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FOURIER TRAJECTORY ANALYSIS FOR IDENTIFYING SYSTEM CONGESTION

Xinyi Wu
Russell R. Barton

The Pennsylvania State University
210 Business Building
University Park, PA 16802, USA

ABSTRACT

We examine the use of the Fourier transform to discriminate dynamic behavior differences between congested and uncongested systems. Simulation continuous time statistic 'trajectories' are converted to time series for Fourier analysis. The pattern of Fourier component magnitudes across frequencies differs for congested versus uncongested systems. We use this knowledge to explore statistical process control methods to monitor nonstationary systems for transition from uncongested to congested state and vice versa. In a sense we are monitoring dynamic metamodel parameters to detect change in the dynamic behavior of the simulation. CUSUM charts on Fourier magnitudes can detect such transitions, and preliminary results suggest that in some cases detection can be more rapid than for CUSUM charts based on queue length.

1 INTRODUCTION

The design and analysis of modern discrete-event stochastic simulation has been closely tied to queuing theory; many simulation models represent a network of queues. The strength of queuing theory, and of most simulation analysis methodology, has been in deriving long-run performance measures (moments, quantiles) for stationary systems. However, many systems in real life are not stationary over time, and a good understanding of the dynamic behavior of real systems can assist managerial decision making. Simulation models can help to design that decision support: characterizing dynamic behavior in a controlled simulation setting can be used to identify effective monitoring methods for real systems. Our objective is to explore simulation analytics methods, in particular Fourier representation, for simulation trajectory data.

This study explores ways to help decision makers identify when parts of a system become congested, or move from congested to uncongested. This can be difficult for complex systems. Monitoring a moving average may lead to significant delays in detection. If monitoring queue length, the value must be relatively high (or low) to take into account the auto-correlated nature of the data. We examine the characteristics of simulated system trajectories, or sample paths using time series based classification methods.

Section 2 gives motivation for the proposed approach, and contrasts it with previous work in frequency domain analysis for simulation. Section 3 highlights technical and theoretical issues raised by this approach. Section 4 presents experimental findings, and Section 5 discusses results and outlines future work.

2 MOTIVATION, STRATEGY AND RELATED WORK

Our main goal is to develop a more effective approach to use dynamic data to identify or distinguish congested from uncongested queuing systems. We expect that by looking at dynamic changes of performance indicators over time, we identify whether the system is becoming congested or not. Real-time managerial decisions to reallocate system resources could then achieve less waste, and better performance. This work is exploratory: we conduct computation experiments to explore whether Fourier representation of simulation trajectories is an effective discriminator between congested and uncongested states. There are two questions we need to answer before proceeding. First, we need a reasonable definition of system congestion. Second, we must choose dynamic performance indicators to monitor and analyze.

2.1 System Congestion

There are various definitions of system congestion in various application areas. The most common definitions for queuing systems is related to the utilization for a server or servers. For a network of queuing systems, we consider its congestion level to be driven by the queue with the highest utilization.

A stable stationary system must have an arrival rate to service rate ratio strictly less than one, or a utilization strictly smaller than one. Otherwise, the queue will theoretically build up without bound. For nonstationary systems, the requirement for long-term stability is more complex, but congestion will be related to the dynamically changing utilization value. For nonstationary systems, we define system congestion as a state over a period of time rather than as a system property over all time. Choosing the length of a time period should take managerial decision making constraints into consideration.

An M/M/1 queuing system has average queue length of 81 when the system utilization is 0.9. We recognize that classifying a utilization of 0.9 as congested is context dependent, but for this study we use 0.9 utilization to assess behavior of simulated systems in a congested state. For sufficient contrast, we use utilizations of .6 to represent uncongested system behavior. Some may consider .6 to be fairly congested.

2.2 Performance Indicator: Queue Length

For queuing systems, many performance measures are affected by system congestion: the number of entities in the system or number of waiting entities, delaying time of entities, the utilization of servers, and idle/busy time of servers are a few. We use queue length at one or more servers as the focus of this study. It is feasible to get real-time values for queue length from a simulation or a real system. Delay time can only be calculated after an entity finishes service, resulting in later identification. From a managerial view, the utilization is not directly observable, while the congestion level is directly observable by queue length, and directly linked to system capacity limits. *We hypothesize that dynamic changes in queue length might signal a transition to high utilization, perhaps sooner than simply monitoring queue length*.

