Proceedings of the 2009 INFORMS Simulation Society Research Workshop
L. H. Lee, M. E. Kuhl, J. W. Fowler, and S. Robinson, eds.

ADVANCES IN MODELING AND SIMULATION OF NONSTATIONARY ARRIVAL PROCESSES

Michael E. Kuhl

Industrial and Systems Engineering Department
Rochester Institute of Technology
Rochester, NY 14623, U.S.A.

James R. Wilson

Edward P. Fitts Department of Industrial
and Systems Engineering
North Carolina State University
Raleigh, NC 27695, U.S.A.

ABSTRACT

We survey various methods for modeling and simulating nonhomogeneous Poisson processes, highlighting their advantages and limitations as approximations to nonstationary arrival processes in simulation applications. We also discuss briefly recent research on inversion and thinning methods for modeling and simulating nonstationary non-Poisson arrival processes, and we propose a combination of these methods that may avoid the disadvantages of both inversion and thinning while retaining the advantages of each method.

1 TIME-DEPENDENT ARRIVAL PROCESSES

Time-varying arrival processes are routinely encountered in practical applications of industrial and systems engineering techniques. To analyze or improve system operation in such situations, discrete-event stochastic simulation is often the technique of choice. Consequently, high-fidelity probabilistic input models are frequently needed to perform meaningful simulation experiments.

Nonhomogeneous Poisson processes (NHPPs) have been used successfully to model complex time-dependent arrival processes in a broad range of application domains (Lewis and Shedler 1976; Lee, Wilson, and Crawford 1991; and Pritsker et al. 1995). A noteworthy application involved organ-transplantation policy decisions. The United Network for Organ Sharing (UNOS) carried out a large-scale application of NHPPs for modeling and simulating patient- and donor-arrival streams in the development and use of the UNOS Liver Allocation Model (ULAM) for analysis of the cadaveric liver-allocation system in the United States (see Harper et al. 2000). ULAM incorporated NHPP models of (a) the streams of liver-transplant patients arriving at 115 transplant centers, and (b) the streams of donated organs arriving at 61 organ procurement organizations in the United States; and virtually all these arrival streams exhibited strong dependencies on the time of day, the day of the week, and the season of the year as well as pronounced geographic effects.

Although NHPPs are used to model a large class of nonstationary arrival processes, NHPPs are inappropriate for some applications in manufacturing, telecommunications, marketing, and other areas. In some cases the Poisson postulates are inapplicable (for example, with nearly simultaneous arrivals or pronounced correlation between arrivals in nonoverlapping time intervals); and in other cases, key characteristics of the target arrival process (for example, its variability about the mean-value function) differ substantially from the corresponding characteristics of an NHPP.

In this paper we survey various methods for modeling and simulating NHPPs, with emphasis on their advantages and limitations in practice. We also discuss recent research of Gerhardt and Nelson (2009) on methods for modeling and simulating nonstationary non-Poisson arrival processes based on inversion and thinning. We propose a combination of these methods that may avoid the disadvantages of both inversion and thinning while retaining the advantages of each method. This paper is intended as a basis for a larger discussion of not only the characteristics of nonstationary point processes for which current methods are inadequate but also potential methods for addressing these issues.

2 NONHOMOGENEOUS POISSON PROCESSES

A nonhomogeneous Poisson process $\{N(t) : t \geq 0\}$ is a generalization of a Poisson process in which the instantaneous arrival rate $\lambda(t)$ at time t is a nonnegative integrable function of time. The mean-value function of the NHPP is defined by

$$\mu(t) \equiv \mathrm{E}[N(t)] = \int_0^t \lambda(z)\,\mathrm{d}z \quad \text{for all} \quad t \geq 0.$$

An NHPP has the following properties (Çinlar 1975): (i) $\{N(t) : t \geq 0\}$ is a counting process; (ii) $N(0) = 0$; (iii) $\{N(t+s) - N(t) : s \geq 0\}$ is independent of $\{N(u) : 0 \leq u < t\}$ for all $t \geq 0$; (iv) $\Pr\{N(t+h) - N(t) = 1\} = \lambda(t)h + o(h)$ for all $t \geq 0$ and $h > 0$; and (v) $\Pr\{N(t+h) - N(t) \geq 2\} = o(h)$ for all $t \geq 0$ and $h > 0$.

