

Traffic Modeling in PLC Networks using a Markov Fluid Model with Autocorrelation Function Fitting¹

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Abstract. In this paper, we present an analysis of VoIP (Voice over IP) traffic and data transfer using PLC (PowerLine Communications) network. We propose a model based on MMFM (Markov Modulated Fluid Models) for data and VoIP traffic in PLC networks. Simulations and comparisons were carried out to verify the efficiency of the proposed traffic model over the Poisson and MMPP (Markov Modulated Poisson Process) models.

Keywords. Markov Chains, Markov Fluid Model, PLC, VoIP, Homeplug.

1. Introduction

The PLC/BPL technology (Powerline Communication / Broadband Powerline), which utilizes the electrical power network to the transmission of high speed data has proved to be an attractive option related to broadband communication services. The operational and economic viability of the the PLC technology is due to the current status of its equipment and low cost solutions. Besides, the possibility to use an existing infrastructure of energy network makes PLC even more attractive [6, 2].

The PLC signal is transmitted through cooper wires (or aluminum) in low and medium voltage distribution networks. The typical bandwidth used by PLC/BLP network is between 1,7Mhz and 30Mhz and the theoretical transmission capacity of PLC channels is up to 600Mbps [3, 8]. In this work, we use equipment that operate at frequencies ranging from 4,3 to 20,9 MHz, presenting data rate up to 16Mbps according to the HomePlug Standard [5]. The HomePlug Standard was developed by HomePlug Powerlie Alliance which defined the method of medium access and specifications of physical layers to low tension networks [9].

In this paper, we describe some characteristics of PLC/BPL technology, performing analyzes of VoIP applications and data transfers using a PLC network. Also, we propose a MMFM based model with autocorrelation function fitting to describe the traffic behavior in PLC networks. To this end, we collected data and VoIP traces in PLC networks in order to compare to the synthetic data from the proposed model and other Markovian models.

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2. Traffic Modeling Based on Markov Chains

The PLC physical medium is quite hostile to the data once there are some electrical network properties which negatively influence high speed communication (attenuation loss, multipath propagation and noise). Traffic modeling can be used to forecast network behavior as well as it can be applied to network planning and dimensioning, performance analysis and network congestion control.

Markov chains are discrete time stochastic processes. A Markov chain represents several possible states and the transitions between one state to another that occur following a certain probability. The probability (p_{ij}) that the next observed state ($X_{n+1} = j$) occurs depends only on the actual state ($X_n = i$).

Poisson model is greatly used in communication systems and can be seen as a birth-and-death Markovian process. According to this model, if x is a random variable corresponding to a random event in a time interval, the probability that x occurs is

$$f(x) = \frac{e^{-\lambda} \lambda^x}{x!}, \quad x = 0, 1, 2, \dots, \quad (2.1)$$

where λ is the parameter (average of x occurrences) of the Poisson distribution and e is the Euler number.

In the MMPP (Poisson Model modulated by a Markov chain) model, the arrivals (traffic process samples) occur following a Poisson distribution with a rate that varies in agreement to a k state of a continuous time Markov chain. This kind of model is used to characterize voice and data traffic. In a MMPP model, the i state represents a data transmission in intervals exponentially distributed with average $1/\lambda_i$ [4, 7].

2.1. MMFM Model with Traffic Autocorrelation Fitting

Fluid models characterize the traffic as a continuous flow. A fluid model typically used to traffic modeling is the Fluid Markovian Model (MMFM) [1].

In the MMFM model, the current state of the subjacent chain determines the flow rate (traffic). In the S_K state, traffic arrives at a constant rate λ_K . The state $\bar{\lambda}_k(t)$ represents the bit rate level of N aggregated sources as shown by Figure 1. The MMFM state-space diagram corresponds to the set of quantized rate levels, that is, a birth-and-death Markov chain [4, 7, 1]. This Markov chain presents $M+1$ states, varying from zero to M . Each state of this model represents the number of active sources. The transitions between the levels occur with exponential transition rates, which could depend on the actual level. The number of states and the transition rates can be determined from the matching of the mean, variance and autocorrelation function of the model to real data [7, 1].

