS is used to estimate the RSSI values on body sensors. The complex nature of on-body channels are measured based on parameters from different layers such as transmission power and body positions of application layer, and RSSI of physical layer. WLAN indoor localisation based on ANFIS is introduced in [27] to reduce false RSSI-distance mapping caused by the unpredictable interference, reflection and multipath effects. With appropriate ANFIS configuration and training inputs, an accurate mapping is obtained.

ANFIS also demonstrated its suitability for video quality prediction over error-prone network, and produced good model prediction accuracy even with unseen data set [28]. Investigation on impact of QoS parameters in both application and physical layers highlights the importance and feasibility of using parameters from different layers to improve model prediction. In [29], a neuro-fuzzy technique is proposed to perform dynamic clustering of WSN nodes and has shown computational fault tolerance capability towards the dynamic and unpredictable behaviour of network parameters and application requirement.

III. EXPERIMENTAL SETUPS

In this section, experiments simulating the network challenges of interests (i) poor deployed environment and (ii) human movement are prescriptively described. All experiments are conducted during non-working hours (i.e. weekdays after 9 pm and weekends) in a static environment with no external interference.

A. *Poor Deployed Environment*

The design of this experiment is to simulate nodes communicating under the influence of reception signal decay, mirroring long distance communication and dense environment.

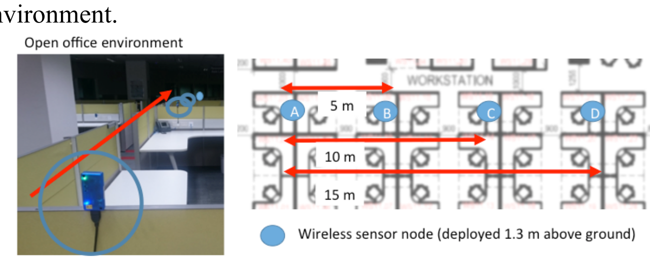


Figure 1. Experiment layout - Poor deployed environment in an open office

Figure 1 illustrates four ZigBee PRO [8] nodes uniformly deployed 5 m apart from one another in an open office (i.e. nodes were placed at 5 m, 10 m, 15 m, and 20 m). For consistency, all nodes are mounted at the same level on desk partitions, 1.3 m above ground, and arranged in the same orientation. Reception signal decay with increasing distance between nodes is expected, but a uniform RSSI decay between nodes may not be possible due to the differences in physical environment (i.e. desks) altering the multipath and fading effects. These differences shall provide a more realistic set of training inputs for ANFIS models as compared to data obtained from computer simulations.

B. Human Movement

The design of this experiment is to simulate nodes communicating under the influence of human movement. All measurements are conducted with the presence of the experimenter only, minimising any possible interference.

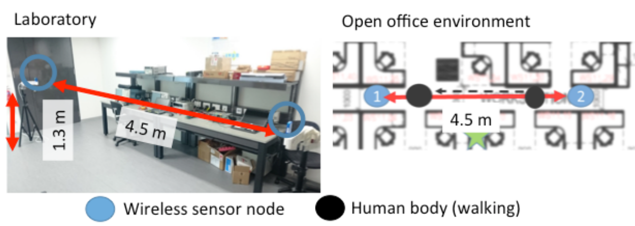


Figure 2. Experiment layout – Human movement in a laboratory and open office

Figure 2 illustrates two ZigBee PRO nodes with line of sight (LOS) communication deployed 4.5 m apart from each other, 1.3 m above floor level. Prescribed human walking sequences with LOS obstruction are then introduced. Experiments are repeated in laboratory and open office where different multipath and fading effects are accounted, providing more realistic training inputs for ANFIS models.

IV. PARAMETERS

In this work, the intention is to exploit information from ZigBee PRO nodes' Neighbour Table (NT) [3]. A node's NT contains connectivity information about its immediate neighbours, including relative RSSI. If node A is not present in node B's NT, node A had simply not connected to node B.

For each experiment, ZigBee PRO nodes are configured to report information of their NT every 4 – 6 seconds (depending on the network size). These information are subsequently post-processed into the following parameters.

