Adaptive Parameters of an Enhanced Backoff Method by Using an Artificial Neural Network Between mobiles in an Industrial Domain

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Summary

The purpose of this study is to discuss the exchanges between mobiles moving in an industrial environment. A simulation approach has been chosen in order reach this study. This novel method aimed to minimize the exchange time between mobiles within an 802.11 cell. The optimization of this time was carried out by modifying the binary exponential aspect of the Backoff algorithm as a first phase, where as a second phase this modified and enhanced BEB method was supported by a Neural Network Function to give us precise output parameters. Those outputs will be learned by the Neural Network Function and will be used in the NS2 simulation to get the new results of the time delay to compare them with the standard BEB method results.

Key words:

WLAN, IEEE802.11, Carrier Sense Multiple Access with Collision Avoidance CSMA/CA, BEB, Artificial Neural Network (ANN), Radial Basis Function Neural Network (RBFNN), Access Point (AP).

1. Introduction

IEEE 802.11 became an essential aspect of our daily life. The IEEE 802.11 standard covers the MAC (Medium Access Control) sub-layer and the physical layer of the OSI (Open System Interconnection) reference model. In 802.11, the MAC sub-layer determines how the channel is allocated, that is who gets to transmit next [13]. In a Basic Service Set (BSS), the stations and the Access Point (AP) can either work in contention mode exclusively, using the Distributed Coordination Function (DCF), or in an alternative mode which is contention-free mode using the Point Coordination Function (PCF).

Wireless networks use radio frequency channels, as their physical medium in a form of electromagnetic radiation to exchange data. BEB has some drawbacks where the performance gets affected causing delay in time during the process in real time. Collisions is one of the main reasons that causes bad performance, and they increase when there is a heavy load of data transmission due to the increase number of contending mobiles on the channel.

Our objective in this study is focused on minimizing the delay of exchanging real-time data between mobiles moving in the same 802.11 cell in an industrial domain. The optimization of this time was carried out by modifying the binary exponential aspect of the Backoff algorithm in order to reduce the access time of the radio medium. This enhanced method purposes for decreasing the delays that happened either when collision occurs or in successful transmission. This issue is treated by changing the way that **CW** (Contention Window) will be set in the following two cases [6]:

- Firstly when a collision occurs, instead of multiplying **CW** by 2, it consists by multiplying it by ***a*,** Where **0 < a < 2**, thus ***CW = CW * a***.
- Secondly when a frame is successfully transmitted, instead of keeping **CW** of the successful transmitted station equals to **CWmin**, we assume that **CW** decreases by ***b***, where **0 < b < 2**, thus ***CW = CW - b***.

Furthermore, we focused our work to select the best values for **a** and **b** according to the following four parameters: the position of the mobile (P), the type of the data (D), the urgency level (U), and the Load weight (L). So to obtain those best values a Neural Network function will be used in this modified method.

This paper is organized as the following: section 2 explains the basic access method Distributed Coordination Function (DCF), where section 3 states the problem of the DCF, in section 4 an explanation of the Radial basis function neural network (RBFNN) is presented, in section 5 the New BEB access method based on Neural Network is illustrated in addition to the comparison between the simulation results of both the basic DCF and the proposed method. Finally, section 6 highlights our conclusion and future work.

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2. Distributed coordination function (DCF)

DCF is the basic medium access in the IEEE 802.11 MAC protocol that allows for automatic medium sharing between compatible PHYs through the use of Carrier Sense Multiple Access with Collision Avoidance *(*CSMA/CA) and a random backoff time following a busy medium condition [2]. CSMA/CA is a "listen before talk" method of minimizing collisions between multiple stations exchanging data on the same medium. The network node checks to see if the transmission channel is idle before a data packet is sent. If the shared channel is determined to be busy, the station defers, else the transmission proceed, and it necessitates receiving back an ACK frame, otherwise it assumes the transmission failed or a collision occurred. Carrier sense attempts to avoid collisions by testing the signal strength in the vicinity of the transmitter. However, collisions occur at the receiver, not the transmitter; that is, it is the presence of two or more interfering signals at the receiver that constitutes a collision [1]. When a station senses, by using the Carrier Sense mechanism, a busy medium, or attempts to transmit again after a successful transmission, or fails in transmission, it selects a random backoff interval after a DIFS (DCF Interframe Space) duration. Where subsequently, it starts decreasing its value by a slot_time, till it reaches zero and that when it senses an idle medium, where on the other hand it freezes its value when it senses a busy medium. So the total time that the station must wait before it can transmit will be the sum of IFS time and backoff time. When multiple stations defers, the one that selects the smallest backoff interval will win the contention. To start the backoff procedure, the STA shall set its Backoff Timer to a random backoff time using the following equation [12]:

