

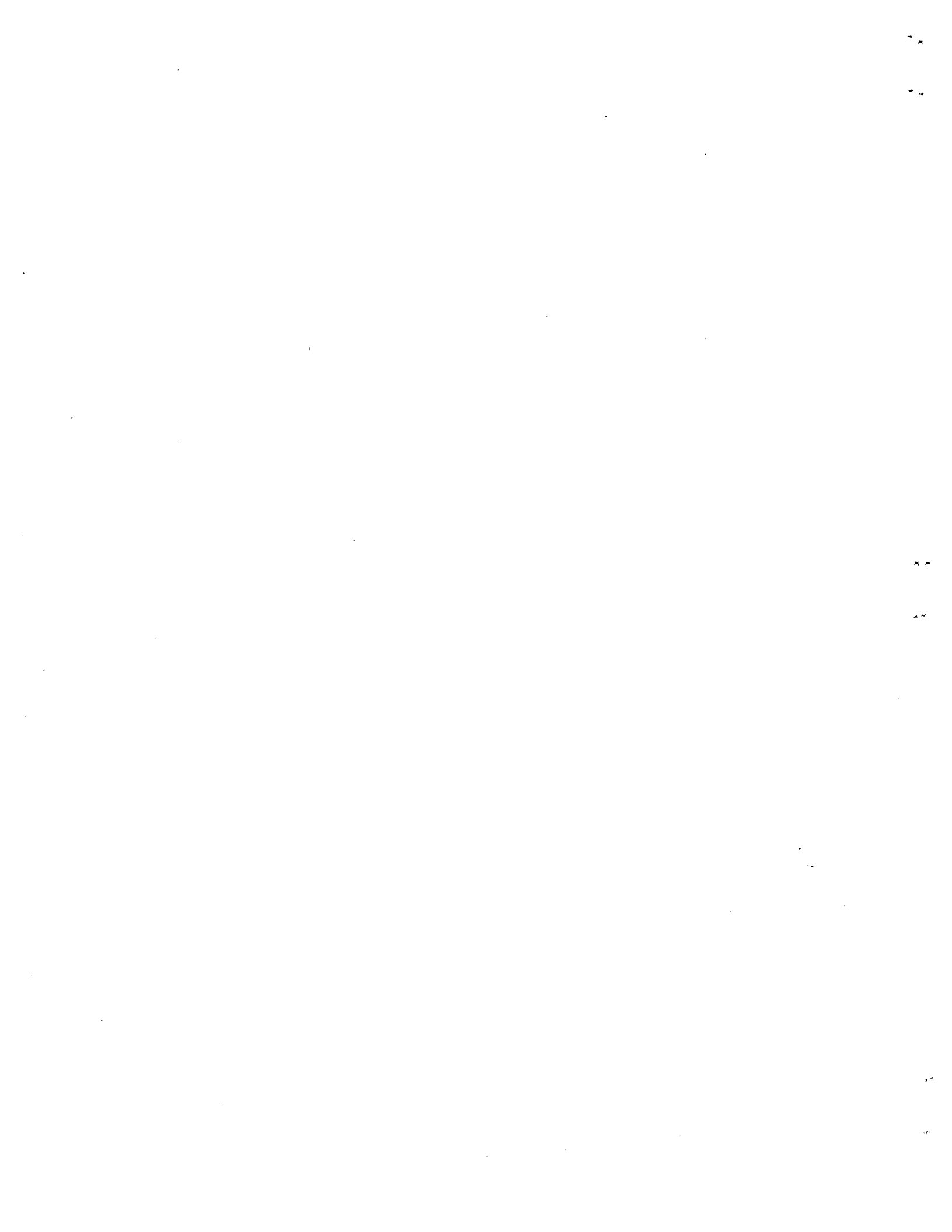
The Single Server Queue in Discrete Time-
Numerical Analysis I

by

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Abstract

This is the first of a sequence of papers dealing with the computational aspects of the transient behavior of queues in discrete time.

It is shown that for a substantial class of queues of practical interest, a wealth of numerical information may be obtained by relatively unsophisticated methods.

This approach should prove useful in the analysis of unstable queues which operate over a limited time interval, but is by no means limited to such queues.

Mathematically the service unit is modeled in terms of a multivariate Markov chain, whose particular structure is used in iterative computation. Many important queue features may then be derived from the n -step transition probabilities of this chain.



1. Introduction

The theory of queues, and more generally that of stochastic models, suffer from the insufficient development of the interface between structural-analytic results on one hand and directly applicable numerical methods on the other hand.

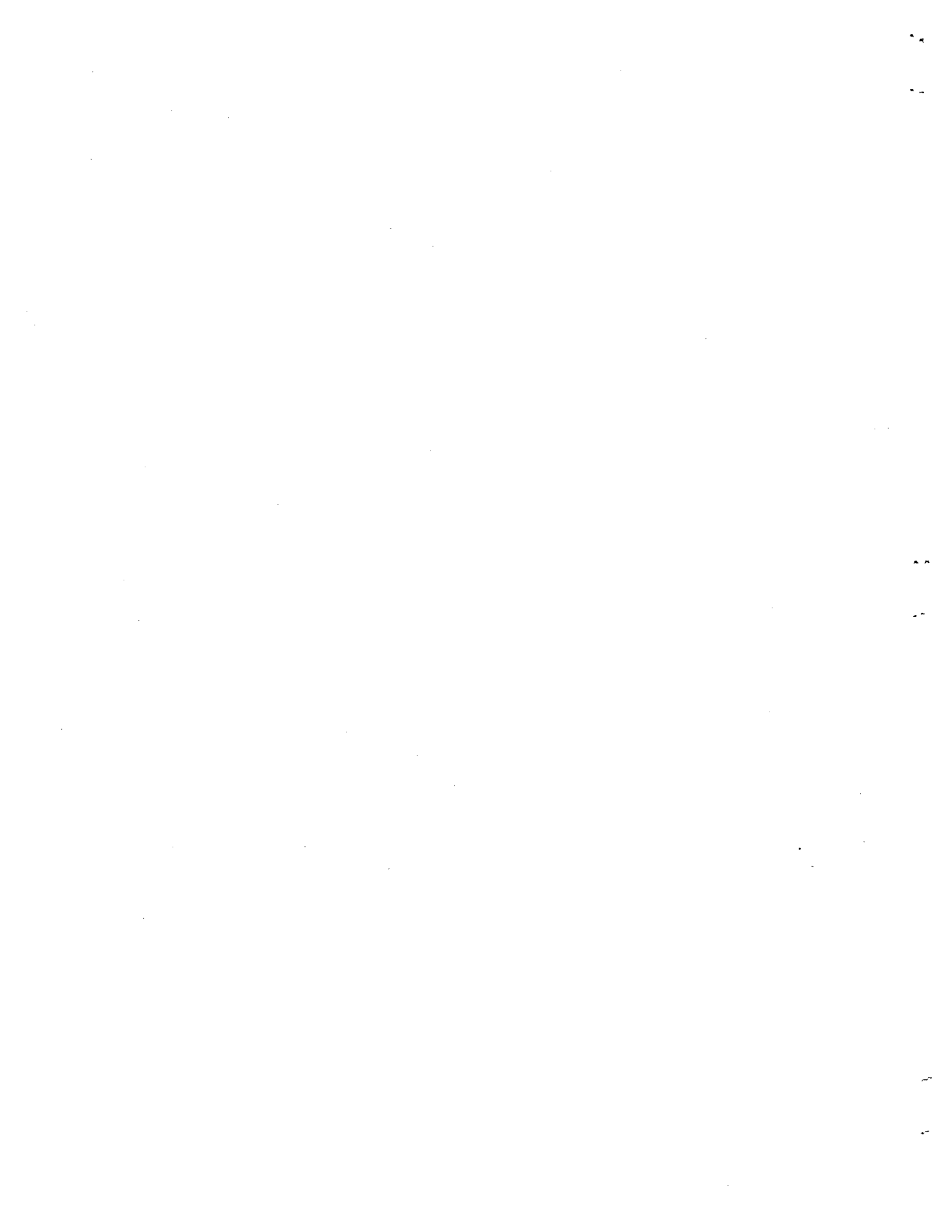
The practical queue analyst tends to use of the extensive theoretical work on service systems only those rare steady-state results, which are analytically simple. This is often done with little regard for the mathematical assumptions underlying these results. Moreover such results usually do not answer the real questions one is facing in the design or the improvement of a service facility.

While simulation techniques are widely used, their implementation requires a thorough understanding of the probability structure of the queue as well as very substantial computing funds. In most instances of simulation studies familiar to this author, the structure of the queue was incorrectly or insufficiently used and exorbitant computing times were reported. One recognizes that simulation is often the only resort in studying a complex system; however, for those models whose structure is mathematically well understood, it is desirable that algorithms making use of the existing theory be developed.

Before we consider one such model in detail, let us discuss some of the difficulties and the desiderata related to such queue algorithms.

a. The finiteness of the waitingline

In reality, unbounded queues do not exist. The unbounded queue is strictly a mathematically convenient abstraction. By removing one "boundary" of the queuelength process one obtains simpler stochastic processes. It further becomes possible to give an elegant treatment of



the intuitive quality of stability of the queue.

In practical situations, there is either a finite waitingroom, usually with loss of those customers who find the waiting space full; or else the buildup of the queue beyond a certain limit creates utter chaos and the object of the study is precisely the design of a sufficiently fast service unit or a sufficiently large waitingroom to make this a very rare event.

Throughout this paper we shall limit our attention to bounded queues. In the numerical examples considered the largest value of the maximum queue length L_1 was at most one hundred.

b. Transient versus Steady-state behavior

There are very few results on the transient behavior of queues, which are analytically explicit. Even the latter are nearly all ill-suited for direct numerical analysis. An interesting discussion of a simple transient queue and the difficulties of its computational analysis may be found in E. L. Leese and D. W. Boyd [1].

The steady-state probabilities of some simple queues are the only ones available in books written for the applied worker. Their relevance to the concrete problems is often limited; they clearly have no bearing whatsoever on the solution of unstable queues. Moreover, since the limiting process by which they are obtained has an averaging (or mixing) property, such results convey no information on the fluctuations of the queuelength and the waiting times. Ignoring such fluctuations in a design may have catastrophic results.

In recent years the study of weak convergence properties of queueing processes and the resulting diffusion approximations have



shed a new light on service systems of which the macroscopic time-behavior rather than the short-range fluctuations is the most important feature. This promising approach is mathematically fairly sophisticated and has not yet received sufficient investigation from the viewpoint of computation.

Our concern in this paper is in a sense with the small-scale service system whose short range behavior is important. Therefore the models studied here are unlikely to be well approximated by a diffusion process. Nevertheless a comparison of both the direct solution and a diffusion approximation method with regards to accuracy and computing time is of interest, but will not be undertaken here.

c. Continuous versus discrete parameter models

It is known that finite $M|G|1$ and $GI|M|1$ queues may be conveniently studied in relation to an imbedded Markov renewal process with a finite number of states. The transient behavior of such queues, as well of many related ones, may be computed in principle in terms of the successive matrix-convolution products of the transition matrix of this imbedded process. If a queue with a waitingroom of size L_1 is investigated, each such a matrix-convolution product may require as many as $(L_1 + 1)^2$ evaluations of the convolution product of two functions. To perform this operation accurately is time-consuming, so that the computer implementation of this analysis is likely to result in considerable computing time.

In an earlier study of the single server queue in discrete time, S. Dafermos and the author [2] argued at length for the advantages of analyzing many queues in terms of a discrete time parameter. These



arguments will not be repeated here. From the viewpoint of numerical analysis the most obvious advantages of a discrete time model are:

- a. The ease with which one or more supplementary variables may be introduced so as to imbed the queueing process in a multivariate Markov process.
- b. The fact that convolution products of sequences of numbers may be computed with much greater ease than those of functions of a real variable may be evaluated accurately.