A. Neighbour Table Connectivity (NTC)

NTC as explained in Table I is similar to Packet Reception Rate. NTC_{AB} in percentage, is the probability node B being captured in node A's NT over a span of 60 seconds. NTC_{AB} indicates the communication success rate from node B to node A.

B. Mean RSSI (MRSSI)

$MRSSI_{AB}$ as explained in Table I, is the averaged RSSI in dBm measured at node A from node B in the span of 60 seconds. $MRSSI_{AB}$ indicates how well node B is communicating to node A in terms of reception signal over time.

TABLE I. CALCULATION OF NTC, MEAN RSSI, SD RSSI AND ACV RSSI FROM FOUR CONSECTIVE NEIGHBOUR TABLES (AN EXAMPLE)

NT A (t = x)		NT A (t = x + 5)		NT A (t = x + 10)		NT A (t = x + 15)	
Entry	RSSI (dBm)	Entry	RSSI (dBm)	Entry	RSSI (dBm)	Entry	RSSI (dBm)
B	-88	-	-	B	-87	-	-
C	-62	C	-62	C	-63	C	-63
D	-78	D	-80	-	-	D	-82

NTC_{AB} = 50%
NTC_{AC} = 100%
NTC_{AD} = 75%

$MRSSI_{AB}$ = -87.5 dBm
$MRSSI_{AC}$ = -62.5 dBm
$MRSSI_{AD}$ = -80 dBm

$SDRSSI_{AB}$ = 0.5
$SDRSSI_{AC}$ = 0.5
$SDRSSI_{AD}$ = 1.6329

$ACVRSSI_A$
$= \frac{1}{n}\sum_{i=1}^{n} CVRSSI_i$
$= \frac{1}{3}(CVRSSI_{AB} + CVRSSI_{AC} + CVRSSI_{AD})$
= -0.011

C. Standard Deviation RSSI (SDRSSI)

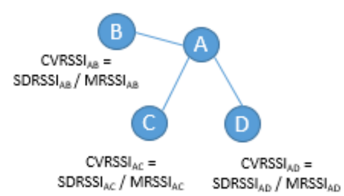
$SDRSSI_{AB}$ is the standard deviation of RSSI in dBm measured at node A from node B. Table I also explains how $SDRSSI_{AB}$ is calculated. $SDRSSI_{AB}$ indicates how much reception signal fluctuation is present between node A and node B over a period of 60 seconds.

D. Average Coefficient of Variation RSSI (ACVRSSI)

$ACVRSSI_A$ as explained in Table I, is the average coefficient of variation of RSSI in dBm of all links found around node A. $ACVRSSI_A$ is a measure of reception signal dispersion of all connecting nodes around node A over a period of 60 seconds. The calculation of $ACVRSSI_A$ is expressed as:

$$ACVRSSI_A = \frac{1}{n}\sum_{i=1}^{n} \frac{SDRSSI_{Ai}}{MRSSI_{Ai}}$$

where n is the number of neighbouring nodes around node A.



V. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

A. ANFIS Architecture

ANFIS [32] combines Fuzzy Logic and Neuro Network into a single data learning technique where it constructs an input-output mapping in form of fuzzy if-then rules with interconnected Neural Network elements and connections.

A two input ANFIS architecture with an adaptive multilayer feed-forward network is shown in Figure 3 consisting of five layers, namely, a fuzzy layer, a product layer, a normalising layer, a defuzzy layer and a total output layer. In each layer, network nodes perform individual functions on incoming signals.

Considering an ANFIS architecture with Sugeno fuzzy model that consists of two fuzzy if-then rules:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$
Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

where x and y are crisp inputs, and A_1 and A_2 are linguistic variables. p_i, q_i, and r_i are consequent parameters.

