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Quality of Service in IEEE 802.11ac and 802.11n Wireless Protocols with Applications in Medical Environments

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Abstract: Wireless computer networks are increasingly important as reliable means of communication in medical environments. Evaluation of Quality of Service (QoS) in wireless computer networks deployed in medical environments can improve network performance and enhance utilization of resources. In this study, the QoS offered by IEEE 802.11n and IEEE 802.11ac wireless protocols was evaluated and compared using multiple point-to-point links for Voice Over Internet Protocol (VoIP) traffic. QoS was evaluated based on Predictive Statistical Diagnosis (PSD) and Probabilistic Neural Network (PNN). PSD and PNN based QoS evaluation methods categorized the VoIP packets into low, medium and high QoS types based on the packets' transmission delay, jitter, and percentage packet loss ratio. Both PSD and PNN allowed QoS for VoIP to be quantified accurately. It was shown that 802.11ac provides a higher QoS for VoIP transmission as compared with IEEE 802.11n. The devised methods can be used in medical environments for evaluation of wireless networks' QoS.

Keywords: Quality of service; wireless computer networks; Wi-Fi; 802.11ac; 802.11n; probabilistic neural networks; Bayesian.

1 Introduction

Growing use of devices and applications that rely on wireless computer networks in the medical field has provided opportunities and challenges. Wireless devices and technologies have been beneficial in the way patients are looked after and have allowed them to be more independent in the daily lives. They made it possible for mobile working where medical staff are less constrained to be at their desks or to carry around patients' medical paper records during patients' visits [1][2]. The technology has enabled clinicians to incorporate new medical observations into the patients' records that are in turn immediately accessible to other staff. Wireless technologies allow some patients that would be kept in hospitals to be discharged earlier and to be remotely monitored in their homes through wireless sensors attached to them or placed around their homes. To facilitate these effectively, the performance of the associated wireless networks needs to meet the expected high standard. In order to determine the compliance of the networks to these standards, suitable tools that indicate their performance or quality of service (QoS) are needed. There are many studies investigating QoS for e-health networks and communications. It has been shown that an improvement in the QoS of the Internet of Things (IoT) can lead to enhanced communication in e-health applications [3]. QoS requirements for achieving reliability in rescue vehicles that involves paramedic assistance [4] and intelligent control of the network topology [5] were reported. Other related QoS issues were reported in several studies, e.g. [6][7].

To handle the demand for Wi-Fi, IEEE introduced further standards with improved performance such as IEEE 802.11g and IEEE 802.11n that provided a throughput rate up to 450 Mbps [8][9].The latest IEEE standard in the WLANs is 802.11ac. It is designed to improve 802.11n bandwidth utilization and throughput rate by incorporating extended multiple wireless signals and antennas, resulting in a larger multiple input/multiple output (MIMO) communication environment that supports up to 8 streams. The channel bandwidth in 802.11ac is up to 80 MHz while the maximum channel bandwidth in 802.11n is 40 MHz [10][11]. IEEE 802.11ac standard operates in the 5 GHz band. After a period Wi-Fi operating in 2.4 GHz bands, their limitations became apparent, mainly due to interference. Interference between 2.4 GHz neighbors can reduce the network performance [8][9].

