Statistical Analysis of Different Traffic Types Effect on QoS of Wireless Ad Hoc Networks

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Abstract

IEEE 802.11 based wireless ad hoc networks are highly appealing owing to their needless of infrastructures, ease and quick deployment and high availability. Vast variety of applications such as voice and video transmission over these types of networks need different network performances. In order to support quality of service for these applications, characterizing both packets arrival and available resources are essential. To address these issues we use Effective Bandwidth/Effective Capacity theory which expresses packet arrival and service model statistically. Effective Bandwidth asymptotically represents arrival traffic specifications using a single function. Also, Effective Capacity statistically describes service model of each node. Based on this theory, at first we modeled each node's service as an ON/OFF process. Then a new closed form of Effective Capacity is proposed which is a simple function and is dependent on a few parameters of the network. Afterward the performance of different traffic patterns such as constant bit rate, Poisson and Markov Modulated Poisson process are statistically evaluated in the case of both single and aggregate traffic modes. Using the proposed model we will show that traffic pattern affects QoS parameters even if all models have the same average packet arrival rate. We prove the accuracy of our model by a series of simulations which are run using NS2 simulator.

Keywords: Effective Bandwidth; Effective Capacity; Performance; CBR; Poisson; Markov Modulated Poisson Process.

1. Introduction

Recently, wireless ad hoc networks became popular, because of its low cost deployment, mobility support and high data rate. Based on these facts, different applications with different quality of service (QoS) requirements run over them. Lost sensitive applications such as web browsing and email and also time critical services, like voice and video traffics are examples of these applications. Providing an assured level of QoS for them need an accurate network performance evaluation.

IEEE 802.11 [1] is the accepted standard which is broadly used in wireless ad hoc networks. It has two major functions: Distributed Coordinate Function (DCF) and Point Coordinate Function (PCF). The former is the basic random access method that is used in both ad hoc and infrastructure wireless networks. PCF is an optional mode of IEEE 802.11 MAC layer that uses a centralized protocol.

In turn, DCF has two operation modes, Basic mode and RTS/CTS[1] mode. In DCF basic access scheme, the source node that has data frame to send, senses the channel and if it is idle (for more than DIFS[2] time), it transmits the frame. Otherwise, the transmission is postponed for a *back off* time which is a random interval uniformly distributed between $[0, cw]$ slot times where cw is the contention window size. A timer is set by that time and it decrements if the channel is idle and it freezes when the channel is busy. The source node commences to transmit if the *back off* timer becomes zero.

Performance evaluation of wireless ad hoc networks has been studied by researchers by simulation or analytical analysis. The majority of studies are under saturated circumstance which means that every node always has a packet to send. Under that condition, traffic characteristics such as inter arrival time and packet burstiness are not taken into account.

Bianchi [2] proposed a two dimensional Markov model under saturation condition. He computed the collision probability, and evaluated the throughput as a QoS parameter. Apart from his work, the average packet

[1] Request To Send/Clear To Send

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[2] DCF Interframe Space

delay is analyzed under saturation condition in [3], [4] and [5]. Since, the majority of internet applications exhibit ON/OFF characteristics [6], saturation condition is not a perfect model for this type of traffic. Assuming Poisson process as packet arrival model, [6-8] consider unsaturated condition by adding an idle state to Bianchi's Markov model.

Ref. [9] argues that internet traffic packet arrival properties and its distribution differ from Poisson process, so it is better modeled by self-similar processes. These processes are not easily applicable and tractable in Markov model due to its complexity.

Moreover, the Markov model only considers the average values of QoS parameters that might not be efficient for time critical multimedia applications [10]. In order to consider QoS boundaries, statistical performance analysis is proposed. Based on this approach, the most important QoS metrics will be the probabilities of exceeding a predefined delay and buffer size bound. Effective Bandwidth/Effective Capacity is an asymptotic statistical approach with sufficient accuracy for our purposes.

For different traffic models such as Constant Bit Rate (CBR), Poisson and Markov Modulated Poisson process effective bandwidth function is introduced. The Effective bandwidth theory characterizes traffic specification using a single function. It quantifies the service rate in order to have a specific queue overflow probability when random traffic is serving. Ref. [11] provides detailed information about it. On the contrary, Effective Capacity specifies queue overflow probability in the case of time varying service rate when constant bit rate traffic is serving. Wu and Negi [12] show that Effective Capacity is the dual of Effective Bandwidth. They proposed new Effective Capacity model for a wireless fading channel and introduced an accurate estimation algorithm to compute Effective Capacity. It should be noted that the proposed model in [12] does not consider multiple access, and all results are reported for a network consists of two nodes.

