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This report describes implementation and exercising of simulation models for a portion of user behavior in the library setting. The emphasis is on user estimations of timing and convenience factors of service and how these are affected by actual service. The report begins with an oversimplified view of the user and becomes progressively more detailed. Comparisons across the several models and alternative suggestions are made. Insofar as the study investigates how features of user behavior might be modelled and what results might be obtained, it can be regarded as a part of a feasibility analysis relating to incorporation of a human component in a library system's simulation. A final matter is a discussion of the relationship of this model to other models in this series of reports. (Author)

USER DETERMINATION OF LIBRARY REQUEST PRESENTATION A SIMULATION

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Kevin D. Reilly

One of a Series of Reports
on File Organization Studies
(NSF Grant GN-422)

Institute of Library Research
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Abstract

This report, an outgrowth of a previous communication (Hayes and Reilly, 1967), describes the implementation and exercising of simulation models for a critical portion of user behavior in the library setting. The emphasis is on (user) estimations of timing and convenience factors of service and how these are affected by actual service. The report begins with an oversimplified view of the user and becomes progressively more detailed. Comparisons across the several models and alternative suggestions are made. Insofar as the study investigates how features of user behavior might be modelled and what results might be obtained, it can be regarded as a part of a feasibility analysis relating to incorporation of a human component in a library system's simulation. A final matter is a discussion of the relationship of this model to other models in this series of reports. The desire to communicate to library personnel and students of library systems analysis dictated a certain simplicity of presentation and accounts for occasional stressing of elementary points.

I. INTRODUCTION

Previous reports (Hayes and Reilly, 1967; Reilly, July 1968; December 1968; January 1969) have described features of digital computer simulation models for analysis of library-based information retrieval systems. Included in these reports are outlines of models and some preliminary results for models at three different "levels": computer processing center; user-behavior models; storage and delivery system for conventional information sources. Applications of the models have also been discussed. The concern of the present report is with the user-behavior models. Let us briefly outline what it is in the user's behavior that we wish to analyse.

A. Description of the User

The bulk of information describing a user is of a static type: location of the user, area of professional work, time development of needs, etc. Such parameters remain fixed throughout the time period analysed in the model and consequently are not critical to the discussion of model dynamics. Therefore, we shall have little occasion to deal with these factors. Their most important usage lies in classifying results (e.g., professors in the university receive statistically better service than graduate students).

Because the emphasis is on the user behavior dynamics, the description of the computer center and library portions of the model may also be kept to a minimum. Furthermore, the time pattern of need development, which is important principally in relation to these descriptions, can be set arbitrarily. For us, one need is developed at each (quantized) time unit.

Two concepts, the probability of consideration to use the library and the estimated service time, are central factors in the model dynamics. The first of these, the probability of consideration, is designated by CON or CON_t, depending on the context (t being a time parameter). CON is used as a threshold in the model: if CON is greater than or equal to a (uniformly distributed on the interval (0,.999)) random number the user then <u>considers</u> the library as a likely solution to his information problems. He then cogitates upon the timing factors involved in his request (see the next paragraph) before finally deciding whether or not to make a request. CON represents an essentially nontemporal aspect in the user's decision. Among such factors are matters of convenience, user lethargy, cumulative inhibitions due to past failures in service seeking.

The second concept, the estimated service time, is designated by EST or EST_t. It is used in conjunction with the need time, NT or NT_t in the obvious fashion: if the estimated service time is (far, perhaps) in excess of the need time for a given need, it is not expedient for the user to make a request even though it may otherwise be very convenient to do so. The EST concept, in our model, involves a probability distribution so that more than one parameter may be utilized in its description.

It will be apparent when reading the paper that additions can be made to the model. In the first instance there is no competition between information sources. We do not allow the failures and success at other sources to affect the user's view of the library. If it is indeed true, as we expect, that most changes in user behavior are likely to occur in his relationship with the library and that the service it provides is by far the most important standard by which it is evaluated, this should not be a severe restriction. In any case, little additional work seems necessary to compensate for any such deficiency.