$$\textbf{Backoff\_time} = \textbf{rand}() * \textbf{Slot\_time}$$

Where **Slot_time** is a function of physical layer parameters, and **rand()** is a random function with a uniform distribution over the interval delimited by zero and CW.
CW is an integer within the range of values of the physical layer $\mathbf{CW_{min}} \leq \mathbf{CW} \leq \mathbf{CW_{max}}$, it resets to CW_{min} after successful transmission and its value increments after each transmission failure thus, $CW = 2^n * CW$, and it keeps increasing up until it reaches $\mathbf{CW_{max}}$. The **Mealy** graph representing the BEB method is illustrated in **Fig. 1**.
Heavy network load causes downgraded performance in the system and that is due to the increasing number of contending stations. In this case, the backoff interval will increment to minimize the collision probability for those contending flows, keeping in mind that large values of backoff may strongly limit the throughput of fewer backlogged flows. In contrast, light network load shows better performance due to the decreasing value of the backoff intervals which reduces the spacing between successive frame transmissions.

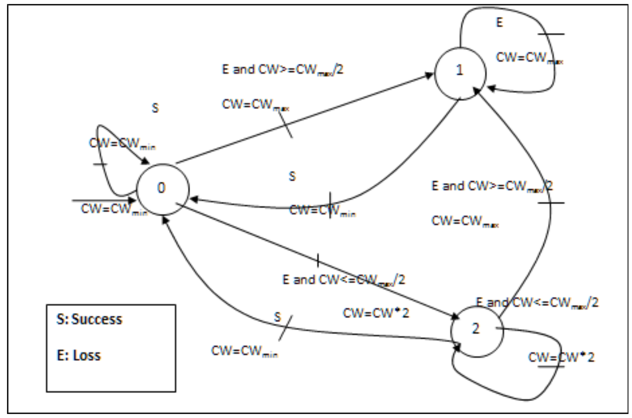

Fig. 1 Mealy graph of the standard BEB

3. Problem of Distributed Coordination Function (DCF)

The adoption of the exponential backoff technique leads to throughput performance strongly dependent on the initial backoff window size and on the number of terminals considered in the network [2]. Delay in time and low performance in throughput can be caused by the errors that occur_due to a collision between frames, or a failure in transmitting either data frame or ACK frame. Additionally, for a certain number of competing stations, different CWmins would lead to great discrepancy of throughput performance. [11]. Fair and effcient medium access is a fundamental problem in wireless networks [10], so the main inefficiency of the DCF mechanism is the consequence of frequent collisions and the entailed wasted idle slots caused by backoff intervals associated to each contention stage. In fact, there are two major factors affecting the throughput performances in the IEEE 802.11: transmission collisions and the idle periods introduced by the spreading of accesses [9]. In order to optimize the channel utilization, the access protocol should balance these two conflicting costs by adopting a binary exponential backoff protocol. IEEE 802.11 backoff mechanism has two main drawbacks **[**3**]:**

- The increase of CW size is obtained paying the cost of a collision,
- After a successful transmission, no state information indicating the actual contention level is maintained.

First case is when a collision occurs; the priority to access the channel will be given to one of the remaining

contending stations based on its smaller backoff time interval.
In the second case, *CW* for the transmitting station will be equal to *CWmin*, as long as it is transmitting successfully; as a result, this keeps a priority for this station to access the channel, while on the other side a delay on transmission will arise for the other contending stations.
Based on those two drawbacks, we observe that the nodes with smaller *CW* have more chances to get access to the medium and after a successful transmission its priority to access the medium raises. This issue affects the performance of the CSMA/CA protocol and causes a delay in time.

