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On Cycle Times and Interdeparture Times in Semiconductor Manufacturing

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Abstract

In this paper we investigate the distributions and the long-range behavior of cycle times and interdeparture times in two semiconductor manufacturing systems. The results were obtained by means of simulation using original work floor level data of semiconductor fabrication facilities. The findings presented here show that for those semiconductor facilities the normal distribution is a very good approximation of the cycle time distribution. This relation holds for different queuing disciplines and varying service time distributions. Furthermore, we show that in some cases the distribution of interdeparture times can be approximated by the exponential distribution. We discuss the few cases where the exponential distribution is not appropriate. Finally, we address the long-range behavior and the degree of persistence of both cycle times and interdeparture times.

1 Introduction

According to Sze (1983) and Münch (1993) semiconductor manufacturing is one of the most complex production processes. Hence, advanced methods are needed to evaluate the performance of these fabrication facilities. The cycle time, i.e. the time a job spends in the production process, is commonly regarded as the major performance measure. Glassey and Resende (1988) point out that, "*minimization of cycle time, and consequently, waiting time, among many effects, decreases the time a wafer is exposed to particles in the clean room, thus increasing yield, improves the response time to changes in the response pattern, reduces in–process inventory, and reduces the engineering response time.*" Other performance measures are for instance production yield, throughput or production rate, and machine utilization or availability.

The manufacturing process of a semiconductor fabrication facility yields entire wafers which may comprise a large number of identical circuits called *dies*. Therefore, wafers have to be cut before a single die can be sent to further fabrication steps like packaging or encapsulation. Clearly, the departure process of the core semiconductor fabrication part is an input process to these operations. This implies that the statistical properties of interdeparture times have to be taken into account in addition to cycle times. It is a well known fact from queuing theory that highly variable or even correlated input to a queuing system has a tremendous negative effect on its performance, e.g. as reported by Livny et al. (1993) and Rose (1995). In other words, if the output process of a system suffers from variability possibly combined with correlation, it affects the performance of subsequent production stages.

Recently, in particular in semiconductor industries, the capability of meeting due dates has become a crucial factor of competitiveness. Consequently, both the mean and variance of performance measures have to be considered, because the probability of meeting due dates decreases with increasing process variability. Thus, a modern manufacturing organization has to deal with this issue in order to be able to compete on the world market. However, standard literature on cycle times only deals with the reduction of *mean* cycle times. Only few articles consider higher moments. For example, Whitt (1993) presented approximations for the first two moments of $GI/G/m$ queues. Recent studies devote attention to the reduction of the variability of cycle times. Kumar (1993) investigates how to achieve this goal in advanced re-entrant flow systems by means of appropriate sequencing rules. Mittler et al. (1995) show that there is no general relationship between sequencing rules and the variance of cycle times in semiconductor manufacturing. This relation depends mainly on the fabrication facility and the product under consideration.

Nevertheless, an operations manager might be interested rather in the probability that the cycle time falls within a fixed interval, than in the variance of cycle times. These probabilities are well known for the standard normal distribution, and hence easy to calculate for normally distributed datasets. The assumption of normally distributed performance measures is widely used in practice based on experience, although there is no knowledge about the actual distribution of the cycle times.

In manufacturing, performance evaluation is usually done under the regime of stationarity, in other words, it is usually assumed that a statistical equilibrium exists. Performance measures are derived directly from the solution of the the steady-state equations, which are solved by state-of-the-art methods[1]. Although much attention has been devoted to arrival and service processes with higher variability compared to Markov processes or to nonrenewal processes[2], the questions whether arrival and service processes are stationary or renewal or whether these processes exhibit long-range dependence have been neglected. This topic is currently discussed in telecommunications research, in particular when investigating LAN traffic[3] and variable bit-rate video traffic transmitted over ATM-networks[4].

Keeping this discussion in mind we statistically analyze the distributions and the long-range behavior of cycle times and interdeparture times in several semiconductor manufacturing systems. We generated long sequences of cycle time samples and interdeparture time samples by simulation using original descriptions of semiconductor fabrication facilities, published by Wein (1988) and Rodriguez and de Ridder (1994). Firstly, our results show that the cycle times in all semiconductor facilities under consideration generally follow approximately the normal distribution. This relation also holds for several queuing disciplines (first-in-first-out (FIFO), earliest due-date (EDD), and shortest remaining processing time (SRPT)), and for the closed loop inventory control (see Spearman et al. (1990)). Secondly, in some cases, the distribution of interdeparture times can be approximated by the exponential distribution. However, we also report some cases, where the exponential distribution is not appropriate. Finally, we discuss the long-range behavior of both cycle times and interdeparture times. We apply the power density spectrum, variance-time plots, and R/S-analysis to evaluate the degree of persistence. Unfortunately, the results of these methods are contradicting in many cases.

The remainder of the paper is organized as follows. We first give an introduction to semiconductor manufacturing in Section 2 and describe the methodology of our experiments in Section 3. Section 4 discusses the stationarity of the mean cycle time. In Section 5 we describe how to fit probability distributions with empirical data. The definition of long-range dependence and the results for the degree of persistence are given in Section 6. We conclude the paper by discussing the impact of the results on stochastic modeling of manufacturing systems and give directions to future research.

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[1]For general overviews we refer to the books of Buzacott and Shanthikumar (1993), Askin and Standridge (1993) and Gershwin (1993).

[2]See Gold (1992), Whitt (1993), Neuts (1989), Chakravarthy (1994), and Buzacott and Shanthikumar (1993).

[3]See Leland et al. (1994)

[4]Among many others, see Beran et al. (1995), Rose (1995), and Grasse et al. (1995).

2 Semiconducor Manufacturing

A semiconductor chip is a highly miniaturized, integrated electronic circuit consisting of thousands of components. Every semiconductor manufacturing process starts with pure, raw wafers, thin discs made of silicon or gallium arsenide. Up to a few dozens of identical chips can be made on each wafer. Depending on the scale of integration, the type of chip, and customer specs, the whole manufacturing process may require up to 500 single steps; the time required to manufacture a wafer may take up to 50 days. Most of the aforementioned operations involve cleaning, deposition, lithography, etching, ion implantation, and testing and are therefore basically of the same type. Note, that there are no assembly operations before reaching the backend stage of the production process. Instead, wafers have to be cut before the dies can be sent to further operation steps. Most semiconductor manufacturing facilities produce only a few distinct types of chips for which the sequence of processing steps may be different. For more detailed introductions to semiconductor manufacturing we refer to Gise and Blanchard (1986), Münch (1993), Sze (1983), and Bohn (1995).

