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Improving Traffic Management in a Data Switched Network Using an Adaptive Discrete Time Markov Modulated Poisson Process

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ABSTRACT

The demand for resources like bandwidth must be met overall due to the growing number of wireless network users. When the number of competing users exceeds the capacity, there are insufficient resources to meet all traffic needs, which results in information loss and necessitates packet retransmissions. By characterizing the throughput in a data network under study, designing the data network traffic model, and developing a Poisson Process Algorithm and a Discrete Time Markov Modulated Poisson Process for data throughput improvement, this paper proposed ways of eradicating these negative consequences as a way to counteract this trend. To improve traffic management, effective capacity and effective bandwidth for Quality of Service (QoS) requirements were achieved by MATLAB simulation. Data network characteristics revealed that there was no network congestion when bandwidth utilization was less than 20 mbps. The created model was adaptive since it allowed high priority packets to transmit first when two packets attempted to contact the same node at the same time, as evidenced by monitoring of traffic nodes. As flow throughput decreases when traffic exceeds network capacity, the Poisson Process Algorithm designed follows Gaussian normal distribution pattern when the departure and arrival timings of packets are mutually independent.

Keywords: Throughput, Data Network Traffic, Poisson Process Algorithm, Traffic Management, Quality of Service

INTRODUCTION

The features of communication traffic have altered dramatically as a result of the Internet's recent rapid expansion. Data traffic has increased to an unprecedented level as a result of rising user demand and the expansion of the broadband network deployment. Voice call, video streaming, and video conferencing are prominent examples of apps that offer real-time content over the Internet. Today's high-speed broadband networks enable video and voice applications over the Internet (VOIP). In today's environment, it is getting more and harder to distinguish between computer networks and network services that are designed to be dependable and strong. It's essential to get a reliable estimate of the computer network performance. Whether they are used for voice or data, networks are built around a variety of different factors, and managing the performance of computer networks entails optimizing how they work in order to maximize capacity, reduce latency, minimize interference and provide high reliability regardless of bandwidth availability and failure frequency (Nnebe et al., 2023; Nnebe et al., 2021). In order to ensure that computer networks are able to handle traffic at the speed, capacity, and reliability that are expected by the applications using the network or necessary in a particular scenario, network performance management entails tasks including measuring, modeling, planning, and improving computer networks. The term Quality of Service (QoS) in the context of networking refers to control strategies that can provide a specific level of performance for data flows in response to demands from an application or user using the network. A network that provides and supports QoS often

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collaborates with an application to create a traffic contract during the session establishment phase and reserves a set amount of capacity in the network nodes based on the contract. The simplest definition of quality is meeting the needs of the client (Irland, 1988). The computer network monitors and makes sure that the QoS assurances are met while the session is active in an effort to uphold the agreement. After the session, the reserved capacities are released. These QoS assurances could be impacted by a number of variables. As a result, designing a network to enable QoS is a difficult process. The first step is to once more have a thorough grasp of the network's traffic. QoS guarantees cannot be given without a thorough understanding of the traffic and the apps that may be using the network. As a result, traffic modeling becomes an important and necessary stage. The analysis of the traffic reveals data such as the typical load, the bandwidth needs for various apps, and several other specifics. Network designers can predict performance for prospective requirements and make assumptions about the networks they are developing based on prior experience by using traffic models.

Wireless channels fluctuate as a result of multipath fading and environmental variables. The QoS requirements of the apps may be impacted by these unpredictable changes in received signal intensity. As a result, source characteristics and a dependable transmission rate vary over time. In this situation, a time-varying server is necessary for the queuing system to assure effective capacity and a link layer model that can guarantee QoS on a wireless channel with changing transmission times. Effective capacity in this context is defined as the most constant arrival rate that a given time-varying service process can tolerate while still ensuring statistical QoS (Seybold, 2005). By capturing the decay rate of the buffer occupancy probability for the queue length, it incorporates the statistical QoS constraint and is derived from the large deviation theory. In the analysis of throughput, the effective capacity of wireless channels mostly concentrates on constant arrival rates. In this research, we focus on conducting throughput analysis of random and bursty source traffic patterns in a data network using Markov source models, including discrete time Markov and Markov Modulated Poisson sources with effective capacity.

Traffic Management in Wireless Multimedia Sensor Network

The important (I)-frames of compressed video are kept, while the other less significant frame types are ignored, in order to improve the received video quality in Base Stations (BS), as suggested by Shyam (2014). Shyam (2014) proposed that wireless sensor nodes (WSN) in a collision region can alter their sending states based on packet priority in the paper titled "A New Approach for Traffic Management in Wireless Multimedia Sensor Network". To improve system performance, retransmissions of dropped packets are also offered with various priorities. The simulations demonstrate that the bandwidth adjustment can effectively secure the high priority packets, and that the retransmission's performance is well suited to satisfy the needs of multimedia applications. For purposes of simulation, MATLAB is utilized. The simulations demonstrate that the new Traffic Management strategy that has been developed performs well in terms of packet protection and retransmission. When being transmitted and retransmitted, I-frames, or critical video frames, can receive additional bandwidth. The performance of video playback can be noticeably better than real-time playing, but the retransmission of the missing packets has no impact on the usual transmission. In this essay, we have examined many system implementation concerns and many traffic management issues in wireless multimedia sensor networks. The results demonstrate that the suggested method is more effective at handling multimedia on wireless sensor networks when compared to other analysis phases.

