Dynamic Admission Control Based on Effective Demand for Next Generation Wireless Networks

Somenath Mukherjee, Rajdeep Ray, Raj Kumar Samanta, Mofazzal H. Khondekar, Gautam Sanyal

Abstract—In next generation wireless networks (i.e., 4G and beyond), one of the main objectives is to ensure highest level of customer satisfaction in terms of data transfer speed, decrease in cost and delay, non-rejection and no drop of calls, availability of '*always-on*' connectivity and services, continuity of connected services, hastle-free roaming in addition to the convenience of use of network services from anywhere and anytime. To take care of these requirements effectively, internet service providers (ISPs) and network planners have to go for major capacity enhancement of network resources and at the same time these resources are to be used effectively and efficiently to reduce cost and to increase revenue. In this work, the effective bandwidth available in a Mobile Switching Center (MSC) of a wireless network providing multi-class multimedia services is analyzed. Bandwidth requirement of the users for a customized Quality of Service (QoS) is estimated. The findings of the QoS estimation are applied for the capacity planning and admission control of the multi-class traffic flows coming into the MSC.

Keywords—Next generation wireless network, mobile switching center, multi-class traffic, quality of service, admission control, effective bandwidth.

I. INTRODUCTION

SINCE the inception of wireless technology, cellular wireless network has come long way from providing analog voice calls to current 4G technologies, like high-speed packet access (HSPA) and long-term evolution (LTE), providing high quality mobile broadband multimedia services with up to several MBPS data rates. The distinct improvements in terms of enhanced network capacity, increased data rate, reduced transmission delay and improved QoS, in combination with the introduction of new generation mobile devices like smart phones and tablets, have encouraged the development of series of new services under certain constraint. It always remains a major challenge to network system engineers. Estimating the effective working bandwidth (data rate) of a wireless link and determining the buffer

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requirement to meet out the network QoS constrain mostly force to adopt conservative design approach [1]. Under such an approach, the system resources remain highly underutilized and network revenue generation remains alarmingly low [2]. The common design approach adopted by the wireless network system designers is to define some traffic parameters related to the traffic classes and analytically estimate the impact of such traffic class on the performance of the network [3], [4]. To establish an analytical model, designers generally take the help of different simulation techniques, where computer generated (synthetic) traffic is fed into the network to test the efficiency, reliability and robustness of such a design. Monitoring the traffic in an MSC of wireless network for a longer time span fetches some important understanding about the internal behavior of network traffic. However, that has never been adequate for making accurate assumptions about the stochastic characteristics of the traffic in a high speed multi-class wireless network [5]. In a multi-hop network, like wireless networks, long range dependency (LRD) of traffic plays an important role in network design [6]. Because of that, the stochastic characteristics of network traffic from a source are observed to be different, at its destination point, from what it was at its originating point. For a known rate function of a traffic class, there are different methods available in the existing literature, to determine the blocking probability of that traffic class. However, when there is an attempt to calculate the blocking probability for hundreds of multi-class traffic inflows into the system, a simple addition or union produces a very conservative result, due to the fact that the peaks of the individual traffic classes are statistically smoothed out over a period of time [7]. With these factors and unidentified parameters, the design engineers still in need to come up with a solution for the MSC dealing with multi-class traffic. Ultimately, it is a trade-off between the bandwidth and buffer requirement that the designers have to optimally decide by developing an efficient mathematical model. As the hardware resources, once manufactured and hence restricted, cannot be modified easily, the designers opt for developing algorithms to make MSC work more efficiently. Incoming traffic admission control algorithm is one of such frequently used software, set by the ISPs, to safe guard the interest of inflexible QoS goals [8]. As stated earlier, it is difficult to calculate the actual value of traffic distribution parameters precisely of a high speed wireless network MSC. As a result, most of the admission control algorithms have to work on approximately defined traffic parameters, with highly conventional worst case bounds, leading to inefficient or under-utilization of resources [9]. Therefore, efficient resource

utilization still remains a tough challenge to attain.

