Deterministic Modeling and Simulation of Error Sequences in Digital Mobile Fading Channels

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***Abstract*— In order to evaluate the performance of wireless communication protocols and design good error control schemes for bursty channels, it is important to develop accurate and simple generative models. In this paper, a novel generative deterministic model (GDM) is proposed for the simulation of bursty error sequences encountered in digital mobile fading channels. The proposed GDM is simply a properly parameterized and sampled deterministic process followed by a threshold detector and two parallel mappers. Simulation results show that this generative model enables us to match very closely any given error-free run distribution (EFRD), gap distribution (GD), and error cluster distribution (ECD) of the underlying descriptive model.**

I. Introduction

Digital mobile fading channels often exhibit statistical dependencies among errors. This results in the fact that errors are grouped together in clusters or bursts. The study of the underlying bursty error process is a prerequisite for the design and performance evaluation of wireless communication protocols as well as coding systems [1]. Error models for characterizing bursty error sequences have therefore been developed, based on either a descriptive approach [2] or a generative approach [3]. A descriptive modeling approach consists of describing the structure of target error sequences by various statistics. A generative modeling approach involves the specification of an underlying mechanism that generates error sequences similar to the modeled sequences [3]. One generative model is preferred to another if it better fits the important statistics of target error sequences.

In the literature, a number of generative models have been presented based on finite [3–5] or infinite [3] state Markov chains or hidden Markov chains [6–8]. Gilbert [9] originally proposed a two-state Markov model. It generates in one state (good state) an error-free sequence and in the other one (bad state) a sequence of errors. Elliot [10] modified Gilbert's model in such a way that errors can also occur with a small probability in the good state. The disadvantage of a two-state Markov model is its limited capability to reproduce the desired burst error statistics. Frichman [4] proposed a class of Markov models having a finite number K of states, which are then partitioned into two groups. The first group consists of j error-free states, while the second group is formed by $K - j$ error states. Simplified Frichman's models (SFMs) with only one error state have received wide applications [11–13]. Moreover, bipartite models were proposed in [5]. The Markov chain used in a bipartite model forms a bipartite graph. Another class of generative models are hidden Markov models [6–8], which lack a direct intuition between the channel behavior and the underlying Markov chain. A higher state Markov model enhances the parametrization problems and makes the subsequent performance analysis of high layer protocols increasingly difficult.

Recently, generative models based on alternative error generation mechanisms, other than Markov chains, were proposed. For instance, chaos equations [14] and context-free grammars [15] were applied to model error sequences in bursty channels. An initial attempt was carried out in [16] to utilize deterministic processes [17], [18], which originally go back to Rice's sum of sinusoids [19], [20], for the development of generative models in digital Rayleigh fading channels. The deterministic process based generative model (DPBGM) [16] was shown to be a promising alternative to Markov models. However, the fittings to the desired error-free run distribution (EFRD) and gap distribution (GD) by using the DPBGM are not as good as the results obtained from a SFM with 6 states [16]. In this paper, an improved DPBGM is proposed which enables us to nearly perfectly match any given EFRD, GD, and error cluster distribution (ECD) of the underlying descriptive model.

The paper is organized as follows. Section II briefly reviews the interested descriptive statistics. A novel generative deterministic model (GDM) is proposed in Section III. Section IV compares the burst error statistics of the underlying descriptive model, the proposed generative model, and a SFM. Finally, the conclusions are drawn in Section V.

