Characterization and Modeling of M2M Video Surveillance Traffic

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***Abstract*—The relevance of machine-to-machine (M2M) communications is growing significantly, largely driven by wireless networks. Internet of Things (IoT) applications will create new demands and challenges that will require high bandwidth, real-time communications or reliability in remote locations. Since M2M applications will generate traffic and transactions that compete for bandwidth and priority, network operators must be concerned of how to handle the enormous increases in their signaling traffic and, in particular, in finding new ways to meet each M2M application's requirements and service level agreements, while protecting the network and making a more efficient use of the available resources. An efficient design and control of the future Internet needs to take into account the main characteristics of the supported traffic and, therefore, accurate and detailed measurements of M2M traffic have to be carried out in order to perform a complete characterization and develop stochastic models that are able to capture the most important statistical properties of the network traffic. This paper considers a particular case of a M2M service, a video surveillance application, and proposes a general methodology that performs a detailed statistical characterization of its traffic, while addressing the main challenges that are involved in the development of an appropriate stochastic modeling approach. The M2M traffic analysis relies on the use of wavelet scalograms, which describe the signal energy on a timescale/time domain and are constructed based on the wavelet coefficients obtained from the multi-scale decomposition of the traffic process, to identify all the different traffic features. An innovative M2M modeling framework based on a multiple state machine is also proposed: its parameters should be inferred from the salient features of the traffic and it should be able to characterize both the download and upload traffic and quantify the overhead that is necessary to guarantee a secure communication.**

***Keywords* - M2M applications, wavelet transform, scalogram, traffic modeling.**

I. Introduction

Machine-to-machine (M2M) communications have emerged as a cutting edge technology for next-generation networks, undergoing a rapid development and inspiring numerous applications. Recently, this topic has attracted much attention from the industry and research communities, mainly due to the following factors: the emergence of wireless communication systems became a premise for the advance of M2M communications; (ii) the development of advanced software components that enable devices to operate intelligently and autonomously; (iii) sensors that can be used to collect information for M2M systems are being widely used and increasingly adopted. According to the Machina Research's Report "M2M Global Forecast & Analysis 2010-20" [1], global M2M connections will increase from one billion at the end of 2010 to 12 billion at the end of 2020, accounting for half of all global data connections. Connections will be dominated by two sectors: consumer electronics (including cameras, music players and TVs) and intelligent buildings (e.g. security and surveillance, HVAC systems), which will account for over 60% of the total. Over 70% of the M2M devices will be connected by short-range technologies (mostly WiFi), while of the remainder wireless cellular technologies (mostly applied to utilities and automotive applications) will dominate. At the end of 2010, M2M accounted for 2% of cellular connections and by 2020 they will reach 19%, or 2.3 billion connections.

This traffic growth will have an increasing impact in network management and dimensioning activities [2]. Mobile network providers are starting to offer M2M integrated applications, which will require the dimensioning and joint management of multiple network elements for an optimal operation. These operations will greatly benefit from the development of new mathematical tools that are able to predict network behavior under new M2M traffic scenarios. A rigorous statistical characterization of the M2M traffic is essential: in the past, several studies have shown that IP traffic properties like burstiness, self-similarity and/or long-range dependence had a significant impact on network performance and behavior and should be included in the modeling frameworks; a similar analysis should now be applied to these new applications, whose traffic should be rigorously characterized in order to design accurate and parsimonious modeling approaches.

The wavelet scalogram, which describes the signal energy on a timescale/time domain and is constructed based on the wavelet coefficients obtained from the multi-scale decomposition of the traffic process, will be used as the statistical fingerprint of each traffic trace segment. The wavelet scalogram communicates the time frequency localization property of the discrete wavelet transform, being possible to capture the correlation that exists between the time variability of the process and the different scales. Wavelet analysis allows the degree of localization to be automatically and appropriately adjusted - large window widths are used for analyzing low frequency components, whereas small window widths are used for investigating high frequency components. Thus, this methodology is able to identify different peculiar behaviors

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even if this information is somehow hidden when performing a classical statistical analysis of the traffic. In this paper, M2M video surveillance traffic will be used to illustrate/evaluate the suitability of the proposed analysis and modeling framework: a set of traffic measurements was made in order to obtain long duration (one week) traces that allow us to identify the main characteristics and trends of this new communication paradigm and understand which features/properties should be taken into account when designing an accurate modeling framework.