The storage capacity used in his work was of a limited capacity, and it is suggested that increasing the storage capacity to accommodate large-scale video data on wireless sensor networks will improve performance. This is a research gap addressed by Shyam (2014). A research paper titled "Traffic Management for Heterogeneous Networks with Opportunistic Unlicensed Spectrum Sharing" by Chun-Hung and Hong-Cheng (2017) looked at how to manage traffic flows among the access points (APs) in a M-tier heterogeneous wireless network (HetNet) in order to maximize per-user-based throughput. According to the proposed opportunistic CSMA/CA protocol, the APs in the first M-1 tier share the unlicensed spectrum with the APs in the Mth tier but can simultaneously use the licensed spectrum. Using a general AP association scheme, they describe the statistical characteristics of the cell load and channel access probability of each AP. It is possible to gain some insight into how channel gains, AP association weights, and void AP probabilities affect the mean spectrum efficiencies for an AP in each tier by deriving tight bounds on those efficiencies for each AP in the licensed and unlicensed spectra in a low-complexity form. The per-user link throughput and per-user network throughput are defined in the paper based on the deduced mean spectrum efficiencies, and they are maximized by suggesting the decentralized and centralized traffic management schemes for the APs in the first M-1 tiers under the restriction that the per-user link throughput of the tier-M APs must be higher than some minimum required value. To validate the derived conclusions and observations, a numerical example of coexisting LTE and WiFi networks is provided. It is shown that these two traffic management approaches can optimize an AP's per-user link throughput and per-user network throughput under the restriction placed on the APs in the Mth tier's per-user link throughput. The key research gap for this work is that too much offloading eventually results in a drop in per-user link throughput. Offloading traffic from the LTE network to the WiFi network initially boosts per-user link throughput. According to research published in a paper titled "Traffic Management in Wireless Sensor Network Based on Modified Neural Networks" by Nadia and Zainab (2014), Wireless Sensor Networks (WSNs) are event-driven network systems made up of numerous sensors nodes that are densely deployed and wirelessly interconnected, allowing the retrieval of monitoring data. Every time an event is recognized in a WSN, the associated data must be transferred to the sink node (data collection node). The network's bottleneck, which may be accidental in nature due to congestion brought on by high data traffic, is the sink node. Data loss, including of crucial data, may result from congestion. Soft computing based on NNs Congestion Controller technique is suggested to accomplish this goal. The WSN traffic is controlled by the wavelet activation function, which is utilized to activate the NN. The proposed method, known as Modified Neural Network Wavelet Congestion Control (MNNWCC), consists of three main operations: the first one is the detection of congestion as congestion level indications; the second one is the estimation of the traffic rate so that the upstream traffic rate is adjusted to avoid congestion in the future; and the third and final operation is the improvement of the Quality of Services (QoS) by enhancing the Packet Loss Ratio (PLR), Throughput (TP), and B. To conduct the simulations, MATLAB (R2012a) was used. The suggested network model consists of 100 stationary sensor nodes that are randomly distributed over a surface area of (100 100 m2), with more than one source directing energy toward a single sink node that is located in the middle of the coverage region. The maximum communication distance between nodes is 25 meters. Each node's buffer has a capacity of 50 packets while the sink node's buffer has a capacity of 250 packets. The data packets are produced from the sources and sent via the multi-hop shortest path algorithm to the sink node. The simulation results demonstrate that the suggested technique can reduce network congestion while enhancing network QoS.

IoT Traffic Management and Integration

The Internet of Things (IoT) is a network of interconnected computing devices, mechanical and digital machines, objects, animals, or people that can exchange data over a network without requiring human-to-human or human-to-computer interaction (Margaret, 2021). The researchers examined network traces from a test-bed of typical IoT devices and described basic methods for fingerprinting their behavior in a research paper titled "An Analysis of Home IoT Network Traffic and Behavior" by Yousef, Hamed, and Richard (2018). We next examine where privacy and security threats appear and how device behavior affects bandwidth using the knowledge and insights gained from this data. They reveal easy methods for getting around attempts to secure gadgets and safeguard privacy. They discovered numerous areas of privacy controversy, including Philips Hue Bridge security flaws and straightforward MAC address randomization circumvention, and they distributed scripts to make performing this type of network trace analysis more convenient. The major lesson to be learned from this work is to start raising knowledge about how typical IoT devices behave in the house in order to reduce privacy issues. Their initial investigation focused on a straightforward scenario in which all IoT devices are inactive. They attempt to determine human activity and assess the privacy risk of doing so by observing behavior when users directly engage with these devices at home and remotely (for example, through an app). The weakness in this research is that it focuses on network privacy and security but neglects to address traffic management in terms of bandwidth management and packet delivery ratio.

Overview of Congestion Control

Links with varied bandwidths and routers with different buffer sizes make up a computer network, which must be shared by a variety of users and applications. If the network is unable to handle the volume of traffic given to the system, changes in the traffic, or poor link quality result in packet delays and losses. A network that supports quality of service (QoS) should actively manage, watch, and coordinate traffic and resource allocations. The following aspects must be implemented by the network components: packet classification and identification, traffic management and queuing, policing, and management of QoS policies. Without proper traffic engineering and resource allocation techniques, lost packets and congestion under significant traffic changes cause the network performance and service quality to decline. Utilizing network performance measuring and monitoring tools, congestion can first be found. There are two basic methods for controlling congestion: congestion control and congestion prevention/avoidance.

When the network is overcrowded, the reactive approach of congestion control is initiated. In order to prevent a fast sender or a large number of senders from blocking the pathways faster than a network can handle, the intermediate nodes take part in congestion control. Using a variety of techniques at the application, transport, network, and data connection layers, such as packet size optimization, rate control, routing algorithms, and admission control, congestion prevention prevents the network from getting overwhelmed (Wang et al., 2007).

Congestion control incorporates design considerations that limit the traffic that is offered in order to adhere to the system's capacity limitations. Understanding how congestion develops and coming up with effective solutions to keep the network working within its capacity are crucial, especially for real-time traffic. Congestion control's fundamental design considerations determine how to respond to feedback from sources and how it offers feedback to sources. The source and destination of the network, also known as the endpoints, typically lack information on the congestion point(s) and cause(s). As a result, application-based adaptation only functions when network endpoints provide adaptation mechanisms, such as those for adjusting the necessary changes in data rate. To notify hosts that congestion has occurred, intermediate nodes can employ network layer techniques like ICMP (Internet Control Message Protocol). However, accuracy and dependability issues with ICMP feedback from routers have been reported (Maruyama et al., 2017).

The researcher used a node priority based hop-by-hop dynamic rate adjustment technique in Prioritized Heterogeneous Traffic-oriented Congestion management Protocol for WSN (PHTCCP) (Monowar, Rahman, & Pathan, 2012) to assure effective rate management for prioritized heterogeneous traffic. For achieving realistic transmission rates of heterogeneous data, the protocol employs weighted fair queuing, intra-queue and inter-queue priorities, etc. The average packet service rate to packet scheduling rate ratio, or packet service ratio, is used to calculate the level of congestion at each sensor node. By employing dynamic transmission rate adjustment, which is managed by modifying the scheduling rate, PHTCCP ensures effective link use. The scheduling rate is lowered to the packet service rate in order to reduce congestion, and a higher link usage is attained by utilizing the extra link capacity. We may conclude that PHTCCP has shorter delay, is viable in terms of memory requirements, and is energy efficient. This protocol offers single path routing and upstream congestion control, and nodes are expected to continuously produce data. DPCCP ensures distributed priority-based fairness with less control overhead while increasing throughput and lowering packet loss. This protocol introduces the congestion index (Cii), which measures the level of congestion at each sensor node based on its unoccupied buffer size (UBSi) and MAC layer traffic rate. Backward and forward nodes selection (BFS), predictive congestion detection (PCD), and dynamic priority-based rate adjustment (DPRA) are the three parts of the DPCC protocol that are responsible for exact congestion discovery and weighted fair congestion control. Discrete wavelet transform (DWT), adaptive differential pulse code modulation (ADPCM), and run-length coding (RLC) are used as compression techniques in Adaptive Compression-based Congestion Control Technique (ACT) by Lee and Jung (2010). Before sending the data to the source node, the ACT first converts the data from the time domain to the frequency domain, then uses ADPCM to narrow the data's dynamic range and RLC to reduce the number of packets. The protocol adds the DWT, which is used for priority-based congestion control and divides data into four groups with distinct frequencies. The ACT determines the quantization step size of ADPCM in inverse proportion to the priorities and assigns priorities to various data groups in an inverse relationship to their respective frequencies. In comparison to other methods now in use, the authors' experimental evidence shows that ACT boosts network efficiency, ensures fairness to sensor nodes, and displays a very high ratio of the accessible data in the sink. When there is congestion in the relaying node, the ACT decreases the number of packets by increasing the ADPCM quantization step size. For a data group with a low priority, RLC creates fewer packets, and to ease the back pressure, the queue is adaptively regulated in accordance with the congestion status.