In most cases of practical interest one may discern an elementary unit of time natural to the particular queue. Many queueing analysts nevertheless insists on thinking of discrete models as approximations to continuous ones. This insistence which may usually be traced to the prevailing attitude in applied mathematics before the advent of the computer, has some appeal for its mathematical elegance, particularly where methods of analysis may be used. From a computational viewpoint, continuous parameter models are often substantially more delicate to analyze and this without yielding additional insight into the real process which is being modeled.

d. Parametric versus general distributions

The insistence on specific parametric families of probability distributions (such as the gamma family) in stochastic models is also largely a holdover from the pre-computer era. Where a parametric assumption has an important structural consequence (e.g. the memory-less property of the negative exponential distribution) one should be very aware of this. However in cases where the parametric assumption yields only marginal simplifications, both the theoretical analysis and the computational methods should ignore it altogether. As a case in point,



the $M|E_k|1$ queue for $k > 1$ is only in some details easier to discuss than the $M|G|1$ queue. There is therefore little point in a special numerical method for the former which does not also include the latter.

In the sequel of this discussion, we shall therefore only stress the structural assumptions that are needed. Such items as service time distributions will be as general as possible.

In most specific models one may assume without loss of generality that service times and related random variables are bounded lattice random variables. This assumption, essential to our approach, is also the one which limits its range of applicability most. Our approach is not well suited to queues in which both very short and very long jobs may arrive. Different methods of numerical analysis are needed for these. It is commonly so that a given numerical method is well suited for a certain range of problems, but fails for similar problems outside this range. The assumptions which limit the applicability of the present model are discussed in the appropriate places in the sequel.



2. The Assumptions of the Model

a. The arrivals

We consider a single server queue in discrete time with a maximum queue length L_1 (*). The elementary time interval is chosen as our time unit. We assume that the numbers of arrivals during the successive unit time intervals are independent, identically distributed random variables. Furthermore $p_\nu, \nu = 0, 1, \dots, K$ is the probability that ν customers join the queue during a given unit time interval. ($p_0 + p_1 + \dots + p_K = 1$). In this discussion and in the FORTRAN program we shall insist that $1 \leq K < L_1$. The restriction $K < L_1$ is not essential and is usually satisfied in practice. Its removal requires minor modifications in the analysis and in the program.

In this discussion we assume that the p_ν are independent of time, but with minor obvious changes the recurrence relations are valid also for queues in which the arrival probabilities vary with time.

b. The service times

We assume that the service times of the successive customers are independent, identically distributed, (integer valued) random variables with values in the set $\{1, 2, \dots, L_2\}$. We denote by $r_\nu, \nu = 1, \dots, L_2$, the probability that a customer requires ν units of service time. The values $L_1 = 100$ and $L_2 = 100$ appear to be practical upper limits to the computer implementation of the method suggested here.

Our assumption that every customer requires at least one unit of service time may easily be removed, but is satisfied in most all concrete

(*) For easy reference, we are using similar, though not identical, notation in the theoretical discussion and in our FORTRAN program.

applications. It suffices to introduce a quantity r_0 that a service time is equal to zero and to modify the recurrence relations accordingly.

As pointed out below, it is also easy to modify our analysis to include the case where the service time density depends on the time at which the service is initiated.

c. The queue discipline

Except in discussing the waitingtimes, the order of service is immaterial. The waitingtimes will be discussed for the first-come, first-served discipline.

To settle the issue of simultaneous arrivals and beginning we assume that all arrivals in $[n-1, n)$ are added to the queue at time $n-0$. If a service starts at time n and requires v units of time, we shall consider it to start at time n and to end at time $n+v-0$.

Only as many arrivals as to maintain the queuelength less than or equal to L_1 are accepted. Any excessive customers are assumed to be permanently lost.

d. The initial conditions

We assume that at time $n = 0$, there are i_0 customers present. $0 \leq i_0 \leq L_1$. If $i_0 \geq 1$, the customer in service at time $n = 0$ requires j_0 , $1 \leq j_0 \leq L_2$ additional units of service time. We make the convention that if $i_0 = 0$, then $j_0 = 0$ and conversely.



3. The Markov Chain

We denote by X_n the queue length at time n and by Y_n the number of additional units of service time required by the customer in service at time n . We make the convention that $X_n = 0$ if and only if $Y_n = 0$.

It follows readily from our assumptions that the bivariate sequence $\{(X_n, Y_n), n \geq 0\}$ is a Markov chain with state space consisting of the point $(0,0)$ and all points (i,j) , $i = 1, \dots, L_1$; $j = 1, \dots, L_2$, and with initial state (i_0, j_0) .

The transition probability matrix of the Markov chain is easily written down. We shall not do so since the recurrence relations make judicious use of its special structure.

For fixed i_0 and j_0 , we define the conditional probabilities:

$$(1) \quad P_n(i, j) = P\{X_n = i, Y_n = j | X_0 = i_0, Y_0 = j_0\}$$

The probabilities $P_n(i, j)$ satisfy the following recurrence relations in n for all $n \geq 0$.

$$(2) \quad (a) \quad P_{n+1}(0, 0) = p_0 [P_n(0, 0) + P_n(1, 1)]$$

$$(b) \quad P_{n+1}(i, j) = p_0 P_n(i, j+1) + \sum_{v=1}^{i-1} p_{i-v} P_n(v, j+1)$$

$$+ r_j \{p_i P_n(0, 0) + p_0 P_n(i+1, 1) +$$

$$\sum_{v=1}^i p_{i-v+1} P_n(v, 1)\}$$

for $i = 1, \dots, K$ and $j = 1, \dots, L_2 - 1$.



$$(c) \quad P_{n+1}(i,j) = p_0 P_n(i,j+1) + \sum_{v=i-K}^{i-1} p_{i-v} P_n(v,j+1) \\ + r_j \{ p_0 P_n(i+1,1) + \sum_{v=i-K+1}^i p_{i-v+1} P_n(v,1) \}$$

for $i = K+1, \dots, L_1 - 1$ and $j = 1, \dots, L_2 - 1$.

$$(d) \quad P_{n+1}(L_1, j) = P_n(L_1, j+1) + \sum_{v=1}^K (1 - \sum_{k=0}^{v-1} p_k) P_n(L_1 - v, j+1) \\ + r_j \{ \sum_{v=1}^K (1 - \sum_{k=0}^{v-1} p_k) P_n(L_1 - v + 1, 1) \}$$

for $j = 1, \dots, L_2 - 1$.

$$(e) \quad P_{n+1}(i, L_2) = r_{L_2} \{ p_i P_n(0,0) + p_0 P_n(i+1,1) \\ + \sum_{v=1}^i p_{i-v+1} P_n(v,1) \}$$

for $i = 1, \dots, K$.

$$(f) \quad P_{n+1}(i, L_2) = r_{L_2} \{ p_0 P_n(i+1,1) + \sum_{v=i-K+1}^i p_{i-v+1} P_n(v,1) \}$$

for $i = K+1, \dots, L_1 - 1$.

$$(g) \quad P_{n+1}(L_1, L_2) = r_{L_2} \{ \sum_{v=1}^K (1 - \sum_{k=0}^{v-1} p_k) P_n(L_1 - v + 1, 1) \}$$

The recurrence is initialized by setting $P_0(i_0, j_0) = 1$ and $P_0(i, j) = 0$ for all other pairs (i, j) . If the distribution of the random variables X_0, Y_0 is given rather than exact values, this simply



amounts to a different definition of the initial array $P_0(i,j)$.

We note that the expressions in curly brackets in the formulas (2 b-g) depend on the first index only. This term corresponds to the case where the instant $n+1$ is the beginning of a new service.

This simplifying feature is used in the organization of the computer program. If the service time distribution depends on the instant of initiation of a service, only the factor r_j in the recurrence relations are affected.

The analogous, but simpler recurrence relations for the unbounded queue were examined analytically by Dafermos and Neuts [2].

The recurrence relations (2) are well suited for iterative computation. The author organized his computation so as to have at the n -th iteration only the quantities $P_n(o,o)$ and $P_n(i,j)$, $i = 1, \dots, L_1$; $j = 1, \dots, L_2$ in memory.

The quantities $P_n(o,o)$ and $P_n(i,j)$, $i = 1, \dots, L_1$; $j = 1, \dots, L_2$ make up the (conditional) joint density of the queuelength X_n and the residual service time Y_n at time n . This joint density is not in itself of great practical use; however from it the distribution (or the density) of the queuelength and the waitingtime at time n can be easily obtained. These "derived" queue features are considered next.

4. Derived Queue Features

a. The Queue Length Distribution

The probability that the queue length at time n is zero, is given by $P_n(0,0)$. For $i = 1, \dots, L_1$, we have:

$$(3) \quad P\{X_n = i | X_0 = i_0, Y = j_0\} = \sum_{j=1}^{L_2} P_n(i,j).$$

Moments of the queue length at time n may be obtained routinely.

b. The Waitingtime distribution

The waitingtime at time n is defined to be zero if and only if $X_n = Y_n = 0$. For $X_n = 1, Y_n = j$, the waitingtime equals j . For $X_n > 1, Y_n = j$ the waitingtime is the sum of j and $X_n - 1$ independent service times. The waitingtime is therefore an integer valued random variable with value between 0 and $L_1 L_2$.

The density $WT_\nu, \nu = 0, \dots, L_1 L_2$ is obtained as follows. Clearly $WT_0 = P_n(0,0)$. The quantities WT_ν for $1 \leq \nu \leq L_1 L_2$ were obtained by evaluating the following convolution-polynomial.

Let $WT(\cdot)$ denote the density $\{WT_\nu, 1 \leq \nu \leq L_1 L_2\}$ and let $R(\cdot)$ be the service time density $\{r_j, 1 \leq j \leq L_2\}$. Finally let $P_n(i, \cdot)$ be the density $\{P_n(i,j), 1 \leq j \leq L_2\}$ for $i = 1, \dots, L_1$, then $WT(\cdot)$ is given by:

$$(4) \quad WT(\cdot) = P_n(1, \cdot) + P_n(2, \cdot) * R(\cdot) + \dots + P_n(L_1, \cdot) * R^{(L_1-1)}(\cdot)$$

where $R^{(k)}(\cdot)$ is the k -fold convolution of $R(\cdot)$ with itself.

The density $WT(\cdot)$ may be computed for each n by one of two procedures.

Either the convolutions $R^{(k)}(\cdot), k = 1, \dots, L_1 - 1$ may be computed

once and for all and only the convolutions with the arrays $P_n(i, \cdot)$ need to be computed at those time points n at which the density of the waitingtime is desired. This procedure results in a substantial increase in the central memory storage required by the program.

Alternatively, the density $WT(\cdot)$ may be computed by a convolution analogue of Horner's algorithm for the numerical evaluation of ordinary polynomials. This procedure consists in the successive evaluation of the sequences

$$(5) \quad WT^{(1)}(\cdot) = P_n(L_1, \cdot)$$

$$WT^{(k)}(\cdot) = WT^{(k-1)}(\cdot) * R(\cdot) + P_n(L_1 - k + 1, \cdot),$$

for $k = 2, \dots, L_1$. The sequence $WT^{(L_1)}(\cdot)$ is the desired sequence $WT(\cdot)$.

The latter procedure does not result in the use of core storage for intermediate quantities. For purposes of comparison and as a guard against rounding errors, both procedures were programmed and tested on large scale examples. The Horner convolution algorithm performed slightly better in all examples and no evidence of rounding errors were found. Its much smaller core requirements make it the more efficient of the two procedures.

Moments of the waitingtime at time n may be routinely computed.