Assuming Markov Modulated Poisson Process (MMPP) as service model, [10] presented Effective Capacity for an IEEE 802.11 DCF shared channel. The proposed Effective Capacity is derived due to the duality between the Effective Bandwidth and the Effective Capacity. One of the disadvantages of the proposed model is that the derived Effective Capacity does not have a closed form function and it should be solved numerically. Also, traffic load affects the accuracy of the model.

Kafetzakis et al. [13] assumed an IEEE 802.11 station as an On/Off Semi-Markovian bursty server and derived the Effective Capacity which is suitable for highly loaded WLAN. However, for unsaturated condition, their approach needs to measure many extra parameters in order to examine Effective Capacity. Moreover, in order to apply their model in call admission control protocols, exchanging many extra signalings are needed.

In this paper, each node is assumed as an ON/OFF process model. During the ON time, the node has full access to the channel and transmits its packets with the maximum channel rate. This duration depends on the packet size and the channel data rate. However, during the OFF time, the node that has a data frame ready to be sent in its buffer waits until it senses the channel as idle. The OFF interval depends on the number of active nodes in the network, their traffic patterns, collision probability, minimum contention window etc. Based on these assumptions, the proposed Effective Bandwidth for ON/OFF process in [14] and its duality introduced in [12], we propose a novel Effective Capacity model that uses a few parameters, for IEEE 802.11 ad hoc networks. Unlike the proposed models in [10] and [13], the introduced Effective Capacity is closed form that depends on average service time of the node, channel capacity and packet size. In order to calculate the average service time of each node, a new Markov model for *back off* time under unsaturated condition is used.

Using the recommended Effective Capacity, the effect of different traffic models on delay are investigated and compared statistically. A stochastic bound is estimated for CBR, Poisson and MMPP in single and aggregate modes of operations. Average arrival rates of all traffics are assumed to be equal. Analytically, it is shown that as the traffic burstiness increases, the stochastic bound increases as well.

To validate our analytical results, extensive simulations are done using NS2-simulator [15]. The simulations result demonstrated the accuracy of the proposed model. Unlike the previous proposed models, our Effective Capacity model depends on a few parameters and it has a closed form. They are the advantages of our model. The proposed model can be used in distributed QoS provisioning and guaranteed based protocols such as call admission control and QoS aware routing algorithms.

The rest of the paper is organized as follows: Section II gives a brief overview of the Effective Bandwidth/Effective Capacity theory. Markov model for *back off* algorithm of IEEE 802.11 DCF mode is introduced in section III and the average service time is evaluated by that model. In section IV the Effective Capacity is proposed. The statistical delay bound for different traffic types are evaluated analytically and are validated by providing simulations in section V. Section VI concludes this paper.

2. Effective Bandwidth / Effective Capacity Theory

As mentioned, the source traffic is statistically modeled by Effective Bandwidth. Assume that A (t) is the amount of arrived traffic during [0, t). According to the Effective Bandwidth theory, it has been assumed that A (t) has stationary increments [11]. Suppose that log-moment generating function of A (t) is defined asymptotically as:

$$\Lambda(u) = \lim_{t\to\infty} \frac{\backslash}{t} \log E\left[e^{uA(t)}\right] \quad (1)$$

And $\Lambda(u)$ exists for all $u \geq 0$. The Effective Bandwidth of A(t) for all $u \geq 0$ is given as [11-12] :

$$\sim(u) = \frac{\Lambda(u)}{u} \qquad u \geq 0 \quad (2)$$

Now consider a server with a constant average service rate, µ, that serves A(t) as shown in Fig. 1.

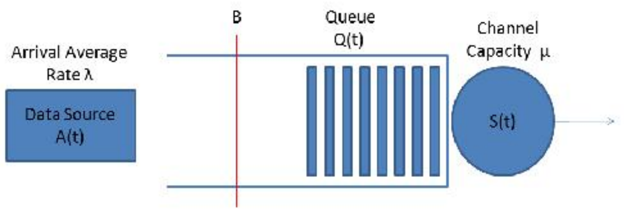

Fig. 1 A server with A(t) as arrival process and S(t) as service process

Q(t) is the queue length at t and S(t) is the number of served bits in [0,t). Based on the proposed theorem, the queue length bound violation probability is shown by [16]:

$$\sup_t \Pr\{Q(t) > B\} \approx e^{-\bar{}_B(«)B} \qquad B \to \infty \quad (3)$$

For smaller value of B, formula (4) is more accurate [12]:

$$\sup_t \Pr\{Q(t) > B\} \approx ¥(«)e^{-\bar{}_B(«)B} \qquad B \to \infty \quad (4)$$

In both equations, $\bar{}_B(«)$ and $¥(«)$ are depended to server rate. It should be noted that $¥(«)$ is the probability of having a non-empty queue. $\bar{}_B(«)$ is called QoS exponent value [12], and is the solution of:

$$\sim(\bar{}) = « \quad (5)$$

Assuming $D(t)$ as packet delay at t, the probability of exceeding a predefined delay value, $D_{\max}$, is given by:

$$\sup_t \Pr\{D(t) > D_{\max}\} \approx ¥(«)e^{-\bar{}(«)D_{\max}} \quad (6)$$

Where $\bar{}(«) = \bar{}_B(«) * «$.