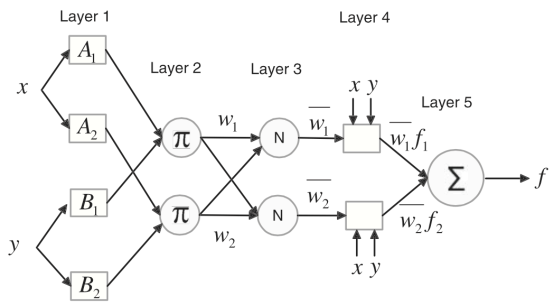


Figure 3. ANFIS architecture [32]

Layer 1 is the fuzzy layer where each node i generates a membership grade of a linguistic label based on input x. The membership relationship can be express as:

$$O_{1,i} = \mu_{A_i}(x) \tag{1}$$

where O_1 denotes the output of layer 1, and μ_{A_i} denotes the membership function.

Layer 2 is the product layer where each node i corresponds to a single Sugeno-type fuzzy rule and calculates the firing strength w_i based on the product of input signals. This relationship can be written as:

$$O_{2,i} = w_i = \mu A_i(x) * \mu B_i(y) \tag{2}$$

where O_2 denotes the output of layer 2.

Layer 3 is the normalising layer where each node i calculates a normalised firing strength $\overline{w_i}$ for a given rule based on inputs w_i. The normalising function can be represented by:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \tag{3}$$

where O_3 denotes the Layer 3 output.

Layer 4 is the defuzzy layer where each node i calculates the weighted consequent value of a given rule using a linear combination of the inputs multiplied by the normalised firing strength $\overline{w_i}$. This defuzzication relationship can be expressed as:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{4}$$

where O_4 denotes the layer 4 output, and p_i, q_i, and r_i are consequent parameters.

Layer 5 is the total output layer where node i calculates the output of all defuzzication neurons and produce an overall ANFIS output. The results can be written as:

$$O_{5,i} = overall\ output = \sum_i \overline{w}_i f_i = \frac{\sum_i \overline{w}_i f_i}{\sum_i \overline{w}_i} \tag{5}$$

where O_5 denotes the layer 5 output.

B. ANFIS based Prediction Models

This paper focuses on differentiating three distinct conditions commonly found in a deployed environment using NT contents extracted from experimented nodes; the three conditions are link failures due to poor deployed environment, link failure due to human movements, and no failure. The functional block diagram is shown in Figure 4. These conditions are then formed into the following three ANFIS–based learning models:

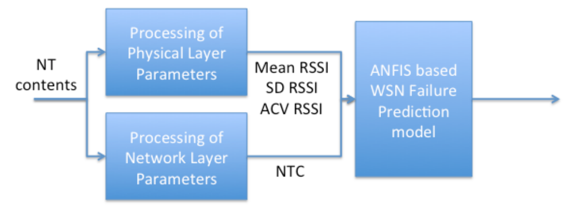


Figure 4. Block diagram of ANFIS-based prediction model

- Model 1: Link Failure due to Poor Deployed Environment vs No Failure
- Model 2: Link Failure due to Human Movement vs No Failure
- Model 3: Link Failure due to Poor Deployed Environment vs Human Movement vs No Failure

1) Link Failure Due to Poor Deployed Environment: Link failures that are caused by either the physical obstructions between nodes or nodes located too far apart. Typical physical obstructions are for instance walls, desk partitions, desk objects, and adjacent floors [30].

2) Link Failure Due to Human Movements: Link failures that are caused by physical presence of a human in close proximity. This could include the position of human relative to the node and the number of people presence around a node [20].

3) No Failure: Best case scenario where a node is not subjected to interference. In this condition, node performs well in terms of connectivity and any failures are negligible.

C. Training and Validation Methods

ANFIS models are trained with supervised learning using inputs and outputs data obtained from the real-world experiments. To better understand the behaviour of different inputs or their combinations thereof under different failures, and to ascertain the best parameter or best combination of parameters that can accurately predict the outcome, each model described in the previous sections is trained using 15 different sets of input parameter presented in Table II.