A second point is that the parameters of CON and EST are effectively not subscripted. This is due in part to our restriction of scope to a single class of materials, etc. In general, at least four subscripts might be required for either parameter, l, m, n, t. where l refers to the class of service (e.g., book, microfilm, facts, bibliographies, etc.); m to the m^{th} user in the collection of users; n, the alternate sources for meeting the need (e.g., personal library, a colleague down the hall, etc.); t, the time.

Finally, there should be plenty of room for alternate suggestions on just how users do behave, since no one can lay down final rules today.

B. Aims of the Study

From the restrictions and simplifying assumptions that we have laid down above, it ought to be clear that at least part of our effort is to discuss random process simulation in basic terms, appropriate to the expected audience of library scientists who often have not had wide experience in such problems. This accounts, again in part, for our mode of presentation in which properties of parts of the overall model are studied in isolation. The isolated models along with variants of the model provide the basis for discussion of an optimal user policy over a range of models. Finally, a basis is provided whereby we can propose and evaluate alternate approaches.

II. CONSIDERATION PROBABILITY MODEL

Our first task involves analysis of the properties of the consideration probability (CON) mechanism. Though such a model is obviously too simple to represent the complex mechanism we are attempting to describe, it does provide a portion of that description. It also allows us to approach the entire model building effort in smaller more digestible morsels.

A. The Linear Model

The "linear model" of so-called Mathematical Learning Theory suggests itself as a useful point of departure. Following Hilgard and Bower (1966), we now formulate the model. Let the possible range of events occurring in any trail, t, be E_o , E_1 , E_2 , corresponding to the three alternatives: no request presented; request presented with success (e.g., response time within required period); request presented with failure. Let CON_t be the probability that a request is made on the t^{th} need for information. Then

$$CON_{t+1} = \begin{cases} CON_t & \text{if } E_o, \\ (1 - \theta)\ CON_t + \theta & \text{if } E_1, \\ (1 - \theta)\ CON_t & \text{if } E_2, \end{cases}$$

where $0 \leq \theta \leq 1$. (Interpretations that the mathematical and other psychologists have sought for the parameter θ present an interesting episode in modern psychology. The reader is referred to the above-cited reference for an introduction to this area.)

B. A Simulation Study

It is useful to simulate this model even though mathematical solutions are available for many of its basic properties. The reasons for this are that it allows us to check at least a portion of our program against known results. It also provides a convenient mechanism for illustrating the known results, since graphical routines and other "editor" functions of the program can be used to portray results. Furthermore, other solution properties that the mathematic analysis cannot readily achieve can be readily uncovered.

Simulation often operates from the particular to the general (Forrester, 1961) opposite of mathematical analysis . Thus we have to make definite assumptions about matters such as probability distributions for AST, etc. The choice of values constitutes a first stage in the experimentation with the model. Parametric analysis (i.e., running the model with several different parameter choices) and scaling (i.e., effectively taking advantage of the relative rather than absolute values of the parameters) allow us a degree of generality. In most simulation studies the initial parameter choices and distributions are imposed upon us by experimental results we already have. For this particular study, our assumptions are only partly based on an existing system. In our (library) environment, the researcher must often first convince authorities that a large-scale experimental study is useful. This is due in large measure to the fact that user studies tend to disrupt ordinary operations. At least one goal of our study is to provide a basis for a detailed experimental analysis of user behavior.

The flow diagram of the consideration probability (only) model is seen in Figure 1. Accompanying it, representing our initial choices for them, are the (particular) distributions of actual service time (AST) (Figure 3) and need time (NT) (Figure 2). (The means of 425 and 375 time units can be scaled for use in other cases as indicated above. For example a time unit of hundreths of hours makes these values correspond to 3.75 and 4.25 hours respectively; a time unit of tenths of hours, to a period of about one week.) These distributions are fixed throughout the model run; it is, therefore, possible to determine a probability that the actual service