A number of studies reported QoS evaluation in multimedia wireless networks based on fuzzy logic and neural networks [12][13]. Neural networks were used to analyze and evaluate overall QoS for Voice over Internet Protocol (VoIP) traffic using networks simulated in a package called NS-2 [12]. The traffic parameters were initially classified into three types of QoS by an unsupervised learning Kohonen neural network. The results were then further processed by a supervised learning neural network called multilayer perceptron (MLP) to determine the overall QoS. The QoS measure obtained by the approach was compared with other QoS evaluation techniques that used fuzzy logic and regression modelling [12]. Fuzzy c-means clustering and Kohonen neural network were compared for their effectiveness to classify QoS into high, medium and low types for real time VoIP traffic [13]. The study also used fuzzy inference system (FIS), multilayer perceptron (MLP) and linear regression to quantify overall QoS for real time applications such as VoIP. However, these studies did not evaluate multiple Wi-Fi protocols such as IEEE 802.11ac and 802.11n. QoS assessments methods reported in studies [12][13] were based on either fuzzy c-means, Kohonen neural network, fuzzy inference system (FIS) or MLP. These methods have a number of shortcomings. For example, the FIS approach requires the user to develop the rules for the method's knowledge base and determine the types and parameters of the membership functions for its inputs and outputs. The rules and membership functions' parameters are specific to each particular application. MLP and Kohonen neural networks need careful training to ensure effective generalization [12]. MLP also requires a careful determination of the number of neurons in its hidden layer(s) to avoid overfitting or poor generalization. Kohonen output is a grid of neurons' (map) that requires interpretation to determine the boundary between individual clusters. The performance evaluations carried out in some studies such as [9][14] were not aimed at measuring overall QoS classification and its variation to traffic change.

In this study, QoS provided by IEEE 802.11ac (80 MHz channel bandwidth) and IEEE 802.11n (20 and 40 MHz bandwidths) wireless standards for VoIP traffic was compared using physical networks. The evolution of QoS considered scenarios that gradually increased the number of point to point (PPP) links between two access points. A Bayesian based method called predictive statistical diagnosis (PSD) and a probabilistic Neural Network (PNN) were developed to determine and quantify QoS for VoIP. These approaches were chosen because they are robust and their operations are not computationally intensive making them suitable for real-time operations.

2 Bayesian theory

Bayesian statistics is a supervised learning classification technique that utilizes probability to deal with uncertainty in information. Bayesian classification allows *apriori* information about the data to be used as part of classification [15][16][17]. It determines unknown events by considering the knowledge of known events, i.e.

$$P(h|e) = \frac{P(e|h)P(h)}{P(e)} \tag{1}$$

where $p(h)$ is the prior probability of hypothesis h, $p(e)$ is the prior probability of evidence e, $p(e|h)$ is the probability of e given h and $p(h|e)$ is the probability of h given e. Using Bayes' theorem the probability that a feature vector $\boldsymbol{X}$ with parameter vector $\boldsymbol{\theta}$ is assigned to a class of type t_1 is given by

$$P(t_1|\boldsymbol{X},\boldsymbol{\theta}) = \frac{P(t_1)P(\boldsymbol{X}|t_1,\boldsymbol{\theta})}{P(\boldsymbol{X})} \tag{2}$$

where $p(t_1)$ is the prior probability of type t_1, $p(\boldsymbol{X}|t_1,\boldsymbol{\theta})$ is the probability density function of $\boldsymbol{X}$ for a given type t_1 and n is number of types. The sum of the probabilities is

$$P(\boldsymbol{X}) = \sum_{t=t_1}^{t=t_n} P(\boldsymbol{X}|t,\boldsymbol{\theta})\, P(t) \tag{3}$$

Equation 2 can expressed as [18],

$$P(t_1|\boldsymbol{X},\boldsymbol{\theta}) = \frac{P(t_1)P(\boldsymbol{X}|t_1,\boldsymbol{\theta})}{\sum_{t=t_1}^{t=t_n} P(\boldsymbol{X}|t,\boldsymbol{\theta})P(t)} \tag{4}$$

The parameter $\boldsymbol{\theta}$ is unavailable however the calibration data set ($\boldsymbol{Z}$) is available. To utilize $\boldsymbol{Z}$, $p(\boldsymbol{X}|t,\boldsymbol{\theta})$ is replaced by $q(\boldsymbol{X}|t,\boldsymbol{Z})$ [15], where

$$q(\boldsymbol{X}|t,\boldsymbol{Z}) = \int_{\boldsymbol{\theta}} P(\boldsymbol{X}|t,\boldsymbol{\theta})\, P(\boldsymbol{\theta}|\boldsymbol{Z})\, d\boldsymbol{\theta} \tag{5}$$

