Traffic Modeling and Characterization for UMTS Networks

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***Abstract* - In this paper, we present a synthetic traffic model for the Universal Mobile Telecommunication Systems (UMTS) based on measured trace data. The analysis and scaling process of the measured trace data with respect to different bandwidth classes constitutes the basic concept of the UMTS traffic characterization. Furthermore, we introduce an aggregated traffic model for UMTS networks that is analytically tractable. The key idea of this aggregated traffic model lies in customizing the batch Markovian arrival process (BMAP) such that different packet sizes of IP packets are represented by rewards (i.e., batch sizes of arrivals) of the BMAP. The effectiveness of the customized BMAP for modeling UMTS traffic is illustrated using the synthetic traffic model previously presented.**

I. Introduction

Traffic modeling and characterization constitute important steps towards understanding and solving performance-related problems in future wireless and wireline IP networks. The central idea of traffic modeling lies in constructing models that capture the important statistical properties of the underlying measured trace data. Third generation (3G) mobile communication systems like the *Universal Mobile Telecommunications System* (UMTS, [1], [5]) are characterized by a migration from voice-only to integrated services IP networks with data rates up to 2 Mbps. Recently, the global wireless industry has created a global partnership project, *the 3rd Generation Partnership Project (3GPP)* [1], for standardization of UMTS. Besides the QoS concept and architecture for UMTS networks, several approaches for traffic modeling and characterization have been outlined by the 3GPP. However, a detailed technical understanding how traffic modeling should effectively be performed for UMTS networks is subject to current industrial and academic research [4].

Traffic models for wireless and wireline IP networks have been addressed in several recent papers. Anderlind and Zander proposed a simple model for future data traffic in wireless radio networks [2]. Anagnostou, Sanchez Papaspiliou, and Venieris proposed a traffic model for multi-service IP networks taking into account individual user descriptions [3]. In the UMTS standard [5] recommendations for traffic models are given, which include parameterized distributions for real-time and non real-time services, but detailed characteristics are presented for WWW traffic only. In [10] the Mobile Wireless Internet Forum (MWIF) proposes, how IP can be applied in Radio Access Networks within 3rd Generation mobile systems. Furthermore, the recommendations of [5] are adopted without further enhancements and extensions. However, these traffic models are not derived from real measurements and are not analytically tractable.

The lack of deriving traffic from existing UMTS networks motivates a characterization of future UMTS traffic based on network environments comprising of comparable characteristics. Kilpi and Norros [7] showed that IP traffic of current Internet Service Providers (ISP) inhibits many characteristics of future UMTS traffic. These common properties include different access speeds, influence of the user behavior due to different tariff limits, and asymmetric up- and downlink traffic. Using a similar approach, Staehle, Leibnitz and Tran-Gia introduced the single user traffic model for modeling IP traffic in wireless networks [11]. The main difference between the measured IP traffic at a dial-in modem/ISDN link and UMTS traffic constitutes of the different bandwidth classes of individual users. Färber, Bodamer, and Charzinski used measured trace data to derive a traffic model for Internet dial-in traffic [6]. They focused on the dial-in behavior of modem and ISDN users by fitting general distributions (e.g., Weibull and Lognormal) to the session interarrival-times and the holding times.

The contribution of this paper is two-fold: First, we characterize an IP traffic trace measured at the ISP dial-in modem/ISDN link of the University of Dortmund. Based on the measured traffic data, we present a synthetic traffic model for UMTS networks applying the idea of the single user traffic model [11]. Second, using this synthetic UMTS traffic model, we introduce an aggregated traffic model that is analytically tractable. The key insight of this modeling approach lies in an appropriate scaling procedure of the measured trace data towards UMTS bandwidth requirements. We brake down the measured IP traffic into session-level traffic, connection-level traffic, and packet-level traffic. Subsequently, we fit the characteristics of these three levels to general distributions trying to closely represent the statistical properties. We characterize trends in current ISP measurements with respect to increasing bandwidth classes. Based on these trends, we scale the bandwidth of the dial-in modem/ISDN links to different bandwidth classes available in UMTS and derive a synthetic traffic load for UMTS networks. As a consequence of adopting statistics through general distributions this traffic model is not analytically tractable.