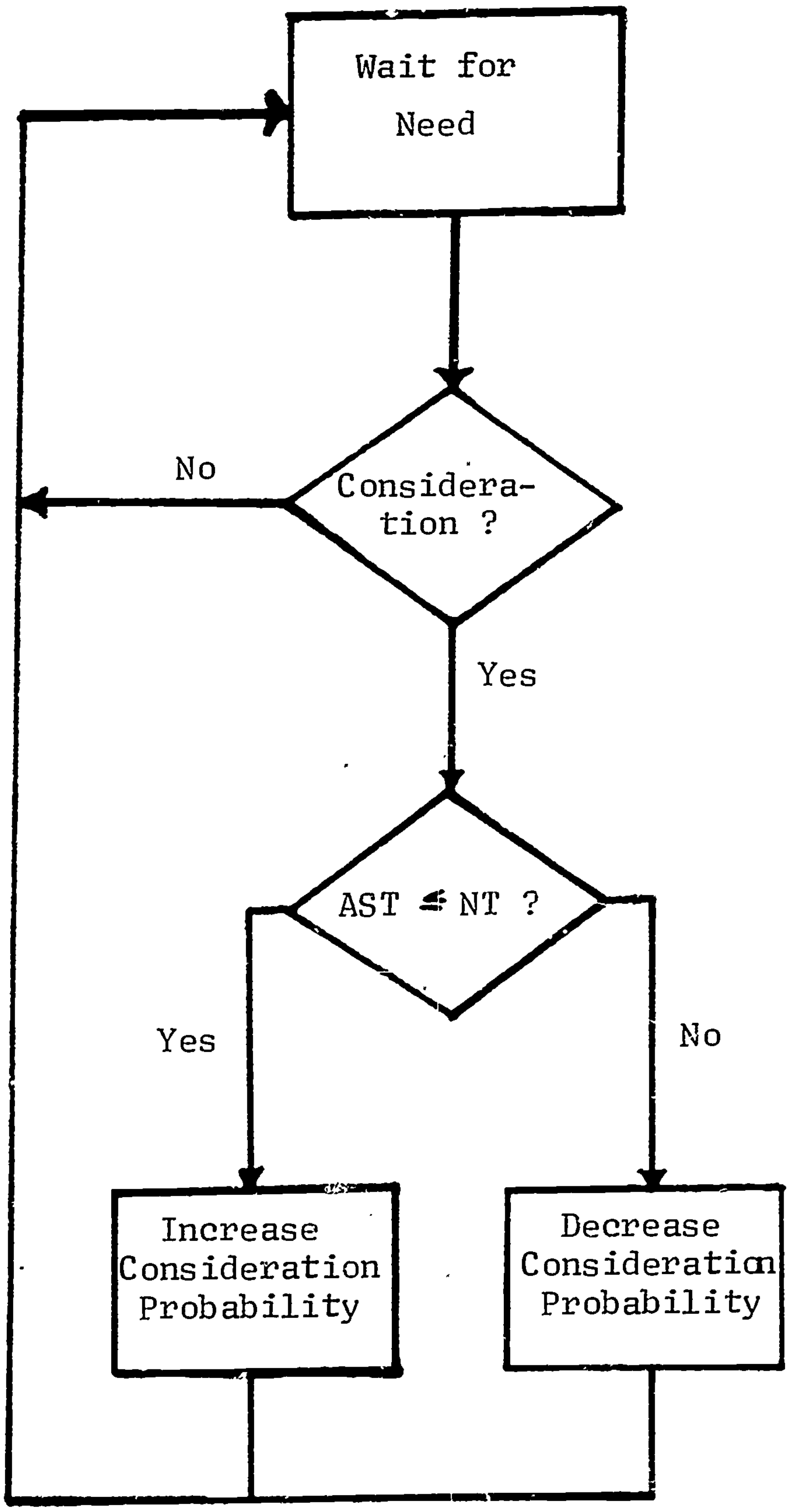

Figure 1: Flow diagram of Consideration Probability Model.