In this article, an effort has been made to evaluate the bandwidth and the buffer requirement of an MSC, in which the traffic sources are considered to be originated from Markov modulated Poisson processes (MMPP) [10], [11]. To start the analysis, traffic sources with known descriptors are assumed. The traffic distribution parameters are estimated from the data produced in the same way as shown in [12], [13]. Initially, the analysis is done with small buffers to establish the relation of data rate (bandwidth) with the probability of overflow (drop). Thereafter, the process continues to consider large buffers. Cramer's theorem [14] is applied to determine an upper bound on the value of the probability of overflow for a given data rate in a buffer-less channel (connection) whereas, Gartner Ellis theorem [15] is used to estimate the said upper bound on the probability of buffer overflow in a connection with buffer. Finally, an admission control algorithm has been proposed to achieve the performance of the MSC within a targeted probability of overflow to maintain the goal of a specified QoS.

The rest of this article is organized as follows: Section II illustrates traffic analysis with small buffers; Section III extends the same analysis on traffic from MMPP sources and with large buffers. Section IV describes the proposed admission control algorithm and Section V evaluates the performance of the algorithm. Section VI concludes the work.

II. MULTICLASS TRAFFIC ANALYSIS WITH SMALL BUFFERS

In this section, the bandwidth requirement of an MSC is analyzed with two classes of traffic. One is streamed traffic, like online multimedia or packet voice, in which delay beyond specified limit is not allowed. Because, it is of no use to deliver those packets after the specified limit of delay for delivery gets exhausted. The other class is elastic traffic which exhibits large peaks followed by no traffic for a prolong duration. For this traffic class, large buffers can significantly lessen the bandwidth requirement of the outgoing communication channel. Here, the traffic analysis is performed with both large buffers and small buffers. The analytical outcomes obtained may be extended to design trade-off between the buffer size and the bandwidth requirement of an MSC. Let us consider that the data arrive from a number of sources and they all are independent identically distributed (IID) random variables which are denoted by $D_1, D_2, D_3 \cdots$ etc. The total data arrived in a time slot t, from m sources, is $\sum_{k=1}^{m} D_k$. The bandwidth requirement B can be estimated by observing the probability $Pr(\sum_{k=1}^{m} D_k > B)$. It is assumed that the outgoing connection bandwidth is B and each traffic source uses a part b of total bandwidth. The objective is to estimate the probability $Pr(\sum_{k=1}^{m} D_k > mb)$. To attain that goal, the incoming traffic flow X is considered as a set of random variables (i.e. $X_1, X_2, X_3 \dots$) and arbitrarily taken any value ε just bigger than the expected or mean value of X, i.e. $E(X)$. Then, from Cramer's theorem [14] we can have

$$\lim_{m \to \infty} \left\{ \frac{1}{m} \ln Pr \left(\sum_{k=1}^{m} D_k > mb \right) \right\} = -\iota(\varepsilon) \qquad (1)$$

where $\iota(\varepsilon) = max_{\theta}(\theta\varepsilon - \ln M(\theta))$, for any $\theta \geq 0$. Here, $M(\theta)$ represents the moment generating function (mgf) of the traffic arrival process. Alternatively we can say, for large m, $e^{-m\iota(\varepsilon)}$ is a good approximation of $Pr(\sum_{k=1}^{m} D_k > mb)$ (the probability of overflow) and not just an upper bound of the incoming traffic admitted into the system. Therefore, the desired QoS can be approximated by:

$$e^{-m\iota(\varepsilon)} = 10^{-\delta} \qquad (2)$$

Here, δ is the QoS parameter or the probability of overflow. Now to estimate the bandwidth requirement of a specific source of input, the marginal distribution of the input data from the specific source is considered. It is shown in that the log moment generating function of traffic data coming from a Poisson's Process can be expressed as:

$$\ln M(\theta) = \lambda(e^{\theta} - 1) \qquad (3)$$

$\theta\varepsilon - \ln M(\theta) = \theta\varepsilon - \lambda(e^{\theta} - 1)$, where $\iota(\varepsilon)$ is a convex function and taken from (1). $\iota(\varepsilon)$ is increasing with θ, so it is differentiable. Therefore, the maxima can be calculated from the equation:

$$\frac{d\iota(\varepsilon)}{d\theta} = 0 \text{ or } \iota'(\varepsilon) = 0 \frac{d(\theta\varepsilon - \lambda e^{\theta} + \lambda)}{d\theta} = 0 \text{ or } \varepsilon - \lambda e^{\theta} = 0$$

We get

$$\theta = \ln\left(\frac{\varepsilon}{\lambda}\right) \qquad (4)$$

Putting the value of θ in (1), the expression for $\iota(\varepsilon)$ can be simplified as:

$$\iota(\varepsilon) = \varepsilon\ln\left(\frac{\varepsilon}{\lambda}\right) - (\varepsilon - \lambda) \qquad (5)$$

