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***Abstract*—Energy consumption is considered the main challenge of MAC protocol design. Especially when MAC protocol is employed in an environment of limited energy resources as a wireless sensor network. Parameters optimization of the shared channel in sensor communications is the aim of any MAC protocol designer. In this paper, we suggest a machine learning-based approach for the improvement of the performance parameters using channel prediction learning. Channel predication learning ensures that all the learning process is done by the node. The proposed machine learning algorithm takes into consideration the fading channel parameters and suggests a solution that is best suited to optimize the performance parameters. The proposed machine learning approach incorporates the use of Sensor-MAC (SMAC) protocol and suggests the best tuned MAC protocol based on the supervised learning GRNN algorithm. We investigate the system performance using simulation scenarios under various configurations. The overall performance improvement is more than 80% based on all the output performance parameters.**

***Index Terms*—Channel Fading, Collision Ratio, Machine Learning, SMAC Protocol, Performance Metrics.**

I. Introduction

Medium Access Control (MAC) is sub-layer of the data link layer. This layer is responsible for frame forward between directly connected communication devices. In most scenarios, the performance of implementing the MAC layer protocols influences the performance of the entire communication system. Researchers and designers have applied many ideas to optimize the efficiency of the MAC sub-layer for reducing communication latency, improving network lifetime, and enhancing the scheduling of frames. Especially, when designing the MAC protocol for limited resource environment such as the Wireless Sensor Network (WSN).The common MAC protocol designed for sensor networks is called Sensor MAC or (SMAC) protocol. Commonly frame collision, Control frame overhead, overhearing, and idle listening are the main four sources leading to energy wastage in the sensor network communications. SMAC protocol targets to reduce the energy loss caused by mentioned four sources of energy wastage. SMAC reduces frame collision by employing RTS and CTS control signals. It minimizes the energy lost by exchanging the radio interface to the off state, This occurs when frame transmission is not targeted to the node, Control frame overhead is eliminated by periodic listen and sleep. SMAC idea is based on a periodic listen and sleep, where each node applies a periodic sleep mode when it switches its radio interface to the off state. In addition, it sets a count-down timer to switch on its interface later. When the count down timer expires, it switches its radio interface to up. Determining of sleep and listen period is based on the duty cycle applied, SMAC nodes send their schedules by broadcast communications. Where many neighbors are connected by the shared channel. Once the channel is free and assigned to a specific node, and the frame transmission is started, the node does not stop its transmission until it completes its buffered frames. For the frame collision avoidance mechanism, a rule of RTS/CTS is employed which performs virtual and physical sense in a shared channel before frame transmission occurs. While NAV vector determines how long the remaining frame transmission will be continued before the shared channel is assigned to another node. This paper suggests a fading channel collision avoidance. Furthermore, this paper presents a clear understanding of *how to employ Machine Learning (ML) for channel collision prediction*. This solution leads to minimizing the power consumption and increasing the channel utilization of wireless sensor communications. The paper is constructed as follows. Section II demonstrates related work of the topic. In Section III, we discuss the employing of machine learning in improving the channel prediction. Moreover, this section presents the algorithm of machine learning ad demonstrates the role of prediction. While the channel modeling and performance metric are discussed in section IV. Section V shows the configuration used to measure the collision ratio based on the channel threshold. Section VI presents the conclusion and future work.