In the MMFM model, the exponential rate $r_{i,j}$ from state iA to the state jA (birth-and-death process) is given by [7]:

$$\begin{aligned} r_{i,i+1} &= (M - i)\alpha, & i < M, \\ r_{i,i-1} &= i\beta, & i > 0, \end{aligned}$$

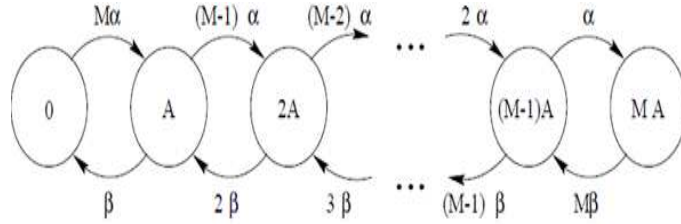


Figure 1: Birth-and-Death Process.

$$r_{i,j} = 0, \quad |i - j| > 1, \quad (2.2)$$

where α represents birth and β , death rates.

The steady-state probability of being in a state k of aggregated source rate is given by:

$$P\{(\bar{\lambda}_N) = kA\} = \binom{M}{k} p^k (1-p)^{M-k}, \quad p = \frac{\alpha}{\alpha + \beta}, \quad (2.3)$$

where N is the number of aggregated sources, M is the number of states and A is the uniform quantization step. A binomial distribution process with parameters: mean $E(\bar{\lambda}_N)$, variance $\bar{C}_N(0)$ and exponential auto covariance $\bar{C}_N(\tau)$ describes the stationary state $\bar{\lambda}_N(t)$ [7], and whose parameters can be given, respectively as:

$$E(\bar{\lambda}_N) = MAp, \quad (2.4)$$

$$\bar{C}_N(0) = MA^2p(1-p), \quad (2.5)$$

$$\bar{C}_N(\tau) = \bar{C}_N(0)e^{-(\alpha-\beta)\tau}, \quad (2.6)$$

where τ is the time variation.

Using equations (2.3) to (2.6), we propose an algorithm for parameter adjusting, where the parameters (M , A , α and β) are updated according to the considered traffic trace. Thus, we can generate samples of a MMFM model using the obtained parameters.

Proposed Algorithm: Computation and Tuning of the MMFM based Model Parameters

Step 1. Compute the mean and the variance of the real traffic time series.

Step 2. Compute the autocovariance function of the traffic trace using the following equation:

$$C(\tau) = E[(\lambda(t) - \mu)(\lambda(t + \tau) - \mu)], \quad (2.7)$$

where $\lambda(t)$ is the traffic process in time instant t , μ is the mean of the traffic process and τ is the time lag used to calculate $C(\tau)$.

Step 3. Find parameter a of the model using a Curve Fitting procedure. That is, the autocovariance function of the traffic trace is given by (2.7) which is adjusted according to equation (2.6) where $a = \alpha + \beta$, i.e., resulting in equation (2.8). In

other words, in this step it is calculated the parameters of an exponential function that better fits to the autocovariance function of the traffic trace under a 95% confidence interval.

$$C_N(\tau) = C_N(0)e^{-a \cdot \tau}, \quad (2.8)$$

Step 4. The value of a computed in the Curve Fitting (step 3) is used to calculate the parameters α and β , by the following equations

$$\beta = \frac{a \cdot M \cdot C_N(0)}{M \cdot C_N(0) + E^2(\lambda_N)}, \quad (2.9)$$

$$\alpha = a - \beta. \quad (2.10)$$

In this step, it is chosen the M value. Notice that the Markov Chain possesses $M+1$ states and N is the number of aggregated sources. In this work, we considered $N = 1$.

Step 5. Once the parameters α and β were obtained, the exponential rates of equation (2.2) are computed.

Step 6. Compute A using the following equation

$$A = \frac{C_N(0)}{E(\lambda_N)} + \frac{E(\lambda_N)}{M}. \quad (2.11)$$

Step 7. The obtained parameter values are used to generate samples of a MMFM based model through a birth-and-death Markov Chain as that represented by Figure 1.