It is assumed that the peak arrival rate r =1 and mean arrival rate λ=0.4. Based on these assumptions, the arrival rate is normalized and then (5) for $\iota(\varepsilon)$ can be rewritten as:

$$\iota(\varepsilon) = \begin{cases} \infty & \text{for } \varepsilon \leq 0 \\ \varepsilon\ln\left(\frac{\varepsilon}{\lambda}\right) - (\varepsilon - \lambda) & \text{for } \varepsilon > 0 \end{cases} \qquad (6)$$

Similarly, for a periodic on-off data source where the peak rate of data arrival from the source is r and the mean arrival rate is p, the same estimation can be done and the traffic arrival process can be expressed as:

$$D_k = \begin{cases} r & \text{with probability p} \\ 0 & \text{with probability } 1 - p \end{cases}$$

The moment generating function of this traffic source is thus:

$$M(\theta) = (1 - p) + pe^{r\theta}$$

From (1) we can write

$$\iota(\varepsilon) = \max_\theta \left(\theta\varepsilon - \ln\left((1-p) + pe^{r\theta}\right) \right) \qquad (7)$$

The optimum value of θ can be obtained, following the same method stated above, as:

$$\theta = \frac{1}{r}\ln\left(\frac{\varepsilon(1-p)}{p(r-\varepsilon)}\right)$$

Replacing this value of θ in equation (7), we can have:

$$\iota(\varepsilon) = \begin{cases} \infty & \text{for } \varepsilon \leq 0 \\ \frac{\varepsilon}{r}\ln\frac{\varepsilon/r}{p} + \left(1-\frac{\varepsilon}{r}\right)\left\{\frac{1-(\varepsilon/r)}{1-p}\right\} & \text{for } \varepsilon > 0 \end{cases} \qquad (8)$$

The graphical presentation of $\iota(\varepsilon)$ against ε is shown in Fig. 1 for both (6) and (8).

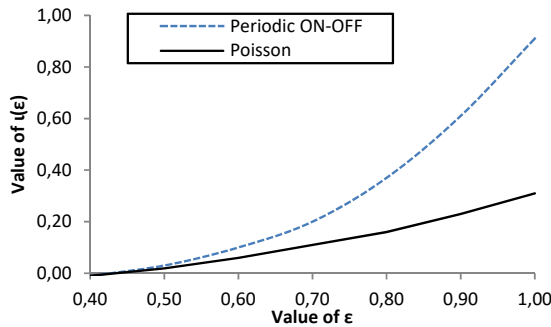Fig.1 Variation of $\iota(\varepsilon)$ against data rate, ε is normalized to maximum bit rate 1

TABLE
COMPARISON OF QOS PARAMETER OF TWO TYPES OF TRAFFICS WITH DIFFERENT DATA RATE

QoS δ	Peak data rate Normalized to 1				
MBR	0.414	0.66	0.721	0.782	0.844
l(ε) 1	0.013	3.093	4.56	6.251	8.155
l(ε) 2	0.02	6.035	9.291	13.35	18.42

MBR: Maximum Bit Rate; 1: Periodic ON-OFF Source; 2: Poisson Source, Mean Arrival Rate $\lambda = 0.4$, Number of Sources = 100.

The bandwidth requirement for a specific packet drop probability can be estimated from the graph. It can also be observed in (2), δ represents quantitative measures of the desired QoS whereas the actual values of the probability of packet drop are computed from (6) and (8). The calculated values of the probability of packet drop are shown in Table I. It can be observed from the table that with marginal buffering, MSC (with fixed bandwidth) provides better QoS for periodic on-off sources than Poisson's source. In other words, for a buffer-less network, traffic from Poisson's sources needs more bandwidth than traffic from periodic on-off sources, to achieve the same level of QoS with the same mean rate of data arrival,.

