Proceedings of the 1993 Winter Simulation Conference
G.W. Evans, M. Mollaghasemi, E.C. Russell, W.E. Biles (eds.)

APPLICATIONS OF THE TES MODELING METHODOLOGY

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ABSTRACT

TES (Transform-Expand-Sample) is a versatile methodology for modeling general stationary time series, and particularly those that are autocorrelated. The salient feature of TES lies in its ability to simultaneously capture first-order and second-order properties of empirical time series ; given a sample data sequence, TES is designed to simultaneously capture any arbitrary marginal distribution and approximate the leading autocorrelations. Practical TES modeling is computationally intensive and can be effectively carried out only with software support. A computerized modeling environment, TEStool, has been designed to support the TES modeling methodology, through an interactive heuristic search approach facilitated by state-of-the-art data visualization techniques.

The purpose of this paper is to present four examples of the effective use of the TES methodology to model various types of time series that arise in a variety of disciplines, ranging from manufacturing to financial modeling, with particular emphasis on video compression. These examples serve to highlight the efficacy and versatility of the TES modeling methodology.

1 INTRODUCTION

Temporal and spatial dependencies are commonplace in a host of commonly encountered random phenomena. Temporal dependence accounts, to a large extent, for burstiness in telecommunications traffic, especially in emerging high-speed communications networks. The combined effect of temporal and spatial dependencies gives rise to fault cascades observed in network management. When formulated mathematically as real-valued stochastic processes, temporal dependencies are often manifested by multiple-lag autocorrelations within a stochastic process, and/or by multiple-lag cross-correlations between processes.

Although spatio-temporal dependencies abound in both computer and communications applications, the natural inclination in modeling these systems is to minimize or eliminate dependencies from model descriptions in order to simplify analysis. A case in point is a queueing system comprised of one or more GI/GI/m queues for which interarrival times and service times are specified as independent, identically distributed (iid) random sequences. The standard argument in support of this approach is that these assumptions endow the models with desirable analytical or numerical tractability. This argument is often vindicated by the insights that analytical models frequently offer, especially when dealing with systems in the design or early implementation stage. Since in such scenarios one is often interested only in a qualitative understanding of design tradeoffs, the modeling effort can succeed with performance measure calculations that are approximate, and the practice of disregarding dependencies in the design stage is frequently justifiable.

Consider, however, performance analysis after the system has been realized. Randomness in the system may arise from one or more stochastic processes. Field measurements may now be available for the modeler to analyze (at this point it is not necessary to distinguish between analytical and Monte Carlo performance evaluation approaches). An analyst in this situation is invariably confronted with two generic and sequential questions:

1. Should one ignore dependence in empirical time series and use a simpler model from the library of renewal processes?

2. If dependence is to be acknowledged, how can it be done in an systematic and effective manner?

Experience has shown that the prevailing practice is to circumvent the second question by electing to use a renewal process model. We emphasize that modelers should be made aware of the fact that over-simplified renewal models may also introduce significant modeling errors.

For example, a little introspection on the nature of burstiness in arrival processes should convince the reader of its deleterious effect on waiting times: many customers arriving in a burst will obviously suffer from increased waiting times, while the lulls separating bursts waste server utilization. Indeed, various studies (see Fendick et al. 1989, Livny et al. 1993, Patuwo et al. 1993) have shown that when autocorrelated traffic is introduced into a queueing system, the resulting performance metrics exhibit significant degradation relative to those estimated by renewal models, often differing by orders of magnitude.

A growing realization of the impact of bursty traffic on queueing system performance has provided the initial motivation for devising input analysis methods that are able to capture dependence in time series (TES included), but the concern extends to other modeling domains as well. Briefly, TES (*Transform-Expand-Sample*) is a non-linear autogressive scheme, encompassing both Markovian and non-Markovian processes (Melamed 1991, Jagerman and Melamed 1992abc). The modeling methodology which has been derived from this scheme constitutes a robust and practical input analysis technique specifically designed to address the second question articulated above.

The TES approach stipulates three requirements that should be satisfied by prospective models (see also Lewis and McKenzie 1991, and Schmeiser 1990 for a related view):

Requirement 1: The marginal distribution of the model should match its empirical counterpart.

Requirement 2: The autocorrelation function of the model should approximate its empirical counterpart.

Requirement 3: Sample paths generated by a Monte Carlo simulation of the model should "resemble" the empirical sample path.

We believe that TES is currently the only input analysis method designed to simultaneously address in a systematic manner these three criteria. Note that they are arranged in decreasing order of importance. The first two constitute quantitative goodness-of-fit criteria, whereas the third one is a qualitative requirement which cannot be defined with mathematical precision. Obviously, Requirement 3 is a highly subjective statement, but its intuitive meaning and purpose should be clear: qualitatively "similar" sample paths can considerably enhance a practitioner's confidence in a candidate model.