As already mentioned, several performance measures are used to assess a semiconductor manufacturing facility. Due to the complex manufacturing environment, there is a huge number of environmental and control factors (cf. Bohn (1995)) which may have more or less impact on a certain performance measure. We confine ourselves to those factors which are connected with the flow of material as done by the MIMAC project (see Rodriguez and de Ridder (1994)). This project identified the following major factors determining the performance:

(1) alternative tools
(2) *batching*
(3) blocking
(4) *breakdowns*
(5) *dispatching / sequencing*
(6) end of shift effect
(7) factory shutdown
(8) *hot lots*
(9) *inspection / yield*
(10) *lot sizes*
(11) operator skills
(12) *operator availability*
(13) *order realease / WIP limits*
(14) *product mix*
(15) redundant tools
(16) *re-entrant flow*
(17) *rework*
(18) *setups*
(19) time bound sequences

We consider the *emphasized* factors only. To evaluate whether these factors have a significant impact on the performance of a semiconductor fab designed experiments have to be conducted. Since experiments concerning operational research issues within real semiconductor manufacturing environments are very expensive and time consuming (due to the large cycle time) and since a large number of experiments has to be conducted, simulation has become a useful tool for the performance analysis of these systems. Examples for the application of simulation in manufacturing can be found in Dayhoff and Atherton (1984), Lohrasbpour and Sathaye (1984), Glassey and Resende (1988), Wein (1988), Schömig and Mittler (1995a) and Mittler et al. (1995) among others.

3 Experimental Design

We generated cycle time and interdeparture time traces for two different datasets of semiconductor manufacturing facilities as depicted in Table 1. A dataset is the description of the material flow extracted from real semiconductor lines and contains the information regarding the factors determining the performance (see previous section). The datasets also include arrival and service time distributions, number of machines and operators, etc. The first dataset was developed by the MIMAC project; its original denotation is "dataset 1". The second dataset is "fab 3" taken from Wein (1988). We point out that the MIMAC dataset is on a more detailed level since operators, hot lots, scrap, and setup are also covered. Wein's model does not cope with these factors. However, it has been used in academia to investigate the impact of sequencing rules, dispatching strategies and related topics (cf. Schömig (1994) and Deuermeyer et al. (1993)). We are able to demonstrate that our findings are valid for different abstraction levels.

Table 1 lists the characteristics of the datasets under investigation. Note that though Wein models a test facility, both datasets describe semiconductor fabrication processes of the same complexity. The main difference besides the abstraction level is the number of work centers. Note that there is no external arrival process of lots when the CONWIP rule is applied. In this case the WIP is kept on a previously fixed level. Finally, in Wein's model the times between failures and downtimes are considered to be Gamma distributed with a shape parameter equal to 1.5 ($CoV = \sqrt{2}$) whereas in the MIMAC dataset these times are exponentially distributed.

The datasets are examined for the following queuing disciplines (see also Table 1)[5]:

FIFO: First-In, First-Out Lots are served in the order of their arrival. There are no priorities.

EDD: Earliest Due Date Lots are served according to their due dates. Lots with earlier due dates are favored. EDD is applied with no due dates set explicitly such that a lot receives service prior to another if it has a longer system lifetime, i.e. it entered the system prior to the other one.

CCS: Closest to Completion by Step CCS selects the job with the highest ratio of the current step number and the total number of processing steps in the job's process flow for service to be given next.

[5] Further details can be found in Wein (1988) and Chance (1994).

SRPT: Shortest Remaining Processing Time Lots with shortest remaining processing time are favored. SRPT is the analog to CCS if service times are considered instead of service steps.

CR: Critical Ratio In case of equal priorities it favors the job with the lowest critical ratio c, which is based on the total remaining processing time ($TRPT$), the due date (DD), and the current time (NOW):

$$c = \begin{cases} \dfrac{1 + DD - NOW}{TRPT}, & DD > NOW, \\ \dfrac{1}{(1 + NOW - DD) \cdot TRPT}, & DD \leq NOW. \end{cases}$$

To perform statistical tests and to calculate autocorrelation functions and power density spectra we had to generate sufficiently long traces for cycle times and interdeparture time, i.e. traces comprising about $5,000$ samples at minimum. In the case of the MIMAC dataset the completion of $5,000$ lots of each product corresponds to approximately 5 years of operation, whereas in Wein's model it corresponds to about 25 years since the factory is a test facility with 0.0236 wafer starts per hour only.

Table 1: *Testbed Datasets*

dataset	MIMAC$_3$	WEIN$_3$
type of factory	commodity	test factory
product mix	2	1
avg. #mask layers	15	13
#processing steps	210 / 245	172
#work centers	83	24
queuing disciplines	FIFO EDD CCS CR	FIFO EDD SRPT —
arrivals	deterministic	deterministic
inventory control	—	CONWIP, 50 lots
Service Times	deterministic	Erlang-2
Load	70 %	95 %

To complete the picture we shall mention the simulation tools we used to generate the traces: The simulation study concerning the MIMAC data sets was conducted using the Delphi simulation tool, a package for simulating large queuing networks, with an emphasis on providing the building blocks for manufacturing simulation, in particular semiconductor manufacturing (see Chance (1994)). The simulation package to examine Wein's model was implemented in MODULA–2 at the Institute of Computer Science of the University of Würzburg. All simulations were run on SUN SPARC workstations.

According to Table 2 the traces generated for dataset MIMAC_1 are denoted by

`mimac1-`<*queuing discipline*>`-`<*product*>

whereas the traces obtained for dataset WEIN_3 are denoted as follows:

`wein3-`<*queuing discipline*>`-`<*det. arrivals* | *closed loop (CONWIP)*>.

4 Stationarity of Simulation Output Data

We apply the test presented by Schruben et al. (1983) for detecting the initialization bias in the mean. This test, which is referred to as the STS83 test, employs the theory of standardized time series and also tests for the null hypothesis that the output mean does not change throughout the simulation run. Furthermore, this test proves to be powerful in detecting transient effects in the mean (cf. Schömig and Mittler (1995b)).

For a significance level of $\alpha = 0.1$ this test rejected the null hypothesis that the time series is stationary in terms of the mean only in case of trace `wein3-srpt-det` (see Table 2). Additionally, we tested for the length of the warm-up period. Surprisingly, in case of the MIMAC_1 dataset there is no warm-up period at all; transient phases occur in Wein's model only (see Table 2). Fig. 1 shows the cycle time of product 1 lots for dataset MIMAC_1 with queuing discipline FIFO employed. Note that there is no warm-up period. We explain this as follows. Although the raw processing time is 328.45, the cycle time of the first lot leaving the fabrication facility is 450.89. The confidence interval for the mean computes to 550.92 ± 8.14. Obviously, the first observation of the cycle time amounts to approximately 60 % of the empirical mean which has been calculated using all 10,000 samples. In our opinion this effect is due to the complexity of the manufacturing process. Remember that there are up to a few hundred processing steps resulting in a high raw process time and that the initial order of the lots (sorted according to their arrival time) is permutated because of the re-entrant flow and occurring rework. Therefore, a particular lot entering an empty system will not leave the system as first; instead it is fed back and is overtaken by other lots. Arriving at a service center it will not find an idle server and has to wait for service. On the other hand, a lot leaving the system first has to wait at the machines in the upstream part of its process flow such that its cycle time does not consist of its raw process time only but also of waiting times that occur in the upstream part of its process flow.