TABLE II. PARAMETERS COMBINATION USED TO TRAIN ANFIS MODEL

Sets	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Mean RSSI	✔				✔	✔		✔			✔	✔	✔		✔
SD RSSI		✔			✔		✔		✔		✔	✔		✔	✔
ACV RSSI			✔			✔	✔			✔	✔		✔	✔	✔
NTC				✔				✔	✔	✔		✔	✔	✔	✔

For all three ANFIS models, 10-fold cross validations are used as described – Training sets are split into 10 subsets, and a holdout method is applied 10 times. Each time, one of the subsets is used as the test set and the other nine as the training set. Subsequently, the average accuracy across all 10 trials is obtained.

VI. RESULTS AND DISCUSSION

In this section, the results from the three ANFIS models described in Section V are discussed and analysed in-depth in the form of box plot diagrams.

A. *Model 1: Link Failure due to Poor Deployed Environment vs. No Failure*

Model 1 differentiates between link failures caused by poor deployed environment and no failures. Figure 5 presents the mean prediction accuracies for all 15 sets of parameter combinations averaged over 10-fold cross validation runs. It can be seen that mean RSSI performed well with averaged accuracies greater than 95% when used on its own or as a joint parameter (set 1, 5, 6, 8, 11, 12, 13). This suggests that mean RSSI is a strong influencer on the prediction outcome and is good at detecting link failures due to poor deployed environment.

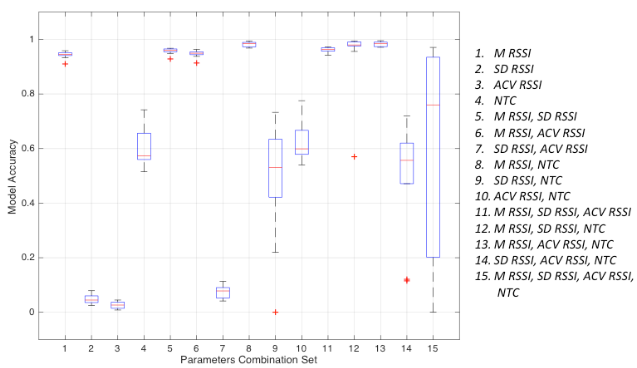


Figure 5. ANFIS prediction results - Link Failure due to Poor Deployed Environment vs. No Failure

Low mean RSSI values are observed to be associated with higher occurrences of link failures caused by poor deployment, while high mean RSSI indicates higher chances of no failure. A probable explanation is that dense physical obstructions such as walls, desk partitions, and adjacent floors impact signal propagation via attenuation or scattering effects. This phenomenon degrades how a signal is received and can lead to a higher chance of link failure [20, 23, 30].

NTC as a single parameter (set 4) produced a prediction accuracy of only 0.603 or 60.3%. It is observed that link failures (i.e. NTC lower than 80%) are always under the influence of poor mean RSSI. However, looking in-depth into model 1's training inputs with mean RSSI of poorer than -86 dBm (371 samples), links with NTC ranged from 80 to 100% take up only 51% of the population. This explains that NTC as single parameter could produces false positive results hence is not at good at detecting link failure due to poor deployment.

In model 1, link failures due to poor deployment and no failures are subjected to minimal variation of multipath and fading effects where the reception strength between nodes remained relatively constant with no more than 1.1 dBm variation. This phenomenon is observed on SD RSSI and ACV RSSI (set 2, 3, 7), which performed poorly. In addition, no distinct performance differences are found between SD RSSI and ACV RSSI as single and/or joint parameters, showing result consistency (i.e. "Mean RSSI & NTC & SD RSSI" (set 12) and "Mean RSSI & NTC & ACV RSSI" (set 13) have prediction accuracies of 0.979 and 0.982 respectively).

B. *Model 2: Link Failure due to Human Movement vs. No Failure*

Figure 6 shows the mean prediction accuracies for all 15 sets of parameter combinations for model 2, averaged over 10-fold cross validation runs. It is observed that none of the parameter combinations produced mean prediction accuracies of more than 90%. This poor performance across all parameter combinations could be debated that model 2 is based on a single human walking profile, which may not be distinctively detected. As explained in [20], the variation in reception strength is relative to the growing number of people around a node. Extrapolating from this, it can be inferred that in situations where there are more human activities around a particular node, model 2 should perform even better.