METHODOLOGY

Poisson and Markov processes were used in this study's traffic management application. In the presence of a Rayleigh fading channel, the performance of reliability and latency in machine-type communication networks with a single transmitter and receiver is evaluated in this research. Delay/buffer overflow limits are applied and two types of Markov processes, Discrete-Time Markov Modulated Poisson process and Continuous-Time Markov Modulated Poisson process, are used to mimic the source's traffic arrivals. Our strategy is based on the dependability and latency outage probability, where the transmitter would transmit information over a set rate because the transmitter does not know the channel condition. The reliability of wireless transmission is determined by modeling the fixed rate transmission as a two state discrete time Markov process. We assess the reliability-latency trade-off using effective bandwidth and effective capacity theories and establish QoS requirements. The effect of various source of traffic coming from MTC devices under QoS restrictions on the actual transmission rate is looked into.

Characterization of the Data Network under Study

This research characterized the data network by carrying out an experiment in the test-bed, Figure 1, to measure the network parameters to know their impact on the network. TEMS instrument is used to gather Data, Figure 2. The network and application performance is measured through several performance metrics such as Bandwidth, Throughput, end to end delay, number of packets sent/Received per sec, and number of bytes sent/Received per send, Table 1.

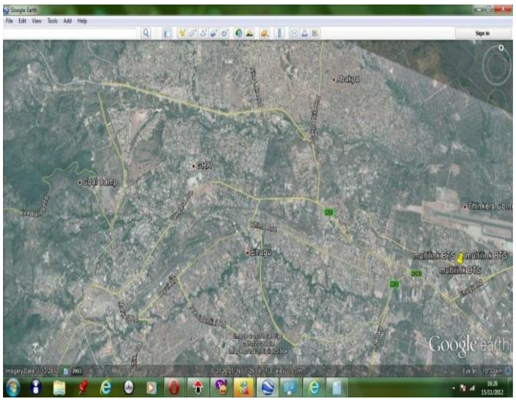

Figure 1: Map of Test- Bed – Enugu Urban Environment

Figure 2: TEMS Measurement Tool used for Field gathering of RSS Data

Table 1: Performance Optimization Setup for Simulation

Performance Monitor	Matlab Script	IPerf
• Packets Sent/Sec • Packets Recv/Sec • Processor Time • Disk Time • Bytes Sent/Sec • Bytes Recv/Sec	• Top Processes • CPU Utilization • Ping (Delay)	• Bandwidth • Transfer Rate

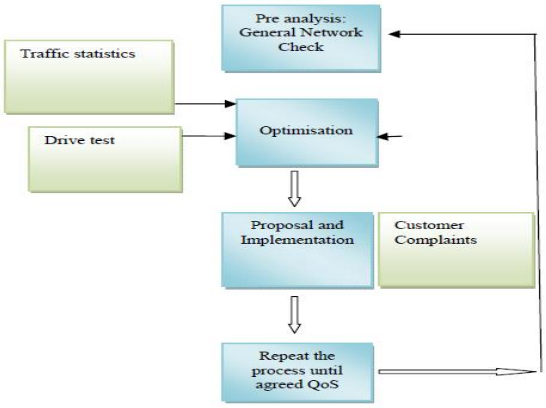

Figure 3: Radio network Optimization process (Mark & Zhuang, 2006)

Data collected from the network are optimized through an optimization process.

Fieldwork Experimental Measurement

This paper also tested the bandwidth utilization. The experimental tool used to verify bandwidth utilization is net-box software (Net-box) which is simply a software used by MTN (Service Provider) in Nigeria to monitor customer performance, and data usage on the network. The procedure used in carrying out the experiment when appropriate Password was logged is as follows:

VLAN: 1061

IP: 197.210.185.26

GATEWAY: 197.210.185.25

JITTER & BANDWIDTH OF CLIENT $\Rightarrow$ 20mb/s

Customer details retrieved were test- run. After the test was run there was a graphical display on the screen or monitor of the Laptop.

The nature or the characteristics of the graph shows data performance as in Figure 4.

Figure 4: Graph showing over Utilization of Bandwidth

From the nature of the Graph; at some points in the Graph below 20mb/s, the Graph was smooth and this shows that the Subscriber have not started over stressing the network by exceeding the allocated bandwidth. When the data indicator goes beyond 20mb/s the client has started over utilizing or exceeded the allocated bandwidth, the Graph is no longer smooth, but starts clipping, and no longer smooth as before, and the network is being over stressed at this time and congestion sets in.

In each of these test scenarios, measurements are designed to study the impact of wireless rate adaptation and link utilization on Quality of Experience (QoE).

To study the impact of rate adaptation, measurements were conducted at three bandwidth levels: 2, 5.5 and 11 Mbps, depending on the distance of the wireless devices from the AP and in each bandwidth level, measurements were designed to study the impact of link utilization on QoE.

Table 2 shows the eleven days measurements: Measurements 1-3 include base configurations, in which no cross traffic and contending traffic is introduced for each data rate.

Measurements day 4-6 include a variety of cross traffic rates, modeling applications with download traffic, but there is no stalling event for each data rate. Measurements 7-9 consist of measurements corresponding to a congested network for each data rate that include a variety of cross traffic rates in order to make the wireless link congested, modeling applications with significant download traffic.

Measurements 10 and 11 consist of measurements corresponding to a congested network for data rates 11 Mbps and 5.5 Mbps respectively with both cross and contending traffic modeling Users applications with both upload and download traffic and more than one User using 3G network.

Table 2: Measurements of Bandwidth Utilization

Measurement Day	Data Rate (Mbps)	Cross Traffic	Contending Traffic
1	11	None	None
2	5.5	None	None
3	2	None	None
4	11	Yes	None
5	5.5	Yes	None
6	2	Yes	None
7	11	Yes	None
8	5.5	Yes	None
9	2	Yes	None
10	11	Yes	Yes
11	5.5	Yes	Yes

Source: Researcher, 2021

The network channel consists of fluctuations in the link throughput and sometimes an error-prone communication environment due to characteristics such as multipath propagation, interference from other sources, decrease signal strength, shadowing, etc. For each bandwidth level the RSSI range is fixed. The actual path capacity is measured using Iperf by measuring UDP throughput of the path and checking the packet loss at a present UDP injection rate and then repeating this process until a suitable injection rate is found that allows the highest rate at which the packet loss is negligible. This is done by injecting a single saturated CBR UDP flow with Maximum Transmission Unit (MTU) of 1460 Bytes for 300 seconds.