Equation 4 then is rewritten as [18]

$$P(t_1|\boldsymbol{X},\boldsymbol{\theta}) = \frac{P(t_1)q(\boldsymbol{X}|t_1,\boldsymbol{Z})}{\sum_{t=t_1}^{tn} P(t)q(\boldsymbol{X}|t,\boldsymbol{Z})} \tag{6}$$

Equation 6 is the predictive density function for an observation $\boldsymbol{X}$ on a case of type t measured on the calibration data $\boldsymbol{Z}$. The right-hand side of equation 5 is evaluated by using

$$q(\boldsymbol{X}|t,\boldsymbol{Z}) = \boldsymbol{St}_d(v_t, \boldsymbol{m_t}, \left\{1 + \frac{1}{n_t}\right\}\boldsymbol{S}_t) \tag{7}$$

where there are n_t cases of type t with observation vectors $\boldsymbol{x}_1, \boldsymbol{x}_2..., \boldsymbol{x}_{nt}$; $\boldsymbol{v}_t$ is the degree of freedom (given by n_t - 1), $\boldsymbol{m}_t$ is the mean vector of the input features and $\boldsymbol{S}_t$ is the covariance matrix. $\boldsymbol{St}_d$ is a d-dimensional student-type density function defined as

$$\boldsymbol{St}_d(v,\boldsymbol{b},c) = \frac{\Gamma[0.5(v+1)]}{\pi^{0.5d}\{[0.5(v-d+1)]\}\,|vc|^{0.5}}\, x\, \frac{1}{[1+(\boldsymbol{X}-\boldsymbol{b})^T(vc)^{-1}\,(\boldsymbol{X}-\boldsymbol{b})]^{0.5(v+1)}} \tag{8}$$

where Γ is the gamma function. By using equation 8, the unknown $p(\boldsymbol{X}|t,\boldsymbol{\theta})$ can be determined for the case of known types. To obtain the probabilities for the test or evaluation data set, equation 8 uses the observation vector $\boldsymbol{X}$ for the cases of known type but retains the mean ($\boldsymbol{m}_i$) and covariance matrices ($\boldsymbol{S}_i$) (i.e. calibration information) for the classification of cases whose types are unknown. This Bayesian based approach is known as Predictive Statistical Diagnosis (PSD) and it will be an approach used in this study to classify network parameters (i.e delay, jitter and %PLR) to three QoS categories as Good, Medium and Low types. PSD has been successfully used for data classification before [18]. The second data classification used in this study is probabilistic neural network (PNN) and was included to allow comparison of their QoS effectiveness.

3 Probabilistic Neural Network (PNN)

PNN introduced by Specht [19] uses a supervised learning algorithm and therefore during its training, representative examples of each data types and their respective categories (types) are required. PNN is based on a statistical approach called kernel discriminate analysis and it is predominantly a classifier. It uses the training examples of known types to alter the approximated distribution functions to best describe its input data [20]. Advantages of PNN include fast training, an essentially parallel structure, and certain convergence to an optimal classifier as number of training examples is increased. PNN is associated to Bayes classification theory [19] and Parzen nonparametric probability density function estimation theory [20]. PNN architecture has four layers referred to as the input, pattern, summation and output as shown in Figure 1.