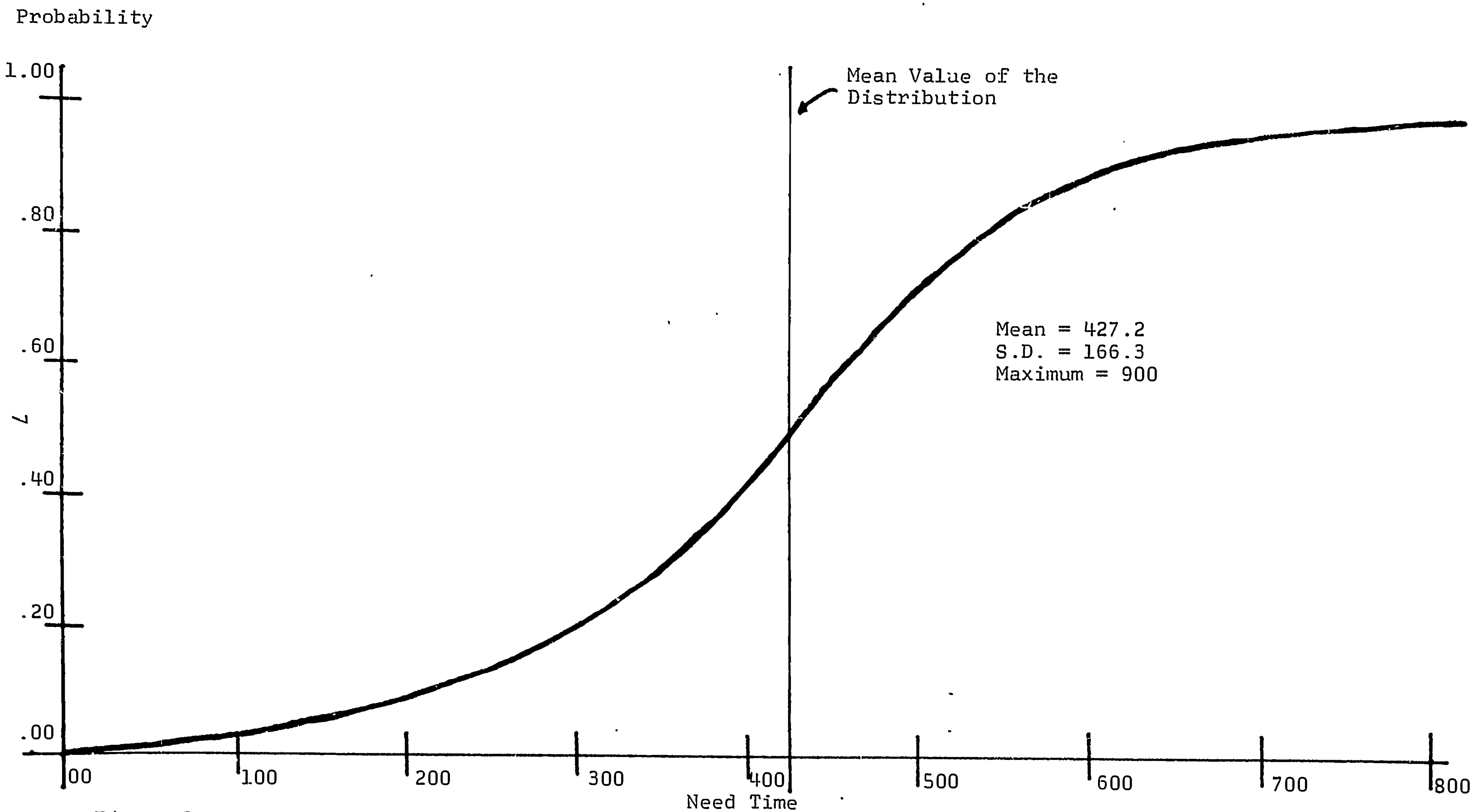

Figure 2: Probability Distribution for Need Time, developed from GPSS/360 function (99.7% confidence of being within about four units from "true" mean.).