The characteristics of M2M traffic are fundamentally independent from human behavior: in particular, the timings of the information exchange are no longer defined by humans [3], although many services may indirectly reflect human activities in some way (like for example M2M video surveillance and M2M car fleet telemetry services in case of non-authorized movement/entries or car accidents, whose periodicity tend to follow exponentially distributed human patterns). So, M2M traffic can no longer be modeled and predicted by traditional approaches and a new modeling paradigm should be developed. The new modeling framework must be a trade-off between generality and mathematical complexity, must be sufficiently generic to incorporate all possible M2M applications and heterogeneous characteristics, while maintaining a low mathematical complexity and high applicability. Privacy and security will be important features of any M2M service and therefore the ability to characterize the additional traffic overhead, to generate and maintain the communication keys, should also be incorporated in the M2M traffic modeling framework.

The accurate characterization and modeling of M2M traffic can be exploited to enhance different traffic engineering and management tasks. In fact, one way to improve network utilization is to mix in the same set of network resources traffic with contrasting behavior (e.g. traffic sources whose periods of higher utilization are in disjoint time intervals). In general, it is beneficial for network operators to cluster their traffic sources into groups of similar traffic profiles and to apply routing policies that are a function of the clustering solution. So, following a measurement phase, a traffic source can be classified into one of predefined groups and its routing can be adjusted accordingly; this may free some resources, which in turn, will allow additional sources to access the network. This functionality can work in pseudo real time and should be applied in a distributed way, mainly at the network traffic entry points.

The paper is organized as follows. Section II discusses the most relevant related work on M2M traffic statistical characterization and modeling; Section III proposes a new modeling framework for M2M traffic; Section IV presents a brief background on wavelet transforms and scalograms; Section V presents some traffic measurements that were made for a particular case of a M2M service, a video surveillance service, in order to illustrate the applicability/suitability of a statistical analysis methodology that is also proposed to identify the main statistical properties of the traffic; finally, Section VI presents the main conclusions.

II. Related work

IP traffic modeling has been an active research field for a long time. The growing diversity of services and applications for IP networks has been driving a strong requirement to make frequent measurements of packet flows and describe them through appropriate traffic models. Several studies have shown that IP traffic may exhibit properties of self-similarity and/or long-range dependence (LRD) [4], [5], [6], [7], [8], peculiar behaviors that have a significant impact on network performance. The heavy-tailed characteristic of the probability distributions (quite different from the simple Gaussian shape) explained network performances that were quite different from the ones predicted by traditional renewal and Markovian models. Besides, the multifractal nature of network traffic, firstly noticed by Riedi and Lévy Véhel [9], lead to the proposal of random cascades [10], [11] and L-system models [12] to describe the scaling behavior of IP traffic. However, the mathematical tractability of Markovian models lead to the development of several ingenious inference procedures that were able to account for these peculiar behaviors [13], [14], [15], [16], [17], [18], [19], [20]: these traffic models were able to match the complex statistical properties of IP traffic while maintaining an analytical simplicity that allow their use for calculating network performance metrics and predicting future traffic values.

Several reports describing the increase of machine-to-machine services, their relevance and future trends have been recently published [1], [2], [21], [22]. However, we did not find any traffic model specifically designed to describe their statistical characteristics: reference [23] is one of the few publicly available studies on this topic, proposing a theoretical model to calculate some characteristics of WPAN (Wireless Personal Area Networks) traffic, although the model still needs some modifications to account for application specific behaviors. So, it is absolutely necessary to conduct a rigorous statistical analysis of real M2M traffic applications and develop a generic analytical framework that is able to describe their relevant properties and predict future traffic values.