III. ANALYSIS WITH LARGE BUFFERS

In this section, the analysis of balanced state stable buffer size is worked out both in respect to discrete time as well as in continuous time. The analysis is started with an empty buffer

in consideration. The volume of data in the buffer at the the ith interval t_i can be denoted by $X_i = max\{(X_{i+1} + D_i - B), 0\}$, where D is the volume of data that arrives in the ith interval, B is the available bandwidth for the outgoing link (the volume of data the link can emit in each interval) and $X_0 = 0$. Assuming the available volume of data V_t at buffer is cumulative, it can be written data arrival process $V_t = 0$ at $t < 0$. That is at time 0- the buffer is empty. According to Reich's equation [12],

$$X_n = \max_{0 \leq i \leq n}(V_n - V_i - (n-i)B)$$

where, for $n \geq 1$, $V_k = \sum_{k=1}^{n} D_k$ and $V_0 = 0$. In the state of equilibrium, $\lim_{n \to \infty} \frac{V_n}{n} < B$. i.e. the rate of data arrival is less than the volume of data that can be transmitted out in that interval of time. Therefore,

$$\text{at } n \to \infty, X \xrightarrow{dist} \max_{k \geq 0}(V_0 - V_k - kB) \qquad (9)$$

Under this condition, the effective bandwidth (EB) requirement can be estimated using the theory of Chernoff's bound 8. For discrete time, the limiting random variable, denoted by X where X is finite with probability 1, can be obtained from (9). Then X is the random volume of data in the MSC buffer, in steady state. Therefore, the probability that are more than x bytes volume of data in the buffer in steady state can be expressed as $P_r(X > x)$. Then Ψ with parameter θ, for any $\theta > 0$, if the bandwidth $B > \{\Psi(\theta) / \theta\}$. If we are able to express the QoS requirement for the MSC on the basis of probability of decay rate, then to ensure a desired decay rate θ, it will be sufficient to choose a bandwidth more than $\{\Psi(\theta) / \theta\}$, by an arbitrarily small positive amount. Therefore, $\{\Psi(\theta) / \theta\}$ can be termed as the EB [16], [17] and it is represented by $e(\theta)$. Now, if the input to the MSC is the superposition of several independent data sources, then the EB of the composite source (input to the MSC) is the sum of the EB of individual input sources for a given θ. That is, if V_n^k where $1 \leq k \leq m$ are independent sources with log moment generating function $\Psi^k(\theta)$, then for the composite source arrival process

$$V_n = \sum_{k=1}^{m} V_n^k \qquad (10)$$

and the log moment generating function

$$\Psi^k(\theta) = \sum_{k=1}^{m} \Psi^k(\theta) \qquad (11)$$

Then, the EB of such composite source is

$$e(\theta) = \sum_{k=1}^{m} e_k(\theta) \qquad (12)$$

where $e_k(\theta)$ is the EB of V_n^k

We are interested to estimate the probability of buffer overflow. It is assumed that the data coming into the MSC at the ith interval with peak rate R and mean rate r. Then,

$$r = \lim_{n\to\infty} \frac{1}{n}\sum_{i=1}^{n-1} D_i \tag{13}$$

Now, from the definition of $\Psi(\theta)$ in (18) we can find that it is finite for all real values of θ and also differentiable. Therefore, similar to (1) of $\iota(\varepsilon)$ we can define:

$$\varphi(\varepsilon) = max_\theta(\theta\varepsilon - \Psi(\theta)) \tag{14}$$

where $\Psi(\theta)$ is the log moment generating function of the data arrival process. If D_i sequence is independent identically distributed (i.i.d) then, $\varphi(\varepsilon)$ defined in (14) is exactly same as shown in (1) for any $\varepsilon > EB$. Since, $\varphi(\varepsilon)$ is non-negative, convex and differentiable, optimized value of θ can be obtained by:

$$\varphi'(\varepsilon) = 0 \text{ and } \Psi'(\varepsilon) = 0 \tag{15}$$

Under this traffic condition, Gartner-Ellis Theorem [18] can be applied and it states that for any $\varepsilon > r$,

$$\lim_{n\to\infty}\left\{\frac{1}{n}\ln Pr\left(\sum_{k=0}^{n-1} D_k > nb\right)\right\} = -\varphi(\varepsilon) \tag{16}$$

With these equations, the lower bound of $Pr(X_n > x)$ can be determined, for large value of x, as

$$(Pr \sum_{k=1}^n D_k > nB) \approx \sum_{s>B} e^{-x\varphi(s)} \tag{17}$$

Now, for calculation of effective desired bandwidth (B) in the MSC, the Quality-of-Service (QoS) parameter (i.e. the probability of decay rate) must not exceed the value of $e^{-\theta x}$.