The traffic rate and the throughput were measured for forty eight days to determine how the number of network users affects the network throughput.

The result of the measurement is as shown in Table 3.

Table 3: Network Throughput Performance Measurement

Day	No of Network users	Throughput (Bytes/Sec)
Day 1	10	67.32
Day 2	25	26.21
Day 3	30	6.24
Day 4	40	5.31
Day 5	12	57.12
Day 6	60	4.56
Day 7	120	28.63
Day 8	185	40.33
Day 9	160	11.88
Day 10	90	9.81
Day 11	213	57.12
Day 12	60	4.56
Day 13	50	6.32
Day 14	150	87.21
Day 15	310	76.24
Day 16	140	25.36
Day 17	121	57.12
Day 18	160	58.56
Day 19	120	28.63
Day 20	185	40.33
Day 21	160	11.88
Day 22	70	10.81
Day 23	513	4.12
Day 24	601	4.56
Day 25	101	7.32
Day 26	253	26.21
Day 27	510	2.24
Day 28	40	27.31
Day 29	12	59.12
Day 30	132	27.56
Day 31	120	28.63
Day 32	185	40.33
Day 33	160	11.88
Day 34	55	27.81
Day 35	213	57.12
Day 36	400	4.56
Day 37	10	67.32
Day 38	25	26.21
Day 39	30	6.24
Day 40	122	8.31
Day 41	380	5.12
Day 42	279	8.56
Day 43	120	28.33
Day 44	185	25.32
Day 45	260	11.88
Day 46	190	9.81
Day 47	213	57.12
Day 48	479	7.56

Source: Researcher, 2021

Research Design

Design of Data Network Traffic Model

Figure 5 represents the python simulation of network nodes and the movement of data from client/server as well as communication links. The python program illustrates the flow of data between client/server. This is achieved by monitoring the traffic on the nodes and where two packets are trying to access the same node at the same time, the system will delay the packet from one of the nodes for the other node with a higher priority to transmit first. The priority is given in the order of voice first, followed by data and finally video. The parameters used for checking congestion on the network include.

1. Size of packet
2. Number of users on the network.

These parameters are manipulated in the python code, and it determines the speed of packet delivery and the possibility of congestion on the network. The higher the number of network users, the slower the packet delivery rate becomes.

Figure 5: Simulation of Network Nodes and the movement of Data from Client/Server

Development of Poisson Process Algorithm

Let us assume a network where number of packets arriving per time point (say in seconds) within a given time interval (t_0, t) (example in 0 to 10 seconds; 0 to 100 seconds, etc.) in a gateway with a specific rate λ_1. We may denote the number of packets arriving in a gateway in a specific time point during a time interval by Y_1. Then Y_1 has a Poisson distribution with mass function:

$$g_1(y_1) = \frac{e^{-\lambda_1}\lambda_1^{y_1}}{y_1!}, y_1 = 0, 1, ...n \quad (1)$$

Again let us assume among the packets arriving in a gateway, the number of packets who reach their destination constitute the amount of throughput of the specific network within the given time interval. Let the rate of packet departure in any time point within the interval be λ_2 and it also has a Poisson distribution. Also, it is evident that the number of packets departed successfully within the interval (throughput) may be denoted by Y_2 depending on the number of packets that arrived in the gateway within each time point of the given interval (t_0, t). So the joint distribution of the number of packet arrival and the number of packet departure can be shown as follows (Leiter & Hamdan, 2016):

$$g(y_1, y_2) = g(y_2|y_1).g(y_1) = \frac{e^{-\lambda_1}\lambda_1^{y1} e^{-\lambda_2 y1} (\lambda_{2y_1})^{y_2}}{(y_1!y_2!)}, y_2 = 0, 1,,n \quad (2)$$

Where y_2i's are assumed to be mutually independent. The number of packets departed, Y_2, out of $Y_1 = y_1$ arrivals, in any time interval, is Poisson with parameter $\lambda_2 y_1$. In a time interval, the possible number of packets to be departed, Y_2 can be shown as the sum of departed packets corresponding to each of 1, 2, ...,,, y_2 possible arrivals and the variable Y_2 is defined as

$$Y_2 = Y_{21} + Y_{22} + Y_{2y1} \tag{3}$$

Then the conditional probability of the total number of packets departed as throughput among the y_1 arrivals occurring in a time interval denoted by $P(Y_2 = y_2 \mid Y_1 = y_1)$) which is shown as Poisson with parameter $\lambda_2 y_1$. Then it can be shown that

$$g(y_2|y_1) = \frac{e^{-\lambda_2 y_1}(\lambda_{2y_1})^{y_2}}{(y_2!)}, y_2 = 0, 1, ..., \tag{4}$$

Where Y_{2i} is a random variable with the number of packets departed (becoming throughput) resulting from i^{th} arrival, and suppose it has a Poisson distribution with parameter; that is,

$$g_2(y_{2k}) = \frac{e^{-\lambda_2}\lambda_2^{y2k}}{(y_{2k}!)}, y_{2k} = 0, 1, ... \tag{5}$$

For the above Poisson-Poisson model (2), it can be shown that

$$E(Y_1) = \mu_1 = \lambda_1 \text{ and } E(Y_2) = \mu_1 = \lambda_1\lambda_2 \tag{6}$$

Development of Discrete Time Markov Modulated Poisson Process for Data throughput improvement

In this research work, the source data arrival in buffer is modeled as a Poisson process, whose intensity is controlled by discrete-time Markov chain. For instance, λ_i is the intensity of Poisson arrival process in the i^{th} state in Markov chain. Therefore source arrival is modeled as Markov modulated Poisson process. We assume irreducible and a periodic transition probability matrix of Markov chain and that is denoted by J, and $\Lambda = \text{diag}\{\lambda 1,\lambda 2,\lambda 3,\cdots,\lambda n\}$ is the diagonal matrix of the Poisson arrival rate in the different state. Afterwards, the effective bandwidth of discrete Markov Modulated Poisson Process is expressed as (Elwalid & Mitra, 2015):

$$B_E(\theta) = \frac{1}{\theta}\log[\text{sp}\left(e^{(e^{\theta}-1)\Lambda_J}\right)] \tag{7}$$

Where sp(.) represents the spectral radius of input matrix and the stationary distribution π of the discrete time Markov chain, which are determined by the following equation:

$$\pi 1 = 1,$$
$$\pi J = 1$$

We assume that $\pi = [\pi 1,\pi 2,\cdots \pi n]$ and $1 = [1,\cdots,1]T$.