2.3 Converting Simulation Trajectory Data into Time Series

Queue length is a continuous time statistic of a discrete event simulation. Its piecewise constant value changes when an entity in the queue begins service or when an entity arrives at a busy server. An example of a queue length trajectory is shown in the upper part of Figure 1. To convert this data into a time series, one might assign a 'time' index to each change in the queue length statistic, but this would treat long sojourns at a particular queue length value the same as short sojourns at that value. We propose sampling the queue length statistic at equal spacing along the trajectory, as in the lower part of Figure 1.

2.4 Time Series Classification Methods

The shape of the trajectory from different simulation systems can vary in characteristic ways. Some of the differences can be identified visually. Figure 2 shows queue length trajectories for *M*/*M*/1 queues with different utilizations. Congested systems have trajectories that wander, with high autocorrelation. Low-utilization queue length trajectories exhibit a series of spikes of short duration with intervening intervals of zero queue length. While the focus here is on Fourier analysis of time series to discriminate between congested and uncongested states, there are other time series classification methods that could be employed.

2.4.1 Shapelets

Over the past several decades, there has been considerable research in time series classification. A novel method, time series shapelets, has shown potential in machine learning for image data (Ye et al. 2010, Rakthanmanon and Keogh 2013). A shapelet is a subsequence of a time series that in some sense maximally represents a class. They are usually local patterns in a time series, characteristic highly a class of time series (Mueen, et al. 2011).

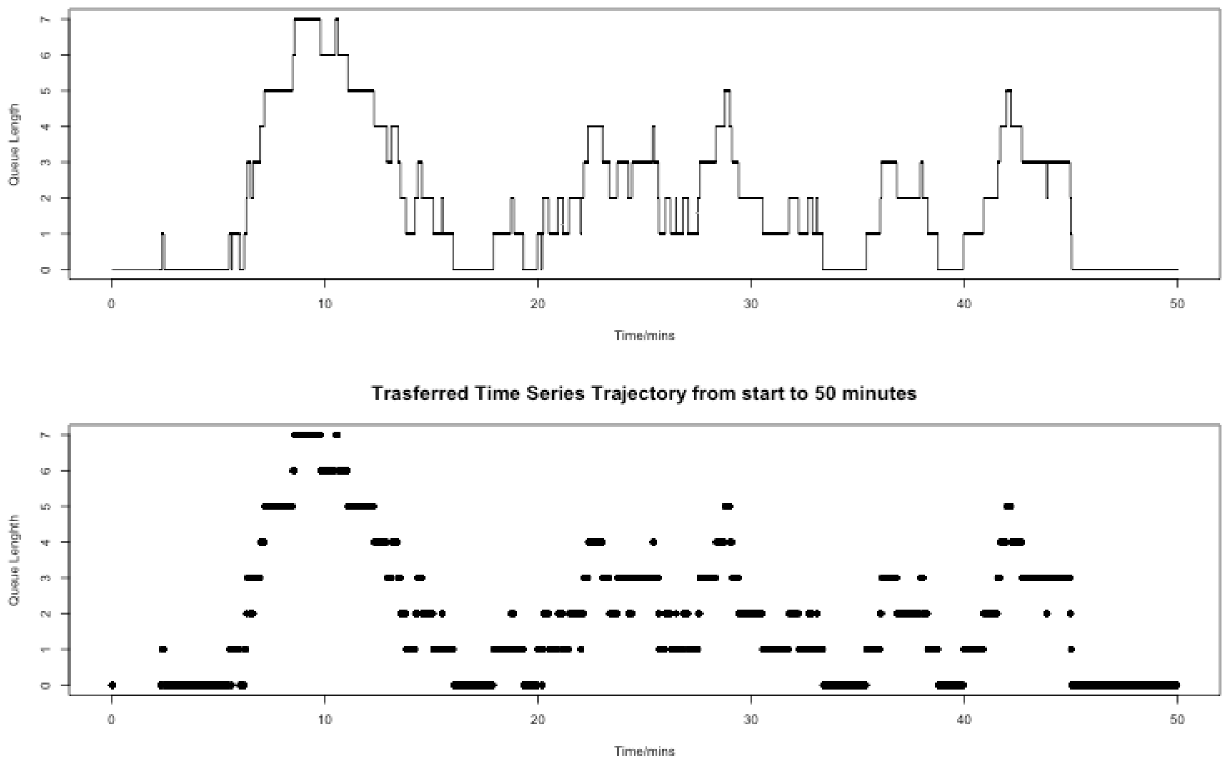


Figure 1: A sample queue length trajectory and a derived time series.

Figure 2: Trajectory of $M/M/1$ systems with utilizations from 0.5 to 1.1.