II. Related Work

Nowadays with the power of the ability to collect by sensing, store big data, and ability of process big amounts of data, machine learning with its different algorithms was employed into many different scientific research fields. The current challenges faced by the internet of things and sensor networks pushed also the wireless networking domain to find suitable solutions to ensure desired network performance. To address these different challenges, ML is essentially used in wireless MAC protocol design. In this paper [1], channel models are presented with their operational teachings and important factors. The parameters are compared using major characteristics. The study has implemented its channel model, furthermore the paper shows challenging problems and research fields of channel modeling. This paper [2], employs machine learning to implement channel modeling and estimation. This paper presents the theoretical framework based on machine learning for channel modeling. This paper employs machine learning of supervised data set in the field of wireless channel prediction using regression analysis. This model was employed for data observation to predict the channel parameters. The paper [3], demonstrates a machine learning approach for minimizing energy wastage, end-to-end delay. Furthermore, the paper suggests a solution to improve the delivery ratio, and data throughput using machine learning. The proposed algorithm considers the parameters and suggests a solution that optimizes the output performance. Where the paper [4] presents a methodical and comprehensive survey on machine learning algorithms that target wireless network improvement. This paper considers the first three layers of the protocol suite. A new approach suggested by [5]. This approach is called Energy-Aware MAC (EA-MAC) algorithm. This paper compares the EA-MAC approach with SMAC protocol and Multi-Layer MAC. This comparison is in terms of energy consumption, average delay, and throughput. From this study, the authors concluded that the proposed approach is more significant in terms of consumed energy and it has a higher throughput than other compared protocols. The paper [6] demonstrates a complete review of machine learning to enhance the performance of MAC protocol in WSN. This enhancement was in terms of energy-saving, throughput, and delay. Where the paper [7] demonstrates both a review of common neural networks models and a comprehensive study of employing neural networks in wireless communications. The authors identify the challenges of implementing neural networks, especially when considering different models and techniques. The paper [8] shows a comprehensive literature review of machine learning methods that were used to solve issues in wireless sensor environments. The deep analysis of each suggested algorithm is compared with the corresponding problem. While the paper [9] uses machine learning as a suitable technique for real-time modeling of the wireless communication performance based on the MAC layer. The paper [10] suggests a detection solution that detects intrusions in wireless networks using deep learning algorithms. This paper employs a machine learning algorithm as security pattern behavior. This mechanism helps administrators to detect and stop internal or external attacks. The paper [11] suggests a beacon interval for centralized opportunistic communication. This beacon interval minimizes the energy consumption and overhead.

III. Machine Learning Usage in the Channel Modeling

Artificial intelligence (AI) is the main topic of sub-topics such as machine learning. The ML is widely employed to enable any system to be intelligent, make an assessment and predict. Applying ML on the traditional channel modeling to predict or estimate the frame forwarding still has space for research. One of the big issues in current wireless communication is sensing the time of the free shared channel, whereas applying ML techniques could improve the throughput and reduce energy consumption. ML can be employed to predict and estimate the shared wireless channel collision and enhance the energy saving of SMAC. Estimating frame collision can be solved by employing machine learning techniques to overcome this challenge. The classic wireless channel modeling is commonly performed using Deterministic or Stochastic methodologies. ML techniques based on training data set as a supervised learning method will be employed to predict the fading channel collision base on a certain dataset. This paper, demonstrates employing machine learning to develop an alternative technique to minimize the collision rate using machine learning techniques. Furthermore, the paper investigates the machine learning methods which will be suitable and capable to derive channel modeling and collision prediction in a better and accurate solution than the traditional models. This section will demonstrate *how to employ an ML algorithm to estimate and predict the frame collision in fading channel using a regression method*. Regression is considered an essential supervised learning technique. Regression is considered as the main method that is employed in machine learning where the regression model the mechanism based on the observed dataset from prior historical measurements or simulations results.

A. Supervised Learning

When ML algorithm targets for learning and predicting, common stages of ML can be divided into three stages. The first stage is training by given datasets of input and output observed. The second stage is testing by learned or observed data, and finally validating and prediction stage which is done by some of the input vectors that have experienced labels as known output. Moreover, in the training stage, the algorithm learning from the available data while in the testing stage, a trained model is employed for predicting the labels or output such as channel modeling estimation. Depending on the datasets type that is used to learn the algorithm, there are three types of datasets which are supervised and semi-supervised, and unsupervised. This paper uses a supervised learning technique that requires input, output, and training datasets to build the model. This model is used for the prediction of future output or even the output of missing input of input vector. If we have some sample space consist of input X_i and we have depended on output label Y_i where i = 1, 2, N, and N number of samples. The target of supervised learning training is to find a function that accurately fitting the relation between the input values and the labels observed as an output. This function of the ML algorithm helps researchers and designers for future predicting of the system output. To measure the accuracy of the function used to model the system. Commonly, the supervised learning datasets can be divide into two main sub-datasets which are the regression model creation datasets, and the validation datasets. One of the main supervised learning is called regression learning. The regression method is used in the estimation of the channel model parameters such as the collision prediction or free channel sensing.