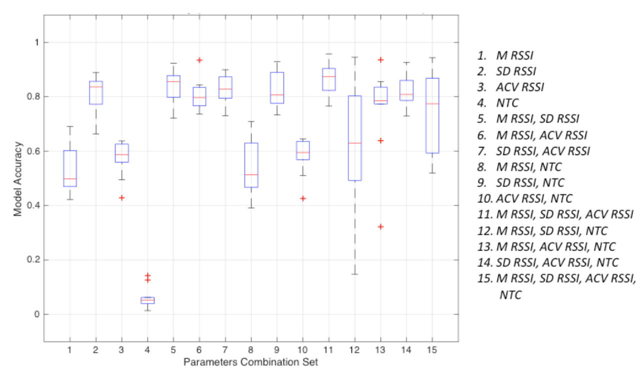


Figure 6. ANFIS prediction results – Link Failure due to Human Movement vs. No Failure

The introduction of human movement alters the multipath and fading effects on signal propagation between communicating nodes. SD RSSI represents the reception signal fluctuation present between nodes and this phenomenon could be observed from set 2, 5, 6, 7, 9, 10, and 14 where prediction accuracies are more than 0.8 or 80%.

It is important to note that single parameter NTC (set 4) performed poorest with a prediction accuracy of only 0.057 or 5.7%. Looking in-depth into model 2's training inputs, no link failures are found under the influence of human movements. This phenomenon can be explained with as long as there are strong receptions between communicating nodes, the influence of temporal human movement (variation in RSSI) on communication failure is negligible.

C. *Model 3: Link Failure due to Poor Deployed Environment vs. Human Movement vs. No Failure*

Model 3 differentiates between the link failures caused by poor deployment or human movement and no failure.

Figure 7 presents the mean prediction accuracies for all 15 sets of parameter combinations averaged over 10-fold cross validation runs. It is clear that any parameter combinations that contain mean RSSI (set 1, 5, 6, 8, 11, 12, 13, 15) has mean prediction accuracy of more than 0.85. Mean RSSI is an averaged RSSI measured across a window period. In other words, a consistently low mean RSSI indicates a long period of consistently poor reception strength and hence indicating a higher probability of poor deployed environment rather than human movement.

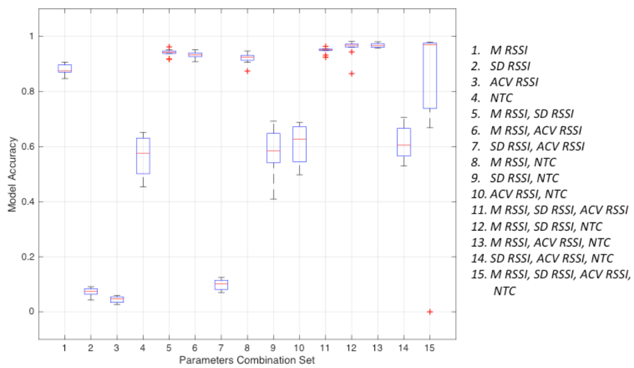


Figure 7. ANFIS prediction results – Link Failure due to Poor Deployed Environment vs. Human Movement vs. No Failure.

Similar to model 1, SD RSSI and ACV RSSI as a single parameter both performed poorly (set 2 and 3) and are found to have no distinct performance difference between them (i.e. "SD RSSI & NTC" (set 9), and "ACV RSSI & NTC" (set 10) have prediction accuracies of 0.589 and 0.613). However, SD RSSI and ACV RSSI as joint parameters with other parameters can improve the overall prediction accuracy (i.e. prediction accuracy of "mean RSSI & NTC" (set 8) improved from 0.923 to 0.975 with the addition of ACV RSSI (set 13)). This phenomenon is observed to be consistent for SD RSSI as well.

Combining parameters from different layers improves the model accuracy. However, this is only true for a selection of combination of parameters. Sets 12 and 13 showed that the combination of parameters from different layers and of different link properties produced a prediction model with accuracy of over 96%; these parameters mirror the properties of channel fluctuations, signal strength and success rate of reception. This highlights the importance of careful selection of parameters to improve the prediction accuracy of ANFIS models.