2.4.2 Autocorrelation Function

Congested queueing systems exhibit high autocorrelation for many performance measures, including queue length. Blomqvist (1967) showed that the rate of decrease of autocorrelation is strongly dependent on utilization for the $M/G/1$ queue. Figure 3 shows autocorrelation plots for queue length for the multi-teller bank example in Law and Kelton (2000). The autocorrelation pattern clearly differs for the four-teller and seven-teller systems. Both have the same arrival rate, so effective utilization is much lower in the seven-teller system. The autocorrelation is closely connected to the Fourier power spectrum, as we discuss below.

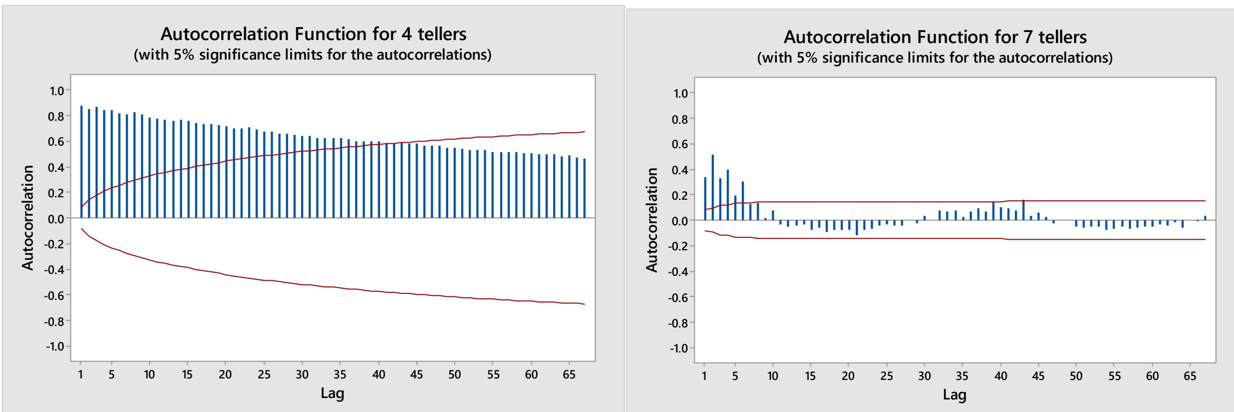


Figure 3: Autocorrelation plots for queue length for the multi-teller bank in Law and Kelton (2000).

2.4.3 Time Series Models

Time series models such as MA, ARMA and ARIMA (Box, Jenkins, and Reinsel 1994) can be fitted to time series data, and differences in fitted model coefficients could be used to discriminate between congested and uncongested systems. This discriminant can be powerful for comparing two stationary systems (as is the simple discriminator of average queue length). Difficulties arise in nonstationary situations, when changes might be not just time series model parameters, but the form of the time series model as well.

2.4.4 Fourier Decomposition

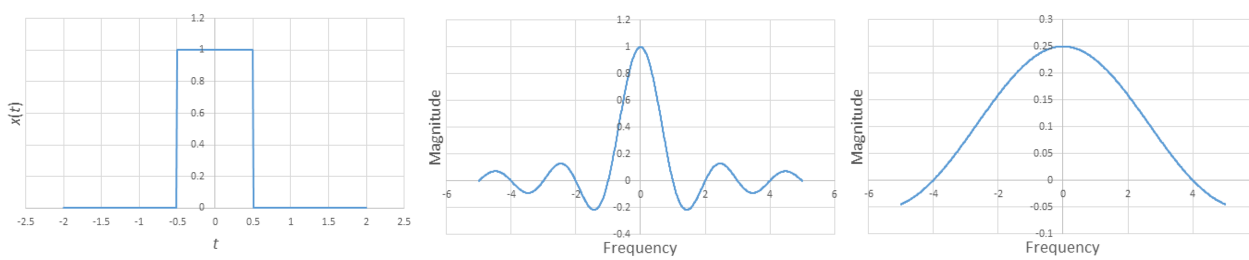
Frequency domain representation of time series have been used for many years in the economics literature. An analysis of economic time series data has found and verified a basic smooth declining shape of Fourier coefficient magnitudes exists in economic data from various sources (Granger 1966, Levy and Dezhbakhsh 2003). In spite of the presence of business cycles, seasonality and trends in economic data, the same basic shape is found regardless of these factors. For time series data, a discrete Fourier transform (DFT) is necessary. This is most commonly implemented using the fast Fourier transform (FFT) algorithm. Our choice of Fourier representation for simulation trajectory data is motivated by the connection between the Fourier transform and the autocorrelation function. The Wiener-Khinchine Theorem (Chatfield 1989) states that the Fourier transform of the autocorrelation function of a function is the power spectrum for a Fourier transform of the function itself. So the rapidly decreasing autocorrelation of uncongested systems should mean relatively large high-frequency components in the power spectrum, i.e. in the magnitude of the Fourier coefficients for the original time series.