5. Report on Computational Trials

A FORTRAN IV program was written by the author and tested on a variety of cases on the CDC 6500 at Purdue University. Even in the largest examples no evidence of rounding errors was found, even though all probabilities were printed to five decimal places and all computations were performed in single precision.

The full output consisted, in addition to the summary of the input data, of the following.

- (a) the mean of the queuelength
- (b) the cumulative distribution of the queuelength
- (c) the mean waitingtime
- (d) the cumulative distribution of the waitingtime
- (e) the joint density of the queuelength X_n and the residual service time Y_n

All these for all values of n up to some upper value to be specified.

Since the full output is very voluminous and contains much more information than may be needed in the analysis of a given queue, options were written into the program which permit the deletion of the items (c), (d) or (e) from the printed output. A further option was created which permits the computation of the waitingtime distribution to be performed at certain specified time points only.

No systematic study of the processing time was made. For smaller examples the computation times were generally below 10 seconds. The following computation times for some larger examples are given for purposes of illustration only.

$L_1 = 30$	(max. queue length)
$L_2 = 6$	(max. duration of one service)
$K = 2$	(max. number of arrivals)
$NNN = 250$	(number of time points computed)

In the following CP is the processing time in seconds and LL is the number of lines of output, including the program listing.

- a. full printed output

CP = 215.159 LL = 19265

- b. the queuelength and waitingtime distributions only.

CP = 157.860 LL = 10656

- c. the queuelength distribution for all time points and the waitingtime distribution only for time points which are multiples of twenty-five.

CP = 23.763 LL = 4916

6. Conclusions

By the use of only the most elementary structural properties, we have shown that the transient behavior of a substantial class of single server queues may be analyzed numerically. The approach presented here should prove itself to be useful in studying the build-up of unstable queues and the fluctuations of queues at traffic lights, highway merging ramps, service counters in public offices and retail outlets and many others.

This approach is well suited for many queueing processes which do not lend themselves to diffusion approximation methods. The amount of computing time used in typical examples also indicates a very substantial saving over that needed to analyze similar models by simulation methods.

Further work is currently being done to extend the applicability of this approach to longer queues and to much longer time periods. This extension however requires the use of mathematically more sophisticated properties of the queueing process.

10

Bibliography

- [1] Leese, E. L. and Boyd, D. W.

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with Variable Arrival Rates

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Appendix

This appendix contains a listing of the FORTRAN IV program written by the author to compute the time-dependent features of the discrete time queue.

A sample output for a small scale problem is also included. This example analyzes a queue with 20 spaces for 20 time points. The computing time for this example was approximately 6 seconds of which 2.2 seconds were used for compilation. The distribution of the queue length is printed for all time points and the distribution of the waiting time is computed and printed for every fourth time point.

PROGRAM QUEUE(INPUT,OUTPUT,TAPES=INPUT)

C THIS PROGRAM WAS DEVELOPED BY MARCEL F. NEUTS - DEPART-
C MENT OF STATISTICS - PURDUE UNIVERSITY - WEST LAFAYETTE -
C INDIANA. OCTOBER 1971.

C THIS PROGRAM COMPUTES THE TIME DEPENDENT FEATURES OF A
C SINGLE SERVER DISCRETE TIME QUEUE WITH A FINITE WAITING-
C ROOM.
C WITH THE PRESENT DIMENSION STATEMENTS A WAITINGROOM OF
C SIZE UP TO ONE HUNDRED MAY BE STUDIED. THE DENSITY OF THE
C SERVICE TIME CAN BE CONCENTRATED ON UP TO THIRTY POINTS.

C THE FULL OUTPUT OF THIS PROGRAM INCLUDES THE FOLLOWING:

- C 1. THE MEAN QUEUE LENGTH AT TIME N.
- C 2. THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N.
- C 3. THE MEAN WAITINGTIME AT TIME N.
- C 4. THE DISTRIBUTION OF THE WAITINGTIME AT TIME N.
- C 5. THE JOINT DENSITY OF THE QUEUE LENGTH AND THE RESIDUAL
C SERVICE TIME AT TIME N.

C ALL THESE ARE COMPUTED FOR N UP TO A SPECIFIED VALUE NNN.

C BY USE OF THE VARIOUS OPTIONS, LISTED BELOW, SOME OF THESE
C FEATURES MAY BE DELETED FROM THE PRINTED OUTPUT.

C THE THEORETICAL DEVELOPMENT OF THE DISCRETE TIME QUEUE
C WITH AN UNBOUNDED QUEUE LENGTH MAY BE FOUND IN:

- C * STELLA C. DAFERMOS AND MARCEL F. NEUTS
- C * A SINGLE SERVER QUEUE IN DISCRETE TIME *
- C * CAHIERS DU CENTRE DE RECHERCHE OPERATIONNELLE - 1971.

C THE FOLLOWING IS A COMPANION PAPER TO THE PRESENT PROGRAM:

- C * MARCEL F. NEUTS
- C * THE SINGLE SERVER QUEUE IN DISCRETE TIME - NUMERICAL
C * ANALYSIS *
- C * PURDUE MIMEOGRAPH SERIES - DEPT. OF STATISTICS.
- C * PURDUE UNIVERSITY - WEST LAFAYETTE - IN - 47907

```

DIMENSION P(100),R(30),PP(100,30),X(100),Y(100,30)
DIMENSION Z(100),W(100),WT(3000)
INTEGER OPT(10)

```

***** THE OPTIONS *****

C IN ORDER TO PRINT OUT THE JOINT DENSITY OF THE QUEUE LENGTH
C AND THE RESIDUAL SERVICE TIME, SET OPT(1)=1 - OTHERWISE
C SET OPT(1)=0

```
READ(5,999) OPT(1)
```

C IN ORDER TO PRINT OUT THE DISTRIBUTION OF THE WAITING-
C TIME, SET OPT(2)=1 - OTHERWISE SET OPT(2)=0

```
READ(5,999) OPT(2)
```


C
 C THE USER MAY WISH TO COMPUTE AND PRINT THE DISTRIBUTION OF
 C THE WAITINGTIME ONLY AT TIME POINTS WHICH ARE A MULTIPLE OF
 C A CONSTANT NR. THIS TO SAVE ON PROCESSING TIME AND ON THE
 C NUMBER OF LINES OF OUTPUT. IN THIS CASE THE IDENTIFIER
 C OPT(3) SHOULD BE SET EQUAL TO ONE AND THE NUMBER NR SHOULD BE
 C GIVEN. OPT(3) AND NR ARE TO BE GIVEN IN AN I1,I2 FORMAT.

C
 READ(5,997) OPT(3),NR
 XNR=NR
 KTEST1=OPT(1)
 KTEST2=OPT(2)
 KTEST3=OPT(3)
 IF(KTEST3.EQ.1) KTEST2=0
 IF(KTEST3.EQ.0) KTEST4=0

C
 C ***** T H E D A T A *****

C
 C L1 IS THE SIZE OF THE WAITINGROOM. L1 IS LT. 101

C
 READ(5,1001) L1

C
 C L2 IS THE NUMBER OF POINTS ON WHICH THE DENSITY OF THE
 C SERVICE TIME IS CONCENTRATED. L2 IS LT. 31

C
 READ(5,1001) L2

C
 C K IS THE MAXIMUM NUMBER OF ARRIVALS PER UNIT OF TIME.
 C K SHOULD BE AT LEAST ONE AND STRICTLY LESS THAN L1.

C
 READ(5,1001) K

C
 C R(J) IS THE PROBABILITY THAT A SERVICE TIME LASTS FOR J
 C UNITS OF TIME.
 C ONE SHOULD VERIFY BEFOREHAND THAT THE SUM R(1)+...R(L2)
 C IS EQUAL TO ONE.

C
 READ(5,1002) (R(J),J=1,L2)

C
 C P(J) IS THE PROBABILITY THAT J CUSTOMERS JOIN THE QUEUE
 C DURING A UNIT OF TIME.
 C THE INDEX J RUNS FROM ONE TO K.

C
 READ(5,1002) (P(J),J=1,K)

C
 C P0 IS THE PROBABILITY THAT NO CUSTOMERS ARRIVE DURING A
 C UNIT OF TIME.
 C ONE SHOULD VERIFY BEFOREHAND THAT P0 + P(1) +...+P(K)
 C IS EQUAL TO ONE.

C
 READ(5,1003) P0

C
 C I0 IS THE INITIAL QUEUE LENGTH.
 C J0 IS THE INITIAL RESIDUAL SERVICE TIME.
 C IF I0=0, THEN J0=0 AND CONVERSELY.
 C I0 SHOULD NOT EXCEED L1.
 C J0 SHOULD NOT EXCEED L2.

C



```

READ(5,1001) IO
READ(5,1001) JO

```

C

```

C NNN IS THE MAXIMUM TIME POINT FOR WHICH THE QUEUE
C FEATURES ARE COMPUTED. NNN SHOULD BE AT LEAST ONE AND
C AT MOST 9999. NOTE HOWEVER THAT THE PROCESSING TIME
C AND THE NUMBER OF LINES OF OUTPUT GROW PROPORTIONATELY TO
C THE VALUE OF NNN.

```

C

```

READ(5,1004) NNN
IF(IO.EQ.0.AND.JO.EQ.0)GOTO 2001
PP(IO,JO)=1.
GOTO 2002

```

2001 P00=1.

2002 N=0

X11=P0

DO 21 I=1,K

X1=I

X11=X11+P(I)

X1=X1+X1*P(I)

21 CONTINUE

DO 22 J=1,L2

XJ=J

X11=X11+R(J)

X2=X2+XJ*R(J)

22 CONTINUE

X11=X11-2.

X11=ABS(X11)

PRINT 1014

PRINT 1022,K,L2,L1

N1=0

PRINT 1007,N1,P0,(J,P(J),J=1,K)

PRINT 1012

PRINT 1010,(J,R(J),J=1,L2)

PRINT 1012

PRINT 1008,IO,JO

PRINT 1012

PRINT 1009,NNN

PRINT 1012

PRINT 1013,x1,x2

PRINT 1006

C

C

C

```

***** D I A G N O S T I C S *****

```

IF(L1.LE.K) GOTO 2005

IF(IO.EQ.0.AND.JO.NE.0.OR.IO.NE.0.AND.JO.EQ.0)GOTO 2005

IF(X11.GT..00000001) GOTO 2005

IF(KTEST3.EQ.1.AND.NR.LT.2) GOTO 2005

C

C

C

L11=L1-1

L21=L2-1

L22=L2+1

M1=L1*L2

K1=K+1

DO 13 I=1,L1

Y(I,L2)=0.0



```

13 W(1)=1.-P0
   IF(K.EQ.1)GOTO 2003
   DO 20 I=2,K
   W(I)=W(I-1)-P(I-1)
20 CONTINUE
C
C AT THIS STAGE THE INPUT DATA HAVE BEEN READ IN, THE
C PP-ARRAY HAS BEEN INITIALIZED AND THE INPUT DATA HAVE
C BEEN PRINTED OUT AND SUBJECTED TO SOME RUDIMENTARY
C DIAGNOSTIC TESTS. THE NEXT LINE STARTS THE MAIN LOOP
C WHICH IS REPEATED NNN TIMES.
C
C ***** THE MAIN LOOP *****
C
2003 N=N+1
   IF(N.GT.NNN)STOP
C
C THIS PORTION OF THE PROGRAM COMPUTES THE NEW PP-ARRAY.
C PP(I,J) IS THE PROBABILITY THAT AT THE TIME CONSIDERED
C THERE ARE I CUSTOMERS IN THE SYSTEM AND THE RESIDUAL
C SERVICE TIME OF THE CUSTOMER BEING SERVED IS J.
C THIS IS FOR I BETWEEN ONE AND L1, FOR J BETWEEN ONE AND
C L2. THE IDENTIFIER P00 CONTAINS THE PROBABILITY THAT THE
C QUEUE IS EMPTY.
C
   PRINT 1000
   PRINT 1017,N
   PRINT 1012
   X00=P00+PP(1,1)
   DO 1 I=1,K
   X(I)=P(I)*P00+P0*PP(I+1,1)
   II=I-1
   DO 3 NU=1,I
   X(I)=X(I)+P(I+1-NU)*PP(NU,1)
3   CONTINUE
4   DO 2 J=1,L21
   Y(I,J)=P0*PP(I,J+1)
   IF(I.EQ.1)GOTO 51
   DO 5 NV=1,II
   Y(I,J)=Y(I,J)+P(I-NV)*PP(NV,J+1)
5   CONTINUE
51  CONTINUE
2   CONTINUE
1   CONTINUE
   DO 6 I=K1,L11
   NU1=I-K
   NU2=NU1+1
   II=I-1
   X(I)=P0*PP(I+1,1)
   DO 7 NU=NU2,I
   X(I)=X(I)+P(I+1-NU)*PP(NU,1)
7   CONTINUE
   DO 9 J=1,L21
   Y(I,J)=P0*PP(I,J+1)
   DO 8 NV=NU1,II
   Y(I,J)=Y(I,J)+P(I-NV)*PP(NV,J+1)
8   CONTINUE
9   CONTINUE