The key idea of the aggregated traffic model for UMTS networks lies in customizing the batch Markovian arrival

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process (BMAP, see e.g., [9]) where different packet sizes of IP packets are represented by rewards (i.e., batch sizes of arrivals). This analytically tractable traffic model employs an efficient and numerical robust parameter estimation procedure presented in [8]. The effectiveness of the analytically tractable model based on the BMAP is illustrated using the synthetic UMTS traffic model previously presented.

The paper is organized as follows. To make the paper self-contained, Section II describes the concept of the single user traffic model and the aggregated IP traffic model using the BMAP. Section III presents the analysis and characterization of the measured IP traffic. In Section IV, we introduce a scaling procedure that adopts the statistical properties of the measured trace data with respect to higher UMTS bandwidth classes. We present the detailed synthetic UMTS traffic model comprising of parameters of general distributions for session-level, connection-level and packet-level and the aggregated traffic model for UMTS networks. Finally, concluding remarks are given.

II. Traffic Modeling Approaches

A. Traffic Modeling using the Single User Traffic Model

The single user traffic model [11] utilizes the notion that a user, who runs non real-time applications (e.g. HTTP, Napster, e-mail, etc.), follows a characteristic usage pattern. Considering this model, a single user can run different applications that may be concurrently active, e.g. WWW browsing while downloading Napster music files. Each application is completely described by its statistical properties. These statistical properties comprise of an alternating process of ON- and OFF-periods with some application specific length or data volume distribution, respectively. Moreover, within each ON-period the packet arrival process is completely captured by the packet interarrival-times and the corresponding packet sizes. Thus, the single user traffic model characterizes the traffic that an individual user generates. In UMTS, we have to distinguish between real-time users and non real-time users. Considering just non real-time users, the single user traffic model is employed on three different levels:

(1) The session-level describes the dial-in behavior of the individual users, characterized by the session interarrival-time distribution and the session data-volume distribution.

(2) The connection-level describes for each individual application the corresponding distribution of connection interarrival-times and connection data volume, respectively.

(3) The packet-level characterizes the packet interarrival-time distribution and the packet size distribution within the application specific connections.

A non real-time user runs applications like HTTP, Napster, e-mail, and various other applications that can be concurrently enabled. During an ON-period, i.e. an application specific connection, the user applies the appropriate application in an active fashion. The interarrival-time between two successive connection starting points of the same application-type and the data volume of each connection are drawn from general distributions, respectively.

The packet interarrival-times within each connection and the corresponding packet sizes are also drawn according to an application dependent distribution. The overall traffic stream of a user constitutes of the superposition of the packet arrival process of all application connections within the user's session. New users enter the considered system environment according to a session interarrival-time distribution and leave the system after transferring a specific data-volume drawn according to a session volume distribution. While this modeling approach is efficient and authentic towards simulation studies, the nature of the generally distributed sources of the single user traffic model does not result in an analytically tractable model that can be integrated as a traffic generating component within analytical models. This motivates a different modeling approach using a stochastic process that matches the crucial properties of the considered IP traffic, e.g. traffic burstiness over a wide range of different time scales [12], while being analytically tractable.

B. Traffic Modeling using the Batch Markovian Arrival Process

The batch Markovian arrival process (BMAP) belongs to the class of Markov renewal processes and is analytically tractable [9]. Consider a continuous-time Markov chain (CTMC, [9]) with $(N+1)$ states $\{0,1,\ldots,N\}$ where the states $\{1,2,\ldots,N\}$ are transient states and 0 is the absorbing state. Based on this governing CTMC, the BMAP can be constructed as follows: Assume the BMAP is in a transient state i for an exponentially distributed time with rate λ_i. When the sojourn time has elapsed, there are $(M+1)$ possible cases for state transitions. With probability $(\mathbf{P}_m)_{i,j}$ the BMAP enters the absorbing state 0 and an arrival of batch size m occurs. Then, the process is instantaneously restarted in state j. Note that the selection of state j ($1 \le j \le N$) and batch size m ($1 \le m \le M$) is uniquely determined by $(\mathbf{P}_m)_{i,j}$. On the other hand, with probability $(\mathbf{P}_0)_{i,j}$ the BMAP enters another transient state $j, j \ne i$, without arrivals. Furthermore, we can define $(\mathbf{D}_0)_{i,j} = \lambda_i \cdot (\mathbf{P}_0)_{i,j}$ for $j \ne i$, $(\mathbf{D}_0)_{i,i} = -\lambda_i$ and $(\mathbf{D}_m)_{i,j} = \lambda_i \cdot (\mathbf{P}_m)_{i,j}$.