In the above properties, the function $f(\cdot)$ is said to be $o(h)$ if $\lim_{h\to 0} f(h)/h = 0$. From these properties we observe that the rate or mean-value function of the NHPP $\{N(t) : t \geq 0\}$ completely characterizes the probabilistic behavior of the process. In the next section we survey nonparametric, parametric, and semiparametric methods for estimating an NHPP from observed arrival streams and for generating independent realizations of the fitted NHPP.

2.1 Nonparametric NHPP Methods

In this section we present the nonparametric methods of Leemis (1991, 2000, 2004) for estimating and simulating an NHPP over a given time interval $[0, S]$. Suppose that k independent realizations of the arrival process over the interval $[0, S]$ have been observed so that we have n_i arrivals on the ith realization for $i = 1, 2, \ldots, k$; and thus we have a total of $n = \sum_{i=1}^{k} n_i$ arrivals accumulated over all realizations of the arrival process. Moreover, let $\left\{t_{(i)} : i = 1, \ldots, n\right\}$ denote the overall set of arrival times for all arrivals expressed as an offset from the beginning of the observation interval $(0, S]$ and then sorted in increasing order. We take $t_{(0)} \equiv 0$ and $t_{(n+1)} \equiv S$ so that for $t_{(i)} < t \leq t_{(i+1)}$ and $i = 0, 1, \ldots, n$, a piecewise linear nonparametric estimator of $\mu(t)$ is

$$\widehat{\mu}(t) = \frac{in}{(n+1)k} + \left\{ \frac{n\left[t - t_{(i)}\right]}{(n+1)k\left[t_{(i+1)} - t_{(i)}\right]} \right\}; \qquad (1)$$

see Leemis (1991). Figure 1 depicts the layout of $\widehat{\mu}(t)$. Equation (1) and Figure 1 provide a basis for modeling and simulating the given arrival process when the arrival rate exhibits a strong dependence, for example, on the time of day.

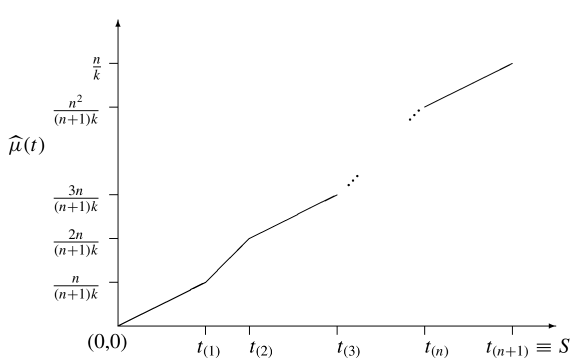

Figure 1: Nonparametric estimator of mean-value function.

Given the estimated mean-value function $\widehat{\mu}(t)$ of the form (1), we can use the inversion algorithm of Leemis (1991) as displayed in Figure 2 to generate a new stream of arrival times $\left\{A_i : i = 1, 2, \ldots\right\}$ over the time interval $(0, S]$ with approximately the same general pattern of dependence on time as in (1).

[1] Set $i \leftarrow 1$ and $N \leftarrow 0$.
[2] Generate $U_i \sim$ Uniform(0, 1).
[3] Set $B_i \leftarrow -\ln(1 - U_i)$.
[4] While $B_i < n/k$ **do**
Begin
Set $m \leftarrow \left\lfloor \frac{(n+1)kB_i}{n} \right\rfloor$;
Set $A_i \leftarrow t_{(m)} + \left\{t_{(m+1)} - t_{(m)}\right\}\left\{\frac{(n+1)kB_i}{n} - m\right\}$;
Set $N \leftarrow N + 1$; Set $i \leftarrow i + 1$;
Generate $U_i \sim$ Uniform(0, 1);
Set $B_i \leftarrow B_{i-1} - \ln(1 - U_i)$.
End

Figure 2: Algorithmic statement of the NHPP simulation procedure of Leemis (1991).