II. Descriptive Statistics

An error sequence is represented by a binary sequence of ones and zeros, where "1" and "0" denote error bits and correct bits, respectively. Following [12], a gap is defined as a string of consecutive zeros between two ones, having a length equal to the number of zeros. An error cluster is a region where the errors occur consecutively without correct bits in between. The length of an error cluster equals the number of ones. In this paper, only the following three burst error statistics are to be considered for brevity of presentation. The first frequently employed statistic is the EFRD $P(0^{m_0}/1)$, which is defined as

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the probability that an error is followed by at least m_0 error-free bits. Note that $P(0^{m_0}/1)$ is a monotonically decreasing function of m_0 such that $P(0^0/1) = 1$ and $P(0^{m_0}/1) \to 0$ as $m_0 \to \infty$. The second one is the GD $G(m_g)$, which is defined as the cumulative distribution of gap lengths m_g. It should be observed that the GD can be calculated from the EFRD [11]. The third one is the ECD $P(1^{m_c}/0)$. The ECD is the probability that, given a correct bit has occurred, it will be followed by m_c or more consecutive bits in error [4].

To avoid a bit-by-bit analysis of an error sequence, a sensible way of recording error data is to list the successive gap lengths and error cluster lengths. From such records, the inference of the EFRD, the GD, and the ECD is straightforward. Consequently, a gap recorder $\mathbf{G}_{rec}$ and an error cluster recorder $\mathbf{C}_{rec}$ are obtained. Here, $\mathbf{G}_{rec}$ is a vector which keeps a record of successive gap lengths, while $\mathbf{C}_{rec}$ records successive error cluster lengths. Let us denote the minimum value and the maximum value in $\mathbf{G}_{rec}$ as m_{G1} and m_{G2}, respectively. This means that the gap lengths m_g satisfy $m_{G1} \leq m_g \leq m_{G2}$. By analogy, we conclude that $m_{C1} \leq m_c \leq m_{C2}$ holds for all entries in $\mathbf{C}_{rec}$. For the derivation of the generative model in Section III, it is convenient to further define the following quantities:

1) N_t: the total length of the target error sequence.
2) $\mathcal{N}_{\mathcal{G}}$: the total number of gaps, which equals the number of entries in $\mathbf{G}_{rec}$.
3) $\mathcal{N}_{\mathcal{C}}$: the total number of error clusters, which equals the number of entries in $\mathbf{C}_{rec}$. Clearly, $\mathcal{N}_{\mathcal{C}} = \mathcal{N}_{\mathcal{G}} + 1$ holds.
4) $N_G(m_g)$: the number of gaps of length m_g in $\mathbf{G}_{rec}$. Apparently, $\sum_{m_g=m_{G1}}^{m_{G2}} N_G(m_g) = \mathcal{N}_{\mathcal{G}}$ holds.
5) $N_C(m_c)$: the number of error clusters of length m_c in $\mathbf{C}_{rec}$. Similarly, $\sum_{m_c=m_{C1}}^{m_{C2}} N_C(m_c) = \mathcal{N}_{\mathcal{C}}$ holds.
6) $\mathcal{R}$: the ratio of the mean value M_c of error clusters to the mean value M_g of gaps, i.e., $\mathcal{R} = M_c/M_g$.

III. The Generative Deterministic Model

It is well known that the statistics of burst errors can be estimated from the level-crossing statistics of fading envelope processes. This suggests the possibility that generative models can be developed from fading processes.

The idea of the proposed generative model is to derive directly from a deterministic envelope process a gap length generator and an error cluster length generator. First of all, the employed deterministic process $\tilde{\zeta}(t)$ must be properly parameterized and sampled with a certain sampling interval T_A. The sampled deterministic process $\tilde{\zeta}(kT_A)$, where k is a nonnegative integer, is then followed by a threshold detector. During the simulation, the level of the deterministic process will be from time to time below and above the given threshold depending on the value of the threshold as well as the chosen parameters. Error clusters are produced at the model's output if the level of $\tilde{\zeta}(kT_A)$ falls below a given threshold r_{th}. The lengths of the generated error clusters equal the numbers of samples in the corresponding fading intervals of $\tilde{\zeta}(kT_A)$. On the other hand, gaps are generated at the model's output if the level of $\tilde{\zeta}(kT_A)$ is above r_{th}. The gap lengths equal the numbers of samples in the corresponding inter-fade intervals of $\tilde{\zeta}(kT_A)$. Consequently, an error cluster length generator $\widetilde{\mathbf{C}}_{rec}$ and a gap length generator $\widetilde{\mathbf{G}}_{rec}$ are obtained. For the generative model, we use similar notations to those presented in Section II by simply putting the tilde sign on all affected symbols, i.e., we write $\tilde{m}_{C1}$, $\tilde{\mathcal{N}}_{\mathcal{C}}$, $\tilde{N}_G(m_g)$, etc.