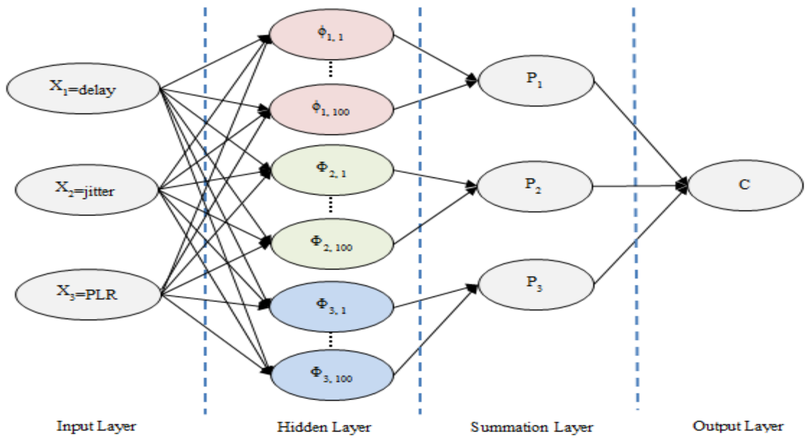


Fig.1 Architecture of a probabilistic neural network

An input data vector (***X***) is fed to the *n* input neurons. The input layer forwards the inputs to the neurons in the pattern layer, dividing them into *k* categories, a category for each classification grouping. The neurons in the pattern layer use a Gaussian kernel to determine their outputs of an input pattern ***X*** from the input layer as

$$\varphi_{k,i}(x) = \sum_{i=1}^{M_k} w_{ki}\, \varphi_{k,i}(x) \quad k = 1, \dots, number\ of\ groups\ (classes) \tag{9}$$

$$\varphi_{k,i} = \frac{1}{(2\pi\sigma^2)^{n/2}} exp\left(\frac{\|x - x_{k,i}\|^2}{2\sigma^2}\right) \tag{10}$$

where $x_{ki} \in R^n$ is the center of the kernel, and σ is known as the smoothing or spread parameter. It sets the size of the kernel receptive field. The summation layer sums the outputs from the neurons associated with each class type and indicates the probabilities for an input data to belong the predefined categories as

$$p_k(x) = \sum_{i=1}^{M_k} w_{k,i}\, \varphi_{ki}(x) \quad k = 1, \dots, number\ of\ groups\ (classes) \tag{11}$$

where M_k is the number of neurons in the pattern layer for class *k*, and $w_{k,i}$ are positive coefficients satisfying $\sum_{i=1}^{M_k} w_{k,i} = 1$. The neuron at the output layer determines the category or type of the input vector (*x*) based on Bayes' decision rule and using the information from the neurons in the summation layer, i.e.

$$c(x) = \arg max_1 \ll k \gg k(p_k) \tag{12}$$

The smoothing (spread) parameter needs to be stated at the start of the training process. PNN was used in this study to process delay, jitter and %PLR and classify packets into Good, Medium and Low QoS types.

4 Methodology

The experiment was based on a network laboratory (area 4 m× 6 m) consisting of two wireless access points and 20 PCs. The design supported 10 point-to-point (PPP) links involving 20 PCs that communicated via access point 1 (AP-1) and access point 2 (AP-2) as shown in Figure 2. The setup gave flexibility of testing for different traffic conditions. The traffic associated with the established PPP links was captured and processed by Bayesian and PNN models to evaluate and compare the performance of 802.11n (20/40 MHz) and 802.11ac protocols.

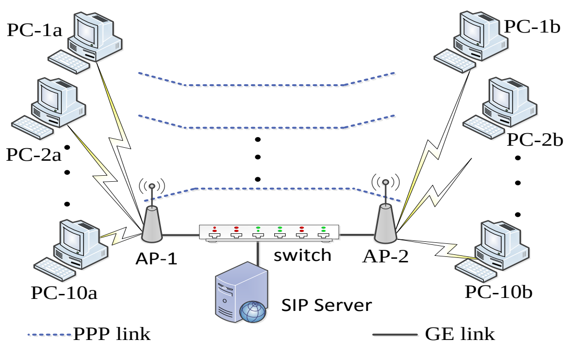


Fig.2 Network layout used in the study

The access points were of type Cisco© AIR-AP1852E. These supported IEEE 802.11 g/n/ac protocols. Cisco© catalyst 3560-CX switch was used to connect the APs and Session Initiation Protocol (SIP) server via 1 Gbps links. On the PC side, wireless adaptors of Linksys© AC1200 were used in all scenarios. [14]. VoIP connectivity was established by SIP server. SIP Softphones ran over the Windows© PC providing SIP VoIP sessions. Real time protocol (RTP) used packet size of 160 bytes and G711a protocol for audio CODEC.