The main advantage of this approach to modeling and simulating time-dependent arrival processes is that it does not require the assumption of any particular functional form for the way in which the arrival rate $\lambda(t)$ depends on the time t since the beginning of the observation interval $(0, S]$. Moreover as $k \to \infty$ so that the number of realizations of the target arrival process becomes large, with probability 1 the estimated mean-value function $\widehat{\mu}(t)$ of Equation (1) converges to the true mean-value function $\mu(t)$ for all $t \in (0, S]$. This means that the simulation algorithm given above (which is based on inversion of $\widehat{\mu}(t)$ so that $A_i = \widehat{\mu}^{-1}(B_i)$ for $i = 1, \ldots, N$) is also asymptotically valid as $k \to \infty$. For more information on this approach to modeling and simulation of time-dependent arrival processes, see Leemis (2004).

2.2 Parametric NHPP Models

Parametric models for the rate function of an NHPP have been developed to represent arrival processes that exhibit systematic changes in the arrival rate over time such as long term trends or periodicities.

Cox and Lewis (1966) present an exponential linear rate function of the form $\lambda(t) = \exp\{\alpha_0 + \alpha_1 t\}$. This rate function has an exponential form to ensure the arrival rate always remains positive. To represent more general long-term trends as well as cyclic behavior with a known frequency ω, Lewis (1972) introduces a rate function of the form $\lambda(t) = \exp\left\{\sum_{i=0}^{2} \alpha_i t^i + \gamma \sin(\omega t + \phi)\right\}$. MacLean (1974) proposes that any continuous rate function can be approximated arbitrarily closely using an exponential polynomial rate function of degree m, $\lambda(t) = \exp\left\{\sum_{i=0}^{m} \alpha_i t^i\right\}$.

To model the occurrence of storms in the Arctic Sea, Lee, Wilson, and Crawford (1991) use an NHPP with rate function of the form

$$\lambda(t) = \exp\left\{\sum_{i=0}^{m} \alpha_i t^i + \gamma \sin(\omega t + \phi)\right\}. \qquad (2)$$

For rapid simulation of an NHPP with the rate function (2), the authors formulate `maxline`, an algorithm to construct a piecewise linear rate function $\widetilde{\lambda}(t)$ that closely approximates $\lambda(t)$ while majorizing $\lambda(t)$ on $[0, S]$; that is, $\widetilde{\lambda}(t) \geq \lambda(t)$ for all $t \in [0, S]$. The advantage of this approach is that the corresponding mean-value function $\widetilde{\mu}(t) = \int_0^t \widetilde{\lambda}(u)\,\mathrm{d}u$ is piecewise quadratic and thus is easily inverted so that a sequence of arrival epochs $\{\widetilde{A}_n\}$ for this process is easily generated by the method of inversion. Then applying the thinning scheme of Lewis and Shedler (1979), the authors formulate an algorithm to generate arrival epochs $\{A_\ell\}$ from an NHPP with rate function $\lambda(t)$ as follows: the epoch $\widetilde{A}_n$ is independently accepted for inclusion in $\{A_\ell\}$ with probability $\lambda(\widetilde{A}_n)/\widetilde{\lambda}(\widetilde{A}_n)$ for $n = 1, 2, \ldots$.

Kuhl, Wilson, and Johnson (1997) and Kuhl and Wilson (2000) extended the work of Lee, Wilson, and Crawford (1991) to handle arrival processes with a general trend or multiple periodicities. The model for the arrival process is an NHPP with rate function of the form

$$\lambda(t) = \exp\{h(t; m, p, \boldsymbol{\Theta})\}, \qquad t \in (0, S], \qquad (3)$$