$\sim(0)$ and $\sim(\infty)$ are the average and maximum arrival rates of A(t). Conceptually, (6) shows that to have an expected delay violation probability equal to £ , the minimum value of serving rate of the server in Fig. 1 should be « which is the solution of $£ = ¥(«)e^{-\bar{}(«)D_{\max}}$ [12].

Now, suppose that the arrival rate is constant and equal to ª . Also, S (t) is the sum of served bits during [0,t). By these assumptions, the Effective Capacity is given by:

$$\sim^c(u) = \frac{-\Lambda^c(-u)}{u} \quad (7)$$

where $\Lambda^c(-u)$ is computed by [12]:

$$\Lambda^c(-u) = \lim_{t\to\infty} \frac{1}{t} \log E\left[e^{-uS(t)}\right] \quad (8)$$

Based on this definition delay violation probability is:

$$\sup_t \Pr\{D(t) > D_{\max}\} \approx ¥^c(ª)e^{-\bar{}^c(ª)D_{\max}} \quad (9)$$

where $\bar{}^c(ª)$ is the solution of $\sim^c(\bar{}^c) = ª$.

Assuming the queue model in Fig. 1 with $\sim(u)$ as the Effective Bandwidth of arrival packets and $\sim^c(u)$ as the Effective Capacity of server, the delay violation probability is computed by (9) where ª is the solution of $\sim^c(ª) = \sim(ª)$.

It should be noted that by considering these results, the violation probability of D(t) from $D_{\max}$ could be calculated for different arrival models.

3. *Back off* Markov Model and IEEE 802.11 Service Model

3-1- DCF overview

The DCF mode of IEEE 802.11 protocol is well suited for wireless ad hoc networks. The DCF is operated in both basic and RTS/CTS access modes. In the basic access method, any node who wants to send a data frame, listens to determine channel status. The node transmits the frame, if it founds the channel idle for a DIFS interval. Otherwise, the node defers the transmission for a random interval which is called *back off* time. In the *back off* state, the node set a timer by the *back off* time and it decrements if the channel senses idle for each slot time duration. When the node senses the channel busy, the timer freezes. The node starts its transmission when the timer expires. Receiver node sends an acknowledgment (ACK) frame if it detects error free frame. The node will arrange to retransmit the frame, if it does not receive an ACK frame after ACK-Timeout period.

The *back off* time is a random waiting time which is chosen from a uniformly distributed random variable in the interval [0, CW -1] slot time where CW is contention window size. $CW_{\min}$ and $CW_{\max}$ are the minimum and maximum sizes of CW , respectively. At the first transmission stage, CW is set to its minimal value, namely, $CW_{\min}$. After each unsuccessful transmission, contention window size is doubled and retransmission process is rearranged. CW value increases until $CW_{\max}$ reaches to the maximum retry limit stage, m' , of retransmission. After that, CW remains unchanged for $m - m'$ stages where m the maximum retransmission step is. The value of m and m' are defined in IEEE 802.11 standard [1]. To sum up, if we define w_i as the contention window size in the i th step:

$$w_i = \begin{cases} 2^i CW_{\min} & i \leq m' \\ 2^{m'} CW_{\min} & i > m' \end{cases} \quad (10)$$

In RTS/CTS mechanism in order to initiate a transmission process, the transmitter node sends an RTS frame if it senses the channel idle. The receiver node responds it by sending a CTS frame.

Both RTS and CTS frames contain an estimated value of transmission time. Therefore, every node that hears RTS or CTS frame, stop sending any requests during the data frame transmission. This mechanism is also called virtual carrier sensing and it partly solved hidden and exposed terminal problems. Consequently, it improves the performance of IEEE 802.11 MAC protocol.

3-2- *Back off* model

In order to compute each node's service time statistics, *back off* time should be modeled accurately. Therefore, we use our analytical model that is proposed in [18]. We introduced the model briefly in this subsection. We consider a wireless ad hoc network consists of N static nodes that are in the transmission range of each other. Assuming Poisson process as packet arrival model, all nodes are under unsaturated conditions. The collision probability is shown by P and is assumed fixed as [2]. Fig. 2 shows a two dimensional Markov model that is evolved from [2], [3] and [8]. Based on the figure, *back off* states are depicted by (*s(t)*,*b(t)*) pair where *s(t)* and *b(t)* are *back off* step and *back off* timer value in each step, respectively. During the analysis, (i,k) is a pair of integers which expresses the value of (*s(t)*,*b(t)*).