In recent work, a computational efficient and numerical robust EM (expectation maximization) algorithm for the parameter estimation process of BMAPs, i.e. estimation of the parameter matrices $\mathbf{D}_0$ and $\mathbf{D}_m$ ($1 \le m \le M$), has become available [8]. In Section IV this estimation procedure is employed for IP traffic (i.e., the packet interarrival-times and the corresponding packet sizes) derived from the single user traffic model. Note that the key idea of considering both the interarrival-times and packet sizes relies in regarding the packet sizes as the rewards (i.e. batch sizes of arrivals) of the BMAP. Based on this parameter estimation, such a customized BMAP constitutes an aggregated IP traffic model considering both packet interarrival-times and packet sizes, while still being analytically tractable.

III. Characterization of Measured IP Traffic

A. Traffic Measurements

In order to get characteristic trace data of current ISP traffic, we conducted detailed traffic measurements at the ISP dial-in modem/ISDN link of the University of Dortmund. During the measurement over a four-week period in January 2001, approximately 110,000 user sessions have been logged. The total data volume sums up to 120 GB. All measurements are conducted at the Ethernet link between the MaxTNT dial-in routers and the router connection to the Internet. We used the *TCPdump* software package running on a Linux client for sniffing all IP packet headers sourced or targeted by dial-in users. For each IP packet the arrival timestamp, the source port, the target port, the packet length, and other TCP header information have been recorded.

B. Traffic Analysis of University of Dortmund ISP Trace

In this section, we present the analysis of the characteristics, which are fundamental for the UMTS traffic modeling approach of Section IV. First of all, we consider the usage fraction of dial-in users partitioned in the bandwidth classes 9.6 kbps, 14.4 kbps, 28.8 kbps, 33.6 kbps, 56 kbps and 64 kbps. The 64 kbps bandwidth class is associated with the class of ISDN users. The usage fractions with respect to the transferred data volume are as follows: 1% for users with a bandwidth less or equal 14.4 kbps, 3% at 28.8 kbps, 10% at 33.6 kbps, 40% at 56 kbps, and 46% at 64 kbps. Referring to the number of dial-in sessions the fractions are 1% at bandwidths less or equal 14.4 kbps, 5% at 28.8 kbps, 12% at 33.6 kbps, 43% at 56 kbps, and 39% at 64 kbps. Obviously the data volume of users with fast dial-in access dominates the corresponding dial-in fraction, e.g., 39% ISDN users produce 47% of the total data volume.

Furthermore, we analyze the application usage pattern of current ISP dial-in users with respect to the overall data volume broken down in HTTP, Napster, e-mail, UDP, FTP, and other TCP applications. HTTP is the dominating application with a fraction of 73%. The popular Napster music download application (i.e., 9%), followed by the e-mail application (i.e., 6%) and other TCP applications (i.e., 6%) constitute further important applications. FTP applications with 2% do not contribute a significant amount of today's application because file transfers are increasingly performed via HTTP. The small amount of UDP applications of 4% demonstrates that dial-in modem/ISDN users, regarding their specific bandwidth capabilities, rarely use real-time applications, which are predominantly transferred via UDP. Indeed, realistic statistical properties of real-time applications cannot be derived from the measured trace data. Therefore, we focus our investigations on non real-time traffic. The identification of the different application types within the enormous amount of measured data is conducted by detailed investigation of the measured IP packet header fields.

By aligning the dial-in routers log file with the trace data we identify all packet headers of a specific session and associate it with the bandwidth class of this session. Thus, we derive session interarrival-time and session data volume statistics for each bandwidth class. Furthermore, in order to perform connection level analysis, for each session the associated TCP connections are restored and sorted with respect to the protocol number, which specifies the application type. Finally, the packet-level statistics within the application specific connections are derived.