III. M2M Traffic Modeling Framework

The most efficient traditional traffic models usually include multiple space states where the transition dynamics are probabilistic and based on underlying exponentially distributed timings. These dynamics are frequently mapped into Markov chains that modulate the data generation process (deterministic or exponentially distributed). Examples of these processes are the Markov Modulated Deterministic Process (MMPP)[24] and the Markov Modulated Poisson Process (MMPP)[17], which assume that the time spent in each state of the space state is exponentially distributed and information objects are generated in periodic and exponentially distributed intervals, respectively.

An efficient M2M traffic model must jointly incorporate traditional deterministic characteristics of automated mechanisms and random characteristics of Artificial Intelligence, network and human processes. Therefore, we propose a modeling framework based on a process ruled by a multiple space state with heterogeneous (deterministic and random) dynamics and generic information (e.g. messages, packets or bytes) generation processes. This framework model will be called Heterogeneous Chain Modulated Generic Process (HCMGP).

The HCMGP modeling framework is a multistage space state process able to model the security bi-directional traffic overhead, the M2M bi-directional communication process and admits the definition of multiple possible events that reflect different application profiles. As a result, each state will define the type of generation process (deterministic, exponential or other) and its corresponding parametrization. Moreover, the dynamics of the state transitions are heterogeneous and can be ruled by deterministic or exponential processes that define the time of permanence in each state and the destiny of the next transition.

The modeling framework parametrization will agree with the assumption that state transitions can follow a deterministic or random distribution. State transitions are ruled in parallel by two (or more) parametric matrices that define, respectively, the next transitions after a deterministic amount of time and the probabilistic transitions after a random period of time. The probabilistic/random transitions can follow an exponential distribution (analogous to Markovian models) or any other distribution. The information generation processes associated with each state will also be parametrized by two (or more) vectors defining, respectively, the deterministic values and distribution function parameters for the rates and the amount of generated information.

The chain modulated nature of the HCMGP modeling framework will allow the usage of the traditional mathematical tools (used on Markovian models) to determine the traffic model resulting from the superposition of multiple M2M sources. Existing mathematical tools allow the computation [17] and reduction [25] of the matrix form descriptors of the superposition model.

The M2M model framework is depicted in Figure 1. The underlying space state of the model comprises two base states: standby and active. The standby state models the terminal conditional upon boot, and may include specific bi-directional start-up transmissions (e.g. configuration, localization or logging messages). The active state models the non-event related operation of the terminal (e.g. localization, logging or periodic metering). The remaining states will model event driven actions of the terminal (e.g. failure report, security event report, non-scheduled metering/logging, upgrades or (re)configuration actions). Two (optional) extra states were included to model the security channel establishment and maintenance (key establishment and renegotiation). The security keys establishment actions are perform upon boot (between the standby and active states) and keys (re)negotiation actions are treated as any other event and can be periodically or protocol based deployed.

IV. BACKGROUND ON WAVELET SCALOGRAMS

The inability of conventional Fourier analysis to preserve the time dependence and describe the evolutionary spectral characteristics of non-stationary processes requires tools that allow time and frequency localization. Wavelet transforms can provide information concerning both time and frequency, which allows local, transient or intermittent components to be elucidated. Such components are often obscured due to the averaging inherent within spectral only methods, like Fast Fourier Transform (FFT) for example.