```



```

6 CONTINUE
  X(L1)=0.0
  DO 10 NU=1,K
    X(L1)=X(L1)+W(NU)*PP(L1+1-NU,1)
10 CONTINUE
  DO 11 J=1,L21
    Y(L1,J)=PP(L1,J+1)
  DO 12 NU=1,K
    Y(L1,J)=Y(L1,J)+W(NU)*PP(L1-NU,J+1)
12 CONTINUE
11 CONTINUE
  P00=P0*X00

```

```

C
C Z(I) CONTAINS FIRST THE DENSITY AND NEXT THE DISTRIBUTION
C OF THE QUEUE LENGTH AT THE TIME POINT CONSIDERED.
C XMN CONTAINS THE MEAN QUEUE LENGTH AT THE TIME POINT
C CONSIDERED.
C

```

```

  XMN=1.-P00
  DO 14 I=1,L1
    Z(I)=0.0
    DO 15 J=1,L2
      PP(I,J)=Y(I,J)+R(J)*X(I)
      Z(I)=Z(I)+PP(I,J)
15 CONTINUE
14 CONTINUE
  Z(1)=Z(1)+P00
  XMN=XMN+1.-Z(1)
  DO 18 I=2,L1
    Z(I)=Z(I)+Z(I-1)
    XMN=XMN+1.-Z(I)
18 CONTINUE
  IF(KTEST3.EQ.0) GOTO 2008
  XN=N
  U1=AMOD(XN,XNR)
  IF(U1.LT.0.9) KTEST4=1
  IF(U1.GT.0.9) KTEST4=0
  IF(KTEST4.EQ.1) GOTO 2010
  IF(KTEST4.EQ.0) GOTO 2009

```

```

2008 CONTINUE
C
C THIS PORTION OF THE PROGRAM COMPUTES THE DISTRIBUTION OF
C THE VIRTUAL WAITINGTIME AT TIME N. THE ALGORITHM IS AN
C ANALOGUE OF HORNER'S METHOD FOR THE EVALUATION OF ORDINARY
C POLYNOMIALS, BUT ADAPTED HERE TO CONVOLUTION PRODUCTS.
C

```

```

  IF(KTEST2.EQ.0) GOTO 2006
2010 CONTINUE
  DO 32 J=1,L2
    WT(J)=PP(L1,J)
32 CONTINUE
  DO 33 J=L22,M1
    WT(J)=0.0
33 CONTINUE
  MN1=1
  MN3=2
  MN4=L2
  DO 34 JX=1,L11

```



```

JX1=L1-JX
MN2=MN4
MN4=MN2+L2
MN5=MN4+2
DO 35 J=2,MN4
JR=MN5-J
WT(JR)=0.0
MN6=MAX0(1,JR-MN2)
MN7=MIN0(L2,JR-1)
DO 35 N(J)=MN6,MN7
WT(JR)=WT(JR)+N(NU)*WT(JR-MN1)
15 CONTINUE
WT(1)=0.0
DO 37 JJ=1,L2
WT(JJ)=WT(JJ)+PP(JX1,JJ)
37 CONTINUE
34 CONTINUE
WT(1)=P00+WT(1)
ZMN=2.-P00-WT(1)
DO 36 J=2,M1
WT(J)=WT(J)+WT(J-1)
ZMN=ZMN+1.-WT(J)
36 CONTINUE
2006 CONTINUE

```

C
C THE PRINT STATEMENTS FOR THE REQUIRED OUTPUT.

C

```

2009 PRINT 1016,N,XMN
PRINT 1012
PRINT 1018,N
PRINT 1012
PRINT 1011,N1,P00,(I,Z(I),I=1,L1)
PRINT 1012
IF(KTEST2.EQ.0.AND.KTEST4.EQ.0) GOTO 2007
PRINT 1021,N,ZMN
PRINT 1012
PRINT 1020,N,N1,P00,(J,WT(J),J=1,M1)
2007 CONTINUE
IF(KTEST1.EQ.0) GOTO 2004
PRINT 1012
PRINT 1019,N
PRINT 1015,P00
PRINT 1012
DO 17 I=1,L1
PRINT 1005,I,(PP(I,J),J=1,L2)
17 CONTINUE
2004 GO TO 2003
2005 PRINT 998

```

C
C THE FORMAT STATEMENTS.

C

```

997 FORMAT(I1,I2)
998 FORMAT(* ATTENTION: THERE ARE ERRORS IN THE INPUT*,
*# DATA. PLEASE CHECK. *)
999 FORMAT(I1)
1000 FORMAT(*I*)
1001 FORMAT(I3)
1002 FORMAT(3F7.5)

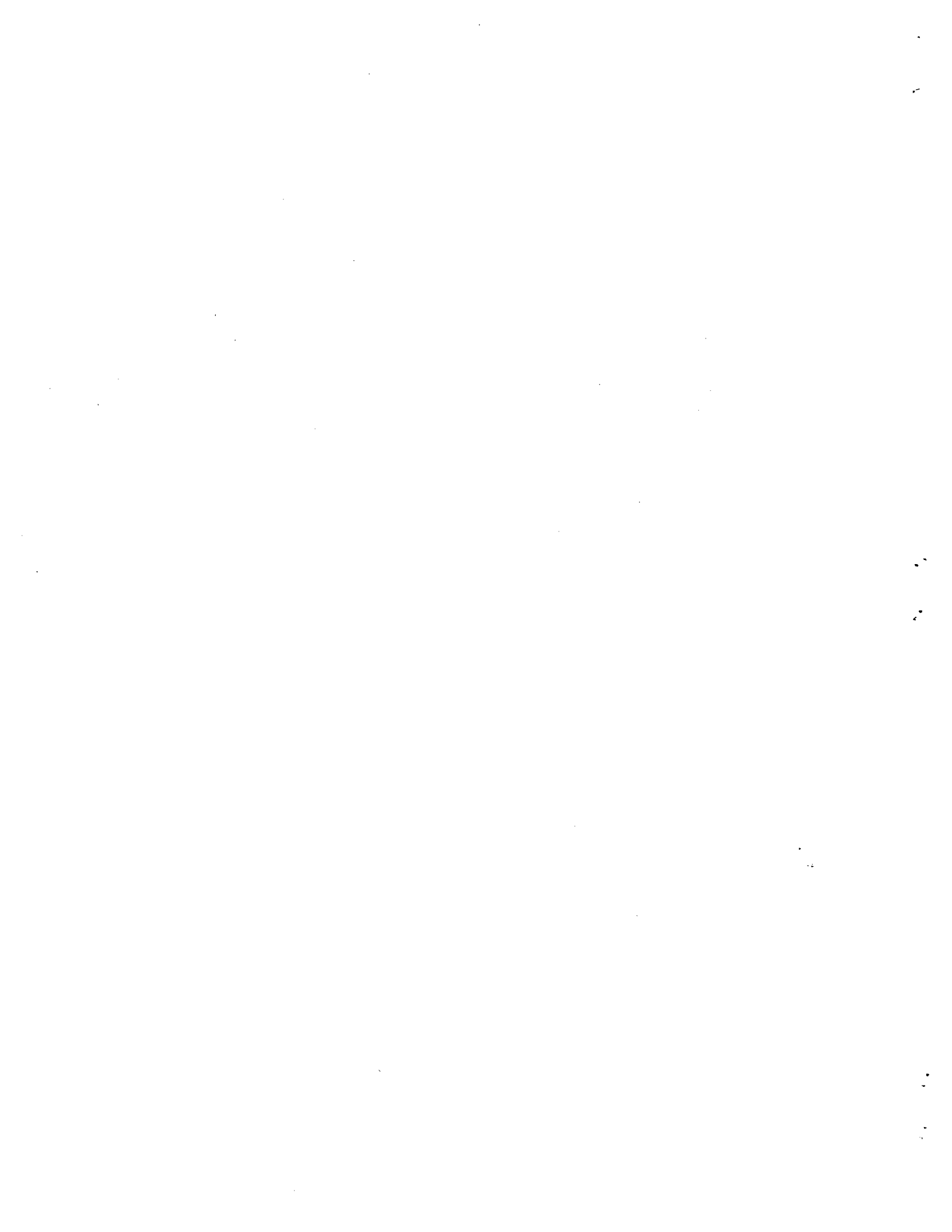
```



```

1003 FORMAT(F7.5)
1004 FORMAT(I4)
1005 FORMAT(3X,I3,10F7.4,(6X,10F7.4))
1006 FORMAT(//)
1007 FORMAT(= THE DENSITY OF THE NUMBER OF ARRIVALS PER=,
  *= UNIT OF TIME=, //(2X,10(I4,F8.5)))
1008 FORMAT(= THE INITIAL QUEUE LENGTH IS =,I3,/= THE=,
  *= INITIAL RESIDUAL SERVICE TIME IS =,I3)
1009 FORMAT(= THE NUMBER OF TIME POINTS COMPUTED IS=,
  *I4)
1010 FORMAT(= THE DENSITY OF THE SERVICE TIMES=, //2X,
  *(10(I4,F8.5)))
1011 FORMAT(3X,10(I4,F8.5))
1012 FORMAT(/)
1013 FORMAT(2X,=THE MEAN NR. OF ARRIVALS PER UNIT-TIME:=,
  *F10.4,/= THE MEAN SERVICE TIME:=,F10.4)
1014 FORMAT(=1=, // // = THE TRANSIENT BEHAVIOR OF A =,
  *=DISCRETE TIME QUEUE WITH A FINITE WAITINGROOM=,
  *//)
1015 FORMAT(= THE QUEUE IS EMPTY WITH PROBABILITY=,
  *F9.5)
1016 FORMAT(= AT TIME N = =,I4,= THE MEAN QUEUE LENGTH=,
  *= EQUALS=,F10.4)
1017 FORMAT(= THE QUEUE CHARACTERISTICS AT TIME N = =,
  *I4)
1018 FORMAT(= THE DISTRIBUTION OF THE QUEUE LENGTH =,
  *=AT TIME N = =,I4/)
1019 FORMAT(= THE JOINT DENSITY OF THE QUEUE LENGTH =,
  *=AND THE RESIDUAL SERVICE TIME AT TIME N = =,I4/)
1020 FORMAT(= THE DISTRIBUTION OF THE WAITINGTIME AT =,
  *=TIME N = =,I4, //(3X,10(I4,F8.5)))
1021 FORMAT(= THE MEAN WAITINGTIME AT TIME N = =,I4,
  *= IS=,F12.4)
1022 FORMAT(= THE UPPER LIMIT OF THE NUMBER OF ARRIVALS=,
  *= PER UNIT OF TIME IS=,I3,/= THE UPPER LIMIT OF THE=,
  *= NUMBER OF UNITS OF SERVICE-TIME PER CUSTOMER IS=,
  *I3,/= THE UPPER LIMIT TO THE NUMBER OF CUSTOMERS=,
  *= IN THE SYSTEM IS=,I4/)
  END