We observe that each statistical measure of the three traffic levels comprise of a *characteristic distribution* which is independent of the dial-in user's bandwidth class, e.g. the HTTP connection interarrival-times are distributed according to a lognormal distribution. Therefore, the distribution of a specific statistical measure differs only by the parameter values of the characteristic distribution for different bandwidth classes. In order to find such a characteristic distribution for a specific statistical measure we use a least-squares regression with respect to the bandwidth classes 9.6 kbps, 14.4 kbps, 28.8 kbps, 33.6 kbps, 56 kbps, and 64 kbps. We consider the following set of probability density functions (pdf): Lognormal, Pareto, Weibull, Gamma, and Exponential. As shown in Section IV the considered statistical measures can be closely matched with these pdfs.

IV. Traffic Modeling of UMTS Traffic

A. Scaling Procedure for Bandwidth Classes of UMTS

Applying the notion of characteristic distributions introduced in the previous section, we use the characteristic distributions derived from the ISP measurement to obtain a traffic model for UMTS. This is closer to realistic future UMTS traffic than just assuming traffic characteristics or obtaining characteristics from networks, which comprise of significantly different characteristics than future UMTS networks.

To obtain the traffic characteristics of the UMTS traffic model we introduce the scaling algorithm outlined in Fig. 1. This scaling procedure utilizes the notion of (1) bandwidth-independent characteristic distributions for the statistical measures on the three traffic levels, and (2) bandwidth-dependent trends in the mean and the variance of each unique statistical measure. In the first step the identification of bandwidth-dependent trends for each statistical measure utilizing a regression method is conducted. The basic idea of the underlying regression models constitutes of the notion of bandwidth-dependent trends and the evolution of mean and/or variance, i.e., bandwidth-dependent changes that are naturally described by one of the functions (a) to (d). We consider this set of functions because they comprise of different asymptotic behavior, e.g., a linear or a logarithmic asymptotic behavior. Subsequently, we utilize the parameterized function, which comprises of the least squares residual value, in order to get the mean and the variance values corresponding to the UMTS bandwidth classes 64 kbps, 144 kbps, and 384 kbps. For each statistical measure, we utilize

Step 1: Find bandwidth-dependent trends in the mean and the variance of the considered statistical measures. Utilize the least-squares regression method on the mean and variance with respect to increasing bandwidth for each statistical measure. We use the following functions as underlying regression models.

(a) $f_1(x) = a + b \cdot \log^2(c \cdot x)$, a double logarithmic shape.

(b) $f_2(x) = a + b \cdot \log(c \cdot x)$, a logarithmic shape.

(c) $f_3(x) = a + b \cdot \log(c \cdot x) + d \cdot x$, a mixture of a logarithmic and linear shape.

(d) $f_4(x) = a + b \cdot x$, a linear shape.

Step 2: Get the parameterized function of Step 1, which comprises of the least squares residual value. Subsequently, use this parameterized function in order to derive values for mean and the variance corresponding to the UMTS bandwidth classes 64 kbps, 144 kbps, and 384 kbps.

Step 3: For each statistical measure, utilize its characteristic distribution and the mean and variance, calculated in Step 2, to get the parameter values of the characteristic distribution. This task can be performed by solving a non-linear equation system, comprising of the analytical formulas for corresponding mean and variance and the values for mean and variance derived in Step 2.

Fig. 1. Algorithm for bandwidth scaling for UMTS networks

its characteristic distribution and the derived values for mean and variance, in order to get the parameter values of the characteristic distribution (see Step 3 in Fig. 1).

B. *Single User Traffic Model for UMTS Networks*

In order to get the detailed parameter set of the UMTS single user traffic model, we apply the scaling procedure of Fig. 1 on the statistical measures of the three different traffic levels. The following presents characteristic distributions and the corresponding parameter values for the statistical measures of the session-level, connection-level, and packet-level. Note, that the parameterized distributions for interarrival-times are second-based, whereas data volume distributions as well as packet length distributions are byte-based. The reason for restricting the UMTS traffic model to the bandwidth classes 64 kbps, 144 kbps, and 384 kbps is two-fold. First, the notion of trends in the statistical measures and the utilization of a scaling procedure by regression methods are based on measurements that comprises of bandwidth classes from 9.6 kbps up to 64 kbps. From this point of view, a trend spotting up to the maximum UMTS bandwidth class (i.e., 2048 kbps) involves too many unknowns. Second, we think that after the commercial launching of UMTS most users will run applications on their hand-held devices using the cheaper and, thus, lower bandwidth classes.