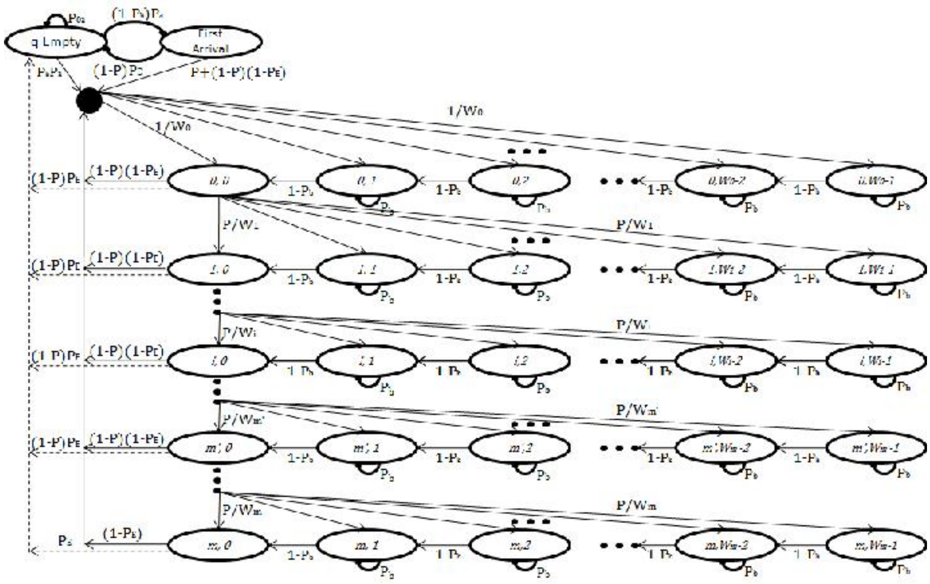

Fig. 2 *back off* Markov model

As Fig. 2 shows, i starts from zero at the first transmission attempt. Due to each unsuccessful transmission, i is incremented in each stage. m is the maximum value of i that is the maximum transmission limit. In order to consider unsaturated condition in our model, a new idle state, $qEmpty$, is introduced in Markov model. After each successful transmission, nodes enter to $qEmpty$ state with the probability of P_E when their buffers are empty. λ and μ are the average arrival rate and average service time of each node, respectively. Also, we express P_{0a} as the probability of having no arrived packet and P_a as the probability of having at least one arrived packet during one slot time interval. When a node is in its $qEmpty$ state, if a packet arrives, the node enters to its $First Arrival$ state.

Let $b_{i,k}$ be the probability of being in (i,k) state. In the steady state, $b_{i,k}$ can be found as:

$$b_{i,k} = \begin{cases} \dfrac{(1-(1-P_b)^{w_i-k})}{w_i(1-P_b)P_b} * \left\{ \begin{array}{l} (1-P)*\rho* \\ \sum_{i=0}^{m-1} b_{i,0} + b_{m,0} *\rho \\ + b_{FirstArrival} *(P \\ + \rho *(1-P)) \end{array} \right\} & i=0 \\ \dfrac{(1-(1-P_b)^{w_i-k})}{w_i(1-P_b)P_b} b_{i,0} & 0 < i \le m \end{cases} \quad (11)$$

In this equation, $\rho = \frac{\lambda}{\mu}$ is the server busy probability and P_b is the channel busy probability. Moreover, let consider $b_{q\,Empty}$ and $b_{First\ Arrival}$ as the probability of being in $qEmpty$ and $First Arrival$ states, respectively. To satisfy the probability normalization condition:

$$\sum_{i=0}^{m} \sum_{k=0}^{w_i-1} b_{i,k} + b_{qempty} + b_{FirstArrival} = 1 \quad (12)$$

Solving (11) and (12), the $b_{0,0}$ can be calculated. Considering $b_{0,0}$ in (13), transmission probability which is expressed by τ , that is dependent on collision probability is given by:

$$\tau = \sum_{i=0}^{m} b_{i,0} + b_{FirstArrival} =$$
$$\left(\frac{1-P^m}{1-P} + \frac{(1-\gamma)*(1-P_b)}{1-(1-\gamma)*(1-P_b)*(1-P)} \right) * b_{0,0} \quad (13)$$

Also, collision probability can be stated as:

$$P = 1-(1-\tau)^{N-1} \quad (14)$$

Collision and transmission probabilities are obtained by applying nonlinear solution in both (13) and (14).