Fast and accurate formulas for the autocorrelation functions and spectral densities of TES models have been developed in Jagerman and Melamed (1992ab). As a result of this research, it became feasible for the TES modeling process to be carried out interactively on a desktop workstation equipped with a high-resolution graphical display. In order to realize this potential, A TES-based modeling package, called TEStool, has been implemented in software. TEStool makes heavy use of visualization in order to provide a pleasant interactive modeling environment which reduces the potential for modeling errors and helps to alleviate the tedium of repetitive search. Since the search for an appropriate TES model is performed within the TEStool visualization paradigm, somewhat akin to that of a video arcade game, it can be conducted by both experts and novices alike.

The remainder of this paper is organized as follows. Section 2 contains a brief overview of TES processes, an outline of the TES modeling methodology, and a concise description of the TEStool software modeling environment. Section 3 demonstrates the efficacy of the TES modeling methodology and the TEStool modeling environment by a range of examples from various application domains. Finally, Section 4 contains the conclusion of this paper.

2 A BRIEF REVIEW OF TES PROCESSES

TES processes are treated in some detail in Melamed (1991) and Jagerman and Melamed (1992abc). An extensive overview of TES processes and the corresponding modeling methodology appears in Melamed et al. (1992), and in Melamed (1993). A summary of the treatment given in these references is offered here.

2.1 TES Processes

For any real x, let $\lfloor x \rfloor = \max\{\text{integer } n : n \leq x\}$ be the integral part of x, and define $\langle x \rangle = x - \lfloor x \rfloor$ to be the fractional part of x. Let $\{V_n\}$ denote a sequence of iid random variables with a common, though arbitrary, density f_V. Further, let U_0 be uniform on [0,1) and independent of the sequence $\{V_n\}$. The random variables V_n are referred to as *innovations*.

There are two major classes of TES processes: TES$^+$ and TES$^-$. TES$^+$ consists of random sequences $\{U_n^+\}$ of the form

$$U_n^+ = \begin{cases} U_0, & n = 0 \\ \langle U_{n-1}^+ + V_n \rangle, & n > 0 \end{cases} \qquad (1)$$

while TES$^-$ consists of random sequences $\{U_n^-\}$ of the form

$$U_n^- = \begin{cases} U_n^+, & n \text{ even} \\ 1 - U_n^+, & n \text{ odd} \end{cases} \qquad (2)$$

The superscripts in Eqs. (1) and (2) are suggestive of the fact that TES processes achieve coverage of the full range of feasible lag-1 autocorrelations (Jagerman and Melamed 1992a); TES$^+$ processes cover the positive range [0, 1], while TES$^-$ processes cover the negative range [−1, 0]. It can be shown (Jagerman and Melamed 1992a) that the TES processes of Eqs. (1) and (2) constitute stationary Markovian sequences with uniform marginals on [0, 1), *regardless* of the innovation sequence selected; in fact, the choice of innovations determines just the second-order structure of a TES process.

In practice, of most interest are transformed TES processes $\{X_n^+\}$ and $\{X_n^-\}$, obtained from Eq. (1) or Eq. (2)

by some transformation D from [0, 1] to the real line (called a *distortion*), i.e.,

$$X_n^+ = D(U_n^+), \quad X_n^- = D(U_n^-). \qquad (3)$$

Uniform TES sequences $\{U_n^+\}$ and $\{U_n^-\}$ of the form (1) and (2) are called *background* sequences, whereas their distorted counterparts $\{X_n^+\}$ and $\{X_n^-\}$ of the form (3) are called *foreground* sequences. The TES modeling methodology (to be explained in Section 2.2) typically employs compound distortions composed of two successive transformations

$$X_n = F^{-1}(S_\xi(U_n)), \qquad (4)$$

where $\{U_n\}$ is any background TES sequence. The inner transformation, S_ξ, is called a *stitching transformation*; it is selected from a family, parameterized by $0 \leq \xi \leq 1$, of the form

$$S_\xi(y) = \begin{cases} y/\xi, & 0 \leq y < \xi \\ (1-y)/(1-\xi), & \xi \leq y < 1 \end{cases} \qquad (5)$$