Recently discussed methods to investigate the long/short-range behavior of time series require stationarity (see Beran et al. (1995) and Grasse et al. (1995)). There are

Table 2: *Sample size and length of warm-up period*

dataset	sample size n	warm-up period
`mimac1-ccs-p1`	$10,000$	1
`mimac1-ccs-p2`	$4,935$	1
`mimac1-edd-p1`	$10,000$	1
`mimac1-edd-p2`	$4,898$	1
`mimac1-fifo-p1`	$10,000$	1
`mimac1-fifo-p2`	$4,935$	1
`mimac1-cr-p1`	$10,000$	1
`mimac1-cr-p2`	$4,908$	1
`wein3-edd-cl`	$11,673$	$1,167$
`wein3-edd-det`	$11,758$	$1,762$
`wein3-fifo-cl`	$11,807$	1
`wein3-fifo-det`	$11,749$	$5,284$
`wein3-srpt-cl`	$11,656$	583
`wein3-srpt-det`	$11,743$	∞

two major types of stationarity, *strict stationarity* and *weak stationarity*. We shall give these definitions in detail (cf. Grasse et al. (1995)):

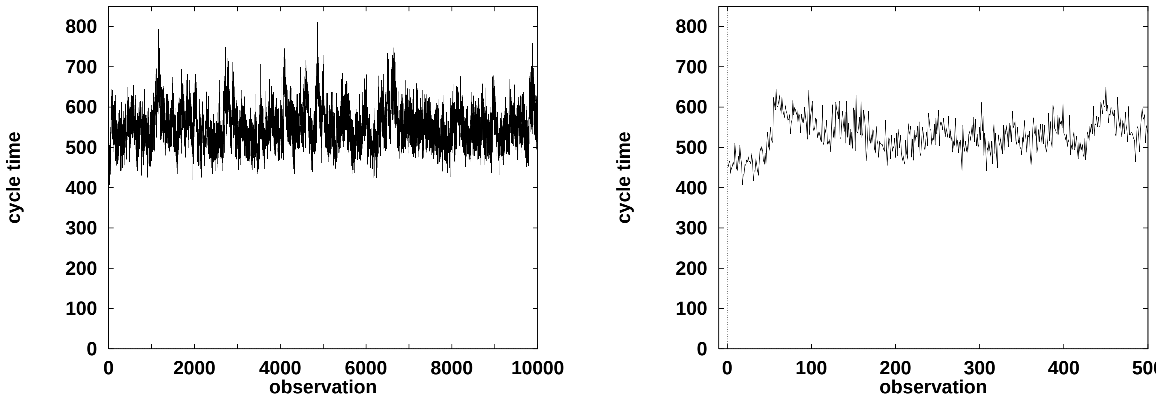
Strict Stationarity A stochastic process is strictly stationary if the joint probability distributions $\{X(t_1), X(t_2), \ldots, X(t_n)\}$ and $\{X(t_1+t_0), X(t_2+t_0), \ldots, X(t_n+t_0)\}$ are identical for any set of times $t_1, t_2, \ldots, t_n$, any t_0 and all positive integers n.

Weak Stationarity A stochastic process is said to be weak stationary if the moments up to order 2 are finite and constant and if the covariance $\mathrm{E}[(X(t_0)-\mu)(X(t_0+\Delta t)\mu)]$ depends only on Δt where μ is the mean.

Since the STS83 test employed tests for the stationarity of the mean only, we point out that it remains to future research to test whether the time series generated for semiconductor fabrication facilities are indeed weakly stationary as required in the context of long-range dependence. For evaluation purposes we nevertheless assume weak stationarity in order to calculate the degree of persistence.

5 Fitting Probability Distributions to Empirical Data

As already mentioned, an operations manager might be interested in the probability that the cycle times falls within a certain interval. To be able to answer this question, probability distributions have to be fitted with empirical data. The fitting procedure can



(a) 10000 samples

(b) first 500 samples

Fig. 1: Cycle time of `set1fifo-70-p1`

cause erroneous answers if one gets confused with *probability density functions* (*pdf*s) and *probability mass functions* (*pmf*s). A pmf is defined for discrete random variables only whereas pdfs apply to both discrete and continuous random variables. However, in the case of a discrete random variable a pdf consists of Dirac impulses at the discontinuities.

We explain the fitting procedure for cycle times only. Interdeparture times can be fitted in the same way. We calculate a histogram with 100 bins and obtain the empirical pmf $P(T = t)$, where T is the random variable for the cycle time. In order to obtain a continuous pdf we need to divide each histogram bar by the width of a bin.

Once a pdf has been fitted, it remains to assess how good the fit is. In the literature one can find many goodness-of-fit tests which check the null hypothesis that the independent samples follow a certain distribution. However, as Law and Kelton (1991, page 382) point out, these tests "*are often not very powerful for small to moderate sample sizes n. [...] On the other hand, if n is very large, then these tests will almost always reject*" the null hypothesis. They conclude that the goodness-of-fit tests should be applied to detect fairly gross differences when the sample size is small. However, since we are concerned with sample size of 10,000 and larger, we abstain from performing goodness-of-fit tests. Instead, we use some heuristic procedures, as also recommended by Law and Kelton (1991). This approach is further justified since the fitted density functions are obviously in either very good accordance with the empirical density functions or the difference is so striking such that a goodness-of-fit test would reject the null hypothesis.

To evaluate the goodness-of-fit heuristically we employ *probability-probability (P-P) plots* and *quantile-quantile (Q-Q) plots*. In these plots probabilities (quantiles) of the fitted distribution functions are plotted versus probabilities (quantiles) of the empirical distribution functions. The better the goodness-of-fit, the better is the accordance of the line plotted as just described and the identity function. Law and Kelton (1991) emphasize that Q-Q plots amplify the difference between the tails of the model and the sample distribution function whereas P-P plots amplify the difference in the middle of these distribution functions.