A. The Parametrization of the Sampled Deterministic Process

The parameters of the sampled deterministic process are determined as follows. The level-crossing rate (LCR) $\tilde{N}_\zeta(r_{th})$ at the chosen threshold r_{th} is fitted to the desired occurrence rate $R_C = \mathcal{N}_{\mathcal{C}}/T_t$ of error clusters. Here, T_t denotes the total transmission time of the reference transmission system, from which the target error sequence of length N_t is obtained. Also, the ratio $\tilde{\mathcal{R}}$ of the average duration of fades (ADF) $\tilde{T}_{\zeta_-}(r_{th})$ at r_{th} to the average duration of inter-fades (ADIF) $\tilde{T}_{\zeta_+}(r_{th})$ at r_{th} is adapted to the ratio $\mathcal{R} = M_c/M_g$. Moreover, in order to detect most of the level crossings and fading intervals at deep levels, i.e., $r_{th} \ll 1$, we must ensure that the sampling interval T_A is chosen sufficiently small. Let us first consider the following continuous-time deterministic process [18]

$$\tilde{\zeta}(t) = |\tilde{\mu}_1(t) + j\tilde{\mu}_2(t)| \tag{1}$$

where

$$\tilde{\mu}_i(t) = \sum_{n=1}^{N_i} c_{i,n} \cos(2\pi f_{i,n} t + \theta_{i,n}) \ , \quad i = 1, 2 \ . \tag{2}$$

In (2), N_i defines the number of sinusoids, $c_{i,n}$, $f_{i,n}$, and $\theta_{i,n}$ are called the gains, the discrete frequencies, and the phases, respectively. By using the method of exact Doppler spread (MEDS) [18], the phases $\theta_{i,n}$ are equated with the realizations of a random generator uniformly distributed over $(0, 2\pi]$, while $c_{i,n}$ and $f_{i,n}$ are given by

$$c_{i,n} = \sigma_0 \sqrt{\frac{2}{N_i}} \tag{3}$$

$$f_{i,n} \quad = \quad f_{max} \sin\left[\frac{\pi}{2N_i}(n - \frac{1}{2})\right] \tag{4}$$

respectively. Here, σ_0 is the square root of the mean power of $\tilde{\mu}_i(t)$ and f_{max} represents the maximum Doppler frequency.

When using the MEDS with $N_i \geq 7$, it has been shown in [18] that the LCR $\tilde{N}_\zeta(r)$ of $\tilde{\zeta}(t)$ is very close to the LCR $N_\zeta(r)$ of a Rayleigh process, which is given by

$$N_\zeta(r) = \sqrt{\frac{\beta}{2\pi}} p_\zeta(r) \ , \quad r \geq 0 \tag{5}$$

where

$$\beta = 2(\pi\sigma_0 f_{max})^2 \tag{6}$$

and

$$p_\zeta(r) = \frac{r}{\sigma_0^2} \exp(-\frac{r^2}{2\sigma_0^2}) \ , \quad r \geq 0 \tag{7}$$

denotes the Rayleigh distribution. It can also be shown that the ADF $\tilde{T}_{\zeta_-}(r)$ and the ADIF $\tilde{T}_{\zeta_+}(r)$ of $\tilde{\zeta}(t)$ approximate very