B. Regression Algorithms

Regression analysis or learning is considered a statistical method. Regression analysis gives a clear understanding of the relationship between two independent and dependent variables. The learning process that is modeled to perform regression analysis simplifies determining which factors are very important, which factors can be canceled and how these factors are impacting on each other. Regression analysis is commonly used for prediction, especially for future output. The regression analysis has many types, this paper will take into account the following regression types which describe the nature of variables and their distribution.

1) Linear Regression: The linear regression model is a common supervised learning technique that is used for implementing the relationship as a function describe the system. This function determines the relation between input space as an independent variable (x) and output as dependent variable (y), Therefore, the output is a linear function of the single input or combination of multiple input variables:

$$y = f(x) = a_0 + a_1x_1 + a_2x_2 + ... + a_mx_m \quad (1)$$

Where x is independent variable and its space is $x = (x_1, x_2, ..., x_m)$, while $a = (a_0, a_1, a_2, ..., a_m)$ are estimated parameters from given training pairs of (x_i, y_i). i= 1, 2,......m.

2) Nonlinear Regression: Nonlinear regression is another type of supervised training technique. Nonlinear regression implements the observed data or labels as a function that describes the system. This function is nonlinear, where it combines the estimated parameters and one or multiple input variables. Nonlinear regression is considered as a polynomial regression model described by the following equation:

$$y = f(x) = a_0 + a_1x + a_2x^2 + ... + a_mx^m \quad (2)$$

C. General Regression Neural Network

The General Regression Neural Network (GRNN) [12] is considered as one method of regression methodology which considered as a supervised learning technique. The GRNN architecture is based on Radial Basis Function (RBF) method. This function is considered as Gaussian distribution. It approximates any function between the input vector and output labels or observations, implementing the function is an estimate from the training dataset. The GRNN is modeled based on nonlinear regression (Eq. 2) for function implementation. The training pairs of data consist of inputs x, with a corresponding output y. This nonlinear regression method which is used by this paper produces the estimated observation value of y, Gaussian kernel function used by GRNN minimizes the squared regression error. The GRNN algorithm can be used for any regression process in which a probability of linearity input and output variables is not justified. The GRNN algorithm is considered as a universal fast approximator for smooth and fitted functions, therefore, GRNN is capable and suitable for solving any smooth function approximation nonlinear relationships. The GRNN algorithm is selected in this paper because of its ability to fast learning and minimum convergence to the optimal regression solution. GRNN is an algorithm for implementing the relationship f(x,y), this relation is modeled by being given a training set. Due to the pdf being determined by the training GRNN is a powerful and faster regression process that has a dynamic behavior structure. It is idea is based on statistical principles, and asymptotically fast converges when increasing the number of samples. GRNN has been considered as better results in terms of the prediction of system functions. For an input vector X, the output of the GRNN is

$$\widehat{Y} = \frac{\sum_{i=1}^{n} y_i \ exp(-\frac{D_i^2}{2\sigma^2})}{\sum_{i=1}^{n} exp(-\frac{D_i^2}{2\sigma^2})} \quad (3)$$

where n is considered as the number of observations, $D_i^2 = (x - X_i)^T(x - X_i)$ is squared value of distance between input variable x_i and the training variable X_i, and σ is the spread or smooth parameter. As the value of σ is increased, the functional approximation is smoother. To implement the data very accurately, the value of the spread or smooth parameter should be smaller than the distance between the input variables.