2.5 Fourier Methodology

We know that a signal can be represented in both time and frequency domains. For the same signal, its representation on each domain is linked by the Fourier transform. The Fourier transform for a function $x(t)$ is

$$s(f) = \int_{-\infty}^{\infty} x(t)e^{-jft}\,dt.$$

For piecewise constant trajectories such as queue length, we hypothesize that examining the magnitude of the Fourier transform for different frequencies can reveal aspects of the rate and magnitude of queue length changes. In addition to the motivation from the connection of utilization-to-autocorrelation-to-Fourier coefficients, consider the Fourier transform of a unit pulse function. Although this is a simple case, the Fourier transform of a sum of any number of trajectory elements is the sum of the Fourier transforms of each element. Note that phase differences can result in reduced magnitudes – the resulting Fourier coefficient magnitudes may decrease. The magnitude of the real and complex components of the Fourier transform for the unit impulse depend on the specific location in time of the pulse. In Figure 4a the pulse is from - $t/2$ to $t/2$ and of amplitude $H = 1$. The Fourier transform for such a pulse, located evenly about zero, has no complex component. It is $s(f) = Ht\sin(\pi tf)/\pi tf$, in this case with $H = 1$ and $t = 1$, which is plotted in Figure 4b. The Fourier representation scales with the amplitude of the pulse, and the frequency composition tends to spread (with decreasing magnitude near the zero frequency) for decreasing pulse width. Figure 4c shows the Fourier transform for a pulse of width $t = 0.25$. There is a larger high frequency content (relative to the zero frequency magnitude) for a pulse of shorter duration, again suggesting relatively larger high frequency components for Fourier transform of a short-duration spike, common in queue length trajectories for uncongested systems.



a. Unit pulse, 1.0 pulse width b. Fourier for 1.0 pulse width c. Fourier for 0.25 pulse width

Figure 4: Fourier representations for unit pulses of width 1 and 0.25.

Although the queue length function is continuous over time, we represent it as a discrete time series as shown in Figure 1 and analyze it via the FFT. Epstein (2005) shows that the discrete approximation approximates the continuous Fourier transform "very well indeed," even for piecewise continuous functions. It is possible to reconstruct a continuous-time signal in time domain by interpolating discrete signal values in the frequency domain from the output of Fourier transform. By comparing it with original trajectory, we can decide which sampling rate to use, balancing fidelity and calculation effort. With $2N$ points one can characterize frequencies up to N cycles per period. For piecewise continuous functions, Epstein suggests that the FFT is an adequate approximation for frequencies up to some value well less than $N/6$. So for our purposes, we made the sampling rate 5-10x larger than the duration of features of interest.

2.5.1 Representation and Reconstruction

We define an infinite signal $x(t)$ in the time domain, and $s(f)$ in the frequency domain. We can represent our signal at any instant t as:

$$x(t) = \sum a_n cos\{2\pi f_n t + \phi_n\} = \sum \hat{X}_n e^{j2\pi f_n t}$$

where the sum is indexed by *n*, the set of frequencies in the discrete Fourier decomposition. The size of contribution a_n, and its phase ϕ_n at *t=0* is defined by $s(f)$ at the appropriate frequency f_n. Fourier coefficients $\hat{X}_n$ could also be written in terms of magnitude and phase as

$$\hat{X}_n = A_n + jB_n$$

where the magnitude $|\hat{X}_n| = \sqrt{A_n^2 + B_n^2}/N$, the phase $\phi_n = tan^{-1}(\frac{B_n}{A_n})$, and *N* is the total number of frequencies. Because our signal is only within a finite time period $[0, T]$, the FFT assumes the signal repeats itself outside of this interval to plus and minus infinity. Consequently it can only contain frequencies which are multiple of a fundamental frequency $f_0 = 1/T$. As a result, we can express the time series in the form

$$x(t) = \sum_{n=0}^{N} a_n cos\{2\pi f_n t\} + \sum_{n=0}^{N} b_n sin\{2\pi f_n t\}$$

where a_n, b_n characterize the magnitude and phase of the *nth* frequency component corresponding to $f_n = nf_0$. Also according to the symmetry of trigonometry, we have $A_0 = a_0, 2A_n = a_n, -2B_n = b_n$.