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well the desired quantities $T_{\zeta_-}(r)$ and $T_{\zeta_+}(r)$, respectively, of a Rayleigh process. They can be expressed as

$$T_{\zeta_-}(r) = \sqrt{\frac{2\pi}{\beta}}\frac{\sigma_0^2}{r}\left[\exp(\frac{r^2}{2\sigma_0^2}) - 1\right] \ , \quad r \geq 0 \tag{8}$$

$$T_{\zeta_+}(r) = \sqrt{\frac{2\pi}{\beta}}\frac{\sigma_0^2}{r} \ , \quad r \geq 0 \ . \tag{9}$$

Consequently, the ratio $\tilde{\mathcal{R}}$ can be determined as follows

$$\tilde{\mathcal{R}} = \frac{\tilde{T}_{\zeta_-}(r_{th})}{\tilde{T}_{\zeta_+}(r_{th})} \approx \frac{T_{\zeta_-}(r_{th})}{T_{\zeta_+}(r_{th})} = \exp(\frac{r_{th}^2}{2\sigma_0^2}) - 1 \ . \tag{10}$$

Now, the task at hand is to find a proper parameter vector $\mathbf{\Psi} = (N_1, N_2, r_{th}, \sigma_0, f_{max}, T_A)$ in order to fulfill the following conditions: $R_C = N_\zeta(r_{th})$ and $\mathcal{R} = \frac{T_{\zeta_-}(r_{th})}{T_{\zeta_+}(r_{th})}$. To solve this problem, we first choose reasonable values for N_1, N_2, and r_{th}, e.g., $N_1 = 9$, $N_2 = 10$, and $r_{th} = 0.01$. Then, performing $\mathcal{R} = \frac{T_{\zeta_-}(r_{th})}{T_{\zeta_+}(rth)}$, σ_0 can be calculated according to the following expression

$$\sigma_0 = \frac{r_{th}}{\sqrt{2\ln(1+\mathcal{R})}} \ . \tag{11}$$

With the help of the relation $R_C = N_\zeta(r_{th})$, f_{max} is given by

$$f_{max} = \frac{\mathcal{N}_\mathcal{C}}{\sqrt{\pi}\sigma_0 T_t p_\zeta(r_{th})} \tag{12}$$

which can finally be simplified as

$$f_{max} = \frac{\mathcal{N}_\mathcal{C}(1+\mathcal{R})}{T_t\sqrt{2\pi\ln(1+\mathcal{R})}} \ . \tag{13}$$

It is clear that f_{max} is completely determined by $\mathcal{N}_\mathcal{C}$, $\mathcal{R}$, and T_t, but not influenced by r_{th} and σ_0. As suggested in [21], the sampling interval T_A for small values of r_{th} can suitably be chosen as follows

$$T_A \approx \frac{4}{\sqrt{5\pi}} T_{\zeta_-}(r_{th})\sqrt{-1 + \sqrt{1 + 10q_s/3}} \tag{14}$$

where q_s is a very small quantity determining the maximum measurement error of the LCR. This implies that the probability of undetectable level crossings at r_{th} is not larger than q_s. The substitution of (8) into (14) results in the following explicit expression

$$T_A \approx \frac{4\sigma_0[\exp(\frac{r_{th}^2}{2\sigma_0^2}) - 1]}{\sqrt{5}\pi r_{th} f_{max}}\sqrt{-1 + \sqrt{1 + 10q_s/3}} \ . \tag{15}$$