Equation (2.9) is obtained by inserting equation (2.4) into (2.5) and (2.6). In a similar way, we obtain equation (2.11) through (2.4), (2.5) and (2.6), where we isolate A in order to be independent of β .

The MMFM model parameters (M , A , α and β), are obtained from equations (2.3) to (2.6). The procedure of curve fitting is applied for obtaining an exponential curve which matches to the autocorrelation function of real data.

3. Test Scenario

The PLC network test scenario based on a indoor environment was implemented in the Laboratory of Telecommunications of the Instituto Federal de Educação, Ciência e Tecnologia de Goiás (IFG) and in the Laboratory of Simulation of the Universidade Federal de Goiás (UFG), using PLC Powerline Ethernet Bridge. The tests were carried out as one of the objectives to evaluate the behavior of VoIP traffic using BPL equipment. To this end, we used in-door equipment which has theoretical limitation of 100m and are based on HomePlug technology.

The topology of the data transmission tests can be seen in Figure 2. Two PLC terminals were used. They are already available commercially (PlugFácil Powerline Ethernet Bridge) which operates with frequency from 4,3MHz to 20,9MHz.

For the voice transmission (VoIP) in PLC networks, free code softwares were used such as Asterisk (central PABX), and X-Lite (customer soft-phone). The VoIP

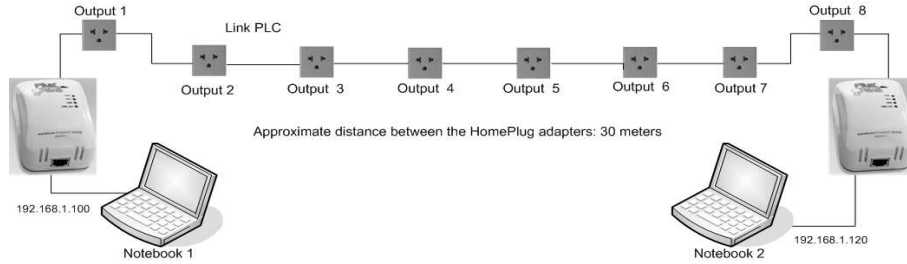


Figure 2: Topology used in the tests of data transfer.

test scenario is similar to that shown in Figure 2. It was carried out conversations of approximately 10 minutes through soft-phone installed in the notebooks, with an approximate distance of 30m. The signaling protocol used in the experimental tests was SIP (Session Initiation Protocol), with the G-711 Voice Codec. In this case, the size of the frames is fixed (214 bytes).

4. Performance of the MMFM Modeling with Traffic Autocorrelation Fitting

We collected 1000 samples of data traces and VoIP in order to evaluate the performance of Markovian models in modeling PLC network traffic.

The proposed MMFM based Model begins with the modeling of the autocorrelation function through the fitting of an exponential function to the autocorrelation of the real process. The parameters of the exponential curve found from curve fitting are used to calculate the intensities of births and deaths of a birth-and-death Markov chain for the synthetic series generation. The bit rate $\lambda(t)$ of the MMFM model is given in packets per second (pps), and the number of aggregated sources is 1.

Figure 3 shows the real data in a PLC network and the synthetic traces generated by the Markovian models. Table 1 presents a comparison between the statistics of the real trace and that of the generated synthetic time series related to the data traffic in the PLC network. As it can be observed, the statistical parameters calculated for the MMFM are closer to the parameters calculated for the real trace of data transfer than the other considered Markovian models.

The Correlation Coefficient measures the degree of correlation (and the direction of this correlation - if positive or negative) between two variables. It can be observed that the correlation between the real data and the MMFM synthetic trace is higher than for the other synthetic time series.

Figure 4 shows the autocorrelation function for the real data and that obtained for the considered models. It can be noticed that the MMFM presents an autocorrelation function closer to that of the real traffic trace. Figure 5 presents the pdf (probability density function) for the real trace and for the synthetic generated

Table 1: Comparison of Statistical Parameters for Data Transmission.