3-3- Service time analysis

To analyze service time, we suppose each node has ON and OFF states. During the ON state, a node sends data frame in channel with full data rate. In OFF state, the node is in its *back off* state and it does not send any frame. Therefore, the average service time is computed by considering the duration of two successful transmissions. Fig. 3 shows this duration for an indexed node which is denoted by node A. As it is depicted in this figure, the time interval between *k*th and (*k+1*)th successful transmission of node A may contain V steps of transmission attempts. Let X_{Si} be a random variable time that node A spends in its *i*th *back off* step. During this interval, various events might be occurred such as:

- Idle time slot,
- Successful and unsuccessful transmission of all stations except A that makes channel busy,
- Unsuccessful transmission of station A.

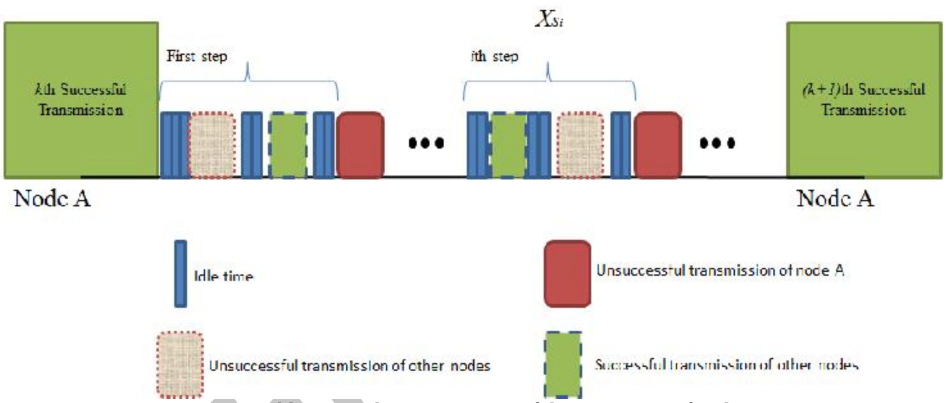

Fig. 3 Possible events during two successful transmission of node A

Therefore, X_{Si} is the spent time in the *i*th stage and can be defined as follow:

$$X_{Si} = N_s * \overline{T_s} \quad (15)$$

where $\overline{T_s}$ is the average slot time [2] that can be computed as:

$$\overline{T_s} = (1-P_{tr})*\sigma + P_{tr} * P_s * T_{su}$$
$$+ P_{tr} * (1-P_s) * T_c \quad (16)$$

where P_{tr} is the probability of having at least one transmitting node and P_S is the successful transmission probability of each node. T_{su} is the channel busy period during a successful data packet transmission time and T_c is the busy period of the channel in the case of collision. Moreover, N_s is a random variable that is uniformly distributed with in [0, w_i -1] as the time slot number in step *i*. The average of X_{Si} is given by:

$$E[X_{Si}] = \frac{1}{\mu_{Si}} = \frac{W_i - 1}{2} * \overline{T_s} \quad (17)$$

i is a random variable with geometric distribution with parameter $q = 1-P$. By calculating the statistical average of $\frac{1}{\mu_{Si}}$, the average service time yields to:

$$\frac{1}{\mu_S} = \sum_{i=0}^{m} \frac{1}{\mu_{Si}} * P^i * (1-P) \quad (18)$$

4. Proposed Effective Capacity Model

As introduced in section II, to compute statistical delay bound by equation (9), an estimation of Effective Capacity is required. Also it has been mentioned that, there is a duality between Effective Bandwidth and Effective Capacity which is proven in [12]. The Effective Bandwidth of the most famous traffic models are calculated and proposed in [11,14].

To have an estimation of Effective Capacity, at first we model service time. We represented IEEE 802.11 node's service time as an ON/OFF model. Supposing service time as an exponential distribution and due to [7-8] assumption which is approximately precise, we can model each node service time as a Markov Modulated Fluid model (MMF) [14]. Fig. 4 illustrates a two state MMF for an IEEE 802.11 wireless node.

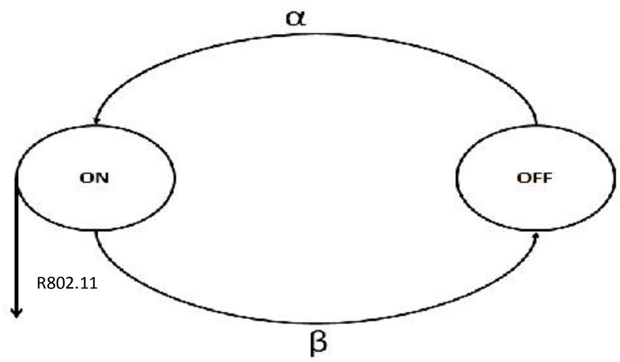

Fig.4 A two state Markov Modulated Fluid model

Fig. 3 clarifies the proposed Markov modulated fluid model in Fig. 4. As the Fig. 4 shows, there are two ON and OFF states. The state of the model alternates between ON and OFF. The average period of being in ON state is $\frac{1}{\ } = \frac{P_{size}*8}{R_{802.11}}$ being in OFF state is $\frac{1}{\sim}$ which is the average service time of a node that is calculated by (18). Also the rate of fluid model is 0 and $R_{802.11}$ as the Markov process is in state OFF and ON, respectively. Moreover, based on the model the probability of being in ON and OFF state is $\frac{\sim}{\sim+\ }$ and $\frac{\ }{\sim+\ }$.