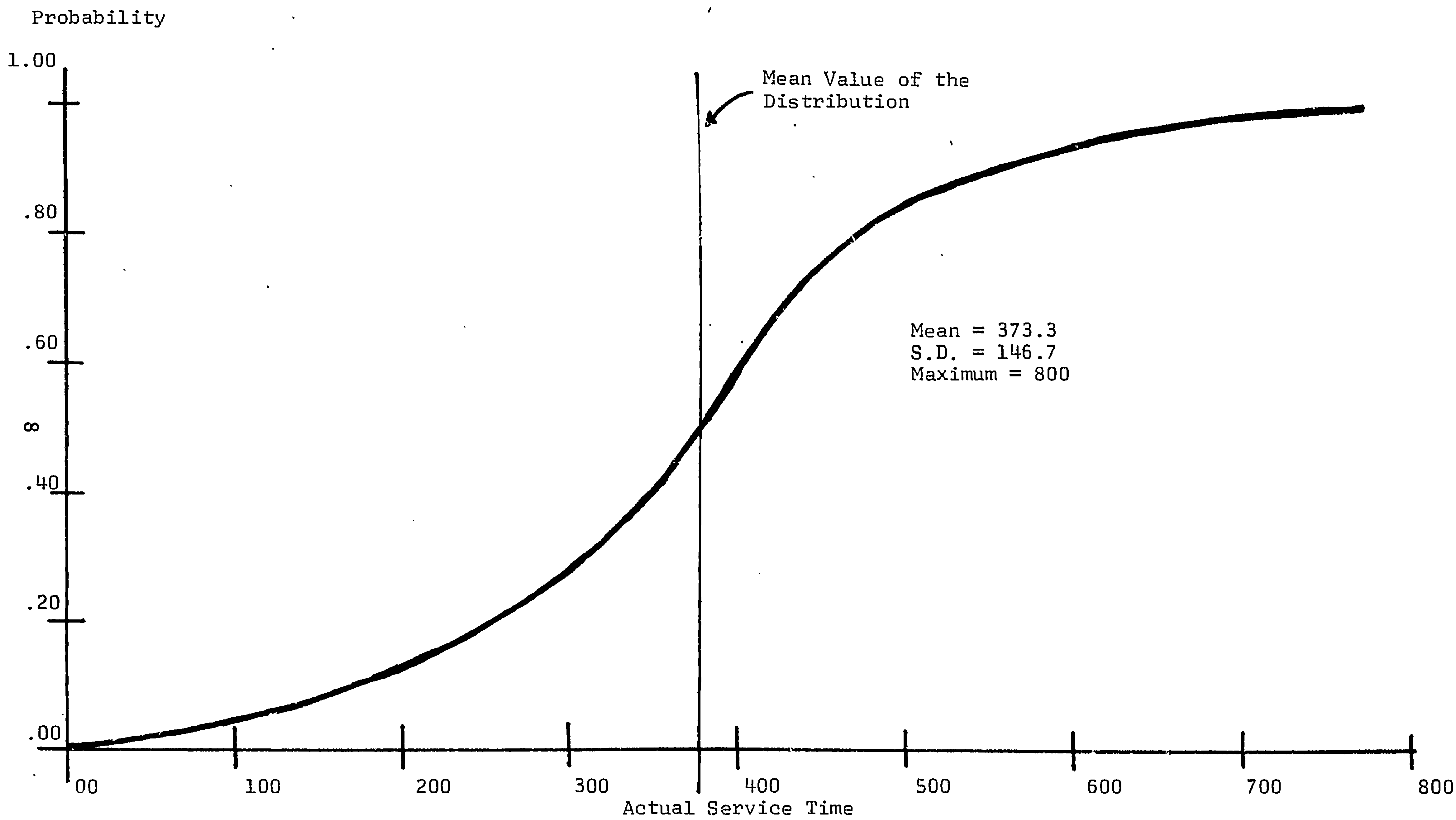

Figure 3: Probability Distribution for Actual Service Time, developed from GPSS/360 function (99.7% confidence of being within four units of "true" mean.).

time is less than the need time. This probability was found to be .610. Later this probability is changed to another value by varying the AST. NT is one of those static properties of the user and would not normally be expected to change in most studies, whereas the AST represents the service time provided by the system, the organization and reorganization of which is the end of the system study. AST might be expected to change during a run depending on the current demands and other factors; in this study, we have not analysed effects of this type of AST change.

Some elementary results from the model are plotted below (Figures 4-6). Figure 4 shows how the consideration probability changes over a few trails. An element of randomness in the probability is apparent in the diagram. Figure 5 illustrates the probability distribution of the consideration probability. (This graph is actually plotted from results for another case in which probability of a successful request is other than .610; but the distributions in both cases are similar.) The distribution is approximately symmetric. The skew exhibited toward the smaller values and the effect it has on the mean are matters of interest that we take up in the discussion below. Figure 6 illustrates the average (over a group of users) of the consideration probability taken at various intervals (evenly spaced along the time line). (These results were taken from another (special) study with a group of users.) The graph illustrates the need for care when sampling at time intervals since there is a bias in the time-sampled data (as we shall see more clearly shortly). The CON curves for the two cases (Figures 4 and 6) are similar in nature though the deviations about the mean are larger in Figure 6 than in Figure 4.