with $h(t; m, p, \boldsymbol{\Theta}) = \sum_{i=0}^{m} \alpha_i t^i + \sum_{k=1}^{p} \gamma_k \sin(\omega_k t + \phi_k)$, where $\boldsymbol{\Theta} = [\alpha_0, \alpha_1, \ldots, \alpha_m,\ \gamma_1, \ldots, \gamma_p,\ \phi_1, \ldots, \phi_p,\ \omega_1, \ldots, \omega_p]$ is the vector of continuous parameters. Kuhl, Wilson, and Johnson (1997) use a form of inversion for simulating NHPPs with a rate function of the form (3). Rate functions of this type were originally used in the UNOS Liver Allocation Model (Pritsker et al. 1995); and although the resulting fits were remarkably accurate, the times to generate realizations of the fitted NHPPs were too large in practice. An extension of the `maxline` procedure of Lee, Wilson, and Crawford (1991) to yield a piecewise linear rate function that majorizes (3) could facilitate rapid simulation of such NHPPs based on thinning, but substantial effort may be required to develop such a procedure.

2.3 Semiparametric NHPP Methods

Semiparametric methods for representing NHPPs have been developed in an attempt to combine the flexibility of nonparametric methods with the smooth, continuous representations of parametric models. Kuhl and Wilson (2001) formulate a nonparametric method for modeling and simulating arrival processes that may exhibit a long-term trend or nested periodic phenomena (such as daily and weekly cycles), where the latter effects might not necessarily possess the symmetry of sinusoidal oscillations. Called a “multiresolution” procedure because of its ability to handle nested cyclic effects, this procedure has been implemented by Kuhl, Sumant, and Wilson (2006) in Web-based software, which is available online via <www.rit.edu/simulation>.

The procedure of Kuhl, Sumant, and Wilson (2006) involves the following steps at each resolution level corresponding to a basic cycle: (a) transforming the cumulative relative frequency of arrivals within the cycle to obtain a statistical model with approximately normal, constant-variance responses; (b) fitting a specially formulated polynomial to the transformed responses; (c) performing a likelihood ratio test to determine the degree of the fitted polynomial; and (d) fitting to the original (untransformed) responses a polynomial of the same form as in (b) with the degree determined in (c).

Kuhl, Sumant, and Wilson (2006) perform a comprehensive experimental performance evaluation to demonstrate the accuracy and flexibility of the automated multiresolution procedure. Figures 3 and 4 depict 90% tolerance bands for the underlying rate and mean-value functions, respectively, of an arrival process possessing one cyclic rate component and a long-term trend, where each tolerance band is based on applying the multiresolution procedure to 100 independent replications of the test process.

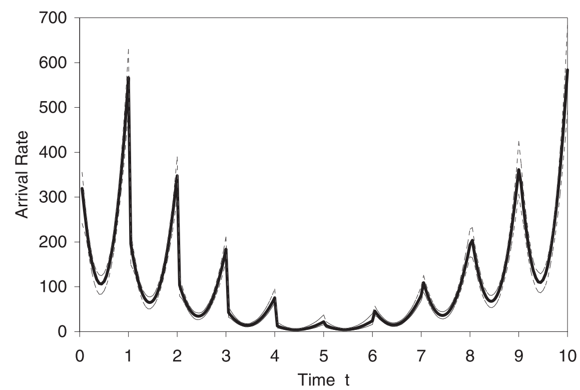

Figure 3: Fitted rate function over 100 replications of a test process with one cyclic rate component and long-term trend.

The inversion scheme of Kuhl and Wilson (2001) for simulating NHPPs fitted by the multiresolution estimation procedure is substantially faster than the corresponding inversion scheme of Kuhl, Wilson, and Johnson (1997) for simulating NHPPs that have a parametric rate function of the form (3).