To sum up, ~ is the changing rate of OFF to ON state.

By these assumptions, the recommended Effective Bandwidth for MMF [14] is given by (19)

$$\sim^{B}_{MMF}(u) = \frac{R_{802.11}*u-(\sim+\ )}{2*u} + \frac{\sqrt{(R_{802.11}*u-(\sim+\ ))^2+4*\sim*R_{802.11}*u}}{2*u} \quad (19)$$

By applying the duality to equation (19), our Effective Capacity model can be derived as:

$$\sim^{c}_{802.11}(u) = \frac{(\sim+\ )+R_{802.11}*u}{2*u} - \frac{\sqrt{(R_{802.11}*u+(\sim+\ ))^2-4*\sim*R_{802.11}*u}}{2*u} \quad (20)$$

As (20) shows, and unlike [10,13] 's Effective Capacity the proposed Effective Capacity is depend on a few parameters namely $R_{802.11}$, P_{size} , and ~. If both $R_{802.11}$ and P_{size} are constant, the equation is related to ~. As explained, ~ is dependent to average service time. Consequently, our proposed Effective Capacity is related to a parameter which could be measured by considering each packet service time in MAC layer. This is the best acheivement of our proposed Effective Capacity that could be used in most QoS guarantees approaches such as statistical call admission controls and statistical QoS aware routing protocols.

5. Simulation Results

In this section we support our Effective Capacity model by extensive simulations using NS2-simulator. In addition, the effect of different traffic models on delay bound are evaluated and compared with each other. In our simulations, a single hop WLAN with different number of nodes is considered where all of the nodes are in their transmission range. All nodes in all scenarios are randomly and uniformly distributed in 150*150 m^2 areas and their transmission range is 250 meters. Each node uses IEEE 802.11 as its MAC layer protocol with data transmission rate ($R_{802.11}$) equal to 2 Mbps. In all simulations, regarding to the number of active nodes (data frame transmitters) two scenarios are considered. In the first scenario two nodes, and in the second one, eight nodes send packets. Moreover, main and background flows are two types of traffics that are considered in each simulation. The background traffic is the same in all simulations and is assumed Poisson traffic. However, the main traffic is one of the CBR, Poisson, MMPP or the aggregated of them. Average arrival rate in both traffics, namely background and main traffics are assumed 32 Kbps and all the packet sizes are fixed and assumed 500 bytes. The reported results are the average of 10 time simulations where each simulation lasts for 500 seconds. Network parameters are summarized in Table 1.

Table 1: Network parameters

Network Parameters	
Number of active nodes	2 and 8
Network area	150*150 m^2
MAC layer protocol	IEEE 802.11
Maximum node speed	0 m/s
Drop policy	DropTail
Antenna type	Omni-directional

5-1- CBR traffic model

The CBR model transports traffic at a constant bit rate. Fig. 5 demonstrates the delay bound violation probability when the main traffic is assumed with that model versus D_{max} . The figure compares simulation and analytical results. Analytical curves are obtained from equation (9) where $\bar{\ }^{c}(a)$ is the solution of equation (20) and a_{CBR} intersection, $\sim^{c}_{802.11}(\bar{\ }^{c}) = a_{CBR}$. a_{CBR} is the average CBR packet arrival rate that is assumed as 32 Kbps. The curves show in both 2 and 8 active node cases, the probability of exceeding D_{max} , decreases exponentially as D_{max} increases. The decreasing trend in both simulation and analytical curves are the same, especially when the value of D_{max} is less than 100 *ms*. In addition, the figure shows that the probability reduction in 2 nodes is more than in 8 nodes. That is because when the number of active nodes grows, it raises the queue delay and the collision probability which leads to increase the average packet delay. Consequently, delay violation probability is affected and increased.