Another interesting feature of this model relates to the behavior of the consideration probability as a function of the probability of success of a request, Prob (success/request). A plot of the mean of CON (labelled

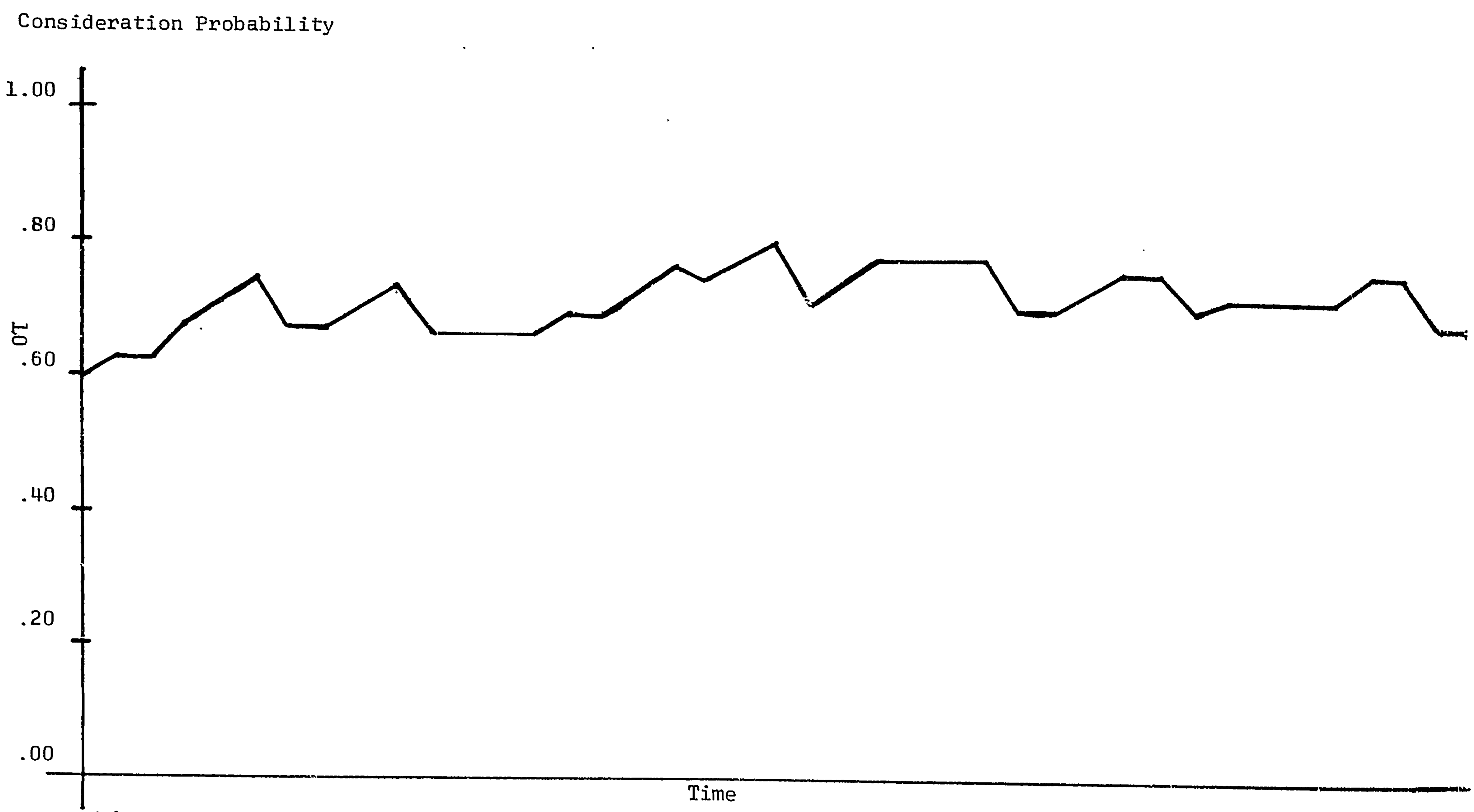

Figure 4: Illustration of the behavior of the Consideration Probability over an arbitrary interval.