```



THE TRANSIENT BEHAVIOR OF A DISCRETE TIME QUEUE WITH A FINITE WAITINGROOM

THE UPPER LIMIT OF THE NUMBER OF ARRIVALS PER UNIT OF TIME IS 5
THE UPPER LIMIT OF THE NUMBER OF UNITS OF SERVICE-TIME PER CUSTOMER IS 9
THE UPPER LIMIT TO THE NUMBER OF CUSTOMERS IN THE SYSTEM IS 20

THE DENSITY OF THE NUMBER OF ARRIVALS PER UNIT OF TIME

0	.95000	1	.01500	2	0.00000	3	.01500	4	.01500	5	.00500
---	--------	---	--------	---	---------	---	--------	---	--------	---	--------

THE DENSITY OF THE SERVICE TIMES

1	.50000	2	.10000	3	.20000	4	.05000	5	.05000	6	.02500	7	.02500	8	.02500	9	.02500
---	--------	---	--------	---	--------	---	--------	---	--------	---	--------	---	--------	---	--------	---	--------

THE INITIAL QUEUE LENGTH IS 0

THE INITIAL RESIDUAL SERVICE TIME IS 0

THE NUMBER OF TIME POINTS COMPUTED IS 20

THE MEAN NR. OF ARRIVALS PER UNIT-TIME: .1450

THE MEAN SERVICE TIME: 2.5000

THE QUEUE CHARACTERISTICS AT TIME N = 1

AT TIME N = 1 THE MEAN QUEUE LENGTH EQUALS .1450

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 1

0	.95000	1	.96500	2	.96500	3	.98000	4	.99500	5	1.00000	6	1.00000	7	1.00000	8	1.00000	9	1.00000
10	1.00000	11	1.00000	12	1.00000	13	1.00000	14	1.00000	15	1.00000	16	1.00000	17	1.00000	18	1.00000	19	1.00000
20	1.00000																		

THE QUEUE CHARACTERISTICS AT TIME N = 2

AT TIME N = 2 THE MEAN QUEUE LENGTH EQUALS .2650

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 2

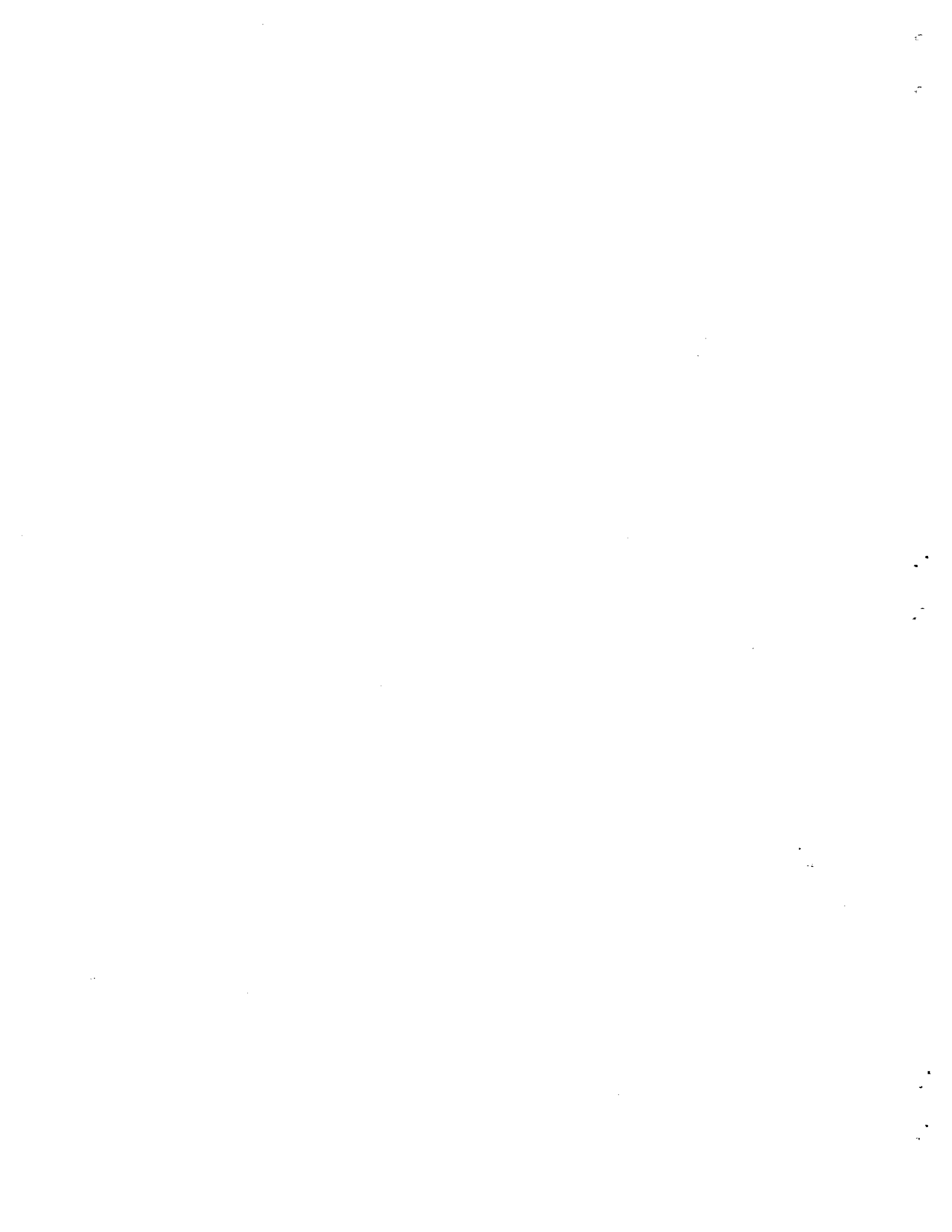
0	.90962	1	.93111	2	.93835	3	.96767	4	.99127	5	.99881	6	.99922	7	.99964	8	.99990	9	.99999
10	1.00000	11	1.00000	12	1.00000	13	1.00000	14	1.00000	15	1.00000	16	1.00000	17	1.00000	18	1.00000	19	1.00000
20	1.00000																		

THE QUEUE CHARACTERISTICS AT TIME N = 3

AT TIME N = 3 THE MEAN QUEUE LENGTH EQUALS .3723

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 3

0	.87232	1	.90174	2	.91707	3	.95615	4	.98700	5	.99680	6	.99797	7	.99904	8	.99970	9	.99994
10	.99998	11	.99999	12	1.00000	13	1.00000	14	1.00000	15	1.00000	16	1.00000	17	1.00000	18	1.00000	19	1.00000
20	1.00000																		







THE QUEUE CHARACTERISTICS AT TIME N = 5

AT TIME N = 5 THE MEAN QUEUE LENGTH EQUALS .5424

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 5

0	.81261	1	.85511	2	.88748	3	.94078	4	.97875	5	.99162	6	.99497	7	.99765	8	.99915	9	.99970
10	.99987	11	.99994	12	.99998	13	.99999	14	1.00000	15	1.00000	16	1.00000	17	1.00000	18	1.00000	19	1.00000
20	1.00000																		

THE QUEUE CHARACTERISTICS AT TIME N = 6

AT TIME N = 6 THE MEAN QUEUE LENGTH EQUALS .6111

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 6

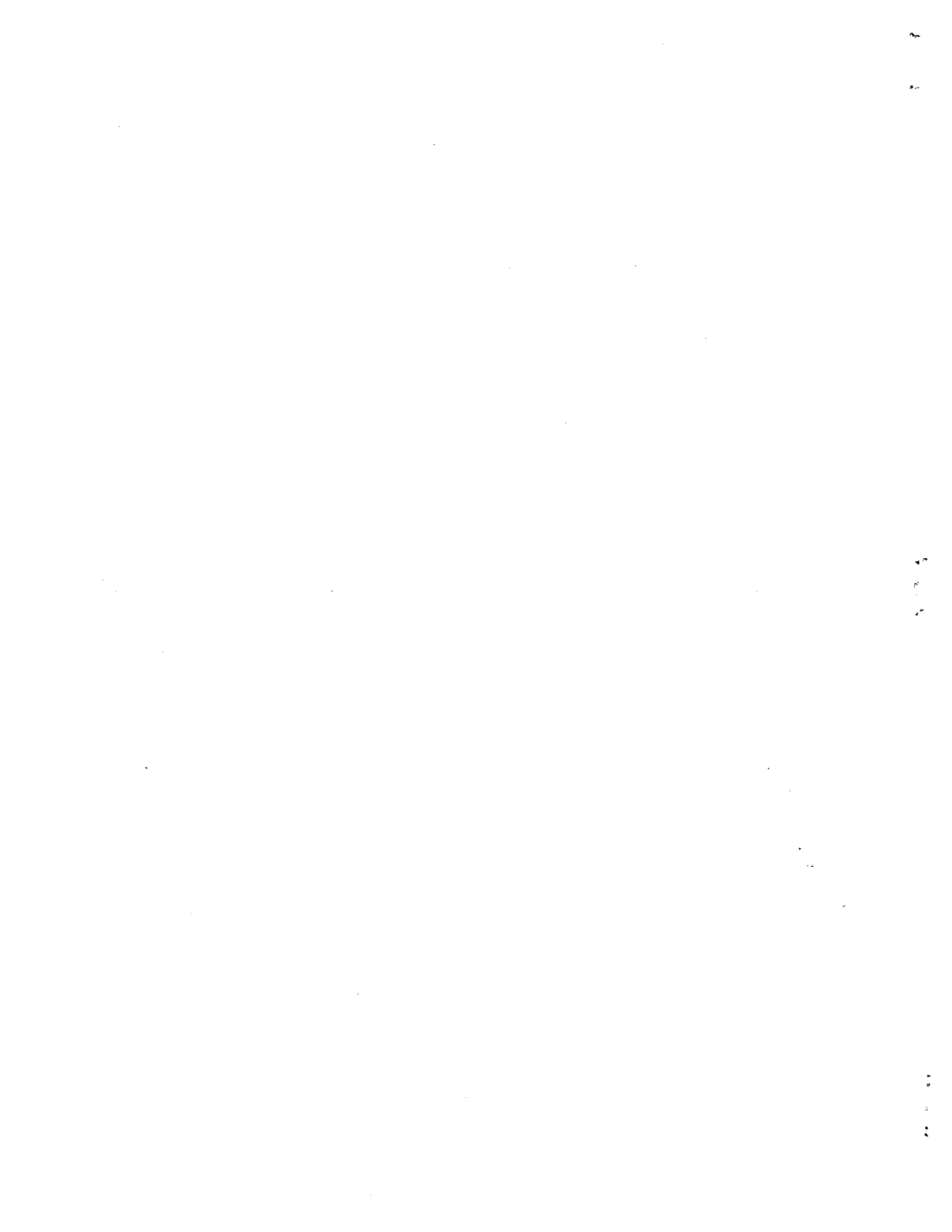
0	.78864	1	.83768	2	.87674	3	.93432	4	.97451	5	.98886	6	.99340	7	.99687	8	.99874	9	.99952
10	.99977	11	.99990	12	.99996	13	.99999	14	.99999	15	1.00000	16	1.00000	17	1.00000	18	1.00000	19	1.00000
20	1.00000																		