By using the obtained parameter vector $\mathbf{\Psi}$, a sampled deterministic process $\tilde{\zeta}(kT_A)$ is generated within the necessary simulation time interval $[0, \tilde{T}_t]$, i.e., $kT_A \leq \tilde{T}_t$. Here, $\tilde{T}_t = T_t\tilde{N}_t/N_t$ with $\tilde{N}_t$ denoting the required length of the generated error sequence. The total numbers of the generated error clusters $\tilde{\mathcal{N}_\mathcal{C}}$ and gaps $\tilde{\mathcal{N}_\mathcal{G}}$ can be estimated from $\tilde{\mathcal{N}_\mathcal{C}} = \lfloor \frac{\tilde{N}_t}{N_t}\mathcal{N}_\mathcal{C} \rfloor$ and $\tilde{\mathcal{N}_\mathcal{G}} = \lfloor \frac{\tilde{N}_t}{N_t}\mathcal{N}_\mathcal{G} \rfloor$, respectively. Here, $\lfloor x \rfloor$ stands for the nearest integer to x towards minus infinity. In this manner, an error cluster length recorder $\tilde{\mathbf{C}}_{rec}$ with $\tilde{\mathcal{N}_\mathcal{C}}$ entries and an gap length recorder $\tilde{\mathbf{G}}_{rec}$ with $\tilde{\mathcal{N}_\mathcal{G}}$ entries are derived.

B. The Mappers

In general, the numbers of samples located in successive fading intervals and inter-fade intervals of $\tilde{\zeta}(kT_A)$ are not suitable to directly generate an acceptable ECD and EFRD, respectively. Two mappers are therefore introduced, which map the lengths of the generated error clusters and gaps to the desired lengths, as explained subsequently. The idea of the mappers is to modify $\tilde{\mathbf{G}}_{rec}$ and $\tilde{\mathbf{C}}_{rec}$ in such a way that $\tilde{N}_G(m_g) = N_{GM}(m_g)$ and $\tilde{N}_C(m_c) = N_{CM}(m_c)$ hold, respectively, where

$$N_{GM}(m_g) = \begin{cases} \lfloor N_{GR}(m_g) \rfloor \ , \\ \quad \text{if } N_{GR}(m_g) - \lfloor N_{GR}(m_g) \rfloor < \mu_g \\ \lfloor N_{GR}(m_g) \rfloor + 1 \ , \\ \quad \text{if } N_{GR}(m_g) - \lfloor N_{GR}(m_g) \rfloor \geq \mu_g \end{cases} \tag{16}$$

and

$$N_{CM}(m_c) = \begin{cases} \lfloor N_{CR}(m_c) \rfloor \ , \\ \quad \text{if } N_{CR}(m_c) - \lfloor N_{CR}(m_c) \rfloor < \mu_c \\ \lfloor N_{CR}(m_c) \rfloor + 1 \ , \\ \quad \text{if } N_{CR}(m_c) - \lfloor N_{CR}(m_c) \rfloor \geq \mu_c \ . \end{cases} \tag{17}$$

Here, $N_{GR}(m_g) = \frac{\tilde{N}_t}{N_t}N_G(m_g)$, $N_{CR}(m_c) = \frac{\tilde{N}_t}{N_t}N_C(m_c)$, μ_g and μ_c are real numbers located in the interval $(0, 1)$, which have to be chosen properly in order to fulfill $\sum_{m_g=m_{G1}}^{m_{G2}} N_{GM}(m_g) = \tilde{\mathcal{N}_\mathcal{G}}$ and $\sum_{m_c=m_{C1}}^{m_{C2}} N_{CM}(m_g) = \tilde{\mathcal{N}_\mathcal{C}}$, respectively. Note that the resulting EFRD $\tilde{P}(0^{m_0}/1)$ will be close to the desired EFRD $P(0^{m_0}/1)$, since $\tilde{N}_G(m_g)$ is almost proportional to $N_G(m_g)$. Also, the resulting ECD $\tilde{P}(1^{m_c}/0)$ will match well the desired one $P(1^{m_c}/0)$.