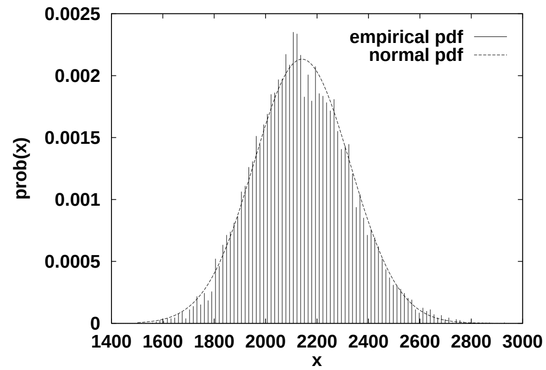
5.1 Cycle Times

As far as the pdf of cycle times is concerned the result of fitting continuous pdfs is that cycle times are normally distributed. This statement is independent of the dataset, the queuing discipline, and the distribution of machine service times. Usually, the shape of the cycle time pdf is as shown in Fig. 2 where the Q-Q and P-P plots are also given. As these plots indicate, there is generally no large deviation between the empirical pdf on the one hand and the fitted normal pdf on the other hand. As Law and Kelton (1991) state, the small differences may also be caused by the medium sized sample.

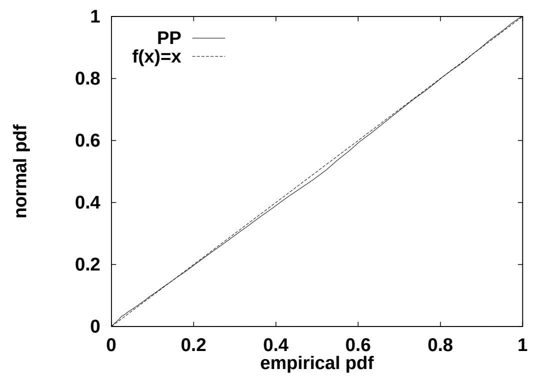
For a few cycle time traces only, the cycle time histogram is slightly skew, i.e. turned to the left indicating that the median is smaller than the mean (see Fig. 3). In this case, the deviation of both the Q-Q line and P-P line from the line with slope 1 and intercept 0 is rather small indicating that the difference of the model pdf and the sample pdf is small, too. The observation that the sample pdf and the fitted pdf differ much more when the fabrication facility is fed by an external arrival stream of lots (here, interarrival times are deterministic) holds for all queuing disciplines and all fabrication facilities under consideration. However, due to the large number of traces, we refrain from showing those plots explicitly.

Nevertheless, further research should be carried out to employ more sophisticated pdfs like the Weibull distribution. This distribution might prove to be much more adequate since it has two parameters to adjust the *shape* and the *scale* of the pdf (cf. Law and Kelton (1991)).

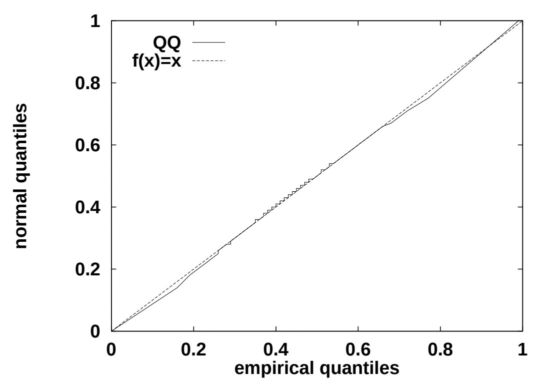
From the statistical point of view the observation of normally distributed cycle times is rather amazing. One of the most important theorems in probability theory, the *central limit theorem* seems to hold although one of its conditions is violated. The central limit theorem states that the probability density of the sum of n independent and identically distributed random variables with the same mean and the same standard deviation converges to the normal density for $n \to \infty$. This also holds for the more general case when the individual random variables follow distinct distributions according to Allen (1990). However, the assumption of independence is violated for the following reason. Mittler et al. (1995) report that due to re-entrant flow, rework, and different process flows which cross each other, there is overtaking of lots in semiconductor manufacturing. Overtaking does not necessarily mean physical overtaking; it is only required that the probabilistic effects caused by a lot during its visit at a particular tool propagate through



(a) prob. density functions

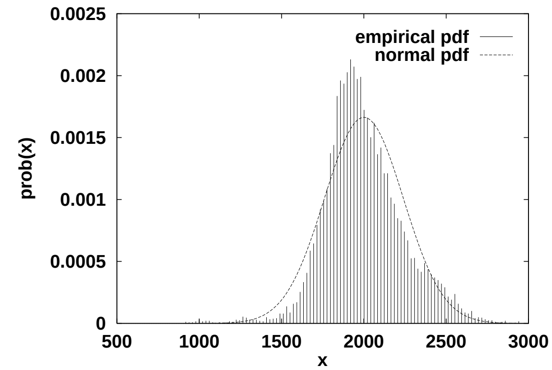


(b) P-P plot

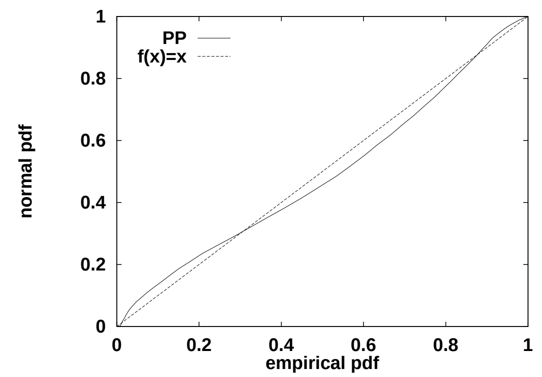


(c) Q-Q plot

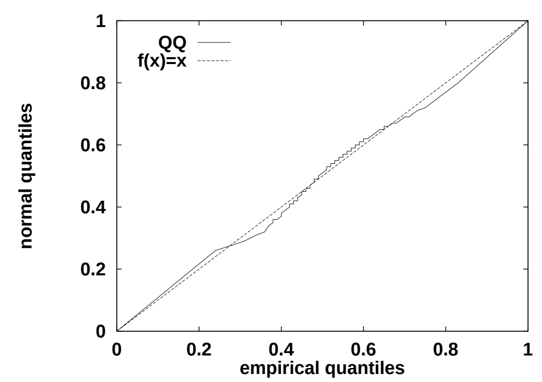
Fig. 2: Cycle time of trace `wein3-edd-cl`: Sample vs. model



(a) prob. density functions



(b) P-P plot



(c) Q-Q plot

Fig. 3: Cycle time of trace `wein3-edd-det`: Sample vs. model

the manufacturing facility, thus affecting its cycle time at subsequent tools[6]. Overtaking in semiconductor manufacturing causes cycle times at successive service centers to be *not mutually independent*. Only higher moments are affected, the mean cycle time remains unchanged in the presence of overtaking. Nevertheless, our results indicate that the sum of the cycle times at subsequent machines is nearly normally distributed.