It can be shown (Jagerman and Melamed 1992a, Melamed 1993) that each S_ξ, $0 < \xi < 1$, constitutes a "smoothing" transformation, in the sense that the corresponding stitched sequence $\{S_\xi(U_n)\}$ appears "smoother" than the underlying $\{U_n\}$. Moreover, all S_ξ, $0 \leq \xi \leq 1$, preserve uniformity (Melamed 1991), i.e., $S_\xi(U_n)$ is also distributed uniformly on [0, 1). The outer transformation, F^{-1}, is the inverse function of some distribution function F. Notice that by the inversion method (see, e.g., Bratley et al. 1987, Law and Kelton 1991), each X_n in (4) has marginal distribution F. Consequently, distortions of the form $D(x) = F^{-1}(S_\xi(x))$, $x \in [0, 1]$, allow us to generate foreground sequences with any prescribed marginal distribution F. In particular, we can match any empirical density function H, obtained as an empirical histogram. The corresponding *histogram distortion* $D_H = H^{-1}$ is given, for $0 \leq x \leq 1$, by Jagerman and Melamed (1992b).

$$D_H(x) = \sum_{n=1}^{N} 1_{[C_{n-1}, C_n)}(x)\,[l_n + (x - C_{n-1})\,\frac{w_n}{p_n}], \qquad (6)$$

where 1_A is the indicator function of set A, N is the number of histogram cells of the form $[l_n, r_n)$, $w_n = r_n - l_n$ is the width of cell n, p_n is the probability of cell n, and $C_n = \sum_{j=1}^{n} p_n$ is the cumulative distribution of $\{p_n\}$ ($C_0 = 0$ and $C_N = 1$). Recall that a histogram H is, mathematically, a step-function density, i.e., a probabilistic mixture of uniform densities.

Intuitively, the modulo-1 arithmetic (fractional part operation), used in defining background TES$^+$ sequences in Eq. (1), has a simple geometric interpretation as a random walk on the *unit circle* (circumference 1), with random step size V_n (Jagerman and Melamed 1992a, Melamed 1993). To fix the ideas, consider the important class of step-function innovation densities f_V of the form

$$f_V(x) = \sum_{k=1}^{K} 1_{[L_k, R_k)}(x)\,\frac{P_k}{R_k - L_k}, \qquad (7)$$

corresponding to mixtures of uniform densities whose support is contained in [-0.5,0.5). These densities can be specified by triplets of the form $\{(L_k, R_k, P_k)\}_{k=1}^{K}$, where K is the number of triplets, $[L_k, R_k)$ is the support of step k, and $0 < P_k \leq 1$ is the mixing probability of step k ($\sum_{k=1}^{K} P_k = 1$); for convenience, it is also required that triplets do not overlap (i.e., $R_k \leq L_{k+1}$, $1 \leq k \leq K-1$). We point out that, in fact, any interval of length 1 can be used to support innovation densities, due to the modulo-1 arithmetic employed in the definition of background TES sequences. However, the symmetry of the interval $[-0.5, 0.5)$ about zero is intuitively compatible with the interpretation of innovation variates as modulo-1 increments (decrements) of a TES$^+$ sequence on the unit circle. Observe that step-function densities can approximate any density arbitrarily closely, while enjoying an ease of specification via the triplets (L_k, R_k, P_k), so no practical loss of generality is incurred.

2.2 The TES Modeling Methodology

Assume that we have at our disposal some empirical sample path data representing a partial process history (e.g., interarrival times of packets on a communications link) to which we wish to fit a TES model. An outline of a typical TES modeling scenario follows (Jagerman and Melamed 1992a, Melamed 1993).

Selecting a TES Sign: The selection of a TES sign is based on the modeler's experience and knowledge of TES processes. Experience shows that TES$^+$ models are most prevalent. TES$^-$ models are more appropriate for empirical sample paths and autocorrelation functions which have a zigzag appearance.

Selecting an Inverse Distribution: When modeling empirical data, the inverse distribution function of the empirical data is the histogram inverse D_H, given in Eq. (6). It is determined by modeler-provided histogram parameters (number of cells and cell width) and the empirical data.

Selecting a Stitching Parameter and Innovation: The core activity of TES modeling is a heuristic search for a suitable stitching parameter and innovation density. The modeler searches through stitching parameters in the range [0, 1] and innovation densities in the space of step-function densities, whose support is contained in $[-0.5, 0.5)$.

We stress that the modeling scenario outlined above is a highly heuristic procedure. The modeler may loop back to any step based on the quantitative fit of the current model's autocorrelation function and the qualitative fit of Monte Carlo sample paths to their respective empirical counterparts. This activity is most efficiently carried out with the visually-oriented software support described in the next section. A great deal is known about the qualitative behavior of sample paths and autocorrelation functions generated by TES processes, as a function of the stitching parameter and innovation density parameters. These are discussed in some detail in Melamed (1991), Jagerman and Melamed (1992a), and Melamed (1993).

2.3 The TEStool Modeling Software

TEStool is a visual interactive software environment designed to support the construction and modification of TES models, to generate simulated sample paths from the models, and to examine their statistics (Geist and Melamed 1992, Melamed et al. 1992).