Extending the semiparametric method of Kuhl, Sumant and Wilson (2006) to model more general nonstationary behavior, Kuhl, Deo, and Wilson (2008) introduce an alternative method to model the mean-value function of the NHPP. The final estimate is obtained for the mean-value function of the following form: $\mu(t) = \mu(S)R(t)$ for $t \in [0, S]$, where $R(t)$ is a monotone increasing degree-r polynomial

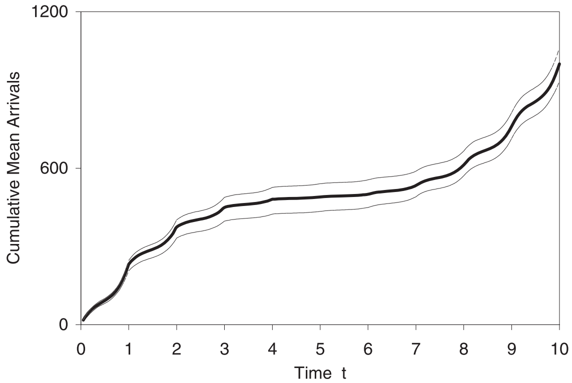

Figure 4: Fitted mean-value function over 100 replications of a test process with one cyclic rate component and long-term trend.

of the form

$$R(t) = \begin{cases} t/S, & \text{if } r = 1, \\ \displaystyle\sum_{k=1}^{r-1} \beta_k (t/S)^k + \left(1 - \sum_{k=1}^{r-1} \beta_k\right)(t/S)^r, & \text{if } r > 1. \end{cases}$$

This methodology can be used to fit an NHPP to one or more realizations of data from the process under study. The primary advantage of this method is that it fits a smooth (differentiable) mean-value function over the interval $[0, S]$.

3 DISCUSSION

Although NHPPs are used to model a large class of nonstationary arrival processes, there are applications where NHPPs do not adequately represent the arrival process of interest. For example, because for an NHPP the random variable $N(t)$ has the Poisson distribution with mean $\mu(t)$ for all $t > 0$, we also have $\mathrm{Var}[N(t)] = \mu(t)$ for all $t > 0$; and thus an NHPP has $\mathrm{Var}[N(t)]/\mathrm{E}[N(t)] = 1$ for all $t > 0$. In many studies of manufacturing systems, telecommunications networks, and consumers' purchasing behavior, the relevant point process exhibits a variance-to-mean ratio that is either substantially more or less than that of an NHPP.

Gerhardt and Nelson (2009) propose methods for modeling and simulating a point process that allow the user to achieve desired values of both the mean-value function and the ratio $\mathrm{Var}[N(t)]/\mathrm{E}[N(t)]$ of the process. Starting from a stationary renewal process $\{N^\circ(t)\}$ with rate 1 and the desired ratio $\lim_{t\to\infty} \mathrm{Var}[N^\circ(t)]/\mathrm{E}[N^\circ(t)] = C$, the authors first generate a corresponding sequence of renewal epochs $\{A_n^\circ : n = 1, 2, \ldots\}$ for the process $\{N^\circ(t)\}$. Finally the authors obtain a point process $\{N(t)\}$ with the desired mean-value function $\mu(t)$ and the corresponding arrival epochs $\{A_n : n = 1, 2, \ldots\}$ by inversion: $A_n = \mu^{-1}(A_n^\circ)$ for $n = 1, 2, \ldots$. The authors show that their inversion procedure yields $\mathrm{E}[N(t)] = \mu(t)$ for all $t \geq 0$ and $\lim_{t\to\infty} \mathrm{Var}[N(t)]/\mathrm{E}[N(t)] = C$. The disadvantage of this method is that in many applications $\mu(t)$ (or an estimate of this function) is not easily invertible.

Gerhardt and Nelson (2009) also propose a method for achieving a point process $\{N(t)\}$ with the desired mean-value function $\mu(t)$ based on thinning. If the corresponding rate function $\lambda(t) = \frac{\mathrm{d}}{\mathrm{d}t}\mu(t)$ has finite upper bound λ^*, then the authors start from a stationary renewal process $\{N^*(t)\}$ with rate λ^*, arrival epochs $\{A_n^* : n = 1, 2, \ldots\}$, and the desired variance-to-mean ratio C; and the corresponding sequence of arrival epochs $\{A_\ell : \ell = 1, 2, \ldots\}$ from a point process with the desired mean-value function $\mu(t)$ is obtained as follows: the epoch A_n^* is independently accepted for inclusion in $\{A_\ell\}$ with probability $\lambda(A_n^*)/\lambda^*$ for $n = 1, 2, \ldots$. The authors show that the resulting thinned point process $\{N(t) : t \geq 0\}$ has mean-value function $\mathrm{E}[N(t)] = \mu(t)$ for all $t \geq 0$. Unfortunately, it is not in general true that $\lim_{t\to\infty} \mathrm{Var}[N(t)]/\mathrm{E}[N(t)] = C$. The other disadvantage of this method is that it may be computationally inefficient if $\lambda(t) \ll \lambda^*$ for a substantial range of values of t.