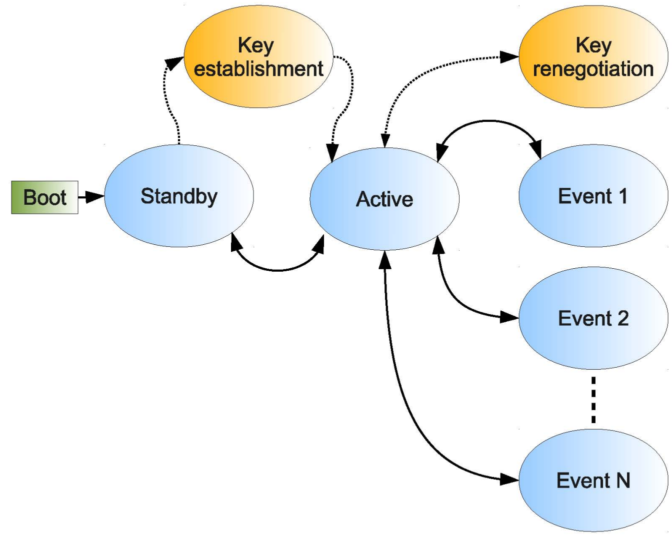

Figure 1: M2M traffic model framework

Wavelets are mathematical functions that are used to divide a given signal into its different frequency components. They consist of a short duration wave that has limited energy. Wavelets enable the analysis of each one of the signal components in an appropriate scale. Starting with a mother wavelet $\psi(t)$, a family $\psi_{\tau,s}(t)$ of "wavelet daughters" can be obtained by simply scaling and translating $\psi(t)$:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi(\frac{t-\tau}{s}) \quad (1)$$

where s is a scaling or dilation factor that controls the width of the wavelet (the factor $\frac{1}{\sqrt{|s|}}$ being introduced to guarantee preservation of the energy, $\|\psi_{\tau,s}\| = |\psi|$) and τ is a translation parameter controlling the location of the wavelet. Scaling a wavelet simply means stretching it (if $|s| > 1$) or compressing it (if $|s| < 1$), while translating it simply means shifting its position in time.

Given a time-series $x(t) \in L^2(\Re)$ (the set of square integrable functions), its Continuous Wavelet Transform (CWT) with respect to the wavelet ψ is a function of two variables, $W_{x;\psi}(\tau, s)$, obtained by projecting $x(t)$ onto the family $\{\psi_{\tau,s}\}$ [26]:

$$W_{x;\psi}(\tau, s) =< x, \psi_{\tau,s} >= \int_{+\infty}^{-\infty} x(t)\frac{1}{\sqrt{|s|}}\psi^*(\frac{t-\tau}{s})dt \quad (2)$$

In analogy with the terminology used in the Fourier case, the (local) Wavelet Power Spectrum (sometimes called Scalogram or Wavelet Periodogram) is defined in terms of normalized energy ($\hat{E}_x(\tau, s)$), for all possible translations (sub-set $\mathbf{S}$) and a predefined sub-set of time scales (sub-set $\mathbf{S}$), as

$$\hat{E}_x(\tau, s) = 100 \frac{|W_x(\tau, s)|^2}{\sum_{\tau' \in \mathbf{T}} \sum_{s' \in \mathbf{S}} |W_x(\tau', s')|^2} \quad (3)$$

The existence of a peak in the scalogram of a time series at a high (low) level indicates that a high (low) frequency component is present in the time series. The volume bounded by the surface of the scalogram is the mean square value of the signal.

Scalograms reveal much information about the nature of non-stationary processes that was previously hidden, so they are applied to a lot of different scientific areas: diagnosis of special events in structural behavior during earthquake excitation, ground motion analysis, transient building response to wind storms, analysis of bridge response due to vortex shedding, among others [27].

V. USE CASE - A VIDEO SURVEILLANCE SERVICE

M2M video surveillance services in public areas, buildings and transportation facilities will be very common in a near future. M2M devices will provide security by means of standard movement alarms or video surveillance cameras. Some applications transmit video continuously, while others only transmit video upon movement detection (triggered by external alarms or image analysis).

When we try to apply the general M2M modeling framework to the video surveillance service, different profiles can be identified, differing only in the amount and rate of information generated when in the active state. In this state, the M2M terminal will periodically transmit video and alarm data with a deterministic rate and size. A generic system can be modeled by a framework with two event states, one that models the alarm reporting and other that models the start/rate change of video streaming upon movement detection. Both event states, which depend on human actions, will occur according to exponential distributions, while their duration will also be exponentially distributed. However, the information generation rate will be deterministic (constant report size and average video rate).