Statistical	Real	MMPP	Proposed MMFM	Poisson
Variance	1,07e+06	7,31e+05	1,57e+06	6,36e+03
Average (pps)	7,20e+03	7,29e+03	7,30e+03	7,21e+03
Standard Deviation	1,04e+03	8,55e+02	1,25e+03	7,98e+01
Maximum Value (pps)	1,09e+04	1,06e+04	1,18e+04	7,44e+03
Minimum Values (pps)	1,17e+03	3,81e+03	5,82e+02	6,95e+03
Peak/average	1,506	1,449	1,62	1,03
Correlation Coefficient	–	-0,2173	0,8931	0,0211

traces. The MMFM model pdf is similar to that of the real data (data traffic), describing better the pdf of the real data than the Poisson model.

Now, we will analyze the performance of Markovian models in modeling the VoIP traffic in PLC networks, including our approach. Table 2 presents a comparison between the statistics of the real trace and those of the generated traces (related to the VoIP communication through the PLC network). As it can be observed, again the statistical parameters for the MMFM are closer to those of the real VoIP communication trace.

Table 2: Comparison of Statistical Parameters - VoIP.

Statistical	Real	MMPP	Proposed MMFM	Poisson
Variance	17,3085	36,9628	26,6979	41,1815
Average (pps)	46,6468	37,3580	45,9587	45,3060
Standard Deviation	4,1603	6,0797	5,1670	6,4173
Maximum Value (pps)	49,5327	60,0000	51,4484	69,0000
Minimum Values (pps)	0	19,0000	0	26,0000
Peak/average	1,0619	1,6061	1,1194	1,5230
Correlation Coefficient	–	0,0379	0,6562	0,0117

Figure 6 presents the autocorrelation function for the VoIP communication and

for the considered Markovian models, where we can observe a slower decaying of the autocorrelation function of the proposed approach such as that of real VoIP traffic trace. Figure 7 shows the probability distribution function for the VoIP communication trace. Concerning the probability distribution function, it can be observed that all the models presented difficulties in providing a probability distribution function exactly similar to that of the real VoIP data. Nevertheless, we could say the proposed MMFM based model provided a satisfactory result for the pdf matching compared to the considered models.

5. Conclusions

The PLC technology is a promising alternative for communication due to the capillarity of the existing electric power network.

The network traffic modeling allows a better planning, dimensioning and analysis of network performance. From the analysis done in this work, we can conclude that the proposed model is efficient in describing the traffic in PLC networks in comparison to other Markovian models. In fact, the results obtained with the MMFM model were adequate for both data and VoIP transmission in PLC networks. Moreover, once the proposed MMFM is simple to implement, it requires less processing time than, for example, self-similar models and can be applied to real-time processing tasks in PLC networks.

Resumo. Neste artigo, apresentamos uma análise do tráfego VoIP (*Voice over IP*) e de transferência de dados usando uma rede PLC (*PowerLine Communications*). Propomos um modelo baseado em MMFM (*Markov Modulated Fluid Models*) para tráfego de dados e VoIP em redes PLC. Simulações e comparações foram realizadas para verificar a eficiência do modelo de tráfego proposto em relação aos modelos de Poisson e MMPP (*Markov Modulated Poisson Process*).