5.2 Interdeparture Times

The results for the sample interdeparture time distribution are quite different. It seems that interdeparture times are exponentially distributed. Surprisingly this conjecture holds for almost all traces generated for Wein's semiconductor fabrication facility, although the machine service times are Erlang-2 distributed (coefficient of variation $1/\sqrt{2}$). As Fig. 5 and Fig. 6 show, this observation holds for all queuing disciplines and for both the deterministic external arrival stream of lots and the CONWIP rule.

The previous observation is not valid for the MIMAC_3 interdeparture time traces (see Fig. 4). The reason is as follows. Remember that the machine service times of the

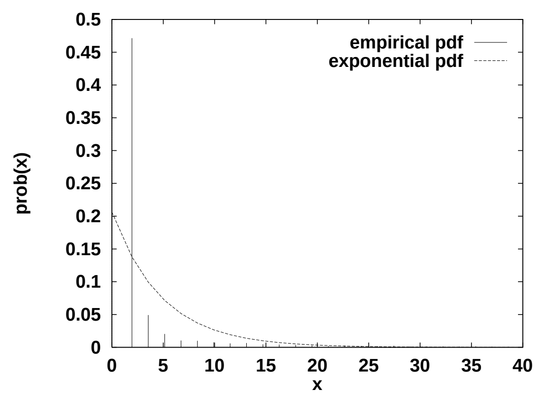
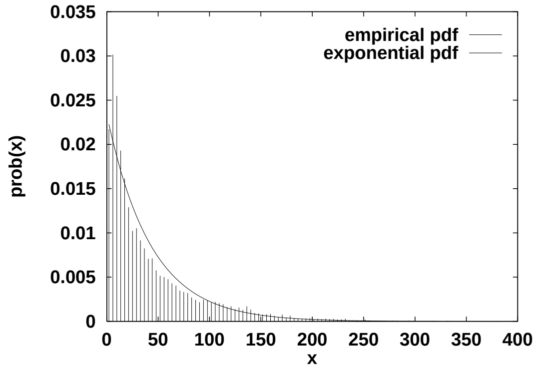


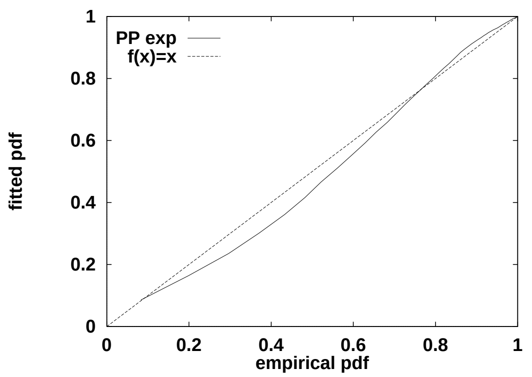
Fig. 4: Interdeparture time of trace `mimac1-ccs-p1`: Sample vs. model

MIMAC semiconductor fabrication facility are deterministic. However, given a saturated ordinary queuing system with no scrap, no breakdowns, no rework, and deterministic service times, the output process is also deterministic. If one drops the assumption of saturation, the minimum interdeparture time is equal to the (mean) service time i.e. deterministic. However, the scrap probability of 10 % at the final service station of the MIMAC dataset and the utilization of 70 % of the bottleneck tool cause the final service station to be busy for 66.4 % (independent of the queuing discipline employed), but the interdeparture time pdf deviates from the deterministic pdf (see Fig. 4).

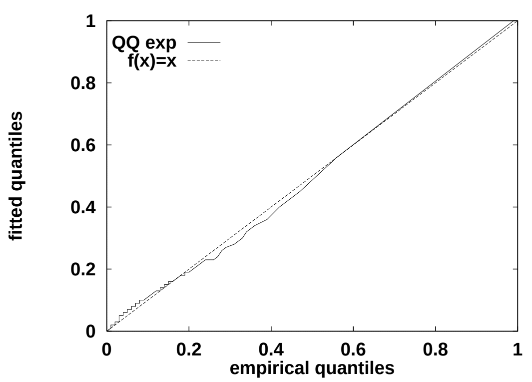
[6]For more details see Walrand and Varaiya (1980), Melamed (1982), Boxma and Daduna (1990), and Mittler and Gerlich (1993).



(a) prob. density functions

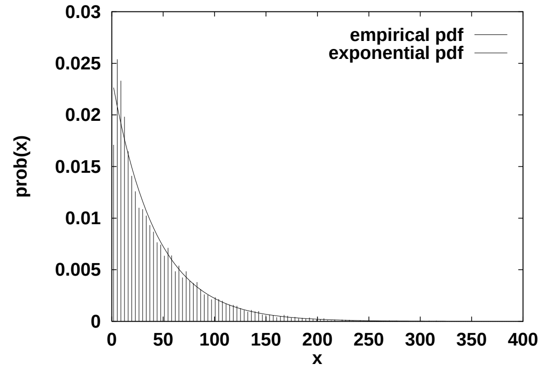


(b) P-P plot

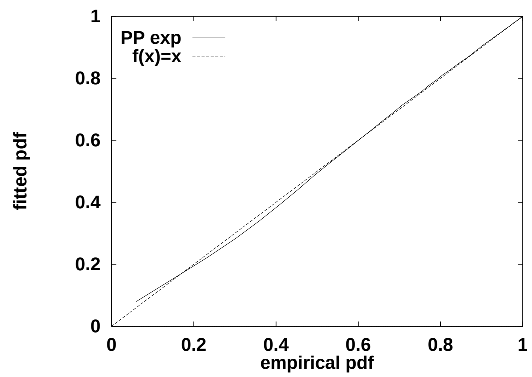


(c) Q-Q plot

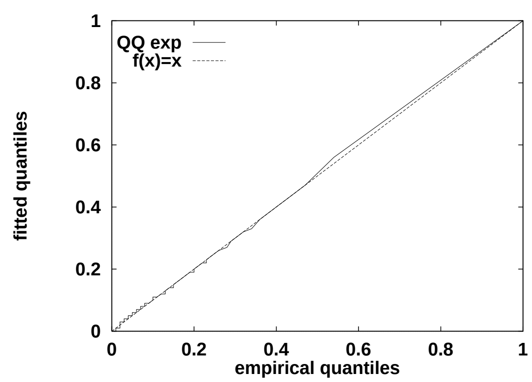
Fig. 5: Interdeparture time of trace `wein3-edd-cl`: Sample vs. model



(a) prob. density functions



(b) P-P plot



(c) Q-Q plot

Fig. 6: Interdeparture time of trace `wein3-edd-det`: Sample vs. model

In this case, the probability distribution function of the interdeparture times has a mean higher than the service time at the final tool. Furthermore, its coefficient of variation is larger than 2. This indicates that the output process is thinned out due to scrapped lots, i.e. interdeparture intervals are elongated when scrap occurs. Thus, scrap contributes to the variation of the output process.