IV. Channel Model and Evaluation Metrics

To evaluate and measure the performance of proposed machine learning algorithm we used the following metrics

A. Additive White Gaussian Noise (AWGN)

AWGN is considered as a common channel model. This model is used to simplify the understanding of the wireless channel. This channel model as the name inspires it consists of a linear addition of in-band or white noise added to the signal with a constant as a spectral density. This rule can be expressed as power watts per hertz of signal bandwidth. Where a Gaussian word is used as a distribution of signal amplitude. The model is simple and it does not consider the fading, Signal frequency, noise or interference, or signal dispersion. However, the model is simple and considered a tractable numerical model. This model helps get insight into the performance of a wireless system. Especially when there is no need of considering the different events of the channel The AWGN channel model can be expressed mathematically based on the following equation

$$r = s_i + n \quad (4)$$

Where s_i is the input signal vector which add to the noise vector n of $(n_1, n_2, n_3, ...n_N)$ and r is i.i.d Gaussian random variables, where this variable with zero mean and variance of $\frac{N_0}{2}$. Finally the noise vector has pdf of

$$P_n(n) = \frac{1}{(\pi\, N_0)^{\frac{N}{2}}}\, exp\, (-\frac{|n|^2}{N_0}) \quad (5)$$

The observed vector has elements of $r = (r_1, r_2, r_3, ...r_N)$ which are considered as an independent Gaussian random variables. Its pdf function can be calculated based on the following equation.

$$P_r(r/s) = \frac{1}{(\pi\, N_0)^{\frac{N}{2}}}\, exp\, (-\frac{|r - s_i|^2}{N_0}) \quad (6)$$

B. Rayleigh Fading Channel

Rayleigh's fading channel model is considered a statistical model. this model shows the impact of signal propagation on the media of the channel. According to this fading model, a signal transfers through the channel medium (transmission channel) will disappear or damping randomly. In addition, this fading channel model will follow the Rayleigh distribution behavior, which is considered as a radial component of the two uncorrelated Gaussian random variables. summation The Rayleigh fading channel model assumes that a common or “default” for worst-case efficiency analysis.

$$p(r) = \begin{cases} \frac{r}{\sigma^2} exp(-\frac{r^2}{2\sigma^2}) & for\ r \geq 0 \\ 0 & otherwise \end{cases} \tag{7}$$

C. Collision Ratio

The collision rate is an important performance parameter, especially in WSNs. The MAC protocol of WSNs communications requires that if a collision occurs the damaged frame will be re-transmitted by the sender until the frame is successfully received at the receiver node. The frame dropped because it reaches the maximum of re-transmissions counts. This re-transmission of the frame is applied to stop re-transmissions when there are bad-quality links. When the maximum tries of re-transmissions are expired, the sender will drop the frame from its buffer. However, the frame or packet loss may be caused by the interference of other sensors modes. Frame re-transmission will cost a lot of time wasted as a delay in addition to energy lost. This also will lead to throughput degradation. Wireless shared channel collision occurs at the receiver. The collision detection in this paper is based on the predetermined threshold limit which is simulated as the power ratio in the wireless shared channel.

D. Signal to Noise Ratio

One of the most faced challenges which still existing in current wireless communication systems is noise. The transmitted signal impact by noise when it passes over the wireless communication channel. Among all different resources which lead to different impacts on signal quality, the white Gaussian noise and in addition to the multi-path propagation are considered as the most noise types effect on the signal quality. The channel noise resources impact on the signal quality is characterized by the term Signal-to-Noise Ratio (SNR) parameter. This signal quality parameter SNR represents an indication or quality measurement of the power ratio. This power ratio is useful to detect the desired signal from the channel background noise power. Commonly, the SNR is measured in decibels, and the higher value of this SNR is an indication of less noise impact on the transmitted signal through the channel.

$$SNR = 10\, log_{10}(\frac{P_{signal}}{P_{noise}}) = 20\, log_{10}(\frac{A_{signal}}{A_{noise}}) \tag{8}$$

Where P is considered as an average power level of a signal and noise, while A is the root mean square amplitude of a signal and noise.