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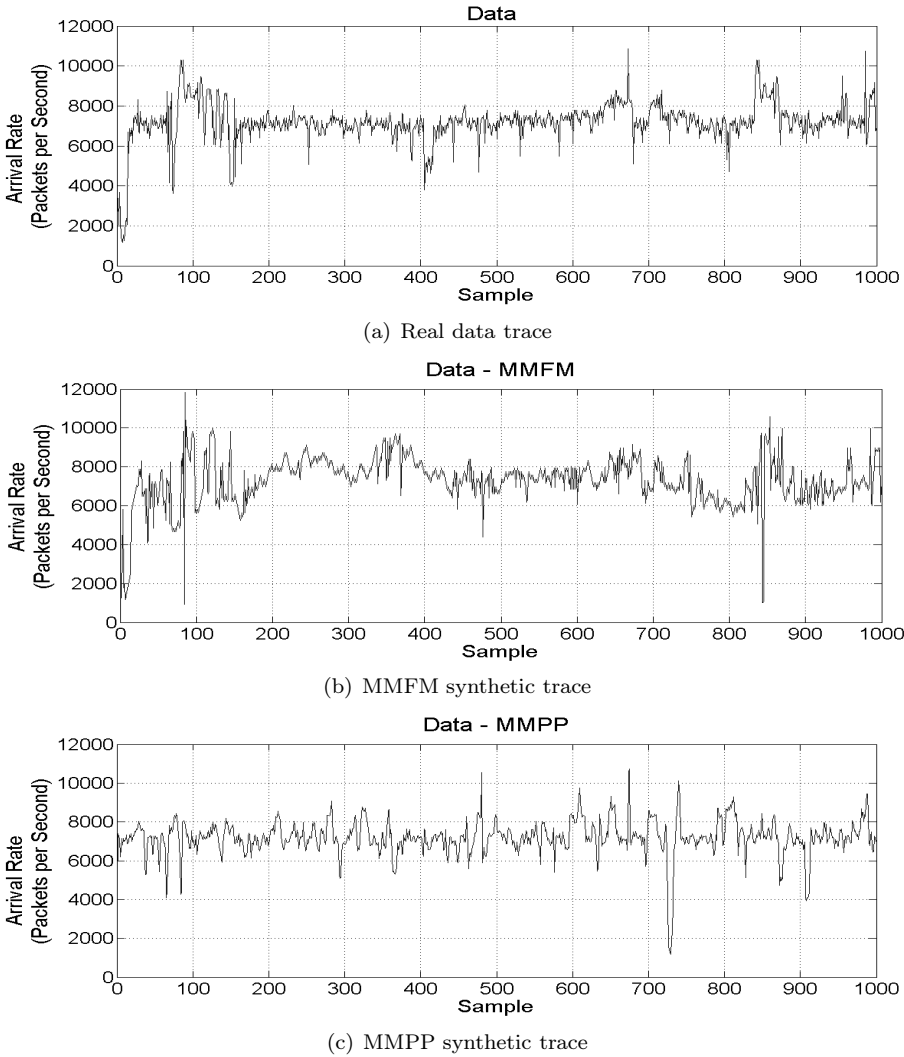


Figure 3: Comparisons among a traffic process and synthetic traces.

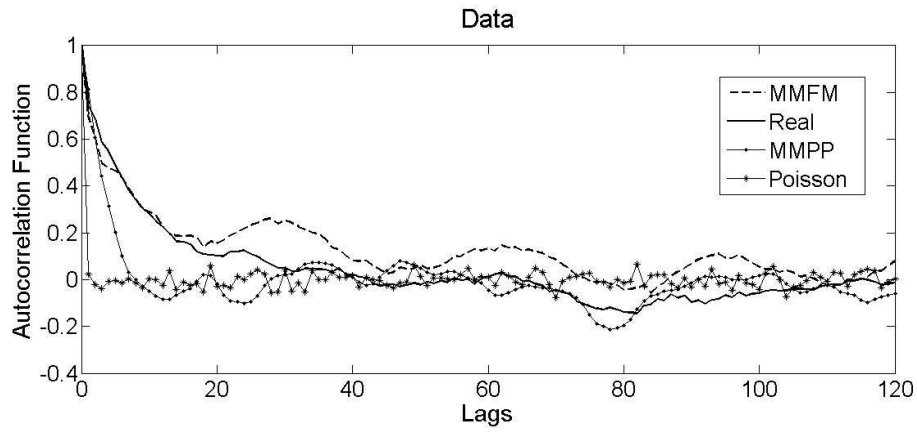


Figure 4: Autocorrelation Function.