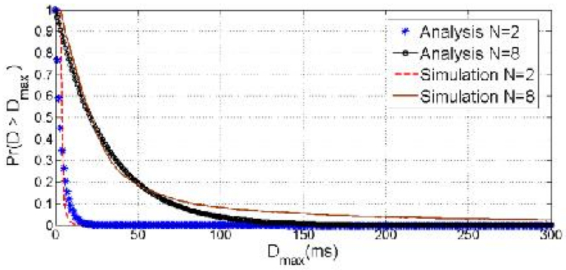

Fig.5 Analytical and simulation results for delay violation probability for CBR arrival model

5-2- Poisson traffic model

To evaluate the effect of Poisson traffic on delay violation probability, we use $\alpha^B_{Poisson}(u)$ as [13]:

$$\alpha^B_{Poisson}(u) = \frac{\lambda_{Poisson}(e^{u*P_{size}}-1)}{u} \quad (21)$$

where $\lambda_{Poisson}$ and P_{Size} are the Poisson average arrival rate and packet size, respectively. As explained, to compute delay exceeding probability by equation (9), $\gamma^c(\lambda)$ and λ should be obtained. To do this, $\alpha^B_{Poisson}(u) = \alpha^c_{802.11}(u)$ should be solved respect to u. The intersection of these equations is plotted in Fig. 6. Therefore, QoS exponent, $\gamma^c(\lambda)$ and λ will be computed analytically.

Fig. 7 compares analytical and simulation results when the main traffic arrival model is Poisson process. Like the CBR case, delay violation probability decreases exponentially. Moreover, as the figures depicted in both cases, analytical and simulation results are matched well which clarify the accuracy of our proposed Effective Capacity model.

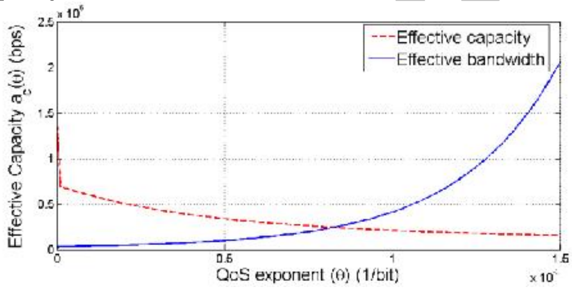

Fig.6 The intersection of proposed Effective Capacity and Effective Bandwidth of Poisson process

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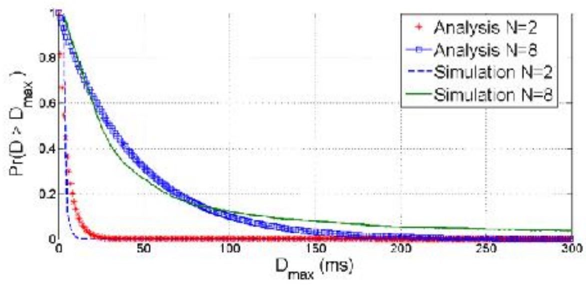

Fig.7 Analytical and simulation results for delay violation probability for Poisson arrival model

5-3- MMPP traffic model

MMPP process is a suited model for bursty traffic sources [17]. Based on this model, the arrival rate of packets changes as the Markov chain states are varied. In this paper we use an MMPP with two ON and OFF states. The Effective Bandwidth of this traffic model is given by [13]:

$$\alpha^B_{MMPP}(u) = \frac{(e^{u*P_{Size}}-1)*\lambda_{MMPP}-(\alpha+\beta)}{2*u} + \frac{\sqrt{((e^{u*P_{Size}}-1)*\lambda_{MMPP}-(\alpha+\beta))^2+4*\alpha*(e^{u*P_{Size}}-1)*\lambda_{MMPP}}}{2*u} \quad (22)$$

where $\frac{1}{\alpha}$ and $\frac{1}{\beta}$ are the average ON and OFF durations. P_{Size} is the packet size and λ_{MMPP} is the average arrival rate of the packets during ON period. Based on these assumptions, average traffic rate is:

$$\alpha^B_{MMPP}(0) = \frac{\lambda_{MMPP}*P_{Size}*\alpha}{(\alpha+\beta)}$$

Assuming traffic rate 32 Kbps, packet size of 500 bytes, and both $\frac{1}{\alpha}$ and $\frac{1}{\beta}$ equal to 1 second, λ_{MMPP} is obtained 15.38. Based on the Effective Bandwidth/Effective Capacity theory, to compute QoS exponent, equations (22) and (19) must be equal. Fig. 8 represents delay exceeding probability in both 2 and 8 active nodes versus $D_{\max}$. As the figure shows, simulation and analytical results are almost matched. However, they are not very similar as in the case of CBR and Poisson arrival model.