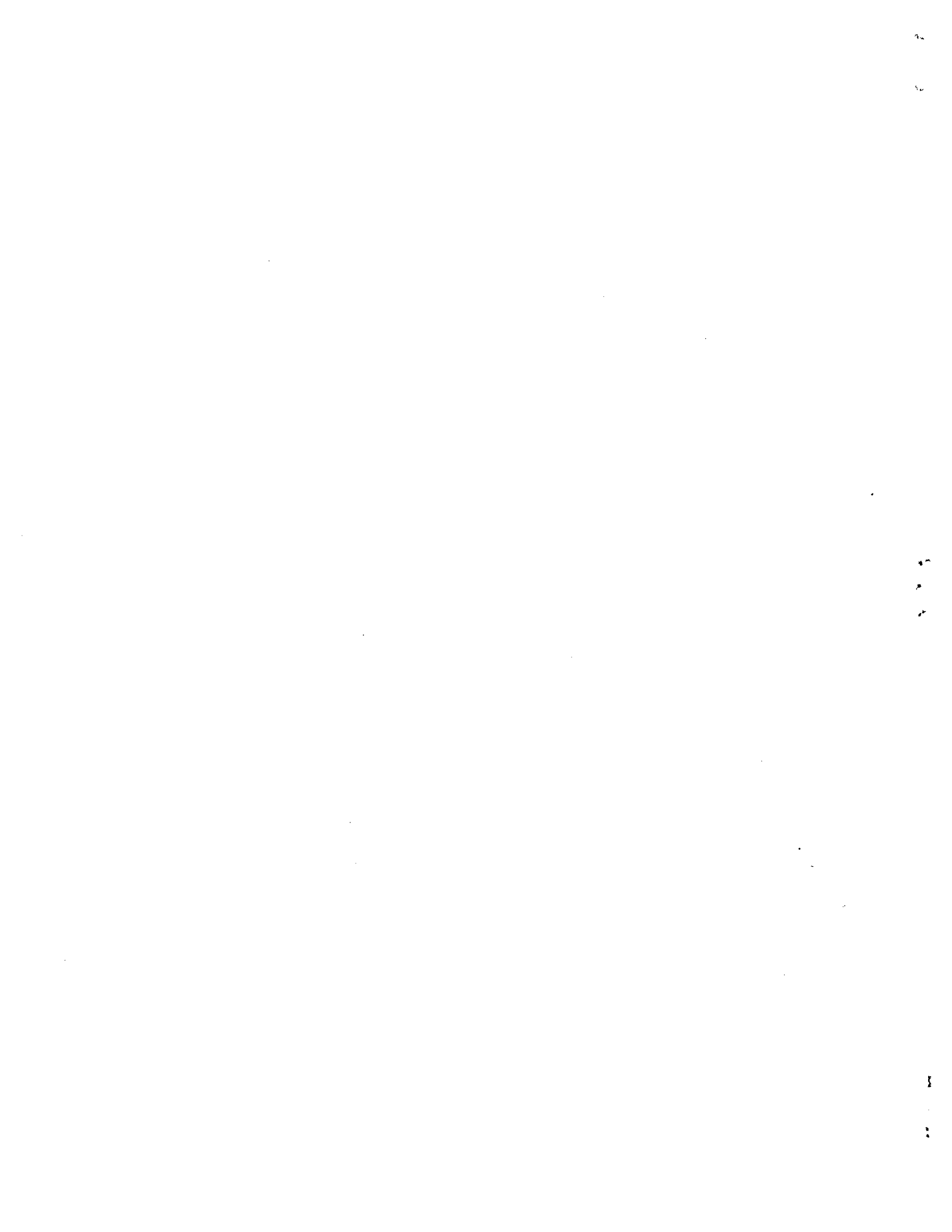
THE QUEUE CHARACTERISTICS AT TIME N = 7

AT TIME N = 7 THE MEAN QUEUE LENGTH EQUALS .6711

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 7

0	.76817	1	.82319	2	.86772	3	.92439	4	.97032	5	.98612	6	.99184	7	.99606	8	.99837	9	.99920
10	.99966	11	.99985	12	.99994	13	.99998	14	.99999	15	1.00000	16	1.00000	17	1.00000	18	1.00000	19	1.00000
20	1.00000																		





THE QUEUE CHARACTERISTICS AT TIME N = 13

AT TIME N = 13 THE MEAN QUEUE LENGTH EQUALS .9014

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 13

0	.69837	1	.77355	2	.83421	3	.90269	4	.95058	5	.97295	6	.98399	7	.99141	8	.99558	9	.99768
10	.99878	11	.99939	12	.99970	13	.99985	14	.99993	15	.99997	16	.99998	17	.99999	18	1.00000	19	1.00000
20	1.00000																		

THE QUEUE CHARACTERISTICS AT TIME N = 14

AT TIME N = 14 THE MEAN QUEUE LENGTH EQUALS .9256

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 14

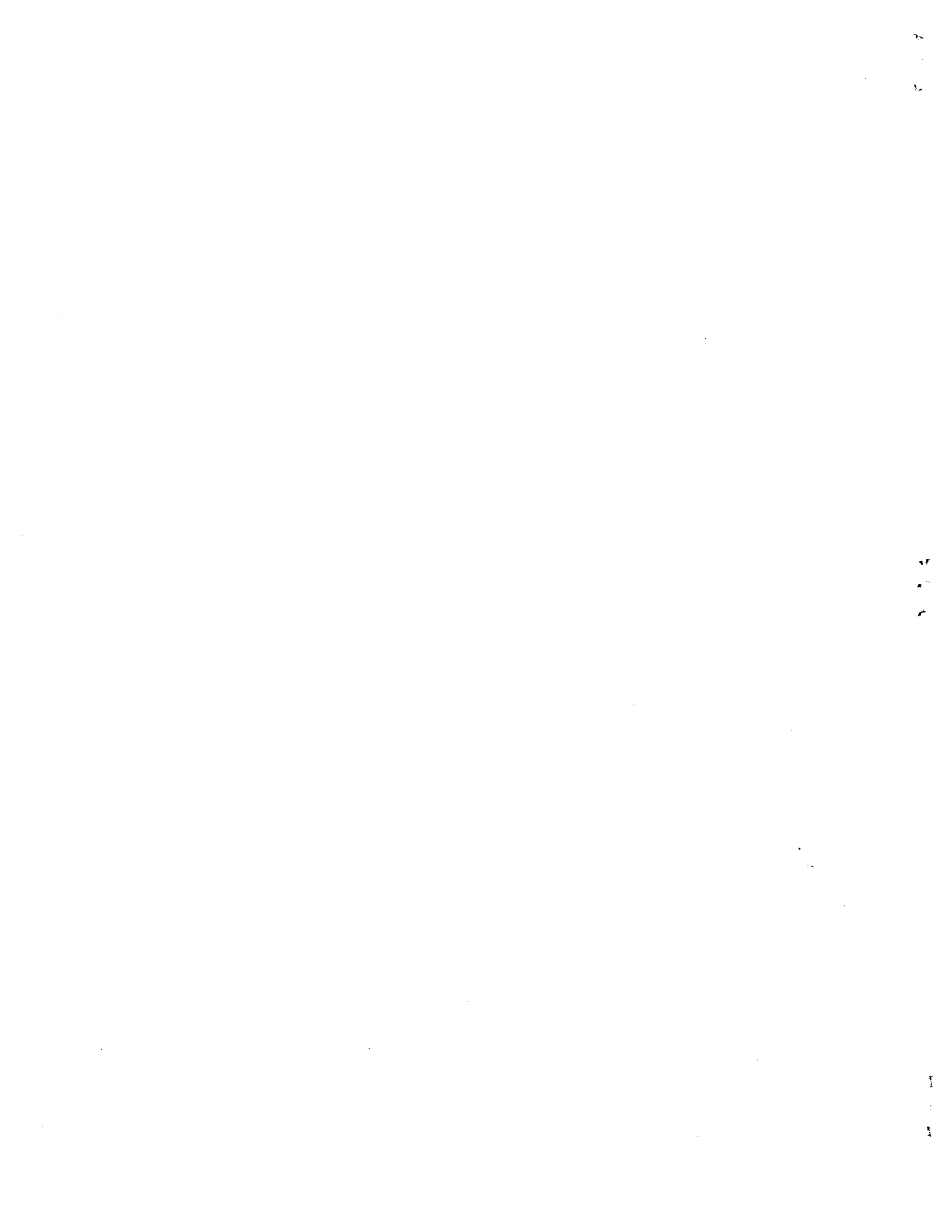
0	.69222	1	.76894	2	.83061	3	.89963	4	.94821	5	.97133	6	.98293	7	.99071	8	.99514	9	.99741
10	.99863	11	.99930	12	.99965	13	.99982	14	.99991	15	.99996	16	.99998	17	.99999	18	1.00000	19	1.00000
20	1.00000																		

THE QUEUE CHARACTERISTICS AT TIME N = 15

AT TIME N = 15 THE MEAN QUEUE LENGTH EQUALS .9474

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 15

0	.68696	1	.76486	2	.82733	3	.89685	4	.94605	5	.96984	6	.98193	7	.99003	8	.99470	9	.99715
10	.99847	11	.99920	12	.99959	13	.99979	14	.99990	15	.99995	16	.99998	17	.99999	18	.99999	19	1.00000
20	1.00000																		





THE QUEUE CHARACTERISTICS AT TIME N = 17

AT TIME N = 17 THE MEAN QUEUE LENGTH EQUALS .9651

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 17

0	.67841	1	.75794	2	.82164	3	.89203	4	.94228	5	.96715	6	.98007	7	.98877	8	.99369	9	.99664
10	.99816	11	.99902	12	.99968	13	.99973	14	.99986	15	.99993	16	.99996	17	.99998	18	.99999	19	1.00000
20	1.00000																		

THE QUEUE CHARACTERISTICS AT TIME N = 18

AT TIME N = 18 THE MEAN QUEUE LENGTH EQUALS 1.0014

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 18

0	.67489	1	.75499	2	.81918	3	.88994	4	.94063	5	.96594	6	.97922	7	.98819	8	.99350	9	.99640
10	.99801	11	.99892	12	.99943	13	.99970	14	.99984	15	.99992	16	.99996	17	.99998	18	.99999	19	1.00000
20	1.00000																		

THE QUEUE CHARACTERISTICS AT TIME N = 19

AT TIME N = 19 THE MEAN QUEUE LENGTH EQUALS 1.0163

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 19

0	.67177	1	.75233	2	.81694	3	.88803	4	.93911	5	.96481	6	.97843	7	.98764	8	.99313	9	.99616
10	.99786	11	.99883	12	.99937	13	.99966	14	.99982	15	.99991	16	.99995	17	.99998	18	.99999	19	1.00000
20	1.00000																		

THE QUEUE CHARACTERISTICS AT TIME N = 20

AT TIME N = 20 THE MEAN QUEUE LENGTH EQUALS 1.0299

THE DISTRIBUTION OF THE QUEUE LENGTH AT TIME N = 20

0	.66898	1	.74992	2	.81491	3	.86630	4	.93771	5	.96377	6	.97768	7	.98711	8	.99276	9	.99593
10	.99771	11	.99874	12	.99932	13	.99963	14	.99980	15	.99990	16	.99995	17	.99997	18	.99999	19	1.00000
20	1.00000																		

