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Modeling self-similar traffic over multiple time scales based on hierarchical Markovian and L-System models

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ABSTRACT

Traffic engineering of IP networks requires the characterization and modeling of network traffic on multiple time scales due to the existence of several statistical properties that are invariant across a range of time scales, such as self-similarity, LRD and multifractality. These properties have a significant impact on network performance and, therefore, traffic models must be able to incorporate them in their mathematical structure and parameter inference procedures. In this work, we address the modeling of network traffic using a multi-time-scale framework. We describe and evaluate the performance of two classes of hierarchical traffic models (Markovian and Lindenmayer-Systems based traffic models) that incorporate the notion of time scale using different approaches: indirectly in the model structure through a fitting of the second-order statistics, in the case of the Markovian models, or directly, in the case of the Lindenmayer-Systems based models. Two Markovian models are proposed to describe the traffic multiscale behavior: the fitting procedure of the first model matches the complete distribution of the arrival process at each time scale of interest, while the second proposed model is constructed using a hierarchical procedure that, starting from a MMPP that matches the distribution of packet counts at the coarsest time scale, successively decomposes each MMPP state into new MMPPs that incorporate a more detailed description of the distribution at finner time scales. The traffic process is then represented by a MMPP equivalent to the constructed hierarchical structure. The proposed L-System model starts from an initial symbol and iteratively generates sequences of symbols, belonging to an alphabet, through successive application of production rules. In a traffic modeling context, the symbols are interpreted as packet arrival rates and each iteration is associated to a finer time scale of the traffic. The accuracy of the different proposed models is evaluated by comparing the probability mass function at each time scale and the queuing behavior (as assessed by the loss probability) corresponding to measured and synthetic traces generated from the inferred models. The well-known *pOct* Bellcore trace is used to evaluate the accuracy of the proposed models and fitting procedures. The results obtained show that these models are very effective in matching the main characteristics of the trace over the different time scales and their performances are similar.

1. Introduction

The complexity associated to mechanisms for traffic generation and control, as well as the diversity of applications and services, have introduced several peculiar behaviors in network traffic, such as self-similarity, long-range dependence and multifractality, which have a significant impact on network performance [1–4]. These behaviors have in common a property of statistical invariance across a range of time scales. Thus, suitable traffic models must be able to capture statistical behavior on multiple time scales. Multi-time-scale characteristics can be incorporated in the parameter fitting procedure or can be intrinsically embedded in the model structure.

This paper extends the work published in [5] by evaluating and comparing the performance of two classes of traffic models, Markovian and Lindenmayer-Systems based models, that incorporate the notion of time scale using different approaches: indirectly via the fitting of the second-order statistics, in the case of Markovian models, or directly in the model structure, in the case of Lindenmayer-Systems based models.

The first Markovian approach proposes a parameter fitting procedure for a superposition of discrete-time Markov Modulated Poisson Processes (dMMPPs) that captures self-similar behavior over a range of time scales. Each dMMPP models a specific time

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scale and the parameter fitting procedure matches, at each time scale, a dMMPP to a Probability Mass Function (PMF) that describes the contribution of that time scale to the overall traffic behavior. The number of states of each dMMPP is not fixed a priori; it is determined as part of the fitting procedure. This model will be designated by superposition model. In the second proposed Markovian model, the construction procedure successively decomposes dMMPP states into new dMMPPs, thus refining the traffic process by incorporating the characteristics offered by finer time scales. This refinement process is iterated until a pre-defined number of time scales are integrated. Finally, a dMMPP incorporating this hierarchical structure is derived. Similarly to the previous model, the number of states of each dMMPP is not fixed a priori; it is determined as part of the fitting procedure. This second model will be designated by decomposition model. The third proposed traffic model is based on stochastic Lindenmayer-Systems (hereafter referred to as L-Systems). L-Systems are string rewriting techniques which were introduced by biologist A. Lindenmayer in 1968 as a method to model plant growth [6] and are characterized by an alphabet, an axiom and a set of production rules: the alphabet is a set of symbols; the production rules define transformations of symbols into strings of symbols; starting from an initial string (the axiom), an L-System constructs iteratively sequences of symbols through replacement of each symbol by the corresponding string according to the production rules. If the production rules are random, the L-System is called a stochastic L-System and can be used to recursively construct random sequences with multi-time-scale behavior.

The accuracy of the different models is evaluated by applying them to the well-known *pOct* Bellcore trace (that exhibits self-similar behavior) and comparing the PMF at each time scale and the queuing behavior (as assessed by the loss probability) corresponding to the measured and to synthetic traces generated from the inferred models. Our results show that the proposed fitting methods are very effective in matching the PMF at the various time scales and lead to an accurate prediction of the queuing behavior.