A. Measurement setup

In order to fully characterize the traffic generated by this M2M service, we made an intensive set of traffic measurements at our networks laboratory. The experimental measurement setup is depicted in Figure 2, where two computers, a webcam and a layer 2 switch were used. Computer 1, which is responsible for creating the data stream, is a micro ITX system with an Intel Dual Core N330 processor with 1.6 GHz, a 2 GB DDR 2 memory and 120 GB of disk capacity. A generic USB 2.0 webcam, with a 640x480 pixel resolution, is attached to computer 1. Computer 2 is a common workstation built with an Intel Core 2 Duo, model E 8500, operating at 3.16 GHz, 4 GB of DDR 2 RAM and 320 GB of disk capacity. Both machines operate using a Linux Ubuntu distribution, version

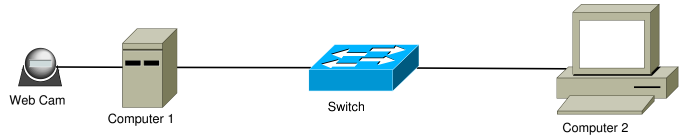

Figure 2: Video surveillance traffic measurement setup.

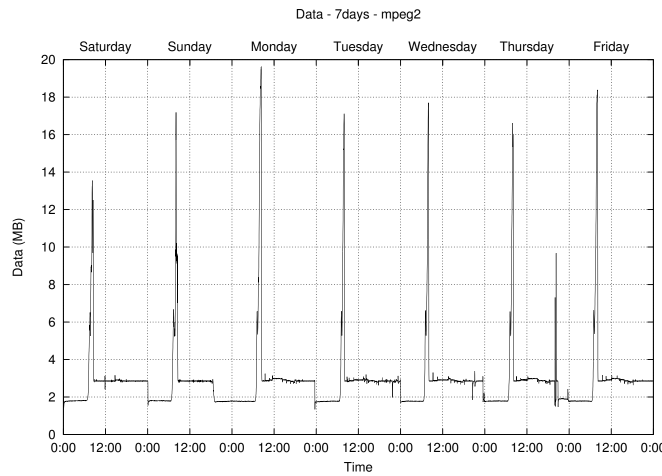

Figure 3: Amount of data over a week period.

10.10, updated and configured by default. The layer 2 switch is a common 10/100Mbps Ethernet switch.

The 'gst-launch' software was used to compose a continuous MPEG2 video stream, running over UDP, with a resolution of 640x480 pixel and 30 frames per second.

B. Traffic characterization

Figures 3 and 4 represent the number of bytes and packets, respectively, received by Computer 2 during a whole week period. As can be seen, there is a clear periodic trend in these plots, corresponding to the repetitive daily activities of the laboratory users. The first peak of these plots corresponds to Saturday, and we can see that the activity levels on Saturday and Sunday are slightly different from the levels of the remaining week days. On weekend days the movement activity is very small, so the variability of the curves is also smaller: on Saturday the laboratory is open, although with a small number of users; on Sunday, it is closed, explaining the drop of the curves in the late afternoon. In fact, on Sunday the activity level corresponds exclusively to sunlight variations (artificial lights are obviously turned off). On working days, the activity level presents some degree of variability (due to the presence of several users in the lab premises) and drops abruptly at 12:00 PM because the lab closes at this instant and lights are turned off. Finally, note that, for all days, there is a marked peak in the early morning, corresponding to the sunlight appearance.