Consider a two state (ON/OFF) model as an illustration and for mathematical tractability. We presume that bits only enter in the ON state and that no bits arrive in the OFF state. For a two state discrete time source model, the transition probability matrix J is therefore defined as:

$$J = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{8}$$

With the transition probability matrix J with simple two state (ON-OFF) model, we assume that the no arrival in OFF state, while λ bits is intensity of the Poisson arrival process in the ON state. Therefore assuming the same generator matrix J as in (6) into (7), we can express the effective bandwidth as

$$B_E(\theta) = \frac{1}{\theta}\log\left(\frac{p_{11}+p_{22}e^{\lambda(e^{0}-1)}}{2} + \frac{\sqrt{(p_{11}+p_{22}e^{\lambda(e^{0}-1)})^2 - 4(p_{11}+p_{22}-1)e^{\lambda(e^{0}-1)}}}{2}\right) \tag{9}$$

where p_{11} determines the probability of staying in OFF state, while p_{22} identifies the probability of being in the ON state. The transition probabilities from one state to another are denoted by $p_{21} = 1-p_{22}$ and $p_{12} = 1-p_{11}$. The average arrival rate in bps is again given by:

$$\bar{\lambda} = \lambda P_{ON} = \lambda \frac{1-p_{11}}{2-p_{11}-p_{22}} \quad (10)$$

Design of a Model for effective capacity in fixed rate wireless transmission using Poisson and Markov processes

The proposed work is based on the following System Model as shown in Figure 6. Assume a single transmitter and receiver with point-to-point link. Moreover, it is assumed that the data generated by the source divided into frames. These frames are first stored in the buffer before transmitting it as illustrated in Figure 7. We consider Rayleigh block fading channel model. Hence, fading coefficient varies independently from one frame to another. The discrete time channel input-output relation of the i^{th} symbol duration is assumed as

$$C[i] = \log_2(1 + \mathrm{SNR}_{Z[i]}) \quad (11)$$

$$y[i] = h[i]\, x[i] + n[i] \;\; i = 1,2, \ldots, n \quad (12)$$

where xi and yi are the channel input and output respectively. n[i] is the zero mean, circularly symmetric, complex Gaussian random noise which is assumed to form an independent and identical distributed sequence (i.i.d) and is normalized to unity. Finally h_i is the channel fading coefficient and it is stationary and ergodic discrete process, thus $z[i] = |h[i]|^2$ is square-envelop of Rayleigh fading block coefficients, which are exponentially distributed with mean 1.

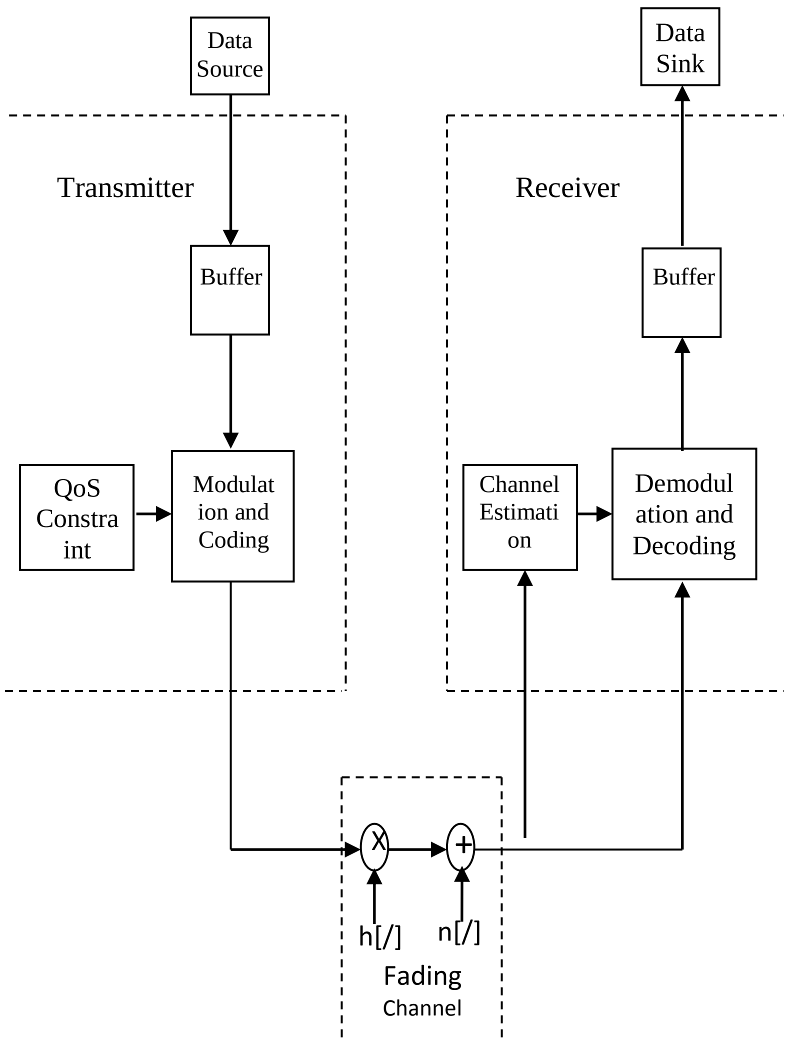

Figure 6: The General System Model

In this work, we assume that the receiver is able to estimate its own channel hi, whereas the transmitter does not know this information, therefore the transmitter would be transmitting information over the fixed rate r bps.

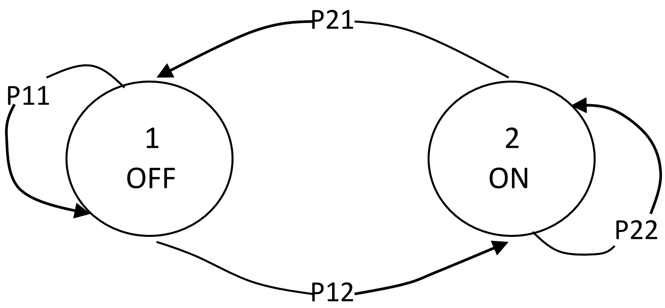

Figure 7: ON-OFF State Transition Model

Therefore, this behavior can be modeled as a two-state Markov Chain such that when r < C then the channel is considered in ON state and reliable communication is accomplished at the rate r. While r ≥ C then the channel is considered in OFF state so we cannot achieve reliable communication at the rate of r. We assume unitary bandwidth. Figure 7 illustrates this process, and we note pij, where i,j ∈{1,2}transition probabilities, which are a function of the SNR and target transmission rate r.