THE MEAN WAITING TIME AT TIME N = 20 IS 2.6088

THE DISTRIBUTION OF THE WAITING TIME AT TIME N = 20

0	.66898	1	.70155	2	.73043	3	.75964	4	.78664	5	.81271	6	.83674	7	.85882	8	.87869	9	.89537
10	.91189	11	.92555	12	.93735	13	.94747	14	.95604	15	.96326	16	.96934	17	.97445	18	.97873	19	.98230
20	.98529	21	.98777	22	.98984	23	.99156	24	.99299	25	.99419	26	.99519	27	.99601	28	.99670	29	.99727
30	.99775	31	.99814	32	.99847	33	.99874	34	.99896	35	.99915	36	.99930	37	.99942	38	.99953	39	.99961
40	.99968	41	.99974	42	.99979	43	.99983	44	.99986	45	.99989	46	.99991	47	.99992	48	.99994	49	.99995
50	.99996	51	.99997	52	.99997	53	.99998	54	.99998	55	.99999	56	.99999	57	.99999	58	.99999	59	.99999
60	1.00000	61	1.00000	62	1.00000	63	1.00000	64	1.00000	65	1.00000	66	1.00000	67	1.00000	68	1.00000	69	1.00000
70	1.00000	71	1.00000	72	1.00000	73	1.00000	74	1.00000	75	1.00000	76	1.00000	77	1.00000	78	1.00000	79	1.00000
80	1.00000	81	1.00000	82	1.00000	83	1.00000	84	1.00000	85	1.00000	86	1.00000	87	1.00000	88	1.00000	89	1.00000
90	1.00000	91	1.00000	92	1.00000	93	1.00000	94	1.00000	95	1.00000	96	1.00000	97	1.00000	98	1.00000	99	1.00000
100	1.00000	101	1.00000	102	1.00000	103	1.00000	104	1.00000	105	1.00000	106	1.00000	107	1.00000	108	1.00000	109	1.00000
110	1.00000	111	1.00000	112	1.00000	113	1.00000	114	1.00000	115	1.00000	116	1.00000	117	1.00000	118	1.00000	119	1.00000
120	1.00000	121	1.00000	122	1.00000	123	1.00000	124	1.00000	125	1.00000	126	1.00000	127	1.00000	128	1.00000	129	1.00000
130	1.00000	131	1.00000	132	1.00000	133	1.00000	134	1.00000	135	1.00000	136	1.00000	137	1.00000	138	1.00000	139	1.00000
140	1.00000	141	1.00000	142	1.00000	143	1.00000	144	1.00000	145	1.00000	146	1.00000	147	1.00000	148	1.00000	149	1.00000
150	1.00000	151	1.00000	152	1.00000	153	1.00000	154	1.00000	155	1.00000	156	1.00000	157	1.00000	158	1.00000	159	1.00000
160	1.00000	161	1.00000	162	1.00000	163	1.00000	164	1.00000	165	1.00000	166	1.00000	167	1.00000	168	1.00000	169	1.00000
170	1.00000	171	1.00000	172	1.00000	173	1.00000	174	1.00000	175	1.00000	176	1.00000	177	1.00000	178	1.00000	179	1.00000
180	1.00000																		

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THE SINGLE SERVER QUEUE IN DISCRETE TIME— NUMERICAL ANALYSIS I

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ABSTRACT

This is the first of a sequence of papers dealing with the computational aspects of the transient behavior of queues in discrete time.

It is shown that for a substantial class of queues of practical interest, a wealth of numerical information may be obtained by relatively unsophisticated methods.

This approach should prove useful in the analysis of unstable queues which operate over a limited time interval, but is by no means limited to such queues.

Mathematically the service unit is modeled in terms of a multivariate Markov chain, whose particular structure is used in iterative computation. Many important queue features may then be derived from the n -step transition probabilities of this chain.

1. INTRODUCTION

The theory of queues, and more generally that of stochastic models, suffer from the insufficient development of the interface between structural-analytic results on one hand and directly applicable numerical methods on the other hand.

The practical queue analyst tends to use of the extensive theoretical work on service systems only those rare steady-state results which are analytically simple. This is often done with little regard for the mathematical assumptions underlying these results. Moreover such results commonly do not answer the real questions one is facing in the design of a service facility, and in rare cases the measures of performance based on steady-state assumptions may actually be misleading. An example of a stable queue with rare arrivals of large groups of customers in which this is the case, is discussed in the third paper in this sequence.

While simulation techniques are widely used, their implementation requires a thorough understanding of the probability structure of the queue as well as very substantial computing funds. In many instances of simulation studies familiar to this author, the structure of the queue was incorrectly or insufficiently used and exorbitant computing times were reported. One recognizes that simulation is often the only resort in studying a complex system. However, for those models whose structure is mathematically well understood, it is desirable that algorithms making use of the existing theory be developed. It is obviously intellectually pleasant to be able to use one's understanding of the mathematical structure to obtain numerical results by efficient algorithms. There are however also many practical reasons for investigating exact, rather than Monte Carlo algorithms, wherever possible. Since this is not the place to discuss these at length, we mention the study of relatively rare events as an example. To obtain a good estimate of the probability that a very stable queue exceeds a certain bound may require long simulation runs, because the simulated paths will only rarely exhibit the event

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of interest. Queues which are nearly critical are also difficult to simulate, because of the substantial stochastic variability of the queue length and the related quantities. For these again, exact algorithms prove to be a useful alternative method of analysis.

The time involved in the preparation and testing of an exact algorithm is probably much greater than in a corresponding simulation study. This aspect must be taken into account in comparisons of the cost and the effectiveness of both approaches. For this reason only models of wide potential applicability should initially be studied by means of exact algorithms. There is furthermore a return which has particular value to the theoretical queue analyst. An algorithm is similar to a theorem in that its applicability is usually far greater than the original problem from which it sprung. As is the case for theorems, algorithms are also interesting because of their limitations. When the latter are recognized, they usually stimulate many questions related to approximations, algorithmic efficiency or structural theorems.

The purpose of this paper and the subsequent ones is to investigate a useful single server queue in detail. Before we consider the model specifically, we first discuss some difficulties and desiderata related to the numerical analysis of a much wider class of queueing problems.

a. The Finiteness of the Waiting Line

In reality, unbounded queues do not exist. The unbounded queue is strictly a mathematically convenient abstraction. By removing one "boundary" of the queue length process one obtains simpler stochastic processes. It further becomes possible to give an elegant treatment of the intuitive quality of stability of the queue.

In practical situations, there is either a finite waiting room, usually with loss of those customers who find the waiting space full, or else the buildup of the queue beyond a certain limit creates utter chaos and the object of the study is precisely the design of a sufficiently fast service unit or a sufficiently large waiting room to make this a very rare event.

Throughout this paper we shall limit our attention to bounded queues. In the numerical examples considered the largest value of the maximum queue length L_1 was, at most, 100.

b. Transient versus Steady-state Behavior

There are very few results on the transient behavior of queues, which are analytically explicit. Even the latter are nearly all ill-suited for direct numerical analysis. An interesting discussion of a simple transient queue and the difficulties of its computational analysis may be found in Leese and Boyd [1].

The steady-state probabilities of some simple queues are the only ones available in books written for the applied worker. Their relevance to the concrete problems is often limited; they clearly have no bearing whatsoever on the solution of unstable queues. Moreover, since the limiting process by which they are obtained has an averaging (or mixing) property, such results convey no information on the fluctuations of the queue length and the waiting times. Ignoring such fluctuations in a design may have catastrophic results.

In recent years the study of weak convergence properties of queueing processes and the resulting diffusion approximations have shed a new light on service systems of which the macroscopic time-behavior rather than the short-range fluctuations is the most important feature. This promising approach is mathematically fairly sophisticated and has not yet undergone sufficient investigation from the viewpoint of computation.

Our concern in this paper is, in a sense, with the small-scale service system whose short-range behavior is important. Therefore the models studied here are unlikely to be well approximated by a diffusion process. Nevertheless a comparison of both the direct solution and a diffusion approximation method with regards to accuracy and computing time is of interest, but will not be undertaken here.

c. Continuous versus Discrete Parameter Models

It is known that finite $M | G | 1$ and $GI | M | 1$ queues may be conveniently studied in relation to an imbedded Markov renewal process with a finite number of states. The transient behavior of such queues, as well as many related ones, may be computed in principle in terms of the successive matrix-convolution products of the transition matrix of this imbedded process. If a queue with a waiting room of size L_1 is investigated, each such a matrix-convolution product may require as many as $(L_1 + 1)^2$ evaluations of the convolution product of two functions. To perform this operation accurately is time-consuming, so that the computer implementation of this analysis is likely to result in considerable computing time.

In an earlier study of the single server queue in discrete time, Dafermos and Neuts [2] argued at length for the advantages of analyzing many queues in terms of a discrete time parameter. These arguments will not be repeated here. From the viewpoint of numerical analysis the most obvious advantages of a discrete time model are:

a. The ease with which one or more supplementary variables may be introduced so as to imbed the queueing process in a multivariate Markov process.

b. The fact that convolution products of sequences of numbers may be computed with much greater ease than those of functions of a continuous real variable may be evaluated accurately.

In most cases of practical interest one may discern an elementary unit of time natural to the particular queue. Many queueing analysts nevertheless insists on thinking of discrete models as approximations to continuous ones. This insistence, which may usually be traced to the prevailing attitude in applied mathematics before the advent of the computer, has some appeal for its mathematical elegance particularly where methods of analysis may be used. From a computational viewpoint, continuous parameter models are often substantially more delicate to analyze and this without yielding additional insight into the real process which is being modeled.

d. Parametric versus General Distributions

The insistence on specific parametric families of probability distributions (such as the gamma family) in stochastic models is also largely a holdover from the pre-computer era. Where a parametric assumption has an important structural consequence (e.g., the memory-less property of the negative exponential distribution) one should be very aware of this. However, in cases where the parametric assumption yields only marginal simplifications, both the theoretical analysis and the computational methods should ignore it altogether. As a case in point, the $M|E_k|1$ queue for $k > 1$ is only in some details easier to discuss than the $M|G|1$ queue. There is therefore little point in a special numerical method for the former which does not also include the latter.

In the sequel of this discussion, we shall therefore only stress the structural assumptions that are needed. Such items as service time distributions will be as general as possible.

In most specific models one may assume without loss of generality that service times and related random variables are bounded lattice random variables. This assumption, essential to our approach, is also the one which limits its range of applicability most. Our approach is not well suited to queues

in which both very short and very long jobs may arrive. Different methods of numerical analysis are needed for these. It is commonly so that a given numerical method is well suited for a certain range of problems, but fails for similar problems outside this range. The assumptions which limit the applicability of the present model are discussed in the appropriate places in the sequel.

2. THE ASSUMPTIONS OF THE MODEL

a. The Arrivals

We consider a single server queue in discrete time with a maximum queue length L_1 . The elementary time interval is chosen as our time unit. We assume that the numbers of arrivals during the successive unit time intervals are independent, identically distributed random variables. Furthermore p_ν , $\nu = 0, 1, \dots, K$, is the probability that ν customers join the queue during a given unit time interval. ($p_0 + p_1 + \dots + p_K = 1$). In this discussion, and in the related FORTRAN program, we shall insist that $1 \leq K < L_1$. The restriction $K < L_1$ is not essential and is usually satisfied in practice. Its removal requires minor modifications in the analysis and in the program.

We further assume that the p_ν are independent of time, but with minor obvious changes the recurrence relations are valid also for queues in which the arrival probabilities vary with time.

b. The Service Times

We assume that the service times of the successive customers are independent, identically distributed (integer-valued), random variables with values in the set $\{1, 2, \dots, L_2\}$. We denote by r_ν , $\nu = 1, \dots, L_2$, the probability that a customer requires ν units of service time. The values $L_1 = 100$ and $L_2 = 100$ appear to be practical upper limits to the computer implementation of the method suggested here.

Our assumption that every customer requires at least one unit of service time may easily be removed, but is satisfied in most all concrete applications. It suffices to introduce a quantity r_0 that a service time is equal to zero and to modify the recurrence relations accordingly.

As pointed out below, it is also easy to modify our analysis to include the case where the service time density depends on the time at which the service is initiated.

c. The Queue Discipline

Except in discussing the waiting times, the order of service is immaterial. The waiting times will be discussed for the first-come, first-served discipline.