TEStool distinguishes three types of statistics. *Empirical* statistics are those associated with the empirical data (sample paths, histogram, autocorrelation function and spectral density). *Simulated* statistics are similarly calculated (estimated) from Monte Carlo simulations of TES models. *Numerical* statistics consist of numerical computations of autocorrelation functions and spectral densities of TES models, based on analytical formulas developed in Jagerman and Melamed (1992ab).

Figure 1 reproduces a typical TEStool screen composed of four tiled canvases. These contain, respectively, sample paths (upper-left canvas), histograms (upper-right canvas), autocorrelation functions (lower-left canvas), and a graphical specification of a TES model (lower-right canvas). Each of the first three canvases displays a pair of statistical graphs: the respective TES model statistics superimposed for comparison on their empirical counterparts. The fourth canvas supports a joint specification of a TES sign, a step-function innovation density, a stitching parameter and an inverse-distribution distortion; the latter is selected from a menu, including distortions of the form (6) constructed from empirical histograms. The buttons in the top border of the display and at the bottom of each canvas provide for various support functions. These include reading and writing datasets, subdividing the screen real estate, opening a TES specification window or menu, performing various types of computations and quitting the session. The most important service, however, is the visual specification of a TES model and the interactive computations associated with it.

The advantage of a graphical specification derives from the fact that a visual representation is easy to grasp, lending itself to intuitive and visual interactions with the TES model. In the visual specification mode, the workstation mouse is used to draw and manipulate non-overlapping rectangles representing a step-function density. For example, rectangle "stretching" is used to modify a step's height and width, while rectangle "dragging" is used to translate a step horizontally. In the visual interactive mode, any changes in model specification trigger an immediate recomputation and display update of model statistics.

With TEStool, the modeler can compare any computed statistics to their empirical counterparts for goodness of fit, and thus render a judgement about whether it is satisfactory or whether another modification to the model is required. In the same way that the player of an arcade game is able to concentrate on the animated display without concern for the underlying software details, the highly visual nature of the modeling search process makes TES accessible to both experts and non-experts alike.

3 APPLICATIONS OF TES MODELS

This section presents a sampling of TES models drawn from various disciplines. The examples range from compressed-video traffic in high-speed telecommunications networks, to machine fault arrivals in a manufacturing plant and financial time series. These examples have been selected to underline both the accuracy and versatility of the TES modeling approach.

3.1 H.261-Compressed Video

Data compression is extensively used to reduce the transmission bandwidth requirements of telecommunications traffic. The idea is to code the data at the source (thereby compressing it to a fraction of its original size), transport the compressed data over a network, and then decode the data at its destination. Video service in emerging ISDN (Integrated Services Digital Networks) is a typical application, for which the exact reproduction of the original signal is not necessary. H.261 is a popular coding standard, which makes use of DCT (Discrete Cosine Transform) and other techniques to compress video spatial units (frames or subframes) (Liou 1991, Reibman 1991). Since such coded units have random (but highly autocorrelated) transmission requirements (in bits), the corresponding coding schemes are referred to as VBR (Variable Bit Rate).

Figure 1 displays the results of TES modeling of an empirical sample path of VBR frame bit rate, for which the coding scheme used was a variant of the H.261 standard. The model was used, in turn, to study the performance of a coded video multiplexer (Lee et al. 1992). In the upper-left canvas, a typical sample path generated by a Monte Carlo simulation of a TES model (diamonds) is superimposed on the empirical data (bullets). The model histogram and autocorrelation function are similarly plotted against their empirical counterparts in the upper-right and lower-left canvases, respectively. The lower-right canvas contains a visual specification of a TES^+ model with stitching parameter $\xi = 0.5$ and an inverse-distribution distortion, constructed from the empirical histogram in the upper-right canvas, by appeal to Eq. (6). The innovation density function consists of two steps and corresponds to a probabilistic mixture of two uniform densities.

Several observations are in order at this point. First, the simulated histogram closely approximates its empirical counterpart as advertised (recall that TES theory guarantees an exact asymptotic match as the simulated sample size increases). Second, since an average scene lasts for only a few seconds and the data available consists of 210 frames, it makes sense to only attempt to match the first 10 autocorrelations or so. Within this range, it would be preferable to approximate shorter-lag autocorrelations at the expense of longer-lags. Furthermore, rather than achieving an exact match to the leading autocorrelations, one primarily aims to capture their functional form (in our case their monotone decreasing structure). And third, although sample path "resemblance" is a highly subjective judgment, the qualitative similarity of the sample paths is surprisingly close to the unaided eye, thereby increasing our confidence in the model.

3.2 MPEG-Compressed VBR Video

MPEG (Moving Picture Expert Group) is an emerging family of compression standards designed to encode audio-visual signals over broadband transmission channels (see Le Gall 1991). This section focuses on MPEG-video, designed to compress a full-motion video stream into a bit rate of about 1.5 Mbits/second. The importance of MPEG derives from its planned central role in facilitating future delivery of multi-media services to customer premises.