Initially one to one PC PPP link was established between PC-1a and PC-1b. The traffic included HD video, VoIP and TCP traffic. Following this test, the number of PPP links was increased to three PCs in each side. PC-1a connected to PC-1b, PC-2a connected to PC-2b and PC-3a connected to PC-3b (i.e. 3 PPP links) at 2 minutes from the start of the transmission. Data packets were captured from the same two computers. Then the number of PPP links was in turn increased to 5, 7 and 10 PCs in each side at times 4, 6, and 8 minutes from the start of the transmission, the transmission ended at 10 minutes. The tests investigated the network behavior and QoS by increasing PPP links between AP-1 and AP-2. Each PC that connected to AP-1 (i.e. PC-1a to PC-10a) in these PPP links transmitted the same traffic that included HD video, VoIP and TCP to its peer PC connected to AP-2. The traffic was sent simultaneously. The manner of increasing the number of PPP links at every two minutes was by manual configuration of the PCs connected to the AP-1 to send traffic to its counter PCs connected to AP-2 as indicated in Table 1.

TABLE 1. Communication timing and the number of links

Time (minutes)	Number of PPP links
0-2	1
2-4	3
4-6	5
6-8	7
8-10	10

Wireshark traffic monitoring tool [21] was installed on PC-1a that was connected to AP-1 and PC-1b that in turn was connected to AP-2 to capture packets. Wireshark captured packets based on protocol type or number such as RTP. The captured packets were processed to determine network end-end delay, jitter and %PLR [15] to quantify overall QoS.

In order to obtain QoS performance for the two wireless standards i.e. 802.11n/ac, one channel was used for IEEE 802.11n (20 MHz bandwidth) in first scenario, then two channels were used for 802.11n (40 MHz). For IEEE 802.11ac, one channel was configured with (80 MHz). Table 2 summarizes wireless channels bandwidth, frequencies and maximum physical data rate.

TABLE 2. IEEE 802.11 standards, frequency and channel bandwidth used in the study

Protocol	Frequency (GHz)	Channel width (MHz)	Maximum data rate (Mbps)	Modulation and Coding Scheme
802.11n	2.4	20	65	7 (1 Spatial stream)
802.11n	2.4	40	135	7 (1 Spatial stream)
802.11ac	5	60	325	7 (1 Spatial stream)

4.1 The operations for both the Bayesian and PNN were:

A. Wireshark was used to capture VoIP traffic packets between PC-1a and PC-1b during all change of PPP links and their associated traffic from start until minute 10 which was the end of 10 PPP link traffic transmissions.
B. Delay, jitter and percentage packet loss ratio (%PLR) were determined. The delay (D_i) is the time taken for a packet to reach from its source to destination. Jitter (J_i) is the magnitude of variations in delay. The percentage packet loss ratio (%PLR_i) is the total number of lost packets compared to total number of sent packets [22].
C. QoS requirements of ITU for VoIP traffic applications were applied to calibrate the PNN and Bayesian methods (i.e. the training examples). A summary of these ITU recommended traffic bounds are:

- Good QoS: delay is less than 150 msec, jitter is less than 1 msec and %PLR is less than 2%.
- Medium QoS: delay is between 150-400 msec, jitter is between 1-3 msec and %PLR is between 2-4%
- Low QoS: delay is more than 400 msec or jitter is more than 3 msec or %PLR is more than 4% [13].

4.2 Bayesian model

The Bayesian technique processed delay, jitter and %PLR values for individual packets and produced an output indicating the QoS category. The algorithm for the Bayesian approach consisted of three parallel routes associated with low, medium and high QoS categories as shown in Figure 3. Three examples lists, one for each QoS type (low, medium and high), were prepared based on ITU recommendations of VoIP. Each list contains 300 examples and each example characterized different levels of delay, jitter and %PLR and the corresponding QoS. These were used to calibrate the Bayesian classifier. Figure 3 indicates the manner traffic measures were associated to each QoS type. When a packet strongly belonged to a class (e.g. low QoS, represented by BC1-route) then the associated probability was close to 1. The same operations are followed for BC-2 (medium QoS) and BC-3 (high QoS). BC-1 used the examples from the low and not low QoS list, BC-2 used the examples from the medium and not medium QoS list and BC-3 used the examples from the high and not high QoS list. Once the values from the paths BC-1, BC-2 and BC-3 were obtained, each received packet was classified to the QoS type associated with the largest value from the corresponding BC path. The results were mapped by values from 0 to 0.34 for packets classified through BC-1 path, 0.35 to 0.65 for packet classified through BC-2 path and 0.66 to 1 for packets classified through BC-3 path. The Bayesian Classifiers (BC-1, BC-2 and BC-3) have used equations number (7) where inputs values X are represented by delay, jitter and %PLR and Z vector represent the training data which contain 300 entry includes classified examples. The test file contained delay, jitter and %PLR for all received packets of 10 minutes transmission.