To settle the issue of simultaneous arrivals and beginnings of services, we assume that all arrivals in $[n-1, n)$ are added to the queue at time $n-0$. If a service starts at time n and requires ν units of time, we shall consider it to start at time n and to end at time $n + \nu - 0$.

Only as many arrivals as to maintain the queue length less than or equal to L_1 are accepted. Any excessive customers are assumed to be permanently lost.

d. The Initial Conditions

We assume that at time $n = 0$, there are i_0 customers present. $0 \leq i_0 \leq L_1$. If $i_0 \geq 1$, the customer in service at time $n = 0$ requires j_0 , $1 \leq j_0 \leq L_2$ additional units of service time. We make the convention that if $i_0 = 0$, then $j_0 = 0$, and conversely.

3. THE MARKOV CHAIN

We denote by X_n the queue length at time n and by Y_n the number of additional units of service time required by the customer in service at time n . We make the convention that $X_n = 0$ if and only if $Y_n = 0$.

It follows readily from our assumptions that the bivariate sequence $\{(X_n, Y_n), n \geq 0\}$ is a Markov chain with state space consisting of the point $(0, 0)$ and all points $(i, j), i=1, \dots, L_1; j=1, \dots, L_2$, and with initial state (i_0, j) .

The transition probability matrix of the Markov chain is easily written down. We shall not do so since the recurrence relations make judicious use of its special structure.

For fixed i_0 and j_0 , we define the conditional probabilities

$$(1) \quad P_n(i, j) = P\{X_n = i, Y_n = j \mid X_0 = i_0, Y_0 = j_0\}.$$

The probabilities $P_n(i, j)$ satisfy the following recurrence relations in n for all $n \geq 0$:

$$(2)(a) \quad P_{n+1}(0, 0) = p_0[P_n(0, 0) + P_n(1, 1)],$$

$$(b) \quad P_{n+1}(i, j) = p_0 P_n(i, j+1) + \sum_{\nu=1}^{i-1} p_{i-\nu} P_n(\nu, j+1) + r_j \left\{ p_i P_n(0, 0) + p_0 P_n(i+1, 1) \right. \\ \left. + \sum_{\nu=1}^i p_{i-\nu+1} P_n(\nu, 1) \right\},$$

for $i=1, \dots, K$ and $j=1, \dots, L_2-1$.

$$(c) \quad P_{n+1}(i, j) = p_0 P_n(i, j+1) + \sum_{\nu=i-K}^{i-1} p_{i-\nu} P_n(\nu, j+1) + r_j \left\{ p_0 P_n(i+1, 1) + \sum_{\nu=i-K+1}^i p_{i-\nu+1} P_n(\nu, 1) \right\},$$

for $i=K+1, \dots, L_1-1$ and $j=1, \dots, L_2-1$.

$$(d) \quad P_{n+1}(L_1, j) = P_n(L_1, j+1) + \sum_{\nu=1}^K \left(1 - \sum_{k=0}^{\nu-1} p_k \right) P_n(L_1 - \nu, j+1) \\ + r_j \left\{ \sum_{\nu=1}^K \left(1 - \sum_{k=0}^{\nu-1} p_k \right) P_n(L_1 - \nu + 1, 1) \right\}$$

for $j=1, \dots, L_2-1$.

$$(e) \quad P_{n+1}(i, L_2) = r_{L_2} \left\{ p_i P_n(0, 0) + p_0 P_n(i+1, 1) + \sum_{\nu=1}^i p_{i-\nu+1} P_n(\nu, 1) \right\},$$

for $i=1, \dots, K$.

$$(f) \quad P_{n+1}(i, L_2) = r_{L_2} \left\{ p_0 P_n(i+1, 1) + \sum_{\nu=i-K+1}^i p_{i-\nu+1} P_n(\nu, 1) \right\},$$

for $i=K+1, \dots, L_1-1$.

$$(g) \quad P_{n+1}(L_1, L_2) = r_{L_2} \left\{ \sum_{\nu=1}^K \left(1 - \sum_{k=0}^{\nu-1} p_k \right) P_n(L_1 - \nu + 1, 1) \right\}.$$

The recurrence is initialized by setting $P_0(i_0, j_0) = 1$ and $P_0(i, j) = 0$ for all other pairs (i, j) . If the distribution of the random variables X_0, Y_0 is given rather than exact values, this simply amounts to a different definition of the initial array $P_0(i, j)$.

We note that the expressions in curly brackets in the formulas (2 b - g) depend on the first index only. This term corresponds to the case where the instant $n + 1$ is the beginning of a new service.

This simplifying feature is used in the organization of the computer program. If the service time distribution depends on the instant of initiation of a service, only the factor r_j in the recurrence relations are affected.

The analogous, but simpler recurrence relations for the unbounded queue were examined analytically by Dafermos and Neuts [2].

The recurrence relations (2) are well suited for iterative computation. The author organized his computation so as to have at the n th iteration only the quantities $P_n(0, 0)$ and $P_n(i, j)$, $i = 1, \dots, L_1$; $j = 1, \dots, L_2$ in memory.

The quantities $P_n(0, 0)$ and $P_n(i, j)$, $i = 1, \dots, L_1$; $j = 1, \dots, L_2$ make up the (conditional) joint density of the queue length X_n and the residual service time Y_n at time n . This joint density is not, in itself, of great practical use; however from it the distribution (or the density) of the queue length and the waiting time at time n can be easily obtained. These "derived" queue features are considered next.

4. DERIVED QUEUE FEATURES

a. The Queue Length Distribution

The probability that the queue length at time n is zero, is given by $P_n(0, 0)$. For $i = 1, \dots, L_1$, we have

$$(3) \quad P\{X_n = i \mid X_0 = i_0, Y = j_0\} = \sum_{j=1}^{L_2} P_n(i, j).$$

Lower order moments of the queue length at time n may be obtained routinely.

b. The Waiting Time Distribution

The waiting time at time n is defined to be zero if, and only if $X_n = Y_n = 0$. For $X_n = 1, Y_n = j$, the waiting time equals j . For $X_n > 1, Y_n = j$ the waiting time is the sum of j and $X_n - 1$ independent service times. The waiting time is therefore an integer-valued random variable with value between 0 and $L_1 L_2$.

The density WT_ν , $\nu = 0, \dots, L_1 L_2$ is obtained as follows. Clearly $WT_0 = P_n(0, 0)$. The quantities WT_n for $1 \leq \nu \leq L_1 L_2$ were obtained by evaluating the following convolution-polynomial.

Let $WT(\cdot)$ denote the density $\{WT_\nu, 1 \leq \nu \leq L_1 L_2\}$ and let $R(\cdot)$ be the service time density $\{r_j, 1 \leq j \leq L_2\}$. Finally let $P_n(i, \cdot)$ be the density $\{P_n(i, j), 1 \leq j \leq L_2\}$ for $i = 1, \dots, L_1$, then $WT(\cdot)$ is given by

$$(4) \quad WT(\cdot) = P_n(1, \cdot) + P_n(2, \cdot) * R(\cdot) + \dots + P_n(L_1, \cdot) * R^{(L_1-1)}(\cdot),$$

where $R^{(k)}(\cdot)$ is the k -fold convolution of $R(\cdot)$ with itself.

The density $WT(\cdot)$ may be computed for each n by one of two procedures. Either the convolutions $R^{(k)}(\cdot)$, $k = 1, \dots, L_1 - 1$ may be computed once and for all and only the convolutions with the arrays $P_n(i, \cdot)$ need to be computed at those time points n at which the density of the waiting time is

desired. This procedure results in a substantial increase in the central memory storage required by the program.

Alternatively, the density $WT(\cdot)$ may be computed by a convolution analogue of *Horner's algorithm* for the numerical evaluation of ordinary polynomials. This procedure consists in the successive evaluation of the sequences

$$(5) \quad WT^{(1)}(\cdot) = P_n(L_1, \cdot),$$

$$WT^{(k)}(\cdot) = WT^{(k-1)}(\cdot) * R(\cdot) + P_n(L_1 - k + 1, \cdot),$$

for $k = 1, \dots, L_1$. The sequence $WT^{(L_1)}(\cdot)$ is the desired sequence $WT(\cdot)$.

The latter procedure does not result in the use of core storage for intermediate quantities. For purposes of comparison and as a guard against rounding errors, both procedures were programmed and tested on large scale examples. The Horner convolution algorithm performed slightly better in all examples and no evidence of rounding errors were found. Its much smaller core requirements make it the more efficient of the two procedures.

5. REPORT ON COMPUTATIONAL TRIALS

A FORTRAN IV program was written by the author and tested on a variety of cases on the CDC 6500 at Purdue University. Even in the largest examples no evidence of rounding errors was found, even though all probabilities were printed to five decimal places and all computations were performed in single precision.

The full output consisted, in addition to the summary of the input data, of the following:

- (a) the mean of the queue length,
- (b) the cumulative distribution of the queue length,
- (c) the mean waiting time,
- (d) the cumulative distribution of the waiting time,
- (e) the joint density of the queue length X_n and the residual service time Y_n .

All these for all values of n up to some upper value to be specified.

Since the full output is very voluminous and contains much more information than may be needed in the analysis of a given queue, options were written into the program which permit the deletion of the items (c), (d), or (e) from the printed output. A further option was created which permits the computation of the waiting time distribution to be performed at certain specified time points only.

No systematic study of the processing time was made. For smaller examples the computation times were generally below 10 seconds. The following computation times for some larger examples are given for purposes of illustration only.

$L_1 = 30$	(max. queue length)
$L_2 = 6$	(max. duration of one service)
$K = 2$	(max. number of arrivals)
$NNN = 250$	(number of time points computed)

In the following CP is the processing time in seconds and LL is the number of lines of output, including the program listing.



a. full printed output

$$CP = 215.159 \quad LL = 19265$$

b. the queue length and waiting time distributions only.

$$CP = 157.860 \quad LL = 10656$$

c. the queue length distribution for all time points and the waiting time distribution only for time points which are multiples of 25.

$$CP = 23.763 \quad LL = 4916$$

The processing time for a large scale iteration of the type needed here can be substantially decreased by writing a program in an assembly language, rather than in FORTRAN. A reduction by 50 or 60 percent can realistically be expected.

For large problems, the computation of the waiting time distribution is by far the most time consuming part of the algorithm. For very stable queues, we recommend neglecting the higher order terms in the convolution polynomial (4). These terms contribute very little, except to the extreme upper tail of the distribution, but add very considerably to the processing time. For queues with a very rapid build-up, some savings may be accomplished by neglecting lower order terms in (4), but this is less significant. For queues which are near-critical, the waiting time algorithm ceases to be practical for queues with $L_1 > 200$, because of the large numbers of operations involved. The problem of finding good numerical approximations to the distribution of the waiting time in this case is challenging and needs further investigation.

6. CONCLUSIONS

By the use of only the most elementary structural properties, we have shown that the transient behavior of a substantial class of single server queues may be analyzed numerically. The approach presented here should prove itself to be useful in studying the build-up of unstable queues and the fluctuations of queues at traffic lights, highway merging ramps, service counters in public offices and retail outlets and many others.

This approach is well suited for many queueing processes which do not lend themselves to diffusion approximation methods. The amount of computing time used in typical examples also indicates a very substantial saving over that needed to analyze similar models by simulation methods.

Further work is currently being done to extend the applicability of this approach to longer queues and to much longer time periods. This extension, however, requires the use of mathematically more sophisticated properties of the queueing process.

A version of this paper, containing a program listing and a specific numerical example, is available as a technical report. It may be obtained from the author upon request, by writing to Professor Marcel F. Neuts, Department of Statistics, Purdue University, West Lafayette, IN. 47907.

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