6 Long-Range Dependence and Degree of Persistence

Currently, as Beran et al. (1995) and Grasse et al. (1995) point out, the number of publications on long-range dependence and self-similarity of time series is increasing. To provide a short introduction to this matter we follow these papers and confine ourselves to the essential material. More details can be found in the original publications. Long-range dependent behavior of time series can mainly be expressed in four different ways: in terms of the autocorrelation function, the power spectral density, the variance of the sample mean, and the rescaled adjusted range or R/S statistic. A time series $X_1, \ldots, X_n$ is said to show long-range dependent behavior if

- the *autocorrelation function* ρ_k decays hyperbolically for large lags k:

$$\rho_k \overset{k\to\infty}{\longrightarrow} c_1 \cdot k^{-\beta}. \tag{6.1}$$

- the *power spectral density* $s(\omega)$ obeys the law

$$s(\omega) \overset{\omega\to 0}{\longrightarrow} c_2 \cdot \omega^{\beta-1} \tag{6.2}$$

  for small frequencies ω. Here, $s(\omega) = \sum\limits_{k=1}^{n} \rho_k\, e^{jk\omega}$ with $j = \sqrt{-1}$.

- the *variance of the sample mean* decreases more slowly than the reciprocal sample size. If $X^{(m)}$ denotes the covariance time series obtained by taking the batch means $X_k^{(m)} = (X_{m(k-1)+1} + \cdots + X_{mk})/m$, $k \geq 1$, of the original time series, this behavior can be expressed as follows:

$$\mathrm{Var}[X^{(m)}] \overset{m\to\infty}{\longrightarrow} c_3 \cdot m^{-\beta}. \tag{6.3}$$

- the *R/S statistic* obeys the law

$$\frac{R(n)}{S(n)} \overset{n\to\infty}{\longrightarrow} c_4 \cdot n^{1-\beta/2}. \tag{6.4}$$

  Here $R(n) = \max\{W_{j,n} \mid 0 \leq j \leq n\} - \min\{W_{j,n} \mid 0 \leq j \leq n\}$ where $W_{j,n} = \sum_{i=1}^{j} X_i - j/n \sum_{k=1}^{n} X_k$ is the adjusted range and $S(n)$ is the sample standard deviation of $X_1, \ldots, X_n$. Usually, the time series X is split into K parts to obtain a number of $R(n)/S(n)$ estimates for each lag n.

In each case $\beta \in [0;\, 2]$ holds. The so-called Hurst parameter $H = 1 - \beta/2$ is widely used to express the degree of dependence: a time series exhibits

- ◇ *short-range dependence* if $1 < \beta \leq 2$ and
- ◇ *long-range dependence* is given if $0 \leq \beta < 1$.

Beran et al. (1995) emphasize two important relations valid for long-range dependent time series. It follows directly from Eqn. (6.1) that the cumulative sum of the autocorrelation function over all lags is infinite, i.e. $\sum_{k=1}^{n} \rho_k = \infty$. Eqns. (6.1) and (6.2) also imply that $s(0) = \infty$. In contrast to long-range dependent time series short-range dependent time series are characterized by summable exponentially decaying autocorrelation functions, i.e. $\rho_k = z^k$ with $|z| < 1$ and $\sum_{k=1}^{n} \rho_k < \infty$. In the case of short-range dependence the power spectral density is finite at frequency $\omega = 0$.

For weak stationary time series the degree of dependence (which is also referred to as the *degree of persistence*), can be estimated by means of the autocorrelation function, the power spectral density, the variance-time plots, or the R/S analysis. For each of these estimators the relations indicating long-range dependence can be written in the form $f(x) = c \cdot x^{g(\beta)}$ where g is a linear function of β. Then, the parameter β can be estimated by taking the logarithm of both sides of this equation which yields $log(f(x)) = g(\beta) \cdot log(x) + log(c)$ and fitting a linear regression line to it. However, the linear regression is very strongly affected by the number of samples used to calculate the least squares fit (cf. Grasse et al. (1995)).

Grasse et al. (1995) complain that in many publications stationarity is only assumed and no statistical means are invoked to test for stationarity. They show that VBR video traffic time series exhibit long-range dependence when weak stationarity is assumed. Using the test procedure developed by Priestley and Subba Rao (1993) and the analysis of variance procedure with two factors they show that the null hypothesis of weak stationarity has to be rejected for a significance level less than 1 %.

In the literature it is pointed out that the application of the CONWIP rule has tremendous effects on the performance of queuing systems (see Spearman et al. (1990)). Using the autocorrelation function and the power density spectrum Schömig and Mittler (1995a), however, have shown that employing the CONWIP rule in semiconductor manufacturing causes cycle times to be periodical, where the period is exactly the number of lots or customers that are allowed to enter the manufacturing facility. In this case the autocorrelation function oscillates around the abscissa having positive and negative values. Therefore, the logarithm of the autocorrelation cannot be taken to estimate the degree of persistence. However, regarding the effect of dependence one might conjecture that cycle times are short-range dependent because of the oscillation of the autocorrelation around the abscissa.

To evaluate the degree of persistence we discarded the initial transient phase of the traces and calculated β for the remaining samples only; the results are given in

Tables 3 and 4. There, β_P denotes the degree of persistence derived from the power density spectrum, whereas β_V is the corresponding value obtained by using the variance-time plot. We used the Bartlett window to overcome the effect of leakage of the power spectral density. Furthermore, we averaged the power spectral densities to get consistent estimators[7]. The degree of persistence β_P was estimated in two different ways: (a) fitting a linear line over the entire power density spectrum and (b) using only the first half of the power density spectrum since the definition of long-range dependence holds for small frequencies only. The variance-time sequence was calculated up to aggregation level $m = 1000$ in steps of 10, yielding a sequence of length 100. We used either (a) the final 90 values or (b) the final 50 values to fit a linear regression line to the variance-time sequence.

6.1 Cycle Times

The linear fit (a) applied to the power density spectrum results to values of β_P which exceed the interval $[0; 2]$ (see column β_P(a) in Table 3) since the original slopes of the linear regression lines are smaller than -1. Fig. 7 (a) shows an example of this effect. From a theoretical point of view Eqn. (6.1) and (6.3) imply that the autocorrelation function and the variance of the sample mean tend to infinity. Nevertheless, "*in practice they converge, if only slowly* " (cf. Grasse et al. (1995)). If we use only the first half of the power density spectrum (linear fit (b)) to calculate the degree of persistence, we get approximately the same results, β_P being slightly smaller. This effect leads to the conjecture that the time series under consideration might not be weakly stationary. Further research should be devoted to this problem.