The statistics at the session level are mainly influenced by user behavior, which is difficult to predict. As the session interarrival-time depends to a large extend on the prizing policy of the UMTS provider, we assume the overall session interarrival-times measured at the ISP as authentic for UMTS data networks. For the measured trace, we derive a lognormal distribution with μ=0.9681 and σ^2=4.3846 as the distribution for session interarrival-times. Furthermore, we assume that UMTS users are partitioned in the considered bandwidth classes as follows: 50% for 64 kbps, 30% for 144 kbps, and 20% for 384 kbps. In order to take into account the bandwidth-dependent transfer data volumes, we get the characteristic distributions and corresponding parameter sets as shown in Table I.

At connection level, the measured data indicates that almost all users, who utilize Napster or FTP applications, only run a single connection within a dial-in session. Therefore, an interarrival-time distribution for connections of these application types is misleading. Thus, we take into account the fractions for using Napster or FTP measured at the ISP. These fractions are derived from measured data of ISDN users, i.e., 1.47% for Napster and 3.05% for FTP. We focus on this bandwidth class because users of lower bandwidth classes hardly utilize these applications. For the remaining applications, the interarrival-time distributions for connections and the data volume distributions per connection are presented in Table II. Recall that UDP applications are connection-less and thus, they are omitted in the statistics for the connection level. UDP applications are assumed to be active during the entire user session and are fully described by its packet interarrival-time and packet size distributions.

Table III presents the application dependent packet interarrival-time distributions. Note that the packet size distributions for HTTP, Napster, e-mail, and FTP follow to a large extend a discrete distribution, where packets of the sizes 40 bytes, 576 bytes, and 1500 bytes constitute the largest

TABLE I
DISTRIBUTION OF SESSION VOLUME

Distribution	64 kbps	144 kbps	384 kbps
Lognormal($\mu;\sigma^2$)	(11.1170;1.9095)	(11.4107;1.9509)	(11.6795;1.9781)

TABLE II
STATISTICAL PROPERTIES AT CONNECTION-LEVEL

		Distribution	64 kbps	144 kbps	384 kbps
HTTP	**Interarrival time**	Lognormal($\mu;\sigma^2$)	(0.5967;2.6314)	(0.1580;3.1507)	(-0.4760;3.8787)
	Data volume	Lognormal($\mu;\sigma^2$)	(7.4343;3.4714)	(7.4708;3.7598)	(7.5458;3.9745)
e-mail	**Interarrival time**	Pareto($k;\alpha$)	(14.4360;2.1345)	(15.1334;2.1254)	(16.0229;2.1223)
	Data volume	Lognormal($\mu;\sigma^2$)	(8.1934;3.3852)	(8.2944;3.5288)	(8.4124;3.6439)
Napster	**Interarrival time**	not available			
	Data volume	Lognormal($\mu;\sigma^2$)	(12.3025;1.5385)	(12.3677;1.5311)	(12.5410;1.5268)
FTP	**Interarrival time**	not available			
	Data volume	Lognormal($\mu;\sigma^2$)	(8.4944;3.6674)	(8.6403;4.1059)	(8.8409;4.3343)

TABLE III
PARAMETERS OF PACKET INTERARRIVAL-TIMES

	Distribution	64 kbps	144 kbps	384 kbps
HTTP	Lognormal($\mu;\sigma^2$)	(-3.2441;4.5137)	(-3.9124;5.1794)	(-4.8507;6.1159)
e-mail	Lognormal($\mu;\sigma^2$)	(-4.4052;4.4970)	(-4.8790;4.9687)	(-5.4096;5.4978)
Napster	Lognormal($\mu;\sigma^2$)	(-4.2614;3.7790)	(-4.0340;3.3242)	(-4.4335;3.5226)
FTP	Lognormal($\mu;\sigma^2$)	(-3.6445;4.9564)	(-3.9076;5.2186)	(-4.1089;5.4194)
UDP	Lognormal($\mu;\sigma^2$)	(-3.2770;5.2887)	(-3.7830;5.6710)	(-4.3020;6.0997)