Several fitting procedures have been proposed in the literature for estimating the parameters of MMPPs from empirical data [7–14]. However, most procedures only apply to 2-MMPPs, which can capture traffic burstiness but have an insufficient number of states to reproduce variability over a wide range of time scales. On the other hand, the fitting procedures for MMPPs with an arbitrary number of states mainly concentrate on matching first- and/or second-order statistics, without addressing directly the issue of modeling over multiple time scales. The application of stochastic L-Systems in the characterization of packet arrival processes was first introduced by the authors in [15], with very good fitting results.

The paper is organized as follows. Section 2 describes the proposed hierarchical Markovian models, including their parameter fitting procedures; Section 3 presents the L-System model and its corresponding parameter fitting procedure; Section 4 presents and discusses the obtained comparison results; and, finally, Section 5 presents the main conclusions.

2. Hierarchical Markovian models

The hierarchical Markovian models are constructed based on the PMF of the arrival process at each time scale, thus enabling them to capture the traffic self-similar behavior over a range of time scales. The number of time scales to consider, L, is fixed a priori and time scales are numbered in an ascending way, from $l = 1$ (corresponding to the largest scale) to $l = L$ (corresponding to the finest one).

2.1. Superposition model

The first traffic model is based on the superposition of dMMPPs, each one representing a specific time scale. The left part of Fig. 1 illustrates the dMMPP construction methodology for the simple case of having only three time scales and two-state dMMPPs at each time scale. The dMMPP associated to time scale l will be designated by dMMPP$^{(l)}$, and its corresponding number of states by $N_{(l)}$. The flow diagram of the inference procedure is represented in the left part of Fig. 2 where, basically, four major steps can be identified: (i) calculation of the data vectors (corresponding to the average number of arrivals per time interval) at each time scale, by applying an iterative aggregation process that starts at the finest time scale and ends at the largest one; (ii) calculation of the empirical PMF corresponding to the largest time scale and inference of the corresponding dMMPP; (iii) for the other time scales (starting from the largest to the finest one), calculation of the empirical PMF, calculation of its deconvolution from the empirical PMF of the preceding time scale and inference of a dMMPP that adjusts the resulting empirical PMF (the shaded part of the flow diagram); (iv) calculation of matrices $\mathbf{\Lambda}$ and $\mathbf{P}$ of the final dMMPP through the superposition of the different dMMPPs that were inferred for each time scale. The different steps of the inference procedure will be detailed later in the section.

2.2. Decomposition model

The second proposed traffic model is constructed based on a decomposition process that successively decomposes the states of a dMMPP corresponding to a certain time scale on new dMMPPs belonging to the immediately following finer time scale, refining in this way the traffic process by including the characteristics that are offered by successively finer time scales. The procedure starts at the largest time scale by inferring a dMMPP that adjusts the PMF corresponding to that scale. As part of the parameter inference procedure, each time interval of the data sequence is attributed to a state of the dMMPP; in this way, a new PMF will be associated to each state of the dMMPP. On the next finer time scale, each state of the dMMPP is decomposed into a new dMMPP that adjusts the contribution of that time scale to the PMF of the state from which the dMMPP descends. In this way, a child dMMPP gives a more detailed description of the PMF corresponding to its parent state. This refinement process is iterated until a pre-defined number of time scales has been integrated into the model. Finally, a dMMP that incorporates this hierarchical structure is derived.

The construction procedure of the decomposition model can be described by a tree where, with the exception of the root node, each node of the tree corresponds to a state of a dMMPP and each level of the tree corresponds to a time scale. The right part of Fig. 1 illustrates the construction methodology of this dMMPP, again for the simple case of considering only three time scales and two-sate dMMPPs at each time scale. Each state of a dMMPP will be represented by a vector that indicates the path from the highest level predecessor (that is, the state at the largest scale, $l = 1$, from which it descends) to itself. So, a state that is located at time scale l will be represented by a vector of the type $\vec{s} = (s_1, s_2, \ldots, s_l),\ s_i \in \mathbb{N}$. Each dMMPP will be represented by the state that originated it, that is, its parent state. So, we consider that dMMPP$^{\vec{s}}$ represents the dMMPP that is generated by state $\vec{s}$ and $\{1, 2, \ldots, N_{\vec{s}}\}$ is the set of its states, where $N_{\vec{s}}$ designates the number of states. The root node of the tree corresponds to a virtual node, designated by $\vec{s} = \emptyset$, and is used to represent the dMMPP that is located at the largest time scale, $l = 1$. This dMMPP will be designated by root dMMPP. In this way, the states of the dMMPPs that belong to the tree structure are characterized by vectors $\vec{s} = (s_1, s_2, \ldots, s_l),\ l \in \mathbb{N}$, with $s_{i+1} \in \{1, 2, \ldots, N_{\vec{s}_{i]}}\},\ i = 0, 1, \ldots, l-1$; here, $\vec{s}_{j]}$ designates the sub-