The picture turns out to be quite different if we consider the degree of persistence β_V estimated using variance-time plots. As Table 3 exhibits, there is both short- and long-range dependence. However, we have experienced that the degree of persistence β_P differs significantly if we change the data used for the linear fit (see Fig. 7 (b)). If we consider variant (b) of the variance-time plots, where only the second half of the data was used to fit a linear regression line, β_V generally increases except for trace `wein3-edd-cl`. In some cases the kind of dependence changes from long-range to short-range dependence, whereas for trace `wein3-edd-cl` we then obtain long-range dependence.

The R/S statistic (β_R) shows long-range dependence throughout all datasets. To obtain the plot and the slope of the regression line the time series was split in $K = 50$ parts. In this case one receives about 50 values of R/S for the 10 logarithmically equally spaced lags (see Fig. 7 (c)). Note that the slope of the regression line is between 0.5 and 1.0 as indicated by the reference lines.

Nevertheless, there are two very interesting effects to be observed from Table 3. First, the degree of persistence β_P is smaller than 1 for product 1 of the MIMAC_1 dataset and

[7] See Oppenheim and Schafer (1989) for more details.

Table 3: *Cycle times: degree of persistence β for datasets MIMAC$_1$ and WEIN$_3$*

trace	β_P		β_V		β_R
	(a)	(b)	(a)	(b)	
`mimac1-ccs-p1`	−0.42	−0.73	0.90	1.01	0.25
`mimac1-ccs-p2`	−0.33	−0.67	1.38	2.10	0.31
`mimac1-edd-p1`	−0.70	−0.88	0.55	0.62	0.26
`mimac1-edd-p2`	−0.52	−0.76	0.82	0.54	0.33
`mimac1-fifo-p1`	−0.42	−0.73	0.90	1.01	0.25
`mimac1-fifo-p2`	−0.33	−0.67	1.38	2.10	0.31
`mimac1-cr-p1`	−0.72	−0.89	0.78	0.85	0.28
`mimac1-cr-p2`	−0.56	−0.78	1.37	1.99	0.37
`wein3-edd-cl`	−0.51	−0.78	1.01	0.70	0.48
`wein3-edd-det`	−0.59	−0.83	0.36	0.43	0.07
`wein3-fifo-cl`	−0.66	−0.90	1.17	1.50	0.64
`wein3-fifo-det`	−0.66	−0.89	0.70	0.86	0.20
`wein3-srpt-cl`	−0.47	−0.76	1.12	1.12	0.54
`wein3-srpt-det`	—	—	—	—	—

larger than 1 for product 2 (implying long-range and short-range dependence, resp.). We do not have a general explanation for this result, but we suspect that the effect is due to the length of the traces. If we terminate the simulation of dataset MIMAC$_1$ after the completion of 10,000 lots of product 1, we get only about 5,000 lots of product 2 (see Table 2). Further research has to be done to investigate the impact of the trace lengths. We discuss this matter in Section 7.

As mentioned above, the CONWIP inventory control causes cycle times to be periodical with a period exactly corresponding to the number of lots allowed to enter the production facility. Thus, for the dataset WEIN$_3$, we obtain short-range dependence only if the CONWIP control is employed, whereas the production facility with a deterministic arrival stream of lots seems to be long-range dependent.

To conclude this discussion we once again point out that the results obtained by using the power density spectrum suggest that the time series are *not weakly* stationary. If weak stationarity is assumed a general statement on the long-range behavior of cycle times in semiconductor manufacturing is impossible. The degree of persistence depends strongly on the product and the manufacturing facility under investigation.

6.2 Interdeparture Times

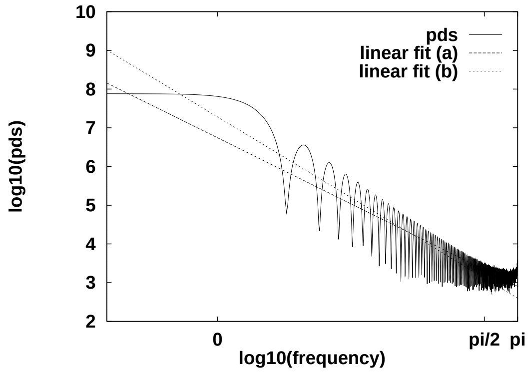
Fig. 8 (a) shows the power density spectrum of the interdeparture time series obtained for dataset `mimac1-edd-p1`. Remarkably, linear fits (a) and (b) yield slopes of slightly smaller than 0 resulting to degrees of persistence β_P in the range [0; 1) which indicates long-range dependence. The difference between the two linear fitting methods is rather small and does not change the time scale of dependence. This behavior is typical of all traces under consideration (cf. Table 4). Furthermore, there is generally no large difference among datasets MIMAC_1 and WEIN_3. In the case of dataset MIMAC_1 the results for both products are approximately the same, whereas for dataset WEIN_3 the behavior of interdeparture times of the manufacturing facility with deterministic arrival process and the system with CONWIP control are alike.

Table 4: *Interdeparture times: degree of persistence β for datasets $MIMAC_1$ and $WEIN_3$*

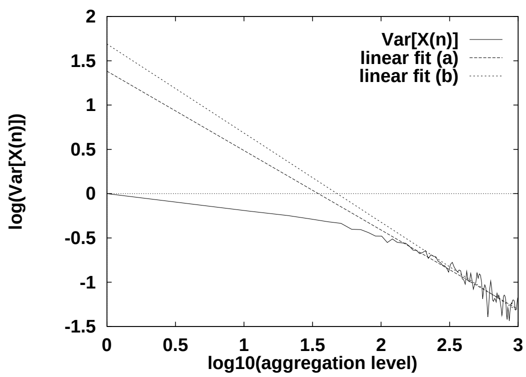
trace	β_P		β_V		β_R
	(a)	(b)	(a)	(b)	
`mimac1-ccs-p1`	0.87	0.73	1.75	1.47	1.24
`mimac1-ccs-p2`	0.92	0.78	1.95	2.08	1.25
`mimac1-edd-p1`	0.89	0.80	1.60	1.37	1.24
`mimac1-edd-p2`	0.95	0.82	2.34	3.24	—[8]
`mimac1-fifo-p1`	0.87	0.73	1.75	1.47	1.24
`mimac1-fifo-p2`	0.92	0.78	1.95	2.08	1.25
`mimac1-cr-p1`	0.89	0.80	1.86	2.03	1.22
`mimac1-cr-p2`	0.94	0.83	1.94	1.80	1.31
`wein3-edd-cl`	0.86	0.74	1.16	0.80	1.24
`wein3-edd-det`	0.86	0.71	1.73	1.76	1.25
`wein3-fifo-cl`	0.73	0.58	1.40	1.70	1.19
`wein3-fifo-det`	0.72	0.55	2.02	2.44	1.22
`wein3-srpt-cl`	0.86	0.74	1.32	1.41	1.27
`wein3-srpt-det`	—	—	—	—	—

In contrast to this observation the slopes of the regression lines of the variance-time plots are smaller than -1 (see Fig. 8 (b) for an example). However, these slopes yield degrees of persistence indicating short-range dependence. There are also some cases where β_V exceeds the upper limit of the interval [0; 2]. In this case, the variance of the sample mean decreases much faster than the reciprocal sample size.