TABLE IV
FRACTIONS OF DIFFERENT PACKET SIZES IN OVERALL TRAFFIC

	Packet size 40 byte	Packet size 576 byte	Packet size 1500 byte	Other packet sizes
HTTP	46.77 %	27.96 %	8,10%	17.17 %
Napster	34.98 %	45.54 %	4.18 %	15.30 %
e-mail	38.25 %	25.98 %	9.51 %	26.26 %
FTP	40.43 %	18,08%	9.33 %	32.16 %

amount of the overall packet sizes. This phenomenon relies on the maximum transfer units (MTU) of Ethernet and SLIP (serial line IP) networks. Most TCP transfer protocols like HTTP, FTP, and POP3 are used to transfer files as fast as possible. Therefore, within a connection the packets are filled up to the MTU of the underlying network protocol. This is usually 1500 bytes in Ethernet networks and 576 bytes in SLIP networks. Packets with a length of 40 bytes are at most TCP acknowledgments with missing data field. Recall, that the TCP/IP header without any options consists of 40 bytes. Table IV displays the fractions of these discrete packet sizes. We observe further, that the remaining packet sizes are distributed uniformly between 40 bytes and 1500 bytes. In contrast to the TCP packets, the UDP datagram sizes follow a bandwidth-independent lognormal distribution with parameters μ=3.9964 and σ^2=1.1852.

C. Aggregated Modeling of the UMTS Traffic Stream

As stated above, the proposed UMTS single user traffic model is not analytically tractable. Thus, it can be employed for simulation studies only. To overcome this restriction, we customize the batch Markovian arrival process such that different sizes of IP packets are represented by rewards (i.e., batch sizes of arrivals) of the BMAP. In order to get the parameter set of this aggregated UMTS traffic model, we apply the parameter estimation procedure proposed in [8] using a trace file, which represents the aggregated UMTS traffic stream. Therefore, this trace file comprises of packet interarrival-times and the corresponding packet sizes.

Applying the UMTS single user traffic model, we generate a synthetic trace file comprising of IP packet traffic reflecting 1 hour of summed interarrival-times representative for a "typical" usage of non real-time traffic in UMTS packet data systems within a considered base station. Based on this synthetic trace file the BMAP parameter estimation procedure is applied for a 3-state BMAP ($N = 3$) with a maximum batch size of $M = 3$. The choice of M is crucial for the mapping process of packet sizes to BMAP rewards (i.e., batch sizes of arrivals) and corresponds to but is not restricted by the fact that a large amount of packets comprise of three different packet sizes (see Table IV).

Recalling the BMAP definition of Section II, this mapping process results in a BMAP parameter set of reasonable size $(M+1)N^2$. We map the packet sizes onto the discrete packet sizes s_m, for $1 \le m \le M$, where s_m is the average packet size of all considered packets comprising of packet sizes between $500 \cdot (m-1)/M$ bytes and $500 \cdot m/M$ bytes. Therefore, arrivals with batch size m, $1 \le m \le M$, represent packet arrivals with a size of s_m bytes. The considered estimation procedure is quite effective and requires less than 200 seconds of CPU time on a Pentium III PC with 128 MB of main memory.

Fig. 2 plots sample paths of the aggregated UMTS traffic stream generated by the single user traffic model (left) and sample paths of the aggregated traffic stream applying the parameterized BMAP model (right). In order to show the effectiveness of our approach these sample paths are plotted on four different time scales, i.e. 0.01 sec, 0.1 sec, 1 sec, and 10 sec. Fig. 2 shows that the customized BMAP captures the average transferred data volume per time unit. Furthermore, the customized BMAP can represent in the considered scenario traffic burstiness over multiple time scales. This constitutes a clear advantage of the customized BMAP over MMPP and other analytically tractable traffic models. Detailed statistical investigations, e.g. R/S statistics [12], emphasize these observations.

CONCLUSIONS

We presented an approach for modeling UMTS traffic based on appropriately scaling measured IP traffic. The approach utilizes the notion of bandwidth-independent characteristic distributions for statistical traffic measures and bandwidth-dependent first and second order statistics, i.e., mean and variance. Subsequently, we derived a synthetic traffic model for UMTS networks using the single user traffic model. We observe that packets of the sizes 40 bytes, 576 bytes, and 1500 bytes dominate the traffic streams. Furthermore, we introduce an aggregated traffic model that is analytically tractable and illustrate its effectiveness using the previously presented synthetic traffic model for UMTS networks. The key idea of this aggregated traffic model lies in customizing the batch Markovian arrival process (BMAP) such that the three different sizes of IP packets dominating the traffic stream are represented by three reward values.