E. Loss Ratio

This section describes the loss ratio, where this loss ratio is related to the frame at the data link layer and in addition to the packet at the network layer. Generally, the frame loss comes from the channel errors detected by Frame Check Sequence (FCS) or can be theatrically computed using Bit Error Rate (BER). While packet loss is related to the transport layer and congestion mechanism. Therefore, we consider the loss rate for both frame and packet. Where packet loss or frame loss ratio $LR_{(F/P)}$ is defined as the percentage ratio of frames that are not successfully forwarded to the next hop or the neighbor compared to the total generated frames. Or may defined as the percentage ratio of packets that are not successfully delivered to the final destination compared to the total generated packets. $LR_{(F/P)}$ is a key function for monitoring and measuring the performance in networks. It can be calculated using the following formula.

$$LR_{(F/P)} = \frac{S_{(FF/DP)}}{T_{(FF/GP)}} X100 \tag{9}$$

Where $LR_{(F/P)}$ is the loss ratio of frame or packet. $S_{(FF/DP)}$ is successfully forwarded frames or delivered packets, and $T_{(FF/GP)}$ is the total forwarded frames or generated packets.

F. Buffer Size

Sample-based signal in MATLAB is the basic type of signal generation, Sample-based signal is considered as the simplest way to construct in a reality a physical signal. The sample-based signal is sampling a real-word signal at a specific sample rate, and output the single sample as received. It is possible using the simulation to generate a frame based on the sample-based signal. Especially when buffer a group of N samples, this leads to create a frame. Therefore, it can be output a train of frames at a rate that is equal to $\frac{1}{N}$ times the rate of the original sample-based. The rate is also called the frame rate of the physical signal. Frame-based is a common format in real-time systems. The Buffer block or space always performs frame-based processing. This block redistributes the symbols in each group of the input to generate an output with a variant frame size. Buffering the sampled signal to a larger frame size leads to an output of a lower frame rate than the original input. The buffer block may be used to investigate frame-based processing delay when considering the size of the buffer based on the number of symbols.

V. Simulation and Numerical Results

The simulation scenario for employing ML in collision estimation and prediction is implemented based on supervised learning with nonlinear regression (Eq. 2). This Ml algorithm is called GRNN (Eq. 3). The evaluation models of wireless channel are based AWGN (Eq. 4 to Eq. 6) and fading channel(Eq. 7). The scenario conducted consists of two wireless nodes the first is A and the other node is B. The evaluation is done by using MATLAB simulator [13]. The simulation of the collision criteria was based on different thresholds as shown in Table I. Figure 1 shows the simulation scenario which compares the two-channel models of AWGN and fading channel. AWGN channel is considered as a simple channel model, where in fact, this type of channel does not well reflect the reality of physical channel. Therefore, for this particular reason, the fading channel was selected as a more realistic model. Fading channel model takes into account the most important channel problems and collision issues. Then the ML algorithm is employed to find practical suitable solutions for predicting the collision event occurrence.

The simulation scenario assumes that there are two nodes A, B. They are both in send mode, and it was assumed that node B is sending and then node A starts to send after a short time,

TABLE I
SIMULATION SETUP

No	Settings	Value(s)
1	Communication Type	Full Duplex
2	Collision Detection	Node A
3	Number of Nodes	2 Nodes A and B
4	MAC Protocol	*SMAC*
5	SNR	20 dB
6	Buffer Size	5 symbols
7	Number of Symbols	1 X 10^6
8	Channel Threshold	1 to 10
9	Machine Learning Algorithm	GRNN
10	Channel Model	AWGN Channel Fading Channel