4. Radial Basis Function Neural Network (RBFNN)

4.1 Artificial neural network: a brief overview

An artificial Neural Network (ANN) [5] is a highly parallel distributed network of connected processing units called neurons. It is motivated by the human brain which is a highly complex, nonlinear and parallel computer. The network has a series of external inputs and outputs which take or supply information to the surrounding environment. Parameters of the network are used to store knowledge acquired from the environment. Learning is achieved by adjusting these parameters in accordance with a learning algorithm. In general, the neural network derives its computing power from, first, the massively parallel distributed structure, and second, its ability to learn and generalize. Generalization is producing reasonable outputs for the inputs not encountered during training. These two information capabilities make it possible for the neural network to solve complex problems.
One of the most used kinds of neural networks is the radial basis function neural network (RBFNN). RBFNN networks have been applied successfully to solve some difficult diverse problems, especially in learning nonlinear multidimensional functions, by training them in a supervised manner with a highly popular algorithm known as the gradient descent algorithm.

4.2 RBF neural network structure

Fig. 2 shows the structure of a typical RBFNN [5], the activation function for the hidden layer is a radial and symmetric Gaussian function (Eq. (2)). The *k*th ($1 \leq k \leq q$) output of the RBFNN is:

$$y_k(X_j) = \sum_{i=1}^{h} w_{ki}\, \emptyset_i(X_j) \quad (1)$$

$$\phi_i(X_j) = e^{-\frac{\|X_j - T_i\|^2}{\sigma_i^2}} \quad (2)$$

Where X_j is the *j*th input vector of the RBFNN. $T_i = (t_{i1}, t_{i2}, \dots, t_{ip})^T$ is the center vector of the *i*th hidden neuron and σ_i is the width parameter of this hidden neuron which is related to the spread of this function around its center. All the network parameters (w_{ki}, t_{il}, σ_i) must be adapted on the training data.

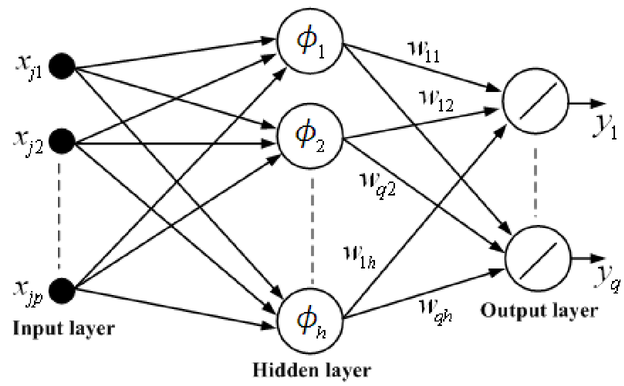

Fig. 2 Structure of RBF neural network

4.3 Learning algorithm

The training procedure of the RBFNN consists in determining the centers of the hidden neurons by an unsupervised technique and the weights of connections of the hidden-output layer and the width parameters by a supervised technique.
The fact that the performance of an RBFNN critically depends upon the chosen centers, we proposed to implement a non-supervised standard algorithm the rival penalized competitive learning algorithm [14] to best determine the centers of the hidden activation functions.
Training the RBFNN is to determine $\alpha = \{w_{ki}, t_{il}, \sigma_i\}$ $(k = 1, \dots, q, l = 1, \dots, p,$ $i = 1, \dots, h)$ such that the error function $MSE(\alpha)$ (mean squared error) represented by Eq. (3) is minimized.

$$MSE(\alpha) = \frac{1}{N} \sum_{j=1}^{N} e_j^2 \quad (3)$$

and

$$e_j = \frac{1}{2} \sum_{k=1}^{q} (y_k(j) - y_{dk}(j))^2 \quad (4)$$

N is the number of training inputs, $y_{dk}(j)$ is the kth element of the desired output vector $Y_d(j) = \left(y_{d1}, y_{d2}, \dots, y_{dq}\right)^T$ corresponding to the jth training input and $y_k(j)$ is the kth element of the calculated output vector $Y(j) = \left(y_1, y_2, \dots, y_q\right)^T$ of the RBFNN. Here the variables to be optimized are the parameters in vector α.