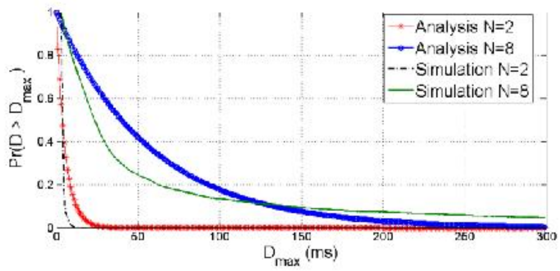

Fig.8 Analytical and simulation results for delay violation probability for MMPP arrival model

5-4- Aggregated traffic

In most computer networks, each node serves both single and aggregated flow at the same time. Therefore, providing assured level of QoS is also important in the case of aggregated traffic. It has been shown that the Effective Bandwidth of aggregated traffic is sum of the Effective Bandwidth of each single traffic flow. In other words, the aggregated Effective Bandwidth of CBR, Poisson and MMPP is given by:

$$\alpha^B_{Aggregate}(u) = \alpha^B_{MMPP}(u) + \alpha^B_{Poisson}(u) + \alpha^B_{CBR}(u) \quad (23)$$

To evaluate upper delay bound for aggregated traffic, we use equation (9) where QoS exponent is obtained by solving $\alpha^B_{Aggregate}(u) = \alpha^C_{802.11}(u)$.

Fig. 9 compares analytical and simulation results when aggregated traffic arrives. The average input traffic is about 100 kbps. As the graph reveals, simulation and analytical results have the same trend that verifies our proposed model for aggregated traffic. However, there is an inconsistency between simulation and analytical results around 100 ms. Actually, this behavior has two major reasons. As explained in section 2, the delay violation probability is upper bounded by exponential function. The QoS exponent directly affects the value of this function. An accurate estimation of QoS exponent will eventuate upper bound precisely. The QoS exponent is estimated by $\sim^{c}(\bar{\ }) = \sim(\bar{\ })$ where both $\sim^{c}(\bar{\ })$ and $\sim(\bar{\ })$ are obtained approximately. Therefore, having an exact evaluation of Effective Capacity and Effective Bandwidth leads us to have precise delay upper bound.

Also, as (6) reveals, an exponential function upper bounds the delay violation probability. It has been shown in [19] that this upper bound is not necessarily an exponential function. [19] Shows that this probability is given generally by:

$$\sup_t \Pr\{D(t) > D_{\max}\} \approx f(D_{\max}) \quad (24)$$

where f is a general function that could be calculated by summing many exponential functions. Therefore to have an accurate estimation of the upper bound, that general function must be considered.

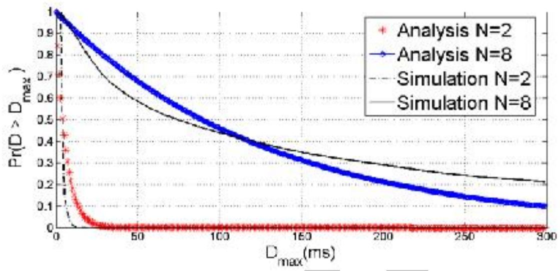

Fig.9 Analytical and simulation results for delay violation probability for aggregated traffic

Finally, Fig.10 is depicted to have comparison between delay violation probabilities of different traffic types where all traffic types have the same arrival rates. As the figure shows, the probability of exceeding from a predefined delay for MMPP is more than the CBR and Poisson process. For example, when $D_{\max}$ is 50 *ms*, delay exceeding probability for MMPP is about 0.6, while it is about 0.4 and 0.3 for Poisson and CBR traffic model, respectively. This comparison reveals that despite the same average arrival rates for different traffic models, the delay violation probabilities are different and strongly dependent to traffic model. MMPP is a bursty traffic model, and in spite of having the same average compare to CBR and Poisson, its delay probability is higher than the others. It can be concluded that the average arrival rate does not completely express a traffic pattern. Therefore, to provide QoS for a specific traffic type, more statistical information such as its arrival model is essential rather than relying on its average.

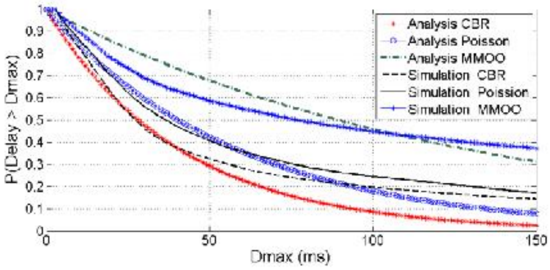

Fig.10 Analytical and simulation results for delay violation probability for CBR, Poisson and MMPP traffic models

6. Conclusion

In this paper the effect of different traffic sources on delay is investigated statistically. To address this issue we used Effective Bandwidth/Effective Capacity theory. To investigate IEEE 802.11 wireless node's service model a novel Effective Capacity is introduced. The effect of CBR, Poisson and MMPP model in both single and aggregated modes are considered. In all reported results, both analytical and simulation results were well matched which prove the accuracy of introduced Effective Capacity model. Also, the results show that despite the same arrival rate for all investigated traffic models, delay bounds are different and depend on traffic pattern types. Due to the burstiness nature of this traffic type, MMPP suffers from the worst delay bound among the other schemes. We conclude that considering the average traffic to provision a QoS for a specific type of traffic is not sufficient, and the traffic model is also essential to be considered.

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