Following (17), a Two State Discrete Time MMPP is taken up to determine the probability of overflow (i.e. QoS parameter), as the source of data. Let's consider the transition matrix of the MMPP Source as:

$$M = \begin{bmatrix} 1-\alpha & \alpha \\ \beta & 1-\beta \end{bmatrix}$$

The ON state peak rate of data arrival is R and in OFF state it is 0. α and β represent the state transition probability of the Markov Chain. Then the log moment generating function

$$\Psi(\theta) = \ln\frac{1}{2}\left[\varepsilon(\theta) + \sqrt{\varepsilon^2(\theta) - 4b(\theta)}\right]$$

where, $\varepsilon(\theta) = \left((1-\beta)e^{R\theta} + (1-\alpha)\right)$ and $b(\theta) = \left((1-\alpha-\beta)e^{R\theta}\right)$.

Using (15), after solving some algebraic equations, the value of $\theta = \frac{1}{\lambda}\ln\frac{1.5\varepsilon}{\lambda(1-\varepsilon)}$ can be achieved for $\alpha=0.4$ and $\beta=0.6$. Likewise, for an MSC with N States and having Continuous Time MMPP traffic sources, the log moment generating function is [10]:

$$\Psi(\theta) = \frac{1}{2}\left[R_p\theta - \alpha - \beta + \sqrt{(R_p\theta - (\alpha+\beta))^2 + 4\alpha R_p\theta}\right] \tag{18}$$

If R_p is the peak rate of data arrival and α, β are the

elements of the state transition matrix $M = \begin{bmatrix} -\alpha & \alpha \\ \beta & -\beta \end{bmatrix}$. From (15), we can find the value of θ:

$$\theta = \frac{1}{R_p}\left[\beta - \alpha + \frac{\sqrt{\alpha\beta}(2\varepsilon - R_p)}{\sqrt{\varepsilon(R_p - \varepsilon)}}\right] \tag{19}$$

For a desired QoS, the probability of buffer overflow for N State Continuous Time MMPP source as well as Two State Discrete Time MMPP source is presented in Fig. 2 and their drop probability (in Log_{10} Scale) with different load factors (LF) is given in Table II.
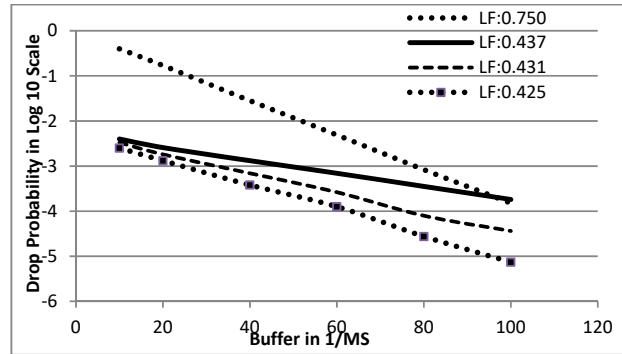

Fig. 2 Overflow or Drop Probability against Buffer size. All the curves are drawn using 100 flows. LF stands for Load Factor

TABLE II
DROP PROBABILITY COMPARISON OF TWO TYPES OF TRAFFICS WITH DIFFERENT LF (IN LOG 10 SCALE)

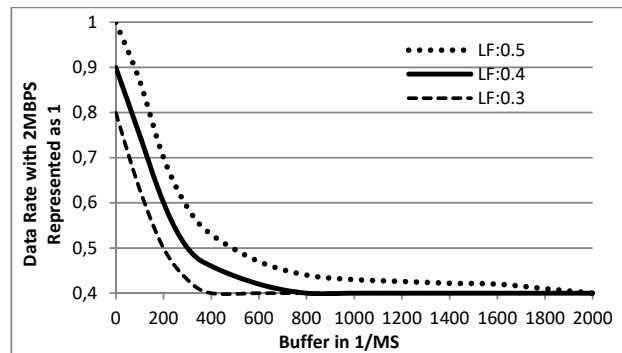| Type of Traffic	Buffer in 1/MS					
	10	20	40	60	80	100
1	-0.4	-0.77	-1.55	-2.31	-3.08	-3.82
2	-2.4	-2.59	-2.88	-3.16	-3.45	-3.74
3	-2.48	-2.74	-3.16	-3.58	-4.1	-4.44
4	-2.6	-2.88	-3.42	-3.9	-4.56	-5.13

Fig. 3 Variation of Buffer requirement of a Continuous Time MMPP Source. LF stands for Load Factor

In Table II, the rows indicate the drop probability as detailed below:
1. Two State Discrete Time MMPP Sources, LF = 0.750
2. N State Continuous Time MMPP Sources, LF = 0.437
3. N State Continuous Time MMPP Sources, LF = 0.431
4. N State Continuous Time MMPP Sources, LF = 0.425

In all the above cases, traffic from 100 different sources is considered. The tradeoff between bandwidth and buffer for different values of λ is given in Fig. 3.