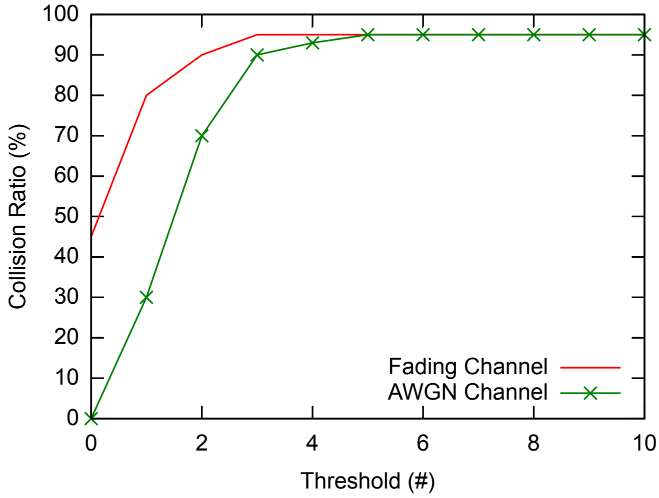

Fig. 1. Collision Ratio of AWGN and Fading Channel Models

the goal is to investigate the effect of node B transmission on node A. When node A wants to transmit, it must first confirm whether the channel is free or not. This is done by listening to the channel, where if node B is sending, then node A will be able to sense the frame sent by B if the frame is transmitted by the channel successfully, and therefore it will be considered that node A senses that the channel is busy and will immediately go to sleep and this is what S-MAC does, but when the frame corrupted due to deep fading, node A can sense this frame inside the channel. Therefore the channel will be considered bussy and a collision will occur.

Figure 2 shows the relationship between the collision ratio of the fading channel at different channel thresholds. Where the signal within the channel was tested based on these thresholds. From Figure 2, it is easy to observe that as the threshold is increased as the collision ratio is increased for the fading channel without ML. This means that node A cannot sense that there is a frame sent inside the channel, and it will send its frame which leads to a collision to have occurred. Therefore, the frame of both senders A and B is lost, thus The receiver will ask every time to re-transmit the lost frame, which will lead to a very large waste of energy.

From Figure 1, it is clear that the collision rate of the fading channel is higher than the AWGN channel. This is because

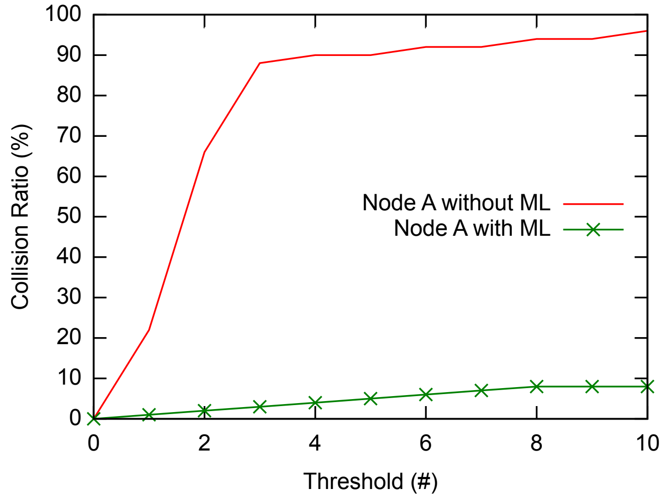

Fig. 2. The Collision Ratio at Node A with and without ML

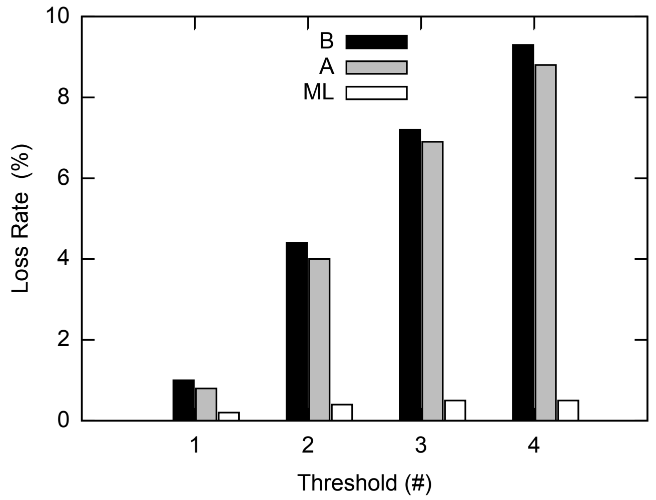

Fig. 3. Loss Ratio at Node A and Node B

the fading channel considers more realistic parameters than the AWGN channel. As a solution to this high collision rate the machine learning has been employed, Therefore, node A in Figure 2 can predict the times that deep fading is expected to occur. Thus employing the GRNN algorithm will help to predict the occurrence of a collision, through the pre-teaching as supervised learning of this function. Where this function has been trained by using about 80 % of the data in the first run of the program, then the function was added to node A, where node A tests the function before it starts the transmission process. When node A senses the channel and finds it free, then node A asks the function whether it is expected that there is deep fading inside the channel or not, the function will respond with yes or no through its previous experience, if the answer is yes, node A will stop transmitting and will immediately go to sleep. When the answer is no, the node will transmit its frame.