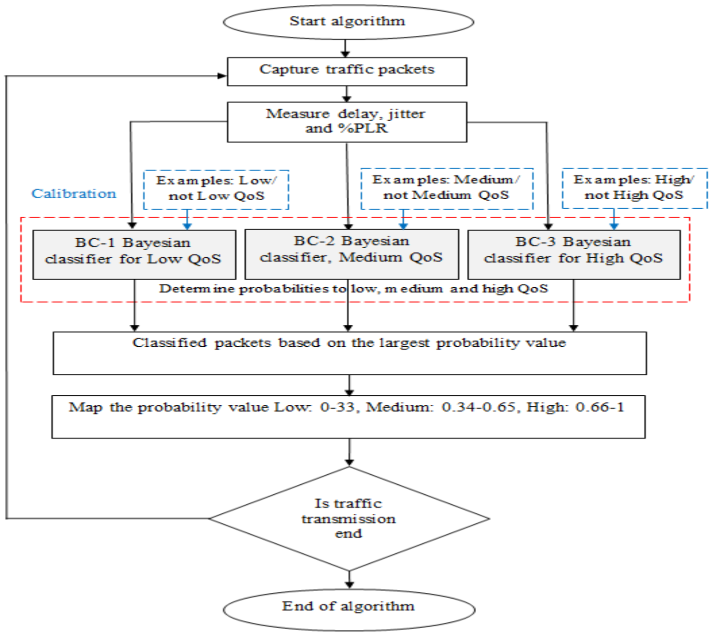


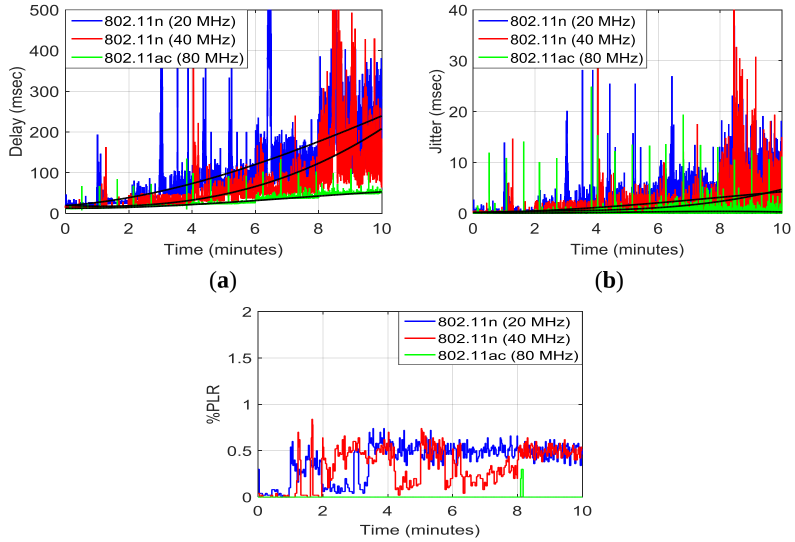
Fig.3 Flow chart for the Bayesian approach

4.3 PNN model

The PNN model shown in Figure 1 was used with three inputs, delay, jitter and %PLR. The training file contained 300 examples prepared based on ITU recommendations for VoIP transmission and each example characterized varied levels of delay, jitter and %PLR and their corresponding QoS (i.e. k=3, represent low, medium and high) include 100 examples per class (i.e. M=100). The test file contained delay, jitter and %PLR for all received packets for 10 minutes transmission. When the value of PNN spread parameter was near zero, the PNN acted as a nearest neighbor classifier. In this study the value of spread was chosen 0.01 by experimenting with different values and considering the performance on classifying the examples in the training file.