A scalogram analysis was applied to the measured data-streams, inferring the normalized energy ($\hat{E}_x(\tau, s)$) in all time slots τ and for time-scales 1 to 64 ($s \in \mathbf{S}, \mathbf{S} = \{1, \ldots, 64\}$). The top plots of Figures 5 and 6 represent, respectively, the

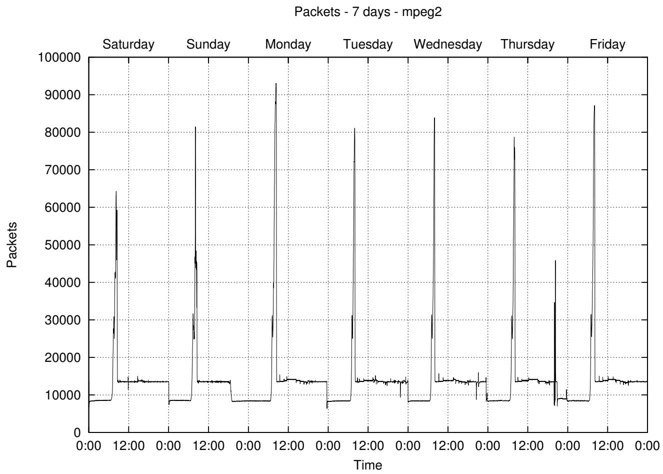

Figure 4: Number of packets over a week period.

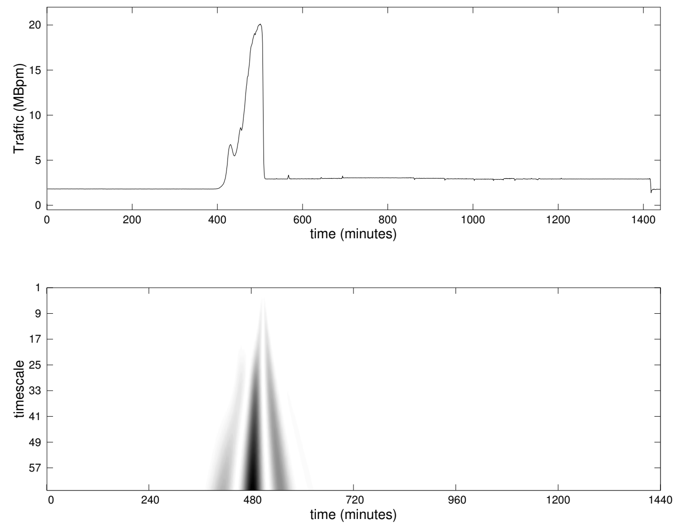

Figure 5: Traffic amount per minute (Top) and scalogram (Bottom) corresponding to a single day.

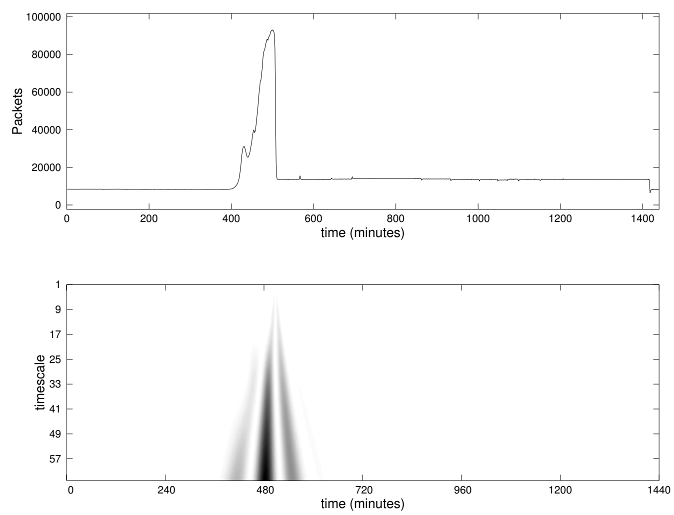

Figure 6: Number of packets per minute (Top) and scalogram (Bottom) corresponding to a single day.