Since the output of FFT returns complex numbers representing Fourier coefficients $\hat{X}_n$ at each frequency, we can calculate the corresponding value of a_n, b_n and reproduce the signal value by interpolating them into above equation at discrete time points. In fact, reconstruction using a subset of the full set of Fourier components will approximate the observed time series. *Thus Fourier representations can be thought of as a metamodel for the dynamic behavior of a discrete-event simulation*. Figure 5 gives a graphical representation of the magnitude of the Fourier components for the discretized trajectory shown in Figure 1.

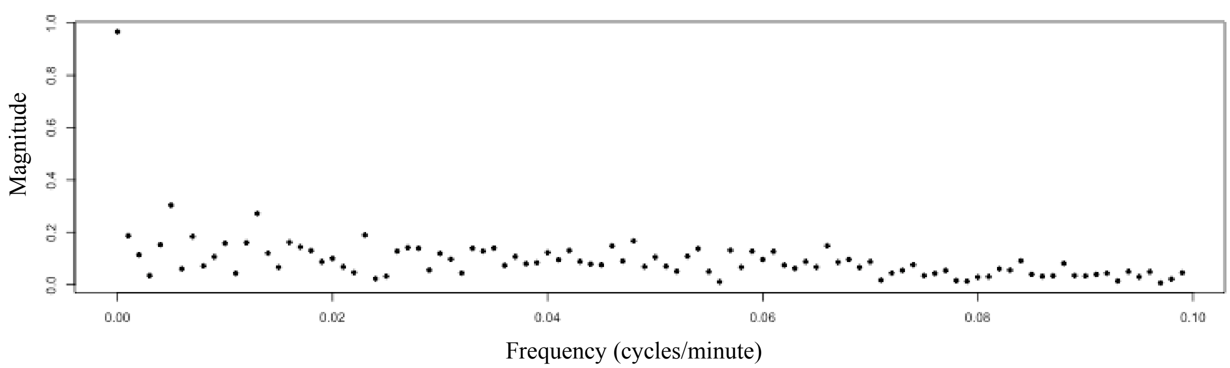


Figure 5: Fourier magnitudes for the M/M/1 queue trajectory in Figure 1.

2.6 Distinction from Prior Frequency Domain Simulation Research

The Fourier approach that we take is distinct from the frequency domain sensitivity analysis by Schruben and Cogliano (1981) and the many subsequent papers. In that research, simulation input parameters were deliberately varied periodically to determine sensitivity of simulation output to the input parameters. By varying different input parameters sinusoidally at (carefully chosen) different frequencies, sensitivities for multiple parameters could be determined from only two simulation runs. We do not seek sensitivity information, and do not sinusoidally vary parameters for that purpose, rather we seek to characterize a system's dynamic behavior by its Fourier signature, for use in discriminant analysis and process monitoring.

Further, the index used for the discrete Fourier calculations in prior frequency domain work was typically an entity index. Input parameters were varied with the entity index, and discrete-time output statistics were analyzed based on the index of the associated entities. Jacobson, Morrice and Schruben (1988) did examine using simulation clock time for the driving frequencies, but still analyzed output using an entity index. There is a problem of interpretation, since the entity indices are spaced unevenly in time, unlike the points in the time series transformation in Figure 1.

Hazra and Park (1994) used fixed-time increments, binning arrival and departure events to characterize the frequency response of an $M/G/1$ queue. Applied in the context of deliberate periodic variation of input parameters, their findings included a result that is useful in our setting: an $M/G/1$ queue acts as a low-pass filter for temporal variations in arrivals, and the pass-band decreases with increases in system utilization. *In certain queueing systems, then, we might expect the Fourier representation to have relatively less high-frequency content if the system is congested*. Eick, Massey, and Whitt (1993) and Green, Kolesar and Svoronos (1991) examined queue trajectories with sinusoidal variation of arrival rates as well, characterizing the impact on the usual steady-state performance measures. Important below, Jagerman (1975) found that an $M_t/M/s$ system saw a more rapid increase in the queue length distribution as a function of increasing arrivals, than for the decrease in the distribution as the system arrival rate decreased. This will be important for our experiments.

3 TECHNICAL ISSUES

Our exploratory investigation considered two issues: i) can patterns in the frequency domain discriminate the dynamic behavior of congested vs. uncongested systems, and ii) can statistical process control methods based on these findings be effective. In order to conduct computation experiments, several technical issues had to be examined.