5 Results and Discussion

Figures 4 (a-c) show the traffic parameter values for the VoIP (i.e. delay, jitter and %PLR). Figures 4 (a) shows the delay values. For the IEEE 802.11n (20 MHz, shown in blue), the delay was 15 msec for 1 PPP link then the it increased to 100 msec for 5 PPP links and then reached the highest level at 230 msec for 10 links. It can be seen from the figure that there were more variations in delay for IEEE 802.11n (20 MHz) as compared to other two protocols. Figure 4 (a) shows delay for IEEE 802.11n (40 MHz, in red) for 1 PPP link. The delay was less than 14 msec and the highest delay was for 10 PPP links at 200 msec. Figures 4 (a) shows delay for 802.11ac (80 MHz, in green).The results show lowest delay, i.e. less than 10 msec for 1 PPP link and less than 20 msec for 5 PPP links and its maximum was 50 msec for 10 PPP links. The black colour plots in Figures 4(a-b) represent data trends obtained by third order polynomials. Figure 4 (b) shows the jitter measurement. For IEEE 802.11n (20 MHz, in blue), jitter was 0.01 msec for 1 PPP link, it increased to 1.2 msec for 5 links and 5 msec for 10 links. For IEEE 802.11n (40MHz, in red) a lower jitter in general was observed as compared to IEEE 802.11n for 1 link (i.e. less than 0.01 msec) and the highest jitter was for 10 links for 4 msec. For IEEE 802.11ac (80 MHz, shown in green), jitter was less than 0.008 msec for 1 link and increased to 1 msec for 5 links and the maximum was about 1.1 msec for 10 links. In general, jitter increased as the number of links increased between the two APs. IEEE 802.11ac showed lowest jitter and IEEE 802.11n (20 MHz) showed highest jitter and more fluctuations than others. Figure 4 (c) shows the results for %PLR. IEEE 802.11n (20 MHz, shown in blue) and IEEE 802.11n (40MHz, shown in red) both showed similar trends for %PLR with a larger %PLR for IEEE 802.11n (20 MHz) as compared with IEEE 802.11n (40 MHz). The IEEE 802.11ac showed lowest %PLR values close to zero, most of the time except, at minute 8 that showed %PLR equal to 0.2%.



(a) (b)

(c)

Fig. 4 (a) Delay (b) Jitter (c) %PLR

Figures 5 (a-f) show the overall QoS classification (packet by packet classification) for the Bayesian and PNN techniques. Figures 5 (a) and (b) show the QoS for IEEE 802.11n (20 MHz) for the Bayesian and PNN approaches respectively. In time period between 0 and 2 minutes with 1 PPP link established, most packets were classified as good QoS as throughput was low. The QoS decreased between medium and low starting at 4 minutes then fluctuated between high, medium and low as traffic increased steadily to the maximum in 10 links. Figures 5 (c) and (d) show the QoS of 802.11n (40 MHz) by Bayesian and PNN respectively. In time period between 0 and 2 minutes with 1 link established, most packets were classified as good QoS as traffic still low. QoS decreased between medium and high starting at 4 minutes where 5 links were established. This continued till minute 8 minutes when 10 links were established and QoS changed to low and medium till the end of transmission because of a large increase in the transmitting data. Figures 5 (e) and (f) show the QoS for IEEE 802.11ac (80 MHz) for 1 link where most packets were classified as good QoS . QoS changed between high and medium, starting from minute 8 where 10 links were established. However, most packets had high QoS. In general IEEE 802.11ac (80 MHz) provided improved operation as compared to IEEE 802.11n (20/40 MHz). Figures 5 (a-f) indicate that the QoS trends for 802.11n and 802.11ac have similar behavior, the QoS in general decreased as the number of PPP links increased. IEEE 802.11ac (80 MHz) shows improved results as compared with IEEE 802.11n (20/40 MHz) and IEEE 802.11n (40 MHz) shows higher performance than 802.11n (20 MHz) for VoIP traffic. A reason IEEE 802.11ac provided improved QoS performance as compared to IEEE 802.11n is that it is able to have a lower %PLR, lower delay and lower jitter which are main factor of VoIP traffic. Overall QoS classifications for the Bayesian and PNN provide consistent QoS classification.