The training of the RBFNN was done by epoch, where every epoch contains N training inputs. After every epoch, the rival penalized algorithm is executed to choose the pertinent set of centers. Then the width parameters are calculated according to simple formula presented in [7]. It is only a rough guide that provides a starting point for the width calculation by the training algorithm. At every training input, a gradient descent algorithm [8] is used iteratively to train the weights of different connections and the width parameters in the opposite direction of the respective partial derivative of the error. The nth correction of these parameters is described as:

$$w_{ki}(n+1) = w_{ki}(n) - \eta \frac{\partial e_j}{\partial w_{ki}} \quad (5)$$

$$\sigma_i(n+1) = \sigma_i(n) - \eta \frac{\partial e_j}{\partial \sigma_i} \quad (6)$$

Where η is the learning parameter and $i = 1, \dots, h,\ k = 1, \dots, q,\ j = 1, \dots, N$.

5. New BEB access method based on Neural Network

Frames in DCF are unsuitable for real-time applications for not having priorities. The authors in **[5],** for instance**,** proposed a modified CSMA/CA protocol method by supporting station priorities along with the real time applications in an ad hoc network. This method is divided into two parts: shorter IFS and shorter random backoff time for higher priority stations. However, in this paper, we ignored the IFS and focus our work on giving priorities for the contending stations based on the inputs of the 4 parameters that are mentioned below.

5.1 Description of the Method

In our proposed method each mobile is characterized by four parameters:

- ***Position*** **(P):** is the position of the mobile with respect to the path in the industry. When there is an intersection point between two paths in a zone then we give a higher priority for the mobile that is nearer to the intersection point; **P**=0 for high priority and **P**=1 for a low priority.
- ***Data Type*** **(D):** specify the type of the data that will be send, two types of data exists: *voice and audio* form a single type with high priority (**D**=0) and *data* is the second type with a low priority (**D**=1).
- ***Urgency*** **(U):** the urgency will be specified by the administrator based on the mobile mission. Urgency will be on two priority level, **U**=0 for high, and **U**=1 for low.
- ***Load*** **(L):** indicates the load (in packets/sec) put on the Access Point while transmitting; our testing took place using the following load weights 20, 40, 60, 80, 100, and 120 packets per second, where packet size is 512 bytes.

This novel method is based on the DCF concept where it uses CSMA/CA, but instead of having **CW*2** when a collision occurs as in standard, it is equal to **CW*a** when transmitting fails, and it's equal to **CW-b** in terms of successful transmission. ***a*** and ***b*** are selected by calling the neural network function. In [4] a distributed algorithm is proposed an enhanced protocol which enables each station to tune its backoff algorithm at run-time, since appropriate tuning of the backoff algorithm can drive the IEEE 802.1 1 protocol close to its theoretical limits. Therefore, we put some effort in order to get best values for **a** and **b** to adjust the backoff value based on the 4 parameters for the sake of having better performance in a real-time testing. Accordingly, when multiplying ***CW*** by ***a***, $0 < a < 2$, it will increase but its chance to reach $\mathbf{CW_{max}}$ take longer than that in standard BEB where it's multiplied by 2 sequentially after each collision. As a result the mobile that chooses a backoff time with **CW*a** will still able to send data paying less cost of a collision.

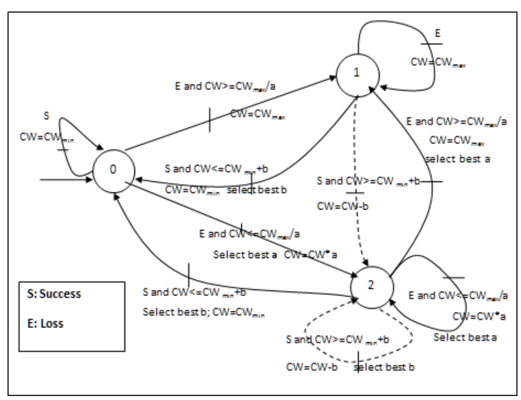

Fig. 3 Mealy Graph describe our method in case of success and collision

When a mobile success in transmitting data, CW will be subtracted by ***b*, *0*< *b* <*2*,** in this case CW will not fall down to **CW_{min}** as in BEB standard where it keeps having the priority among other contending mobile, but decreasing CW by ***b*** will increase the priority for other contending mobiles to send.

The **Mealy** graph representing the enhanced BEB method is illustrated in Fig. 3.