One may choose to provide more buffer (as buffer is a cheaper resource) instead of opting for high bandwidth to manage elastic traffic depending on his QoS requirement.

IV. ADMISSION CONTROL ALGORITHM

In the above sections of this article, we have dealt with traffic sources with known traffic descriptors. With this type of traffic sources, the relationship among the probability of overflow, buffer space and bandwidth have been established. For admission control at the MSC, every new traffic flow coming into the system has to be either accepted or rejected in the interest of maintaining the predefined desired QoS requirement. The primary task to come into this decision is to derive the traffic descriptor or the rate function accurately by observing the traffic flows through a reasonably small time window. A larger time window requires larger computation time that delays the decision about the admission of the traffic flow. Further, in larger time window, the sharp statistical changes of the traffic flows get averaged out and so the probability of transient overflow may be smoothed out. Measurement based admission control techniques have been adopted by many researchers [19]-[21], [17]. A 20 ms time widow was considered in their work by Fernández-Veiga et al. [20] to derive the rate function and the corresponding probability of overflow. Pandit et al. [19] used the likely burst period of the new traffic flow as the time window for analysis of their admission control algorithm.

The techniques to derive the probability of overflow discussed above mostly require the distribution function of the traffic flow. It was observed under this work that in case of a new traffic flow, it is practically difficult to access the actual distribution function just by monitoring the traffic flow passing through this small time window. However, an approximation may possibly be estimated, leading to the doubtful rejection of the traffic flows which could possibly be accepted. This decision of rejecting an incoming flow for the sake of maintain the targeted QoS, sometimes may cause frequent packet drops leading to underutilization of available network resources. In this paper, the transient loss probability of the proposed admission control algorithm has been derived by applying a generalized form of Erlang loss formula. In the proposed algorithm, the probability of drop can be calculated for multiclass traffic with variation of the parameters like distribution function of the new traffic flow, packet length etc. Chiera et al. [22] suggest a blocking technique using Erlang Blocking formula. Mandjes and Ridder [21] also used the same formula to calculate the probability of drop for each class separately and served the traffic flows by the principle of M/M/n/n queue to develop their admission control algorithm [23]. In this paper, the strategy is different from that. The probability of blocking for multi-class traffic has been calculated with the help of Kauffman Robert formula [24] [25]. Here, the formula is improvised for buffer capacity instead of bandwidth. It is assumed that transmission of data is taking place at the full bandwidth capacity. The probability of buffer overflow has been calculated beyond its stationary buffer length. The said probability is denoted by $P_B(k)$ below, as shown by Mitra and Weinberger [24], Bhattacharjee and Sanyal [25]:

$$P_B(k) = \frac{1}{g} \sum_{r \in S_B(k)} \prod_{k=1}^{K} \frac{\rho_k^{r_k}}{r_k!} \tag{20}$$

where B represents the total buffer capacity, k stands for the class of the new incoming traffic flow, K is the total number of traffic classes, $S_B(k)$ denotes the set of packets as defined in (22), r_k is the number of packets of kth class traffic present in the buffer, ρ is the load factor of kth class traffic flows, n stands for the total number of unit buffers. g is normalization constant to make the total probability 1 and it is defined as

$$g = \sum_{r \in S} \prod_{k=1}^{K} \frac{\rho_k^{r_k}}{r_k!} \tag{21}$$

$$S_B(k) = \{r: B - r^T \cdot b < b_k\} \tag{22}$$

S belongs to the set of all possible combination of all classes of traffic flows. In this admission control algorithm, a running value of $P_B(k)$ is calculated for all traffic classes ($k = 1, 2, \cdots K$) of traffic flows. Then the total sum of the buffer overflow probability (i.e. probability of call drop) is calculated as

$$P_B = \bigcup_{k=1}^{K} P_B(k) \tag{23}$$

Under this situation one of the following two events may arise to influence decision:

1. If a packet belonging to traffic class k departs from the MSC, the existing value of $P_B(k)$ is divided by to get the new value of $P_B(k)$. The current value of P_B is computed using (23).