Coded picture sequences in MPEG are composed of cycles. A coded picture can be either an Intrapicture (I-frame), Predicted picture (P-frame) or Bidirectionally Predicted picture (B-frame). The sequence of picture (frame) types within each cycle are deterministic, though the corresponding bit rates are VBR, and therefore, random. MPEG type sequences can be chosen as an MPEG parameter, depending on the application. The particular type sequence chosen in the case study described here had a length-nine cycle of the form IBBPBBPBB... (see Figure 2). Observe that the marginal distributions of I-frames (largest magnitudes), P-frames (medium magnitudes) and B-frames (smallest magnitudes) are apparently very different. Consequently, MPEG-compressed sequences exhibit randomness as well as determinism, and are decidedly non-stationary, all of which precludes the straightforward type of modeling approach described in Section 3.1.

The approach devised for MPEG-encoded sequences required a composite TES model. First, each subsequence of MPEG frame types was modeled as a separate TES sequence as in Section 3.1 — I-frames and B-frames each by a TES^+ model and P-frames by a TES^- model. Second, a Monte Carlo simulation generated each of the three MPEG frame type bit rate subsequences and the sample paths were superposed (interleaved) from the three TES bit rate models to form the correct type sequence. And third, in order to induce cross-correlations into frame bit rates comprising individual cycles, the TES background variate of each cycle-inaugurating I-frame was reused to obtain the corresponding background variates for the first P-frame and B-frame within the same cycle. Subsequent P-frames and B-frames within the same cycle were generated normally from their individual TES models.

Figure 2 displays sample paths and derived statistics for both the empirical MPEG sequence and the composite TES model following the format of Section 3.1, except that the lower-right canvas displays the spectral densities (power spectra) rather than a TES model. The autocorrelation functions and spectral densities in Figure 2 were formally computed from a single sample path *as if* the sequences were stationary, and therefore represent averaged estimates of different correlation coefficients. Nevertheless, Figure 2 exhibits excellent agreement for all statistics, as well as a marked similarity in functional form between the empirical and model sample paths.

3.3 Machine Fault Arrivals

Traditional reliability models analyze the arrival of faults by assuming that their interarrival times (up times) are independent random variables (Barlow and Proschan 1975). Figure 3 depicts a TES model of machine up times, incorporating temporal dependence, based on measurements taken from a semiconductor manufacturing line. Specifically, these data represent several months of up times of a machine engaged in the photolithographic processes of a wafer fabrication facility.

Many of the faults in semiconductor equipment are related to a machine processing wafers "out of specification", rather than mechanical failures. Consequently, several corrective actions may be related to an inaugurating "out of specification event", resulting in bursty fault arrivals. Such burstiness may result in temporal dependencies among up times (another cause of burstiness may be a multimodal marginal distribution of up times). Since poor equipment reliability has been identified as a major cause of uncertainty in semiconductor manufacturing (Harrison et al. 1990), it is very important that the corresponding reliability be modeled correctly.

An interesting feature of this example is that it relies solely on the less common TES^- model in order to capture the functional form of the autocorrelation function.

The reader's attention is drawn again to the quality of the of the model fit. Notice that while the model does not precisely match the empirical autocorrelation function, it does provide a good approximation which also captures its functional form. In addition, the qualitative "resemblance" of the sample paths is also good, and the histograms match closely, as expected.

3.4 Financial Time Series

Stochastic models of financial time series are used extensively to guide buy/sell decisions in financial markets. Financial models are used both for short-term forecasting to guide day-to-day trading, and for mid-term scenarios to guide long-term planning (1 to 5 years). Most quantitative investment strategies generate Monte Carlo scenarios to estimate internal parameters of various financial models (Hull 1989). Many financial models, such as diffusion processes used for interest rates, share the shortcoming that they are difficult to calibrate against historical data in a formal manner.

Figure 4 displays a TES model of a sequence of "real" quarterly returns from Treasury Bills (nominal interest rates minus inflation rate) for the period 1950-1990. Each data point is the average of all daily returns in the respective quarter. The TES model approximates the leading autocorrelations and gives rise to sample paths with considerable qualitative similarity to the observed historical price sequence. In view of the relatively low magnitude of the empirical autocorrelations, it is doubtful that such "black box" models would be useful as reliable predictors of future yields. However, they can be used to generate random scenarios for use in financial simulations.

4 CONCLUSION

This paper has surveyed a range of TES models from a variety of disciplines. The purpose of the survey is to demonstrate the efficacy of the TES modeling approach in simultaneously capturing first-order and second-order statistics of empirical time series, and to highlight its versatility and flexibility by addressing a variety of applications with a mix of TES-based models.