3.1 Potential Problems of the Time Interval Selection

In order to apply FFT to an output sample path of queue length changes over time, the trajectory must be transformed into time series data. And we need to choose a time sampling interval small enough to enable capture of key dynamic features. If we select the minimal observed positive time interval observed between events in the original data as the time interval, the total number of points in the time series would be computationally intractable for some systems. On the other hand, if we use a too-large interval, we will fail to capture some queue length changes that occurred in the trajectory data.

3.1.1 Time Interval Selection -- 10^{-k} Percentile Value of Inter-arrival/Service time Distribution

For the simulation systems in this paper, inter-arrival times have been assumed to be exponentially distributed. We consider using a 10^{-k} percentile time of the corresponding exponential distribution as the sampling interval. There are two main reasons for this. First, since the queue length in a system will be strongly related to entity arrivals, by selecting the 10^{-k} percentile value of the interarrival time distribution, the probability that the next arrival is in a different interval is $1\text{-}10^{-k}$. Second, this 10^{-k} percentile value can be easily calculated for Poisson arrivals.

In this paper, we will have used a 10^{-3} percentile value. This means, we expect to have around 0.001 possibility to include more than one queue length change within new time interval, and around $(0.001)^2$ possibility to include consecutive two changes. If an inclusion is detected, we shift the event to the next interval and shift all later trajectory transition points by the same amount. This allows keeping all queue change events in the time series representation, with only a small perturbation to the original data values.

In order use the fast FFT algorithm calculations (Cooley and Tukey 1965) we further decrease the interval value, to give a number of points over the duration of the simulation trajectory that is a power of 2.

3.1.2 Time Interval Selection – Fidelity

When using the adjusted distribution 0.001 percentile value as time interval resulted in total points at 2^{20}, or 1,048,576 to the MTB. Is this enough? There are two additional justifications that we considered for the time interval choice. First, the importance of short-duration queue length changes from a managerial perspective. For the bank teller example, queue length changes of less than a second in duration probably have little meaning to the manager, and we suspect are not critical in determining system congestion.

Second, a sufficient sampling rate guarantees the fidelity of our FFT. Combined with minimal managerially interesting time intervals, this can lead to a minimal time interval choice, based on the Nyquist-Shannon sampling theorem and the results in Epstein (2005). Thus we have discontinuity in our trajectory, and the FFT output from a relatively low sampling rate would actually represent a signal with strong ringing artifacts – the Gibbs phenomenon. In order to better separate systems with different congestion levels, we need to guarantee a more precise transform outcomes by sampling at higher than the Nyquist frequency for sine waves with period equal to the minimal interesting time interval. We further examined plots of the reconstructed signals to be satisfied that our sampling rates were adequate.

3.2 Frequency Component Selection for Discrimination

In order to better differentiate systems, we need to select the Fourier coefficient magnitude value(s) which could best distinguish system trajectory characteristics. Define the magnitude of the (complex) Fourier coefficient at frequency f_n as C_n or C[n]. We examined three indicators of congestion: The first magnitude value C_1(but this is just the mean queue length), the average value of the second through k_1 coefficient magnitudes, $\frac{\sum_{i\in[2,k_1]} C_i}{k_1-1}$ and the average coefficient magnitude over selected set of frequencies from k_2-k_3, $\frac{\sum_{i\in[k_2,k_3]} C_i}{k_3-k_2}$. The first measure is the mean queue length, not really an interesting Fourier component but a legitimate competitor for discrimination. The second excludes the average, but is an average of the next few low frequency components. And the selection of k_2 and k_3 are based on examination of the time duration of small spikes mentioned above in relation to Figure 2. We use $k_1 = 5$, and scan a trajectory to set k_2 so that half of the observed spike interval values are less than the corresponding period, with k_3 set larger.

3.3 Statistical Process Control for Autocorrelated Data (SPC)

Traditionally, control charts are used to continuously monitor system performances over time with specified upper and lower limits. The existence of a large amount of historical data set and the assumption that process observations are i.i.d are typical conditions to effectively and efficiently implement control charts (Snoussi et al. 2005). For this paper, the systems under study are often networks of queues. Output will exhibit significant autocorrelation. One strategy for monitoring autocorrelated time series is to fit a time series model such as those described above during a calibration period and then monitor the residuals via CUSUM or EWMA (Apley and Shi 1999; Runger, Willemain, and Prabhu 1995; Nenes and Taragas 2005). Our concern with this approach is the uncertainty in model form. Apley (2002) discusses handling uncertainty in parameter values, but potential epistemic uncertainty remains. This is of special concern if the nonstationarity evidenced in unknown changes in model form. The cumulative sum (CUSUM) chart was specifically proposed and tested for monitoring queue performance metrics of an *M*/*M*/1 queuing system. Chen and Zhou (2015) demonstrated that CUSUM was effective for monitoring estimated system parameters inter-arrival rate and service rate.