2. If a new traffic flow of class k arrives into the MSC, the flow is monitored over a time window and the packets received are stored in a buffer. Monitoring window time extended up to one peak of the traffic flow following the suggestion of Pandit and Meyn [19]. Fixed time window is not considered to generalize the algorithm and to make it suitable for any available bandwidth. Since the weighted round robin queue is being served by a single processor, the packet departure rate μ_k and the number of packets n_k of traffic class k currently in the queue is known. Then the number of new packets n_k' coming into the system is counted. Thereafter, additional load $\omega = \frac{\rho_k^{n_k'}}{\delta}$ is calculated, where $\delta = \prod_{i=n_k+1}^{n_k'+n_k} i$. Then the modified value of $P_B(k)$ is recalculated as: $Prev\_P_B(k) = P_B(k)$ and $P_B(k) = P_B(k) \cdot \omega$ and the overall probability of drops (or the buffer overflow) P_B is recomputed as $Prev\_P_B = P_B$ and $P_B = (P_B - Prev_{P_B}(k)) \cup P_B(k)$. Now, if ξ considered to be the set probability of packet

drops (QoS) target, then the new flow is rejected when $P_B > \xi$ and the modified value of $P_B(k)$ and P_B is replaced by the previous values, i.e., $P_B(k) = Prev\_P_B(k)$ and $P_B = Prev\_P_B$. If the new incoming flow is accepted, the existing queue of class k is merged with the temporary buffer and the process repeated with the new values of $P_B(k)$ and P_B. The computation is initiated with an empty buffer and allowing one packets at a time to come into the system. Thereafter, all future estimations require only incremental calculations. Therefore, admission control does not add extra overhead on the MSC.

V. PERFORMANCE ANALYSIS

NS-2 simulator is used for the experimentation and analysis of performance of the admission control algorithm. Raw traffic data are collected from the system log of MSC of an ISP providing wireless services. The behavior of network traffic and the value of drop probability are studied through statistical analysis of the collected. Then a simulated MSC environment with similar types of traffic is created and tested with the proposed admission control algorithm. The observed values of the drop probability against varying buffer size are presented in Fig. 4 and the numerical comparison of some values is given in Table III.

TABLE III
NUMBER OF SOURCES = 100. DROP PROBABILITY COMPARISON OF TWO TYPES OF TRAFFICS WITH DIFFERENT LF (IN LOG 10 SCALE) WITH 3 DIFFERENT TREATMENTS ON THE SET OF FLOWS

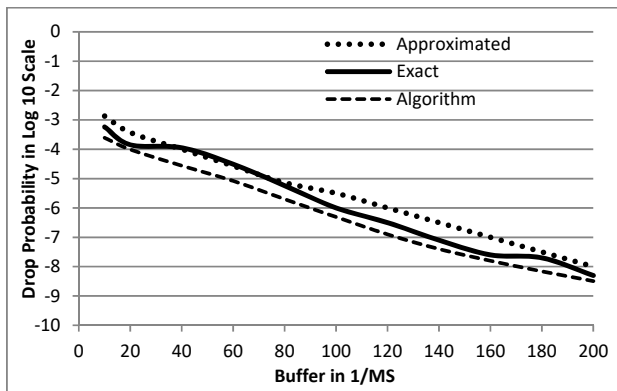| Type of Traffic	Buffer in 1/MS										
	10	20	40	60	80	100	120	140	160	180	200
1	-2.87	-3.43	-4	-4.57	-5.14	-5.5	-6	-6.5	-7	-7.5	-8
2	-3.24	-3.85	-3.95	-4.51	-5.24	-6	-6.5	-7.1	-7.6	-7.7	-8.3
3	-3.61	-4.01	-4.56	-5.08	-5.7	-6.31	-6.9	-7.4	-7.8	-8.161	-8.492

Fig. 4 Call Drop Probability shown with estimated, exact and obtained through proposed algorithm

VI. CONCLUSION

In this paper, network traffic analysis is done with known traffic descriptors using the knowledge base of existing sciences of network engineering. An admission control algorithm has been worked out based on the outcome of the traffic analysis. The algorithm is not based on assumptions but based on the differential behavior of the multi-class network traffic in an MSC. The bandwidth and buffer size relationship have been kept adjustable to the device manufacturer's choice. The MSC can fit to a wide range of devices through the trade-off between bandwidth and buffer size.

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