traffic amount and the number of packets per minute corresponding to a single day (since their patterns are repetitive), while the bottom plots illustrate the corresponding scalograms, in terms of normalized energy over time and timescale (darker means more energy). The scalograms allow us to identify and quantify the most relevant traffic variations, knowing exactly the time instants and resolutions where they are more noticeable. If a more detailed analysis of any segment of the data trace is necessary, it is possible to calculate a new scalogram that is confined to a small portion of the signal. As an illustrative example, the top plots of Figures 7 and 8 represent the traffic amount and the number of packets per minute corresponding to a generic dawn period, respectively, while the bottom plots illustrate their corresponding scalograms. This type of detail can be used to identify important frequencies that are characteristic of some particular behaviors of a M2M service. This analysis step will have obvious consequences in the modeling phase of the M2M service: the knowledge of the different energy components and of the timescales where they are visible is an important input to the modeling effort, allowing the identification of the different model states and contributing to the inference of the various model parameters.

VI. CONCLUSIONS

This paper discussed the new paradigm that M2M traffic carries for network operators. In face of several new challenges that are imposed by M2M services, namely the periodicity of the traffic profiles and the partial/total absence of human influence, a new modeling framework able to conform with the major current and future M2M applications was presented. This approach is based on a multiple state machine and can be a valuable tool for dimensioning, optimizing and maintaining M2M services over future networks. In order to perform a complete characterization of the M2M traffic, this paper considered a particular case of a M2M service, a video surveillance application, and proposed a general methodology that is able to perform a detailed statistical characterization of the generated traffic: the traffic analysis framework relies on the use of wavelet scalograms, which describe the signal energy on a timescale/time domain and are constructed based on the wavelet coefficients obtained from the multi-scale decomposition of the traffic process.

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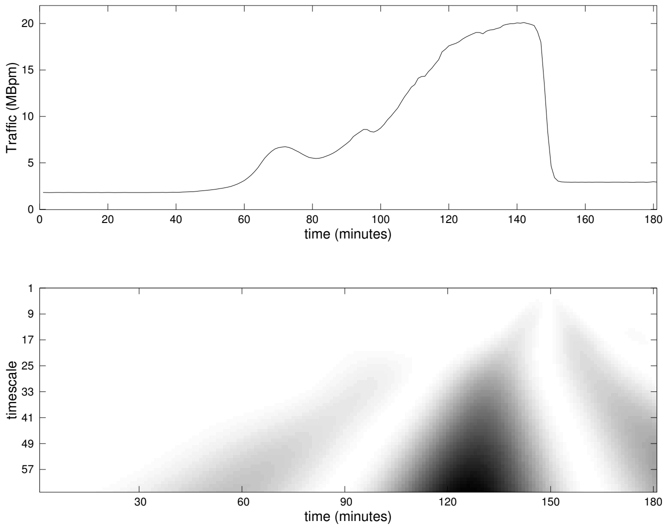

Figure 7: Traffic amount per minute (Top) and scalogram (Bottom) corresponding to the dawn period.

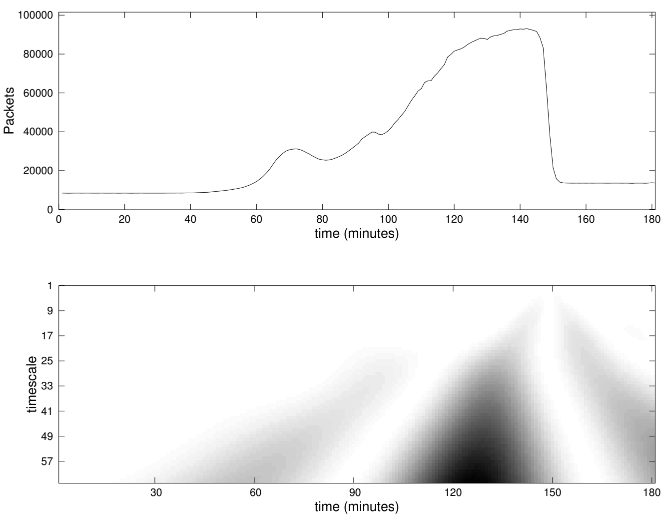

Figure 8: Number of packets per minute (Top) and scalogram (Bottom) corresponding to the dawn period.

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