Figure 2 illustrates the relationship between the ratio of collision and channel thresholds with and without adding machine learning. From figure 2 it is clear to observe that the GRNN function greatly reducing the collision rate across the different

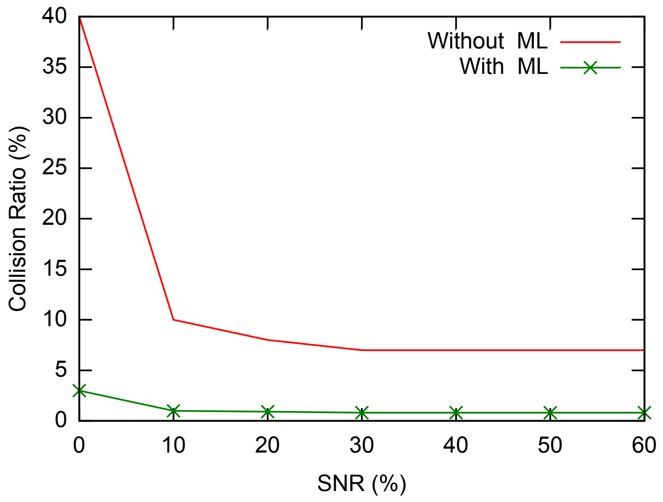

Fig. 4. SNR and Collision Ratio

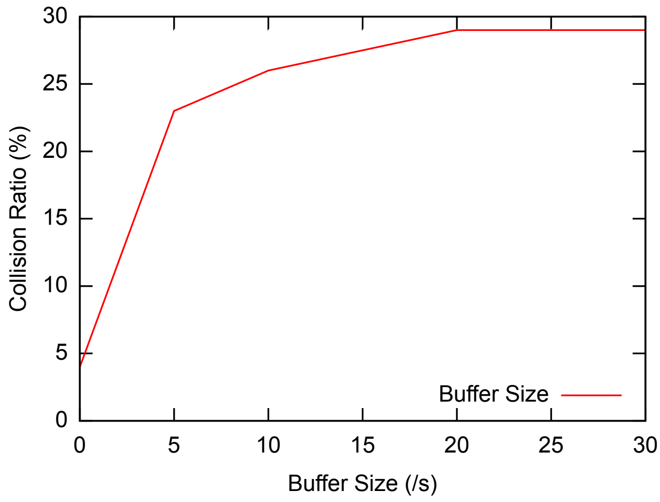

Fig. 5. Buffer Size and Collision Ratio

channel thresholds, it shows that at threshold 1 the collision rate was about 20% without employing ML by node A, but when using the function by node A the collision rate at the threshold 1 was about 2%, and also at threshold 2, the collision rate without the machine learning function was about 60%, but when node A uses the GRNN function the collision ratio was about 5%. This is improvement leads to save energy and increase the throughput. Figure 3 shows that the loss ratio (Eq. 9) at node A and node B without employing ML based on GRNN. Also the figure demonstrates the loss ratio at node A by employing machine learning at four different channel thresholds. From Figure 3, it is notable that as the threshold increased as the loss ratio will increase. Furthermore, the loss rate at node B is higher than the ratio at node A. This is because any loss at node A will leads to loss at node B. Also it is clear from Figure 3 that when employing the GRNN function the frame loss rate does not exceed 0.5 % at any threshold.

Figure 4 shows that it is notable that as SNR (Eq. 8) increases as the collision ratio is decreasing. Especially when employing the ML function of GRNN. This improvement of collision ratio by employing GRNN with increasing SNR leads to an increase the channel utilization and throughput. One of the parameters that was used during this simulation is the buffer size, which represents the number of symbols inside a single frame. The buffer size was related to a number of frames, Where every frame changed in size by the included number of symbols. Figure 5 illustrates the relationship between collision ratio and frame size where as the frame sizes increases as the collision ratio increased.