Next, we will only concentrate on the procedure of properly modifying $\tilde{\mathbf{C}}_{rec}$. The same procedure applies also to $\tilde{\mathbf{G}}_{rec}$. For each error cluster length value m_c ($m_{C1} \leq m_c \leq m_{C2}$), we first find the corresponding values $\ell_{m_c}^1$ and $\ell_{m_c}^2$ ($\tilde{m}_{C1} \leq \ell_{m_c}^1$, $\ell_{m_c}^2 \leq \tilde{m}_{C2}$) in $\tilde{\mathbf{C}}_{rec}$ to satisfy the following conditions

$$\sum_{n=\ell_{m_c}^1}^{\ell_{m_c}^2 - 1} \tilde{N}_C(n) \quad < \quad N_{CM}(m_c) \tag{18}$$

$$\sum_{n=\ell_{m_c}^1}^{\ell_{m_c}^2} \tilde{N}_C(n) \quad \geq \quad N_{CM}(m_c) \ . \tag{19}$$

Let us define

$$N_{\ell_{m_c}^2} = N_{CM}(m_c) - \sum_{n=\ell_{m_c}^1}^{\ell_{m_c}^2 - 1} \tilde{N}_C(n) \ . \tag{20}$$

Clearly, $\sum_{n=\ell_{m_c}^1}^{\ell_{m_c}^2-1} \tilde{N}_C(n) + N_{\ell_{m_c}^2} = N_{CM}(m_c)$ holds. This indicates that if we map all error cluster lengths between $\ell_{m_c}^1$ and $\ell_{m_c}^2 - 1$, while only $N_{\ell_{m_c}^2}$ error cluster lengths of $\ell_{m_c}^2$ in $\tilde{\mathbf{C}}_{rec}$ to m_c, then $\tilde{N}_C(m_c) = N_{CM}(m_c)$ will be satisfied.

Therefore, we find the entries between $\ell^1_{m_c}$ and $\ell^2_{m_c} - 1$ in $\widetilde{\mathbf{C}}_{rec}$, and then replace them by m_c. Also, find the entries with the value $\ell^2_{m_c}$ in $\widetilde{\mathbf{C}}_{rec}$, but replace only $N_{\ell^2_{m_c}}$ of them by m_c. Note that $\ell^1_{mC1} = \tilde{m}_{C1}$ and $\ell^2_{mC2} = \tilde{m}_{C2}$ hold.

In summary, the mapper for the error cluster length generator works as follows: if n ($\ell^1_{m_c} \leq n < \ell^2_{m_c} - 1$) samples of the deterministic process are observed in a fading interval, then a mapping $n \rightarrow m_c$ is first performed and afterwards an error cluster with length m_c is generated. The resulting error sequence is simply the combination of consecutively generated gaps and error clusters. The block diagram of the obtained generative model is depicted in Fig. 1.

Due to the fact that the proposed error generation mechanism does not require any random generators, the obtained generative model is completely deterministic. This motivates us to call it GDM. We stress that, although the simulation set-up phase (determining the parameter vector and designing the mappers) of the GDM requires a relatively long time, the simulation run phase (generation of error sequences) is fast. Therefore, the proposed GDM can be considered as a fast error process simulator, since it determines directly gap and cluster lengths instead of bit sequences.

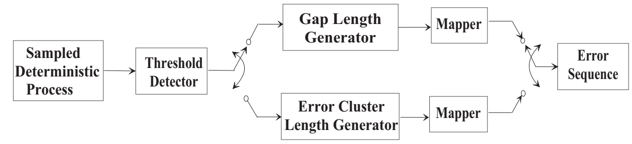

Fig. 1. The block diagram of the proposed generative deterministic model.