The major applications of TES to date have been to capture the burstiness exhibited by autocorrelated traffic in high-speed telecommunications networks, mainly VBR video. Two TES-based modeling approaches to coded video have been described in some detail: a simple TES source model of frame bit rates for H.261 coding and a more complex superposition of multiple TES models interleaved in a deterministic sequence for MPEG coding. A source model of machine fault interarrival times in a manufacturing context has demonstrated the ability of TES models to capture bursty fault arrivals. Finally, an example from financial modeling suggests that TES models can capture the statistical signature of financial time series, and demonstrates its potential to model random phenomena which might be used in financial scenario simulations.

We conclude that the TES modeling methodology offers a new and powerful approach to input analysis, particularly in the domain of Monte Carlo simulations. We have emphasized that practical TES modeling relies entirely on software support to carry out heuristic searches for appropriate models, and have described the TEStool visual interactive software which we designed and implemented for this purpose. The user interface of TEStool casts the search process into the intuitive activity of successively modifying a visual parametric representation of the TES model. The TEStool modeling environment has been found to yield remarkably accurate TES models in a reasonable amount of time. It has also transformed a potentially tedious search for an appropriate model into a pleasant activity, not unlike that of a video arcade game.

Acknowledgments

We are grateful to John Fowler, John Mulvey, Dipankar Raychaudhuri, Amy Reibman, and Daniel Reininger for providing the empirical data and for providing valuable information on the respective applications.

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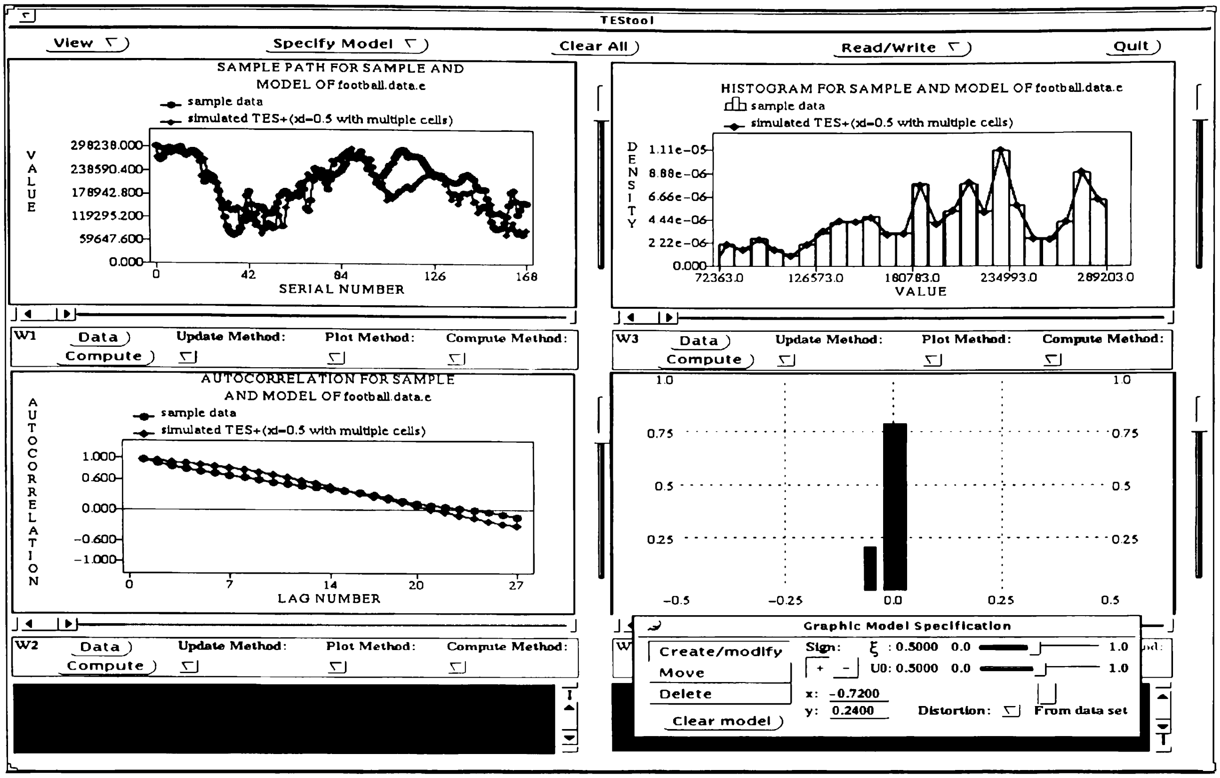

Figure 1: A TES model of H.261-compressed VBR video.