We believe that a combination of the inversion and thinning inversion methods of Gerhardt and Nelson (2009) may be constructed to overcome the disadvantages of both methods while retaining the attractive features of each method. First we seek a rate function $\widetilde{\lambda}(t)$ that majorizes and closely approximates the target rate function $\lambda(t)$ and that also has an easily invertible mean-value function $\widetilde{\mu}(t) = \int_0^t \widetilde{\lambda}(u)\,\mathrm{d}u$ for all $t \in [0, S]$; and we use inversion to generate the associated point process $\{\widetilde{N}(t)\}$ with asymptotic variance-to-mean ratio C and arrival epochs $\{\widetilde{A}_n : n = 1, 2, \ldots\}$. For example, if we can construct a piecewise linear rate function $\widetilde{\lambda}(t)$ that closely approximates and majorizes $\lambda(t)$ as in Lee, Wilson, and Crawford (1991), then we have a piecewise quadratic mean-value function that is easily inverted.

To complete the combined inversion-and-thinning procedure, the authors' thinning method is applied to the arrival epochs $\{\widetilde{A}_n : n = 1, 2, \ldots\}$ to obtain the desired sequence of arrival epochs $\{A_\ell\}$ from the point process with the target rate function $\lambda(t)$ as follows: the epoch $\widetilde{A}_n$ is independently accepted for inclusion in $\{A_\ell\}$ with probability $\lambda(\widetilde{A}_n)/\widetilde{\lambda}(\widetilde{A}_n)$ for $n = 1, 2, \ldots$. It appears that the authors' justification for their thinning procedure with a constant majorizing rate λ^* can be extended to show that with the nonconstant majorizing rate function $\widetilde{\lambda}(t)$, the thinned point process $\{N(t)\}$ has the desired mean-value function $\mathrm{E}[N(t)] = \mu(t)$ for $t \in [0, S]$. Moreover, if the majorizing rate function $\widetilde{\lambda}(t)$ closely approximates the target rate function $\lambda(t)$ for all $t \in [0, S]$, then it is intuitively clear that the point processes $\{\widetilde{N}(t)\}$ and $\{N(t)\}$ should exhibit closely similar behavior so we also have $\mathrm{Var}[N(t)]/\mathrm{E}[N(t)] \approx \mathrm{Var}[\widetilde{N}(t)]/\mathrm{E}[\widetilde{N}(t)] \sim C$ for large t. As for the case of an NHPP with rate function of the form (3), the main practical problem with this approach can be the difficulty of constructing the majorizing rate function $\widetilde{\lambda}(t)$. In any case, a rigorous justification of this approach would be a useful complement to the results established in Gerhardt and Nelson (2009) for modeling and simulation of nonstationary non-Poisson processes via inversion and thinning.

4 CONCLUSIONS AND RECOMMENDATIONS

In this paper we have surveyed nonparametric, parametric, and semiparametric methods for modeling and simulating NHPPs; and we have also reviewed similar procedures for handling nonstationary non-Poisson arrival processes. From this discussion some suggestions for future work have emerged; and it appears that further significant advances can be expected in both approaches to handling nonstationary arrival processes.

REFERENCES

Çinlar, E. 1975. *Introduction to stochastic processes* Englewood Cliffs, New Jersey: Prentice-Hall.

Cox, D. R., and P. A. W. Lewis. 1966. *The Statistical Analysis of Series of Events* London: Chapman and Hall.