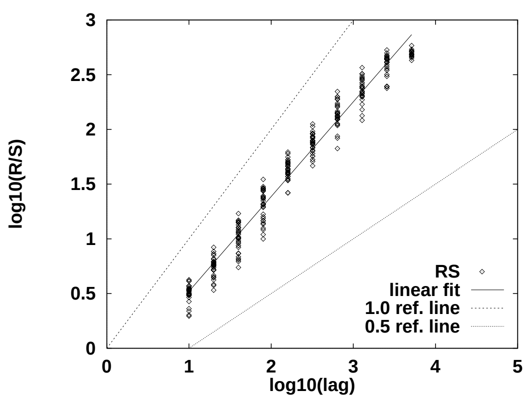
[8]Due to the shortness of the time series the linear regression failed to give a finite slope.



(a) Power density spectrum



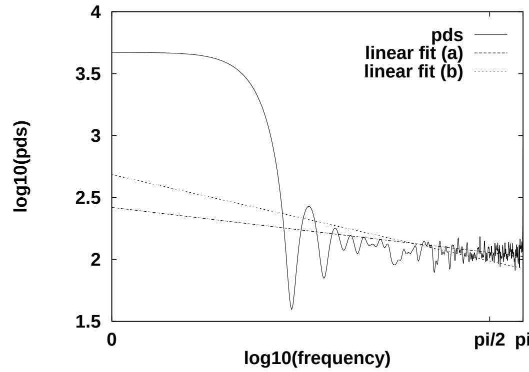
(b) Variance-time plot



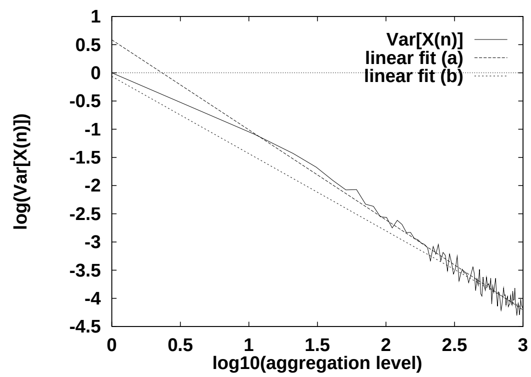
(c) RS plot[a]

Fig. 7: Cycle time of trace `mimac1-ccs-p1`

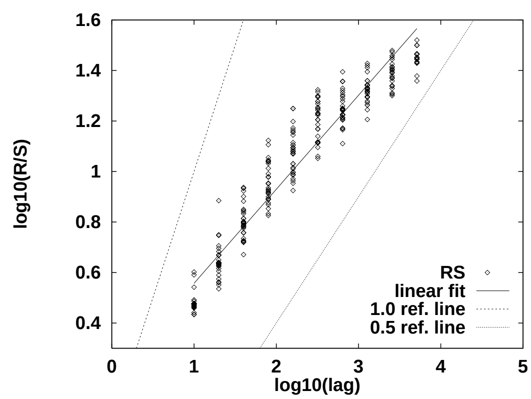
[a] The lower and upper reference lines correspond to slopes of 0.5 and 1.0, respectively.



(a) Power density spectrum



(b) Variance-time plot



(c) RS plot

Fig. 8: Interdeparture time of trace `mimac1-edd-p1`

The R/S analysis supports the results of the variance-time plots by indicating short-range dependence throughout all data sets. (See Fig. 8 (c) for an example. Note that the slope of the regression line is smaller than 0.5 as indicated by the reference lines.) Again we have chosen $K = 50$ and the 10 lags are logarithmically equally spaced.

Due to the contradicting results obtained from power density spectra on the one hand and variance-time plots and R/S analysis on the other hand further research has to be done to investigate the type of dependence.

7 Conclusion and Outlook

In this paper we investigated the distribution and the long-range behavior of cycle times and interdeparture times in semiconductor manufacturing. To perform statistical tests and to calculate autocorrelation functions and power density spectra we had to generate sufficiently long traces for cycle times and interdeparture times. The simulated time corresponds to more than five years of real operation time. To assure competitiveness on the world market the technological processes in semiconductor manufacturing have to be improved permanently. Furthermore, the equipment is continuously renewed. Therefore, it is quite unrealistic to run a semiconductor manufacturing facility for a long time without any changes. However, in modern telecommunication systems sufficient long traces can be generated by simulating these systems for only a few seconds of operation.

Up to now the feature of permanent mutation has been disregarded when analyzing time series obtained from semiconductor manufacturing systems. Nevertheless, these factors have to be taken into account since the evidence of the results obtained by the aforementioned statistical methods is strongly affected by the assumption of stationarity. However, it remains to explore whether time series generated for semiconductor manufacturing systems that are changed continuously are weakly stationary. Regarding the type long-range behavior, we conclude that the significance of the degree of persistence is limited since it is affected by the choice of the data used to compute the regression lines. Therefore, confidence intervals for the degree of persistence have to be calculated as proposed in the literature (see Grasse et al. (1995) and Beran et al. (1995)). In our opinion the major problem regarding the long-range behavior is that the degree of persistence is an asymptotic measure. In practice, however, the time series are of finite length and therefore the methods to estimate the degree of persistence may yield more or less correct results.

With respect to the distribution of cycle times and interdeparture times there is still some work to be done. Since the models of semiconductor manufacturing systems incorporate either deterministically or Erlang-2 distributed service times, it remains to explore the effect of higher moments of the service times distribution, i.e. the coefficient of variation. Nevertheless, it is amazing that the normal distribution is a very good approximation of the cycle time distribution and that at least for Wein's model the exponential distribution is in good accordance with the sample interdeparture time distribution. Furthermore, it is worth examining goodness-of-fit tests to investigate the quality of the distributions fitted to empirical data.

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