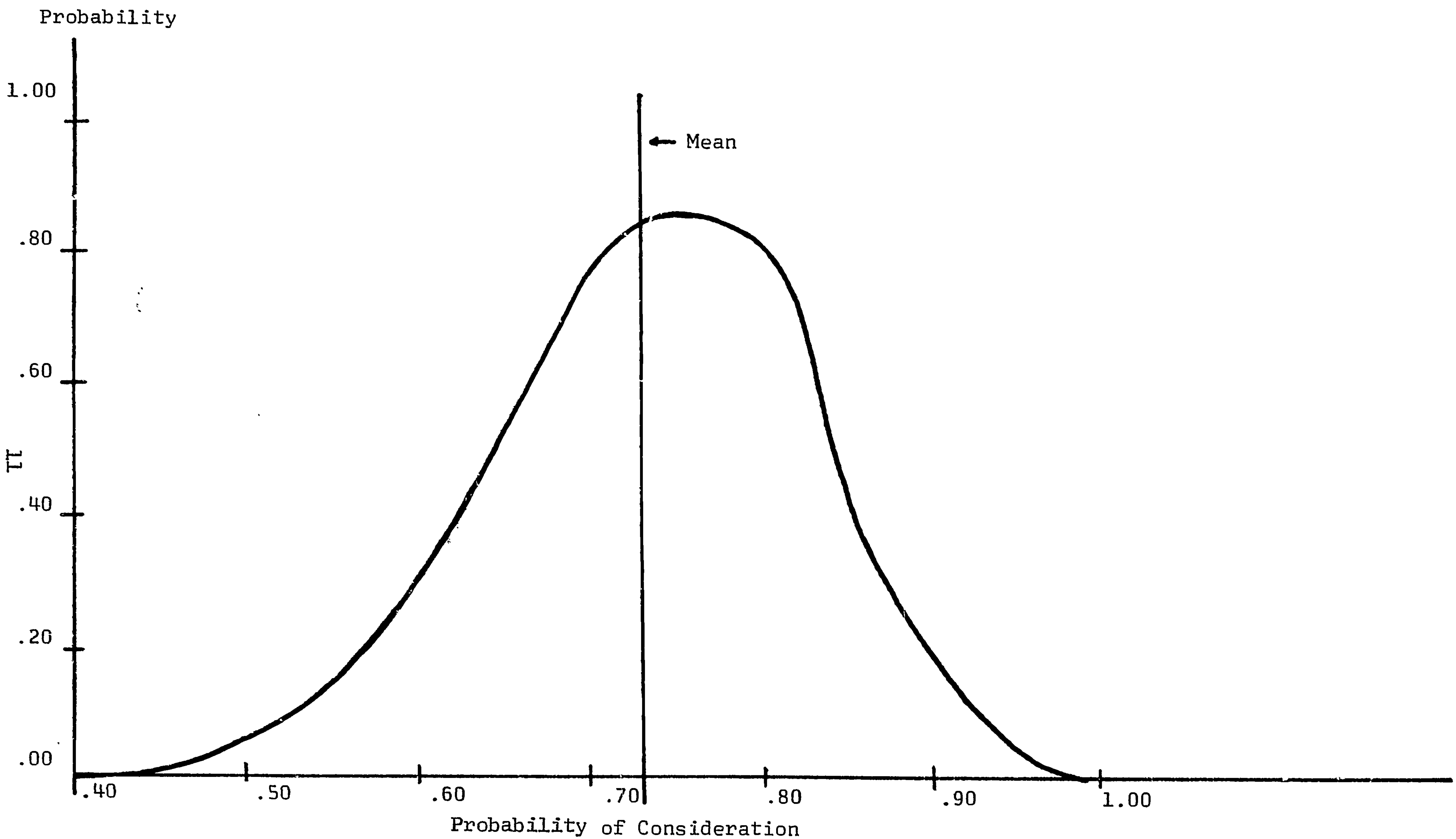

Figure 5: Probability Density for the Probability of Consideration over a large number of experiences.