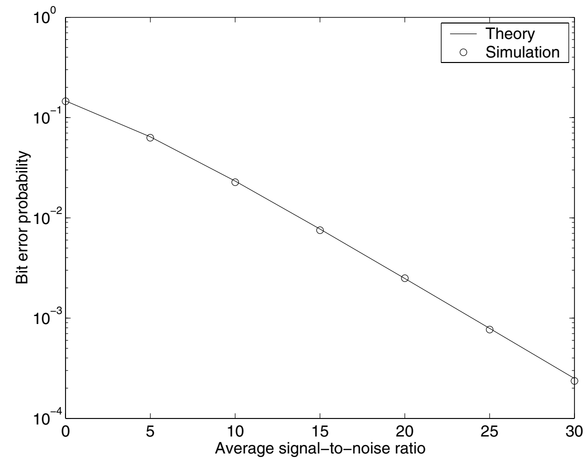

Fig. 2. The BEP for coherent QPSK systems by using the MEDS ($\sigma_0^2 = 1/2$, $f_{max} = 74$ Hz, $N_1 = 9$, $N_2 = 10$).

IV. Simulation Results and Discussions

In this section, the performance of the novel GDM is investigated by applying the mechanism to an experimental error sequence. The adopted reference transmission system is a coherent QPSK system with a Rayleigh fading channel [16]. The transmission rate was set to be $F_s = 144$ kb/s, which is the same as specified for vehicular users in UMTS systems. The underlying Rayleigh fading channel was again modeled by the deterministic process in (1). Its parameters $c_{i,n}$, $f_{i,n}$, and $\theta_{i,n}$ were determined by using the MEDS. The mean power was given by $\sigma_0^2 = 1/2$ and the maximum Doppler frequency was chosen as $f_{max} = 74$ Hz, which corresponds to a carrier frequency of 2 GHz and a vehicle velocity of 40 km/h. The numbers of sinusoids were chosen as $N_1 = 9$ and $N_2 = 10$. The average bit error probability (BEP) of the whole transmission system was obtained by evaluating $N_t = 8 \times 10^6$ transmission bits. The total transmission time is therefore $T_t \approx 55.6$ s. Fig. 2 depicts the simulated BEP together with the theoretical BEP given in [22] versus the average signal-to-noise ratio (SNR). A SNR of 15 dB was selected for the generation of the target error sequence. This corresponds to a BEP of 7.5341×10^{-3}. The relevant burst error statistics were obtained from the resulting error sequence. Altogether $\mathcal{N}_{\mathcal{C}} = 49379$ error clusters and $\mathcal{N}_{\mathcal{G}} = 49378$ gaps were obtained. The lengths of the error clusters range from $m_{C1} = 1$ to $m_{C2} = 10$, while the lengths of the gaps range from $m_{G1} = 1$ to $m_{G2} = 29099$. The ratio $\mathcal{R}$ equals 0.0076.

The procedure described in Section III is applied here for obtaining the GDM. The chosen parameter vector for the deterministic process was $\mathbf{\Psi} = (9, 10, 0.01, 0.0813, 4107.7$ Hz, 1.0961 μs). Other quantities were determined as follows: $\tilde{N}_t = 10 \times 10^6$, $\tilde{T}_t = 69.4444$ s, $q_s = 0.01$, $\mu_g = 0.25745$, and $\mu_c = 0.751$. The average BEP, the EFRD, the GD, and the ECD calculated from the generated error sequence were compared to those of the target error sequence. Also, the relevant results of a SFM were presented for comparison purposes. The parameters of a SFM with K states are obtained by fitting the weighted sum of $K-1$ exponentials to the EFRD $P(0^m/1)$ [4]. In this paper, a SFM with 6 states was employed. Our experiments on SFMs with different states have shown that no better fitting can be obtained by using more than 6 states.

The average BEPs obtained from the GDM and the SFM equal 7.5341×10^{-3} and 7.4323×10^{-3}, respectively. Figs. 3–5 show the EFRDs, the GDs, and the ECDs of both generative models and the descriptive model, respectively. As expected, the near perfect match is observed in all three curves for the GDM. The SFM enables a very good approximation to the EFRD and the GD of the descriptive model. This comes no surprise since this model is based on the fitting of the EFRD. However, the SFM fails to capture the feature of the ECD with good accuracy. Both generative models require relatively long time in the simulation set-up phase, but the simulation run phase of the GDM is approximately 4 times faster than that of the SFM.