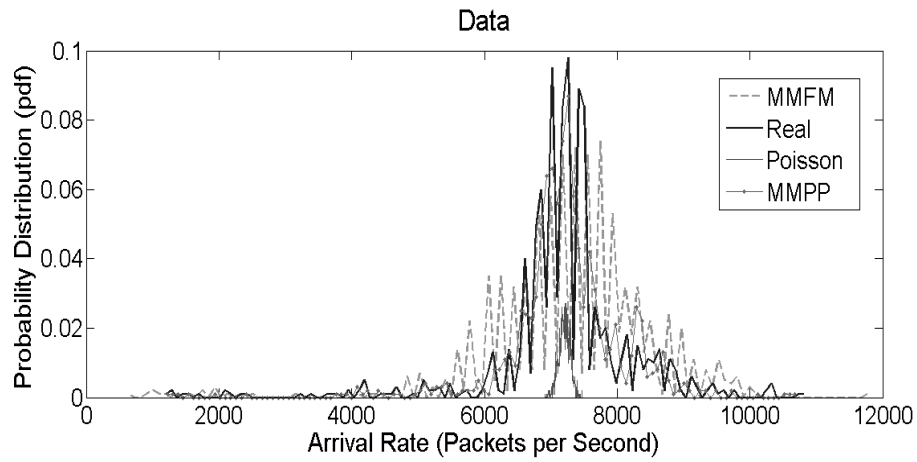


Figure 5: Probability Distribution Function (pdf).

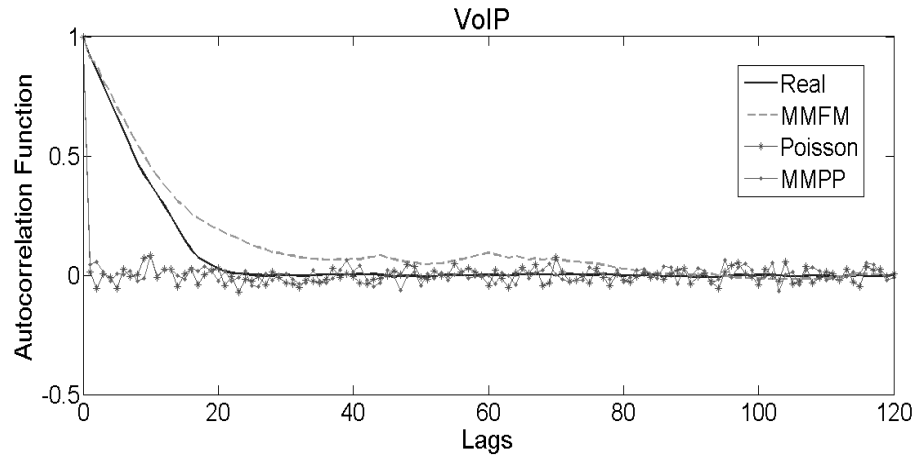


Figure 6: Autocorrelation Function

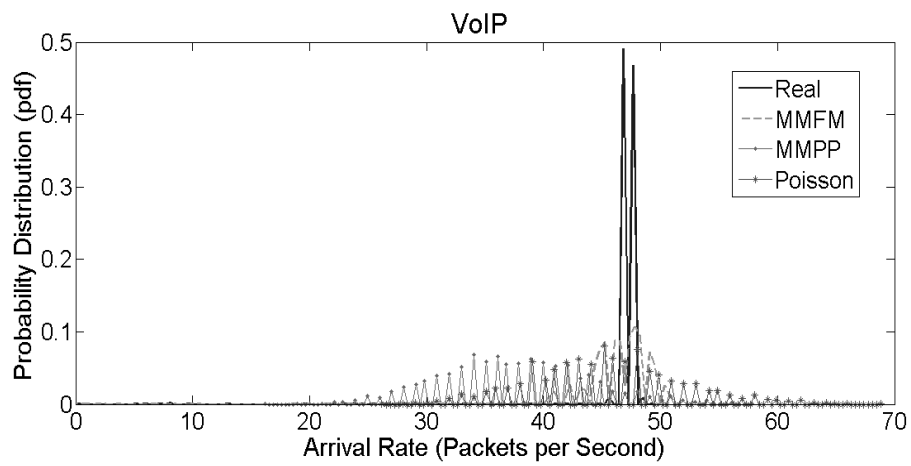


Figure 7: Probability Distribution Function (pdf)