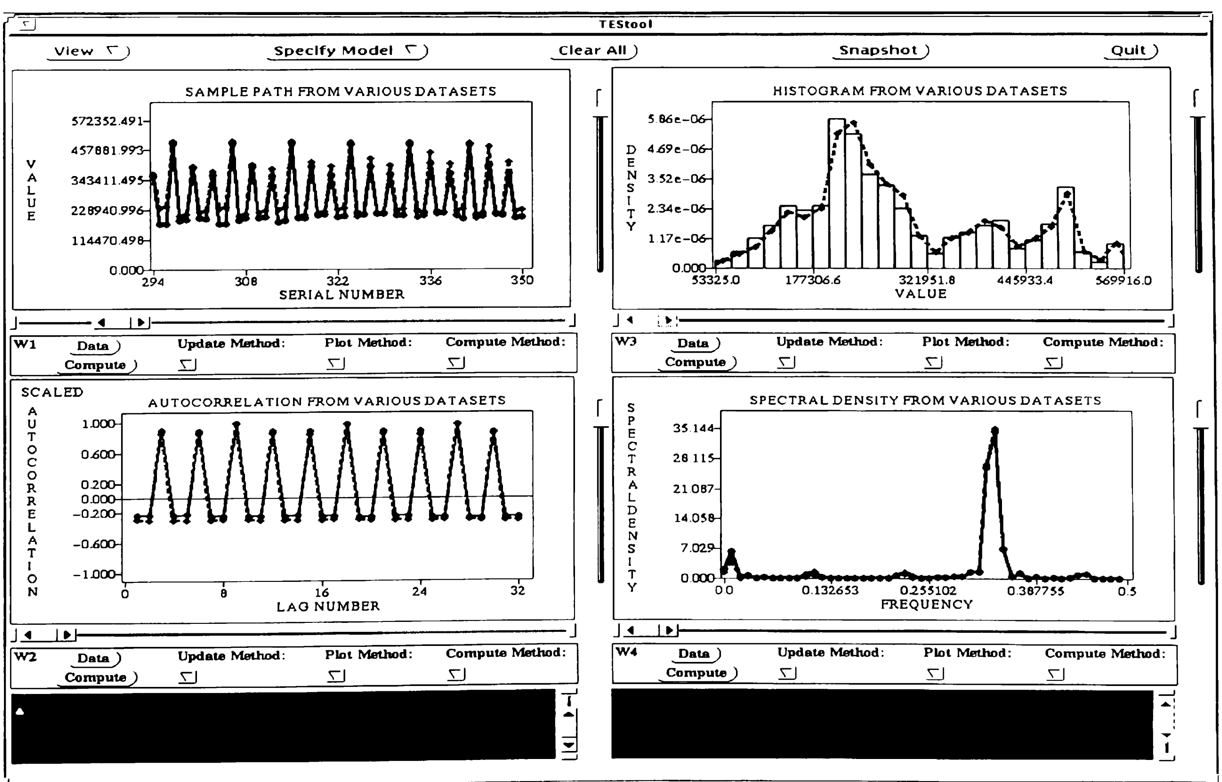

Figure 2: A superposed TES-based model of MPEG-compressed VBR video.