5.2 Bloc Diagram of the New Method

Fig. 4 shows the bloc diagram of the new BEB method

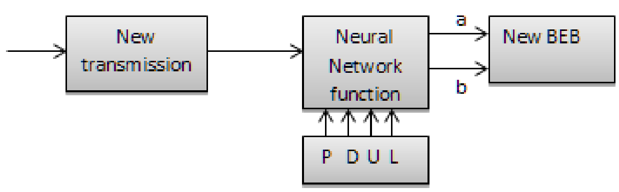

Fig. 4 Bloc Diagram of the New BEB Method

5.3 Objective of the simulation

In our enhanced method, and as described in the above sections, we want to minimize the delay time of BEB between two mobiles exchanging data in an industrial cell. Therefore, in case of collision we multiply CW by ***a*,** and in case of successful transmission we subtract ***b*** from CW. Thus, to select the right values of **a** and **b, we** use a neural network function. The values of ***a*** and ***b*** relay on the values of inputs entered to the neural network. ***a*** and ***b*** are considered as the main output parameters that the mobile station will take into consideration to transmit data avoiding collision.

5.4 Adopted RBFNN network model

A-RBFNN network model structure

The input vector of our RBFNN network consists of four parameters: position, data type, urgency and load. The output vector consists of two outputs: ***a*** and ***b***. The RBFNN model is then composed of an input layer with four inputs, one hidden layer with 6 hidden neurons and an output layer with two output neurons (Fig. 5).

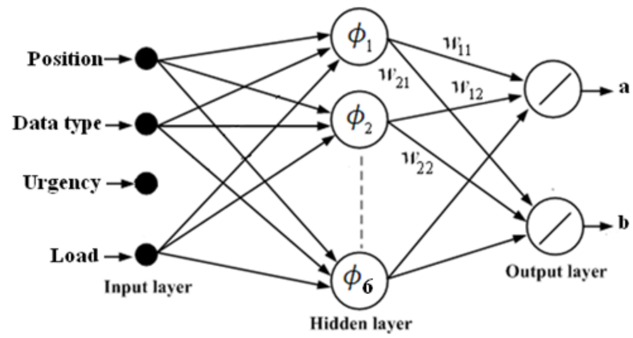

Fig. 5 Structure of the RBFNN adopted network.

B-Training data set and training procedure

Table 1 lists the ranges of input and output parameters of the RBFNN network used to generate the training procedure. The training data set contains 48 samples, each sample is represented by the following vector: *(Position, Data type, Urgency, Load, a, b)^T*.

Table 1: Training parameters ranges

Parameter	**Type**	**Range**
Position	Input	[0,1]
Data type	Input	[0,1]
Urgency	Input	[0,1]
Load	Input	[20,120]
a	Output	[1,2]
b	Output	[1,2]

When the training set is prepared, the RBFNN network is trained by the gradient descent algorithm. In Fig. 6, the mean squared error is plotted as a function of the number of iterations.

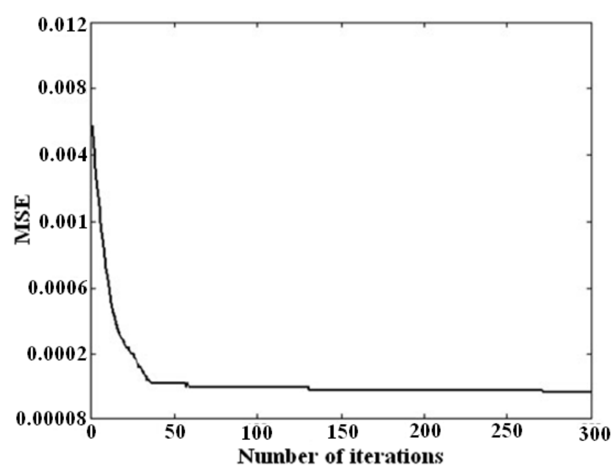

Fig. 6 MSE as a function of the number of iterations

5.5 Simulation of the enhanced industrial Backoff method and comparison with the basic method

A- Simulation Model

The simulation model consists of several mobiles connected to an Access Point (AP) as represented in Fig. 7.