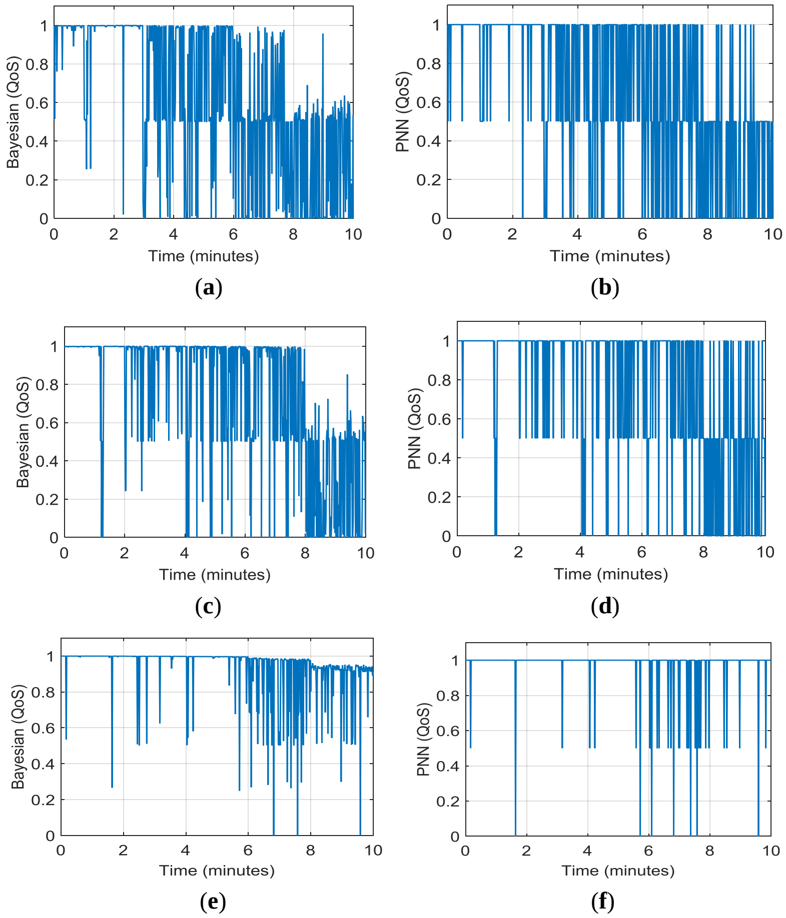


Fig. 5. QoS classification by Bayesian and PNN: (a) and (b) are for IEEE 802.11n (20 MHz), (c) and (d) are for 802.11n (40 MHz) and (e) and (f) are for IEEE 802.11ac (80 MHz)

6 Conclusions

This study developed innovative approaches to determine quality of service (QoS) in wireless computer networks that have applications in determining network performance in medical environments such as hospitals. Two methods of determining QoS were developed. One was based on probabilistic neural network (PNN) and the other used predictive statistical diagnosis (PSD). These were applied to evaluate QoS for Voice over Internet Protocol (VoIP) wirelessly transmitted using IEEE 802.11ac and IEEE 802.11n protocols. IEEE 802.11ac showed consistent behavior for delay, jitter and percentage packet loss ratio as the number of VoIP transmission links increased. Tests showed that jitter was the main traffic parameter that caused low and medium QoS for packets in IEEE 802.11ac. Both Bayesian and PNN approaches successfully classified VoIP packet into Low, Medium and High QoS categories and provided consistent results.

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