4 EXPERIMENTS

To test our proposed methods, we examined three different queuing systems with different levels of complexity. All three simulations used two different combinations of key parameter settings in order to achieve target levels of utilization, each setting with 50 replications. The systems were an *M*/*M*/1 queue with utilizations of 0.6 and 0.9, and the Multi-Teller Bank and Job Shop models from Law and Kelton (2000). The Multi-Teller Bank simulation used five tellers and utilizations of 0.6 and 0.9. For each system, two sets of experiments were performed: first, Fourier analyses of entire trajectories were computed, and coefficient magnitudes were examined for their ability to discriminate between congested and uncongested systems. Generally we found that Fourier magnitudes could be used to distinguish between congested and uncongested systems, although this was weakest for the *M*/*M*/1 queue. Figure 6 shows magnitude comparison for congested and uncongested trajectories for the multi-teller bank simulation. There is little overlap in the average magnitude of C[k_2:k_3] coefficients so the discrimination is good.

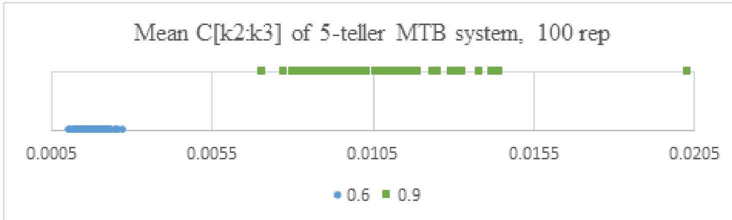


Figure 6: Fourier coefficient magnitudes for congested/uncongested Multi-Teller Bank systems.

4.1 Preliminary SPC Results

For examining the effectiveness of Fourier methods for detecting change in congestion we employed the common testing regime of a fixed change in congestion (utilization) following the calibration period. In the SPC setting, the window of trajectory data used to determine Fourier coefficients is necessarily small. We used nonoverlapping windows whose lengths were determined by managerial considerations: how quickly might one wish to detect a shift? For the *M*/*M*/1 system the window was set to 10 minutes, with subgroup size 3. Note that there were only .6 or .9 arrivals per minute. For the Multi-Teller Bank (terminating simulation), the window was set to 15 minutes with 1 arrival or 1.5 arrivals per minute. For the Job Shop (non-terminating simulation), the window was set to 4 hours.

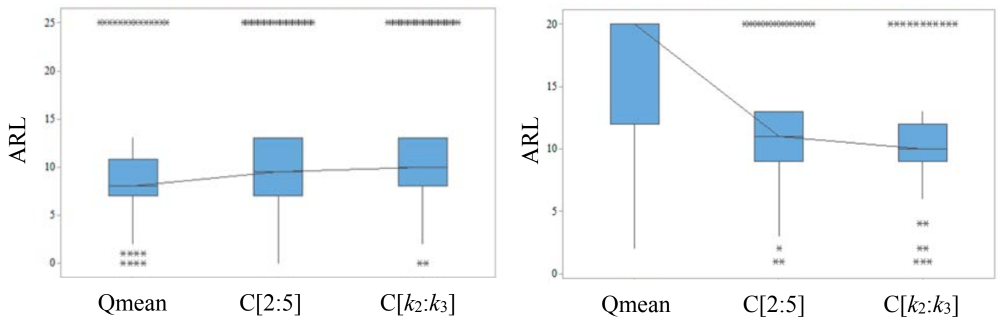
While discriminatory power is clear in Figure 6, the small window for SPC resulted in much lower power. Because there were many failures to detect in our *M*/*M*/1 experiments, we summarize those in Table 1. Since the k_2 and k_3 values are set based on nominal system behavior, they were different for congested (2 and 5) from uncongested (5 and 25). For the downshift, k_2-k_3 and 2-5 are identical ranges.

Table 1: SPC performance for the *M*/*M*/1 queue. Shift between utilizations of 0.6 and 0.9.