Gerhardt, I., and B. L. Nelson. 2009. Transforming renewal processes for simulation of nonstationary arrival processes. *INFORMS Journal on Computing* forthcoming.

Harper, A. M., S. E. Taranto, E. B. Edwards, and O. P. Daily. 2000. An update on a successful simulation project: The UNOS liver allocation model. In *Proceedings of the 2000 Winter Simulation Conference*, ed. J. A. Joines, R. R. Barton, K. Kang, and P. A. Fishwick, 1955–1962. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

Kuhl, M. E., S. Deo, and J. R. Wilson. 2008. Smooth flexible models of nonhomogeneous Poisson processes using one or more process realizations. In *Proceedings of the 2008 Winter Simulation Conference*, ed. S. J. Mason, R. R. Hill, L. Mönch, O. Rose, T. Jefferson, and J. W. Fowler, 353–361. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

Kuhl, M. E., S. G. Sumant, and J. R. Wilson. 2006. An automated multiresolution procedure for modeling complex arrival processes. *INFORMS Journal on Computing* 18 (1): 3–18.

Kuhl, M. E., and J. R. Wilson. 2000. Least squares estimation of nonhomogeneous Poisson processes. *Journal of Statistical Computation and Simulation* 67:75–108.

Kuhl, M. E., and J. R. Wilson. 2001. Modeling and simulating Poisson processes having trends or nontrigonometric cyclic effects. *European Journal of Operational Research* 133 (3): 566–582.

Kuhl, M. E., J. R. Wilson, and M. A. Johnson. 1997. Estimating and simulating Poisson processes having trends or multiple periodicities. *IIE Transactions* 29 (3): 201–211.

Lee, S., J. R. Wilson, M. M. Crawford. 1991. Modeling and simulation of a nonhomogeneous Poisson process having cyclic behavior. *Communications in Statistics—Simulation* 20:777–809.

Leemis, L. M. 1991. Nonparametric estimation of the cumulative intensity function for a nonhomogeneous Poisson process. *Management Science* 37 (7): 886–900.

Leemis, L. M. 2000. Nonparametric estimation of the cumulative intensity function for a nonhomogeneous Poisson process from overlapping realizations. *Management Science* 46 (7): 989–998.

Leemis, L. M. 2004. Nonparametric estimation and variate generation for a nonhomogeneous Poisson process from event count data. *IIE Transactions* 36 (12): 1155–1160.

Lewis, P. A. W. 1972. Recent results in the statistical analysis of univariate point processes. In *Stochastic point processes,* ed. P. A. W. Lewis, 1–54. New York: John Wiley & Sons.

Lewis, P. A. W., and G. S. Shedler. 1976. Statistical analysis of non-stationary series of events in a data base system. *IBM Journal of Research and Development* 20:465–482.

Lewis, P. A. W., and G. S. Shedler. 1979. Simulation of nonhomogeneous Poisson processes by thinning. *Naval Research Logistics Quarterly* 26:403–413.

MacLean, C. J. 1974. Estimation and testing of an exponential polynomial rate function within the nonstationary poisson process. *Biometrika* 61:81–85.

Pritsker, A. A. B., D. L. Martin, J. S. Reust, M. A. Wagner, O. P. Daily, A. M. Harper, E. B. Edwards, L. E. Bennett, J. R. Wilson, M. E. Kuhl, J. P. Roberts, M. D. Allen, and J. F. Burdick. 1995. Organ transplantation policy evaluation. In *Proceedings of the 1995 Winter Simulation Conference*, ed. C. Alexopoulos, K. Kang, W. R. Lilegdon, and D. Goldsman, 1314–1323. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.

AUTHOR BIOGRAPHIES

MICHAEL E. KUHL is an associate professor in the Industrial and Systems Engineering Department at Rochester Institute of Technology. His e-mail address is <mekeie@rit.edu>.

JAMES R. WILSON is a professor in the Edward P. Fitts Department of Industrial and Systems Engineering at NC State University. His e-mail address is <jwilson@ncsu.edu>.