Therefore, we have the effective capacity for fixed rate transmission as follows

$$C_E(\text{SNR},\theta) = \begin{aligned} & -\frac{1}{\theta}\log\left(1-\left(1-e^{-\Psi}\right)\right)(1-e^{-\theta r})) \\ & = -\frac{1}{\theta}\log\left(1-e^{-\Psi}\right)(1-e^{-\theta r})) \\ & = -\frac{1}{\theta}\log\left(1-e^{\,-\frac{2^r-1}{\text{SNR}}}\right)(1-e^{-\theta r})) \end{aligned} \quad (13)$$

Simulation Model for effective capacity in fixed rate wireless transmission Using Poisson and Markov Processes with MATLAB

To implement the Model for effective capacity in fixed rate wireless transmission using Poisson and Markov processes, a MATLAB SIMULINK Model was developed for the Poisson and Markov processes and a MATLAB script was used to code the equation for the Poisson and Markov processes as shown in Equation 13.

Figure 7 shows the MATLAB – SIMULINKA Model for Poisson and Markov processes. The Model generates packets using a Markov-Modulated Poisson process, which is a Poisson process whose rate depends on the state of a Markov Chain (ON/OFF). In particular, the process is an interrupted Poisson process because the “off” state prevents packet generation.

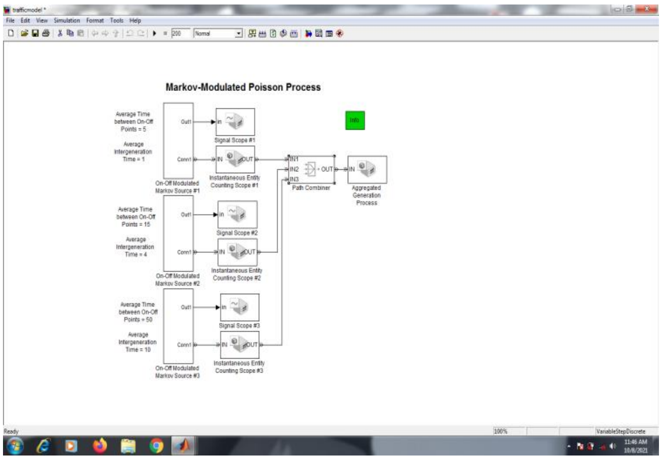

Figure 8: MATLAB SIMULINK Model for effective capacity in fixed rate wireless transmission using Poisson and Markov Processes

The model includes three independent on-off modulated Markov sources so you can see how their behavior depends on the rate of the Poisson process when the Markov chain is in the “on” state.

The Path Combiner block aggregates the outputs of all the On-Off Modulated Markov Source subsystems. Each of the On-Off Modulated Markov Source subsystems behaves as follows:

- The Time-Based packet Generator block models the Markov chain by generating a packet each time the chain changes state.
- The Entity Departure Event to Function-Call Event conveys the state change to the Create Generator Selection Variable subsystem, whose output changes from 0 to 1 or vice versa.
- The block labeled Generator 1 models the Poisson process by generating packets that attempt to depart from this On-Off Modulated Markov Source subsystem. (By contrast, the packets that represent the state changes of the Markov chain do not depart from this subsystem.)
- The Enabled Gate block regulates departures from the subsystem. If the state of the Markov chain is “off,” the gate is closed and packet cannot depart

Research Flow Chart

The Research Flow-Chart follows the pattern of the General System Model.

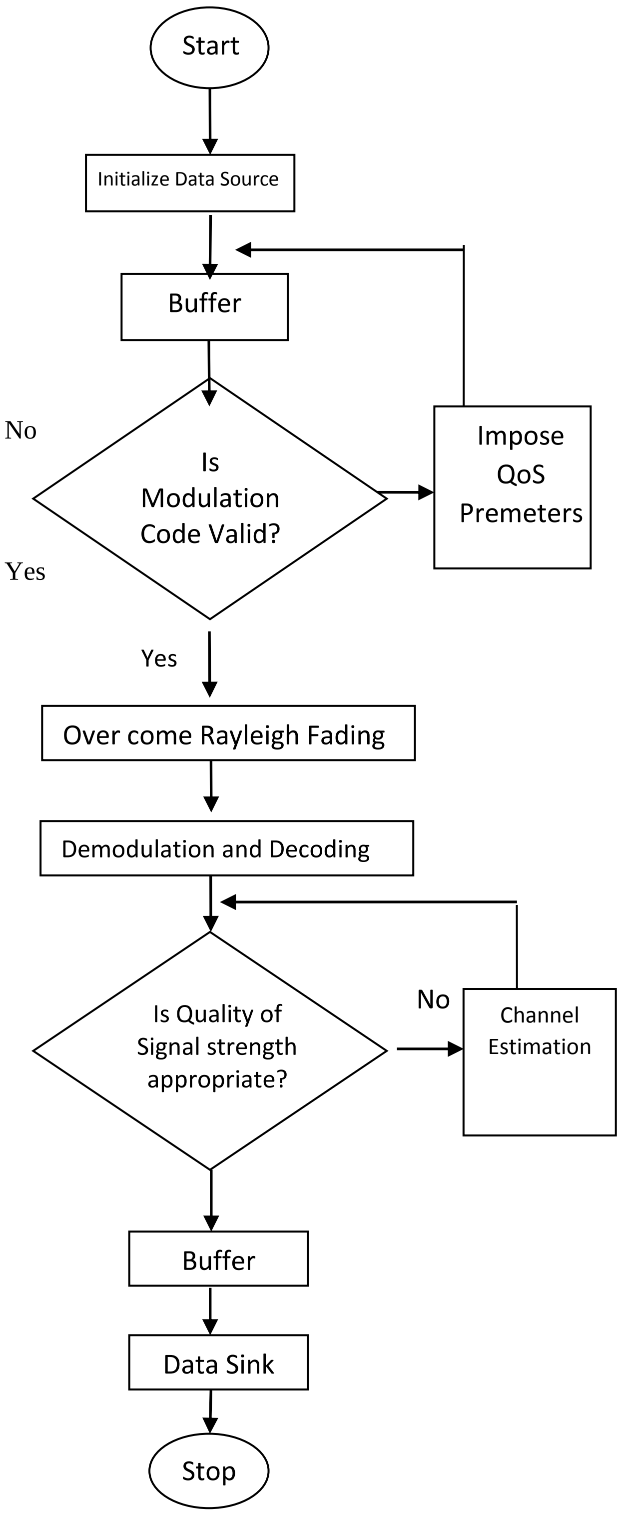

Figure 9: Flow Chart of General System Model

RESULTS AND DISCUSSION

The simulation carried out in MATLAB – SIMULINK was to determine effective capacity for data transmission in a data network. The simulation parameters used are as shown in Table 4.

Table 4: Simulation Parameters

Parameter	Value
Simulation time	90s
Rayleigh fading block coefficients	1
Transmission fixed rate r	0 – 10 bps
Channel state	ON/OFF
SNR	10, 100
QoS exponent θ	1 – 10
Traffic Pattern	CBR
Channel negotiation (Δ)	1.27 ms
UPD traffic flow	1 Mbps
Packet size	64 Kb

Simulation Results

Network Characterization Result

From the experiment carried out to measure the effect of the number of network Users on the network throughput, Table 3 was generated. The experiments involved monitoring the network users in a data center for forty eight days and then each day the average throughput per day was recorded. Figure 10 show the result of the test conducted.