M/M/1 System	Identifier	Total # of Replication	# of Replication, Change Identified	ARL
Upshift	Q mean	100	100	16.4
	C[2:5]		94	26.7
	C[k2:k3]		91	28.1
Downshift	Q mean	100	41	29.6
	C[2:5] / C[k2:k3]		85	27.2

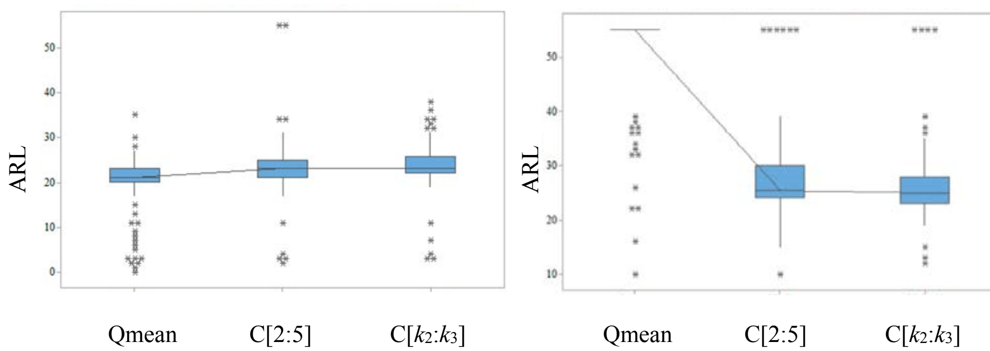
Figures 7-8 show boxplots of the time until signal for each of the SPC statistics that we examined for the Job Shop and the Multi-Teller Bank. Each boxplot is based on 100 replications. Failure to detect replications are plotted at the upper limit. In Figure 7b local queue mean failed to detect in 90/100 replications.

The preliminary results in the table above and the figures below suggest that the dynamic behavior of queue length, as characterized by nontrivial Fourier coefficients C[2:5] or C[k_2:k_3], can be used to detect changes in system congestion, and can be superior to SPC monitoring of local average queue length when systems move from a congested state to an uncongested state. We expect that the ability to detect trajectory shifts of this sort are disadvantageous for the queue length measure is related to the observation by Jagerman (1975) cited above. We expect that the autocorrelation of local average queue length (or C[1]) will be higher than the autocorrelation for higher order Fourier coefficient magnitudes, perhaps a different view of the same phenomenon.



a. Uncongested-to-congested b. Congested-to-uncongested

Figure 7: SPC average run length for congestion transition scenarios, Multi-Teller Bank.



a. Uncongested-to-congested b. Congested-to-uncongested

Figure 8: SPC average run length for congestion transition scenarios, Job Shop.

5 SUMMARY

We have two interesting findings in this investigation. First, it appears that frequency domain methods can be used to distinguish the dynamic behavior of congested versus uncongested systems. Second, this power can be applied in a monitoring situation, to allow decision makers to react to changes in system dynamics. Simulation provides a mechanism to test such dynamic detection (and control) procedures before they are implemented on a real system. But these findings are preliminary; much remains to be done.

First, we have not attempted to optimally select i) sampling frequency, ii) identification of Fourier components with maximal discriminatory power. Second, discriminatory power may be magnified by retaining the multivariate nature of the Fourier coefficients. In particular, using a multi-variate SPC method, may result in better and more accurate SPC signaling. And for all of these opportunities, it will be important to provide theoretical and empirical performance estimates, to be sure that the methods merit adoption.

Finally, for the SPC method implemented here, we move the time window of Δt width by Δt to construct the next observation data for control charting. This corresponds to nonoverlapping batches. It may be possible to improve responsiveness using overlapping samples for construction of Fourier magnitudes, for SPC.

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AUTHOR BIOGRAPHIES

XINYI WU is working as a supply chain consultant at AT Kearney. She recently graduated from Penn State University with her Master's dual degree in Industrial Engineering and Operations Research. She is interested in discrete event simulation, supply chain modeling and optimization. Her email address is wuxinyi8@gmail.com.

RUSSELL R BARTON is professor of supply chain and information systems and professor of industrial engineering at the Pennsylvania State University. He currently serves as senior associate dean for research and faculty in the Smeal College of Business. He received a B.S. degree in electrical engineering from Princeton University and M.S. and Ph.D. degrees in operations research from Cornell University. He serves as the I-Sim representative on the INFORMS Subdivisions Council and chairs the QSR Advisory Board. He is a senior member of IIE and IEEE and a Certified Analytics Professional®. His research interests include applications of statistical and simulation methods to system design and to product design, manufacturing and delivery. His email address is rbarton@psu.edu.