VI. Conclusion and Future Work

This paper proposes a machine learning-based solution for the collision prediction of fading channels. The proposed GRNN algorithm suggests the best tuned SMAC protocol based on supervised learning. The results show that the collision rate was reduced by GRNN to about 80 %. As a deep investigation, we analyzed the impact of SNR and buffer size. As future work, we have planning to consider the impact of node density as the number of nodes and node degree.

References

[1] A. Habib and S. Moh, "Wireless channel models for over-the-sea communication: A comparative study," *Applied Sciences*, vol. 9, no. 3, 2019. [Online]. Available: https://www.mdpi.com/2076-3417/9/3/443

[2] S. M. Aldossari and K. Chen, "Machine learning for wireless communication channel modeling: An overview," *Wirel. Pers. Commun.*, vol. 106, no. 1, pp. 41–70, 2019.

[3] H. B. Pasandi and T. Nadeem, "MAC protocol design optimization using deep learning," in *2020 International Conference on Artificial Intelligence in Information and Communication, ICAIIC 2020, Fukuoka, Japan, February 19-21, 2020*, pp. 709–715.

[4] M. Kulin, T. Kazaz, I. Moerman, and E. D. Poorter, "A survey on machine learning-based performance improvement of wireless networks: Phy, MAC and network layer," *CoRR*, vol. abs/2001.04561, 2020.

[5] M. Premkumar, M. Kathiravan, and R. Thirukkumaran, "Article: A novel mac algorithm for energy aware wireless sensor networks," *International Journal of Computer Applications*, vol. 58, no. 5, pp. 1–4, November 2012.

[6] N. Zuriatunadhirah binti Zubir, A. F. Ramli, and H. Basarudin, "Optimization of wireless sensor networks mac protocols using machine learning; a survey," in *2017 International Conference on Engineering Technology and Technopreneurship (ICE2T)*, 2017, pp. 1–5.

[7] N. Ahad, J. Qadir, and N. Ahsan, "Neural networks in wireless networks: Techniques, applications and guidelines," *J. Netw. Comput. Appl.*, vol. 68, pp. 1–27, 2016.

[8] M. A. Alsheikh, S. Lin, D. Niyato, and H. P. Tan, "Machine learning in wireless sensor networks: Algorithms, strategies, and applications," *IEEE Commun. Surv. Tutorials*, vol. 16, no. 4, pp. 1996–2018, 2014.

[9] M. Kulin, E. D. Poorter, T. Kazaz, and I. Moerman, "Poster: Towards a cognitive MAC layer: Predicting the mac-level performance in dynamic WSN using machine learning," in *Proceedings of the 2017 International Conference on Embedded Wireless Systems and Networks, EWSN 2017, Uppsala, Sweden, February 20-22, 2017*, P. Gunningberg, T. Voigt, L. Mottola, and C. Lu, Eds. Junction Publishing, Canada / ACM, 2017, pp. 214–215.

[10] V. L. L. Thing, "IEEE 802.11 network anomaly detection and attack classification: A deep learning approach," in *2017 IEEE Wireless Communications and Networking Conference, WCNC 2017, San Francisco, CA, USA, March 19-22, 2017*. IEEE, 2017, pp. 1–6.

[11] S. Sati and K. Graffi, "Adapting the beacon interval for opportunistic network communications," in *2015 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2015, Kochi, India, August 10-13, 2015*. IEEE, 2015, pp. 6–12.

[12] D. Specht, "A general regression neural network," *IEEE Transactions on Neural Networks*, vol. 2, no. 6, pp. 568–576, 1991.

[13] X. Raimundo and S. Salous, "Bit error rate comparison of MATLAB multipath fading channel simulator and measurement based channel simulator using real measurement data," in *International Symposium on Signals, Systems, and Electronics, ISSSE 2012, Potsdam, Germany, October 3-5, 2012*. IEEE, 2012, pp. 1–6.