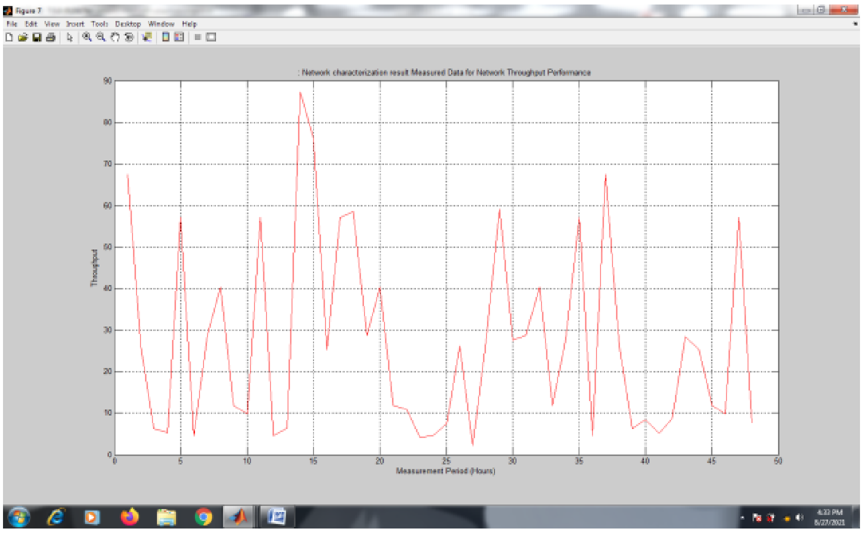

Figure 10: Test Bed Result on Effect of Data Traffic (Number of Network Users) on flow throughput

Figure 10 shows the throughput behavior of a flow with varying amounts of data traffic. The measurement was taken for different days and the average throughput computed per a day. The result shows that the flow throughput declines only when the flow traffic exceeds the network capacity.

MATLAB Simulation Result for Maximization of Effective Network Traffic Capacity

This paper investigated which characteristics (SNR, QoS exponent and transmission rate) maximize the effective network traffic capacity.

In a wireless communication system, it is generally presumed that by increasing SNR, the performance of the system is increased. Few Tables from experiments carried out are shown to buttress the point. Table 5 and Table 6 show the result obtained from simulation of Equation 12 in this paper for maximizing the effective network traffic capacity. Also Table 7 and Table 8 show the result obtained from simulation of Equation 8 for maximizing the effective bandwidth.

Table 5: Effective Network Capacity as a function of SNR with fixed transmission rate r = 1 bps and QoS exponent θ = 1

SNR	CE QoS exponent θ = 1
0	0
10	0.3229
20	0.4146
30	0.4691
40	0.5081
50	0.5383
60	0.5631
70	0.5841
80	0.6023
90	0.6184
100	0.6328

Source: Equation 12

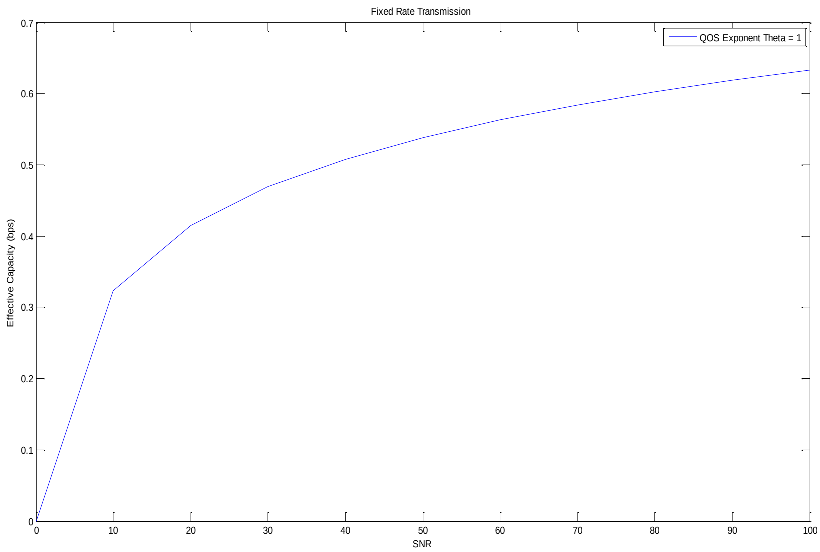

Figure 11: MATLAB Simulation Result of Effective Network Capacity as a function of SNR with fixed transmission rate r = 1 bps and QoS exponent θ = 1

Figure 11 shows the effective network traffic Capacity obtained from Equation 12 as a function of SNR for fixed value of transmission rate r. The simulation considers SNR values which are in linear (0 to 100). The QoS exponent (θ) used is 1. It is clearly observed that the effective network traffic capacity is increasing when SNR increases. However, effective capacity gradually slows its improvement in larger values of SNR. The increase in SNR produces drastic boost at certain point in effective network traffic capacity due to the fixed transmission rate which may lead to waste of scarce resources. Figure 12 shows MATLAB

Simulation Result of Effective Network Capacity as a Function of SNR with fixed transmission rate r = 1 bps and QoS exponent θ = 0.1.

Table 6: Effective Network Capacity as a function of Transmission rate for different values of SNR = 10 and fixed QoS =1

Transmission rate (r)	CE SNR= 10
0	0
1	0.3229
2	0.2535
3	0.1416
4	0.0538
5	0.0099
6	0.0004
7	0.00002
8	0.00001
9	0
10	0

Source: Equation 12

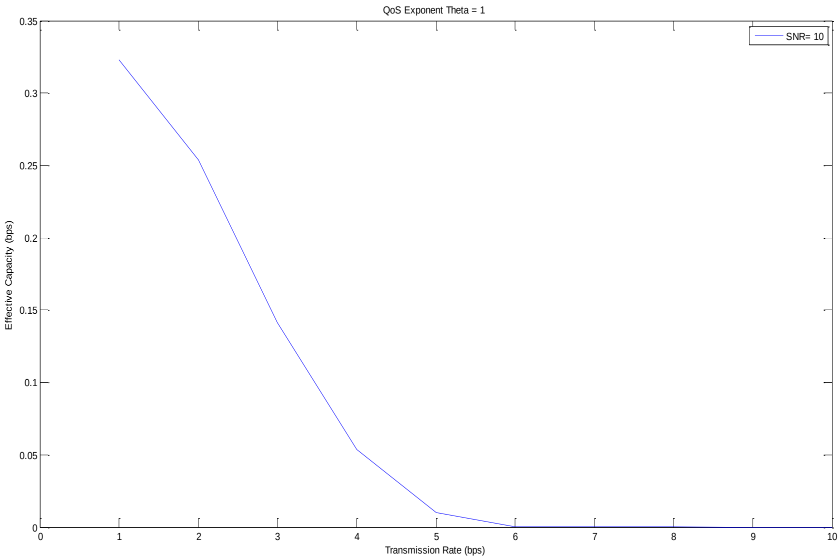

Figure 12: MATLAB Simulation Result of Effective capacity as a function of fixed transmission rate for different values of SNR = 10 and fixed QoS = 1

From Figure 13, the effective capacity as a function of transmission rate r for different value of SNR with fixed QoS constraint θ could be seen. It is clearly visible that the effective capacity increases as transmission rate increases, but after certain limit the effective capacity gradually starts decreasing due to fixed value of SNR. If one increase the transmission rate it will degrade the performance of effective network transmission capacity. For example, when SNR = 10 and θ = 1 then the maximum effective capacity can be supported by optimum transmission rate of 0.32 bps.