D. *Comparison of all three ANFIS models*

Table III presents the mean prediction results obtained from all three ANFIS models trained with 15 different combinations of parameters. The parameters are ranked accordingly to the averaged prediction accuracies across all three ANFIS models – from most to least accurate. It is clear that mean RSSI stands out among all parameters as the top 8 best predictors are trained with parameters combinations consisting of mean RSSI.

The parameter combination of mean RSSI, ACV RSSI and NTC (set 13) has the best performance for all three models, stressing the importance of combining link properties of channel fluctuations, signal strength and communication success rate.

TABLE III. SET OF PARAMETERS COMBINATION RANKED ACCORDING TO MEAN PREDICTION ACCURACIES COMPUTED FROM ALL THREE ANFIS-BASED DEPLOYMENT MODELS

No.	Parameters Combination Set	Accuracies			
		Average	PDE vs. NF	HM vs. NF	PDE vs. HM vs. NF
13	M RSSI, ACV RSSI, NTC	0.917	0.982	0.793	0.975
11	M RSSI, SD RSSI, ACV RSSI	0.915	0.952	0.863	0.929
5	M RSSI, SD RSSI	0.913	0.958	0.839	0.94
6	M RSSI, ACV RSSI	0.893	0.948	0.799	0.931
12	M RSSI, SD RSSI, NTC	0.864	0.979	0.647	0.965
8	M RSSI, NTC	0.813	0.982	0.536	0.923
1	M RSSI	0.782	0.944	0.524	0.879
15	M RSSI, SD RSSI, ACV RSSI, NTC	0.768	0.642	0.756	0.904
14	SD RSSI, ACV RSSI, NTC	0.648	0.509	0.823	0.612
9	SD RSSI, NTC	0.637	0.501	0.822	0.589
10	ACV RSSI, NTC	0.609	0.619	0.594	0.613
4	NTC	0.408	0.603	0.057	0.565
7	SD RSSI, ACV RSSI	0.335	0.073	0.83	0.1
2	SD RSSI	0.312	0.046	0.817	0.073
3	ACV RSSI	0.218	0.025	0.585	0.044

The results of individual ANFIS model showed that parameters can behave vastly different under different conditions. In other words, careful selection of parameters is necessary in order to obtain the best prediction accuracy of a desired model. In another example, even though set 15 consists of the highest number of parameters (mean RSSI, SD RSSI, ACV RSSI and NTC), it does not necessary translate to the best prediction result. This implies that adding more training inputs to the ANFIS models may not necessary produce better prediction results.

VII. CONCLUSION

In this paper, three ANFIS models for WSN failure prediction have been developed, capable of diagnosing the cause of link failure to either poor deployment or human movement. The ANFIS models trained with different combinations of parameters are evaluated and have shown that ANFIS is a suitable technique for WSN link failure prediction.

The training of ANFIS models with multiple parameter combinations provides a learning approach to understand how parameters behave under different conditions. Unlike developing a typical Fuzzy model [25], expert knowledge is not required. This is particularly useful if the behaviour of the individual and joint parameters are unclear.

In this work, the combination of mean RSSI, ACV RSSI and NTC (set 13) produced the best prediction results for all ANFIS models. Mean RSSI, ACV RSSI and NTC, which mirror the properties of signal strength, channel fluctuations, and communication success rate respectively, highlights the importance of using cross-layer parameters to improve prediction accuracy.

Mean RSSI is captured in all top 8 best predictors (Table III) while NTC is only found in 3 of them. The poor prediction accuracies of NTC have shown that a communication success rate parameter alone is not sufficient to link quality estimation. This is also supported in [13, 25]. The results indicate that physical layer parameter such as the RSSI may perform better than a network layer parameter at describing the geometry of an environment (influenced by poor deployment and human movements).

Care should be taken as to which parameter combination to use as not every parameter combination produces the best prediction result. The key for a robust prediction model is to first understand the operating behaviour of parameters under different network challenges, followed by a careful selection of training parameters for ANFIS models.

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