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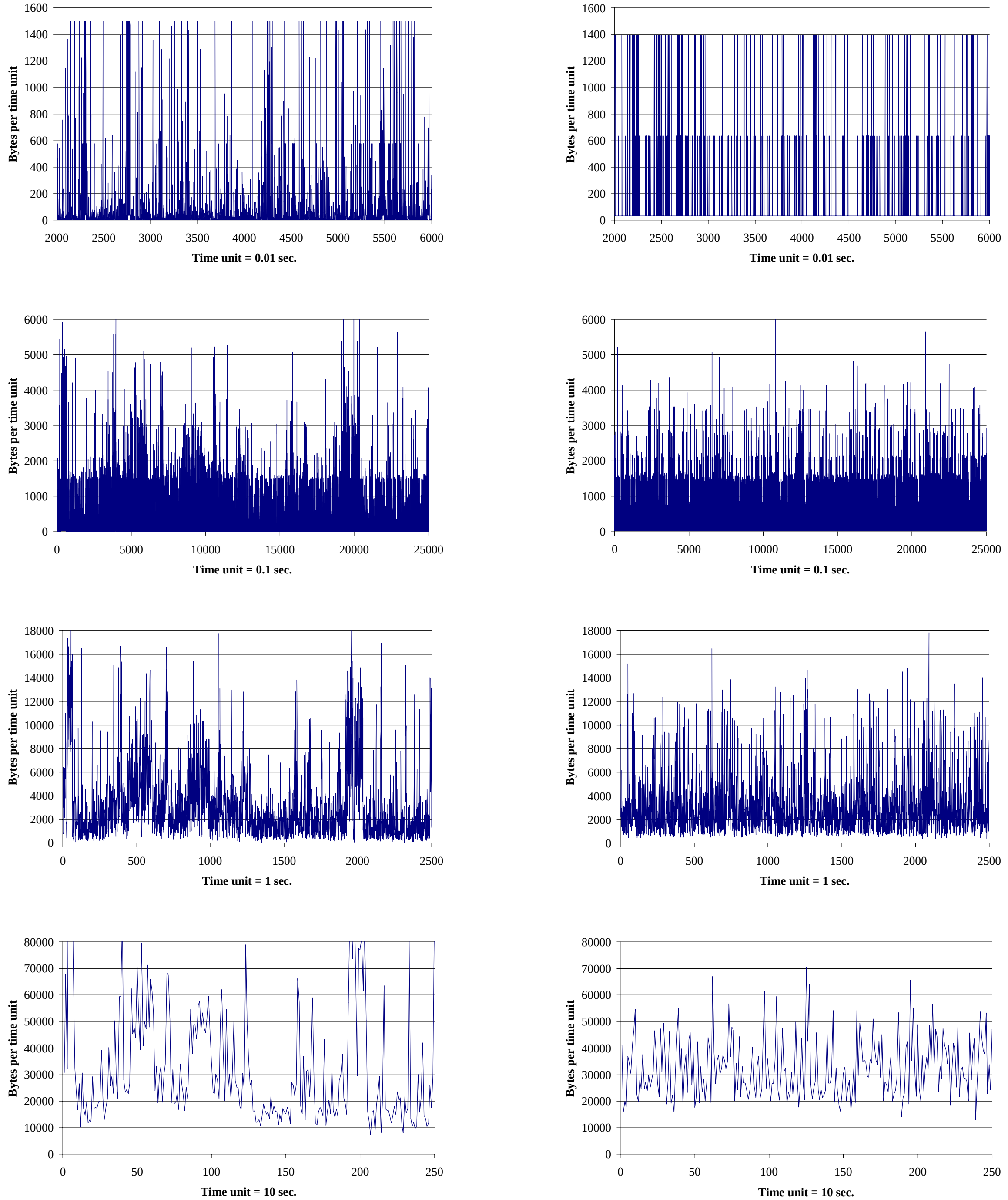

Fig. 2. Sample paths of single user traffic model (left) and customized BMAP (right) over multiple time scales

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