V. Conclusion

This paper has proposed a novel generative model. The design procedure runs as follows. In the first step, the burst error statistics are calculated from the target error sequence, which is supplied here by the simulation of a coherent QPSK transmission system with a Rayleigh fading channel. In the second step, the reference transmission system is replaced simply by a properly parameterized and sampled deterministic process followed by a threshold detector and two parallel mappers. During the simulation, if the level of the deterministic process is below (above) the given threshold, an error cluster (a gap) occurs at the model's output. Then, two mappers are introduced to map the lengths of the generated error clusters and gaps to the desired lengths. The error sequence is obtained by combining consecutively generated error clusters and gaps. The merit of the proposed GDM lies on the fast generation of error sequences and its ability to fit nearly perfectly any given EFRD, GD, and ECD of the underlying descriptive model.

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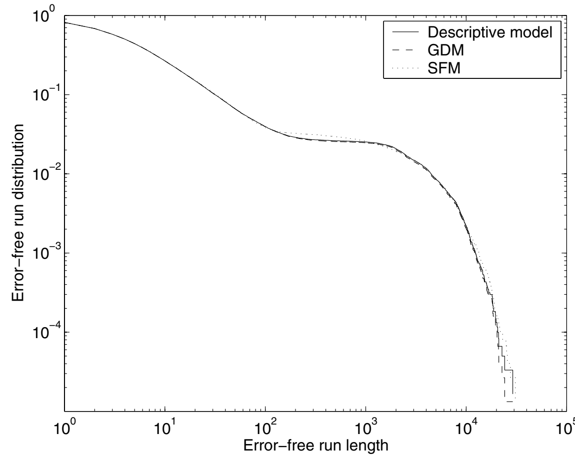

Fig. 3. The EFRDs of the generative models and the descriptive model.

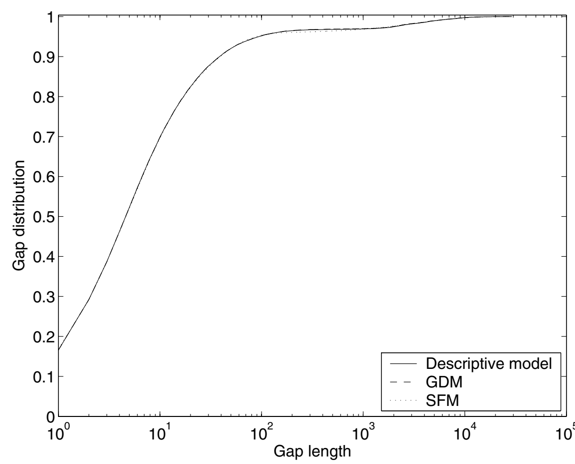

Fig. 4. The GDs of the generative models and the descriptive model.

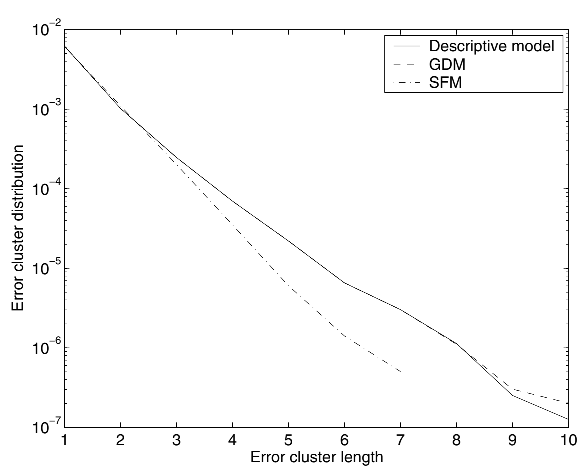

Fig. 5. The ECDs of the generative models and the descriptive model.