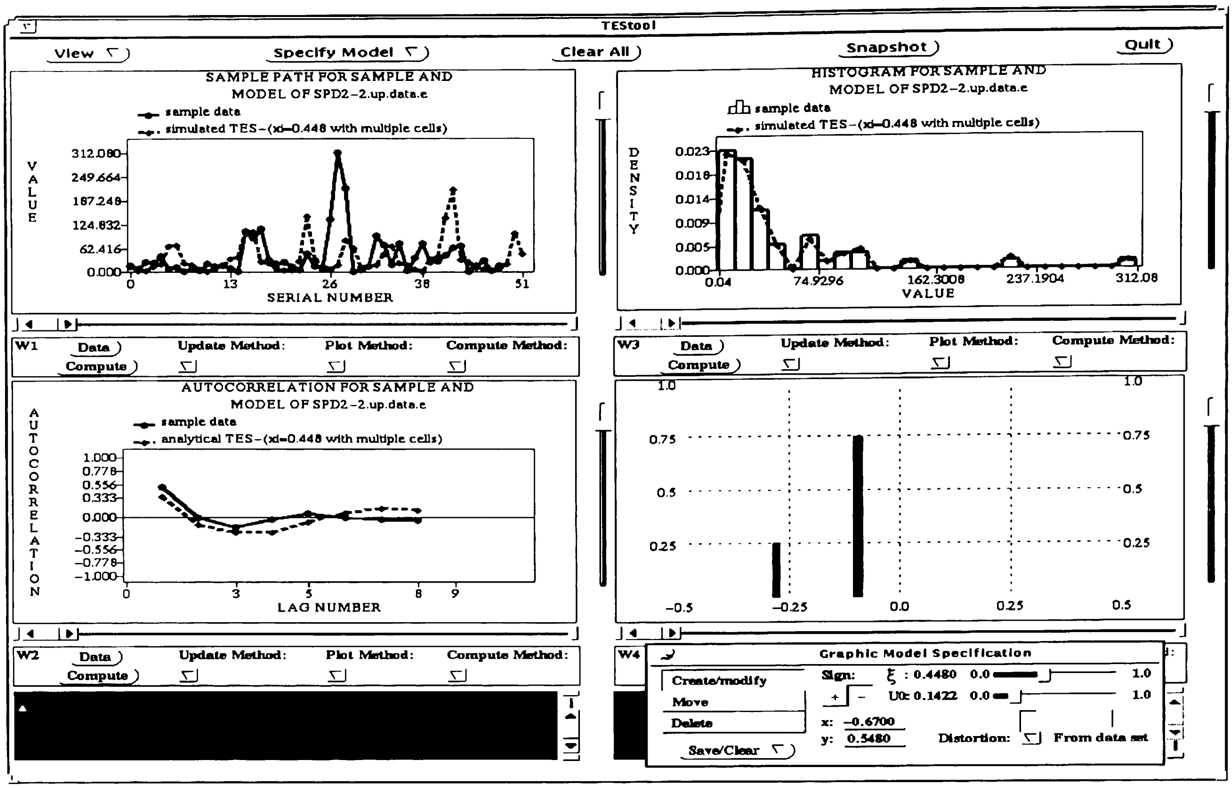

Figure 3: A TES model of machine fault interarrival times.

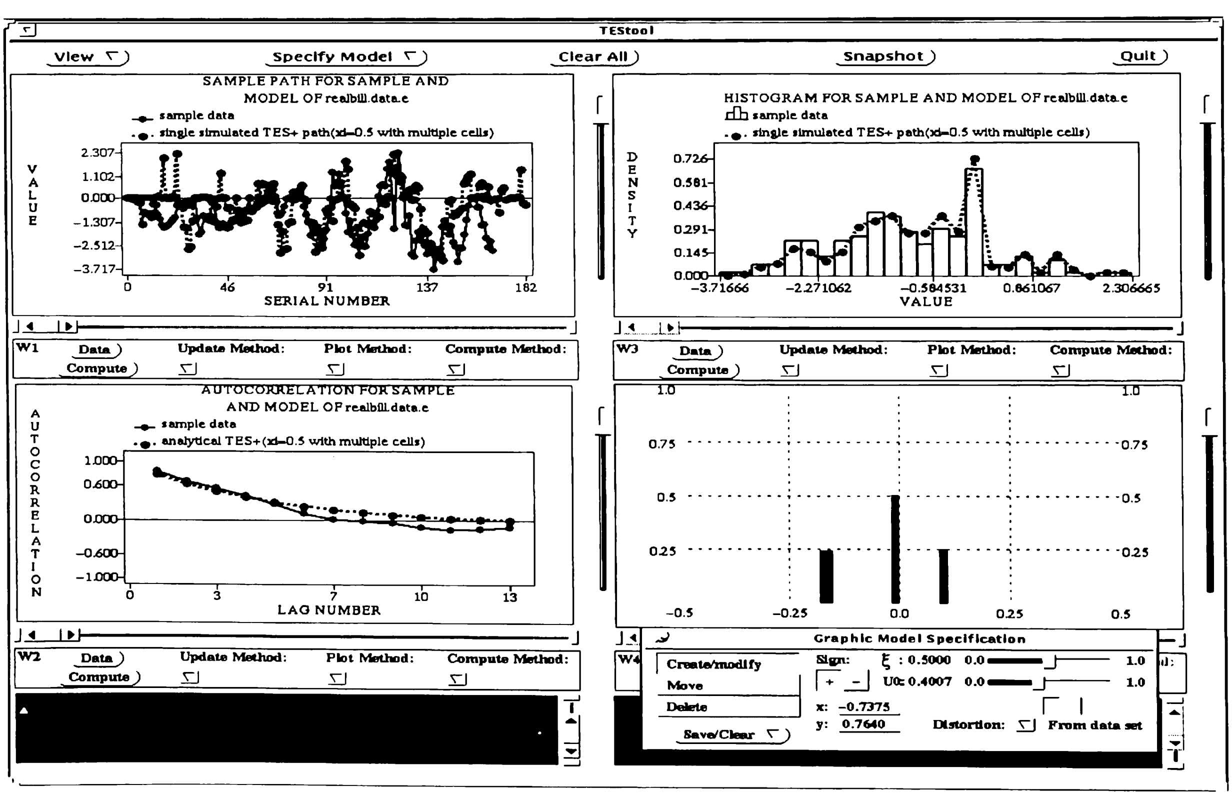

Figure 4: A TES model of real Treasury Bill yields.