Table 7: Effective Network Bandwidth as a function of QoS exponent θ with fixed transmission rate r = 1 bps

QoS exponent θ	BE r = 1
0	Inf
1	0.2902
2	0.2537
3	0.3600
4	0.3903
5	0.4019
6	0.4080
7	0.4120
8	0.4149
9	0.4171
10	0.4188

Source: Equation 8

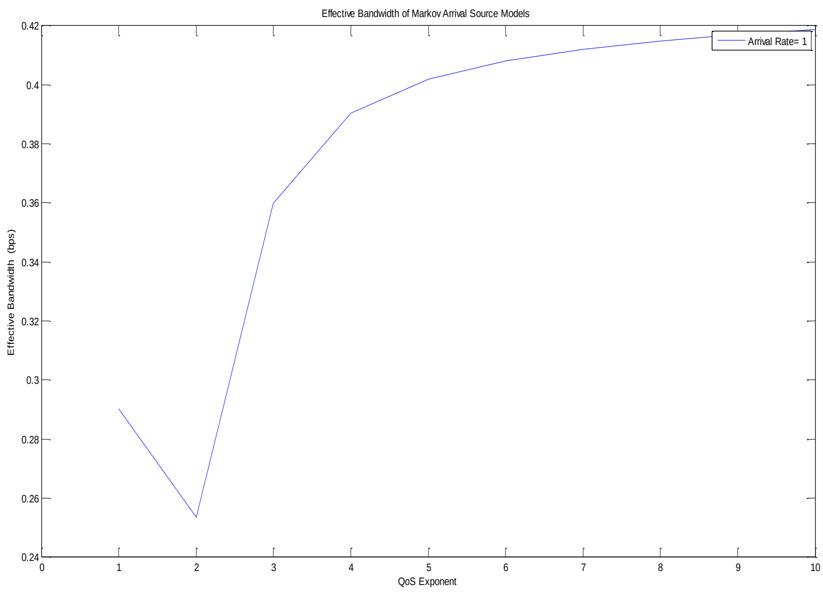

Figure 13: MATLAB Simulation Result of Effective Network Bandwidth as a function of QoS exponent θ with fixed transmission rate r = 1 bps

Table 8: Comparison of Effective Network Bandwidth as a function of QoS exponent θ with fixed transmission rate r = 1, 2 bps

QOS exponent θ	BE r = 1	BE r = 2
0	Inf	Inf
1	0.2902	0.5074
2	0.2537	0.7807
3	0.3600	0.8161
4	0.3903	0.8298
5	0.4019	0.8376
6	0.4080	0.8428
7	0.4120	0.8465
8	0.4149	0.8492
9	0.4171	0.8514
10	0.4188	0.8531

Source: Equation 8

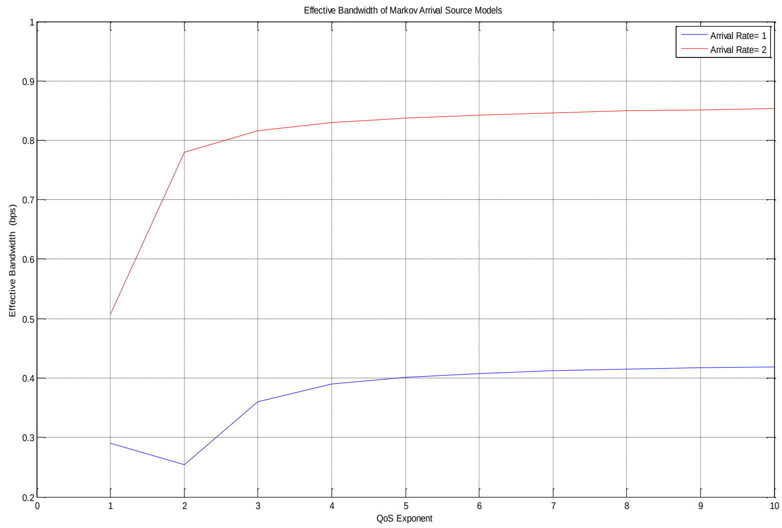

Figure 14: Comparison of MATLAB Simulation Result of Effective Network Bandwidth as a function of QoS exponent θ with fixed transmission rate r = 1, 2 bps

CONCLUSION

This research formulated effective transmission rate model to achieve adequate reliability and latency requirement for traffic management. The research incorporated Poisson and Markov source models to investigate their performance over sources arrival traffic and Rayleigh fading channel. From the simulation result, it was discovered that the source, buffer, and channel characteristics have major impact on the performance of model when certain QoS constraints are imposed. Moreover, we introduced a throughput metric that captures the behavior of sources burstiness and channel condition in the design of effective transmission link when certain level of reliability and latency is required. Moreover, increased source burstiness and stringent QoS requirement all need an increase in SNR gain to fulfill reliable communication. In conclusion, results obtained further showed that efficient use of transmission rate boosts the performance of communication system. Hence, optimizing the effective network traffic capacity and effective bandwidth with respect to the transmission rate, allows for high link throughput while allowing larger arrival rates. This paper detailed the analysis of the performance of delay constrained on fixed rate transmission, when source arrival of data is bursty. First, it provided a literature review for queuing constraint, effective bandwidth, effective Capacity, Markov sources and throughput and overview of congestion control. When considering Rayleigh fading channels, we obtained a closed form for the optimum effective network traffic capacity, where transmitter therefore transmits at a fixed rate, which is a key contribution of the research. Moreover, we investigated the effect of SNR and QoS constraints on optimum effective network traffic capacity. The analysis was not limited only to determining the throughput through the maximum average arrival rate that can be supported by fading channel while satisfying QoS constraints, but we explored the impact of randomness and burstiness to optimum effective capacity and delay probability as well, which are also another key contribution of this paper and as far as we are aware, such analysis has not yet been reported in any literature. The research introduced a detailed numerical analysis and investigated the impact of the randomness and burstiness on the reliability and latency of the wireless link, given different channel conditions.

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