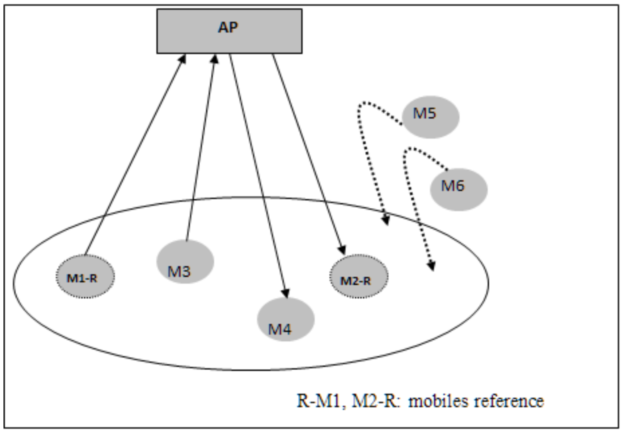

Fig. 7 Simulation model

B- Simulation Scenario

We had two reference mobiles moving in an AP cell. We increased the network load periodically by either increasing the emission frequency between mobiles moving in this cell or by introducing a new communicated pairs of mobiles (see Fig. 7). At each period we show the delay between the two reference mobiles.
If D is the transmission delay between the mobile references, it can be defined as the time between sending the message and the time corresponding to receive this message by the mobile receiver T_{rec}, thus, D =Max (T_{rec} – T_{tran}).
Note that the delay time depends on the output parameters ***a*** and ***b***, where ***a*** and ***b*** are the results given by the Neural Network function which will be called at each communication between the two reference mobiles according to the four input parameters P, D, U and L.

C- Results

The results shown in Fig. 8 and Fig. 9 represent the delay time between the two references mobiles in accordance to the load of the network. While comparing the results we got from both the new method and the standard BEB method, we can observe the big difference in the time delay between them; the enhanced method that calls the neural network function perform a very low time delay as compared to the standard BEB method, particularly when the load exceeds 80 packets/sec (Fig. 9).

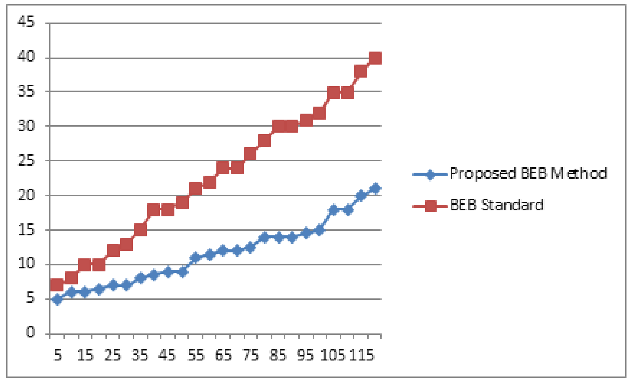

Fig. 8 delay of transmission between the two-reference mobiles when the load is less than 120 packets/sec.

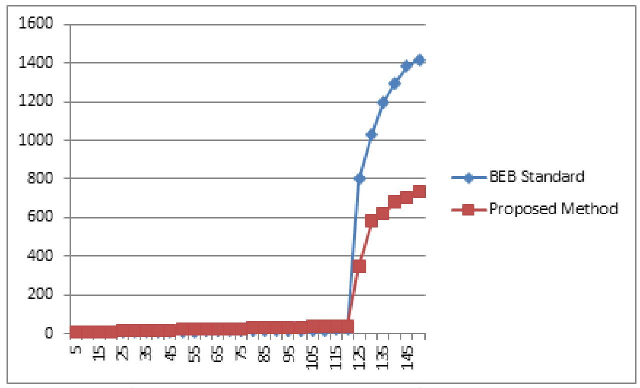

Fig. 9 delay of transmission between the two reference mobiles when the load exceeds 120 packets/sec.

6. Conclusion

In Conclusion, DCF standard model has some problems when it comes to time delay caused by collisions or by alternative success. A new method was proposed in order to decrease the time delay where *CW* is multiplied by **a** instead of 2 when a collision occurs and subtract **b** when a transmission successes. For more accuracy results, an Artificial Neural Network function known as Radial Basis Function Neural Network (RBFNN) was applied successfully to select the best values of **a** and **b**. The advantages of this method is that before each communication process we choose the values of ***a*** and ***b*** according to the real time position, urgency of mobiles, data type, and load of network, however, in BEB method the values of ***a*** and ***b*** are fixed on 2 and the CW are fixed on CW_{min} .
After several simulations had been done in NS2 based on the learned parameters, employment of Neural Network Function for the modified BEB showed better performance where the time delay it shows is smaller comparing to that of the basic BEB method.

The future work will be focused on improving the performance of this modified method by finding the best IFS for each mobile based on its priority level.

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