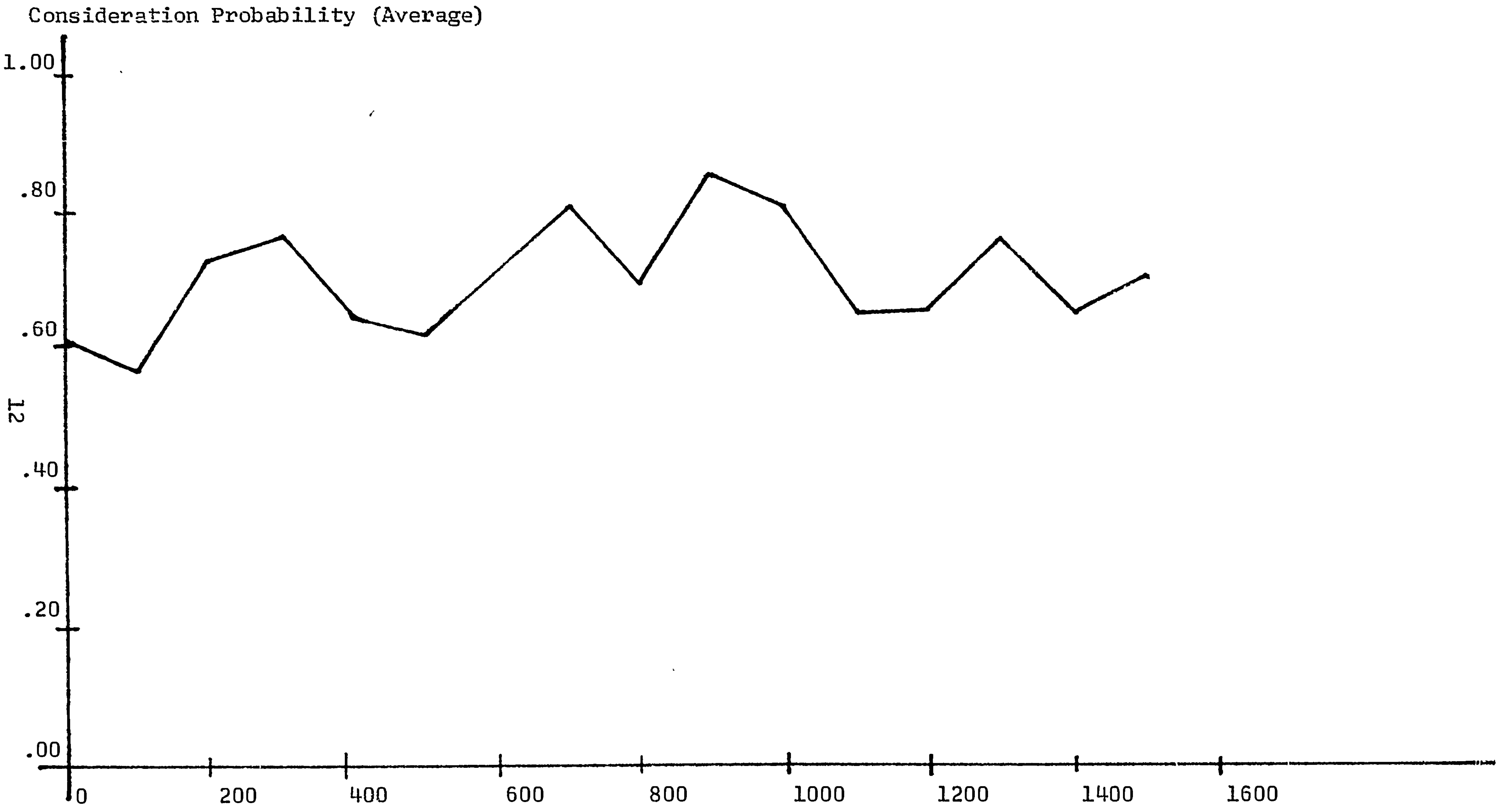

Figure 6: Consideration Probability (averaged over a number of similar users) at every 100th time period.

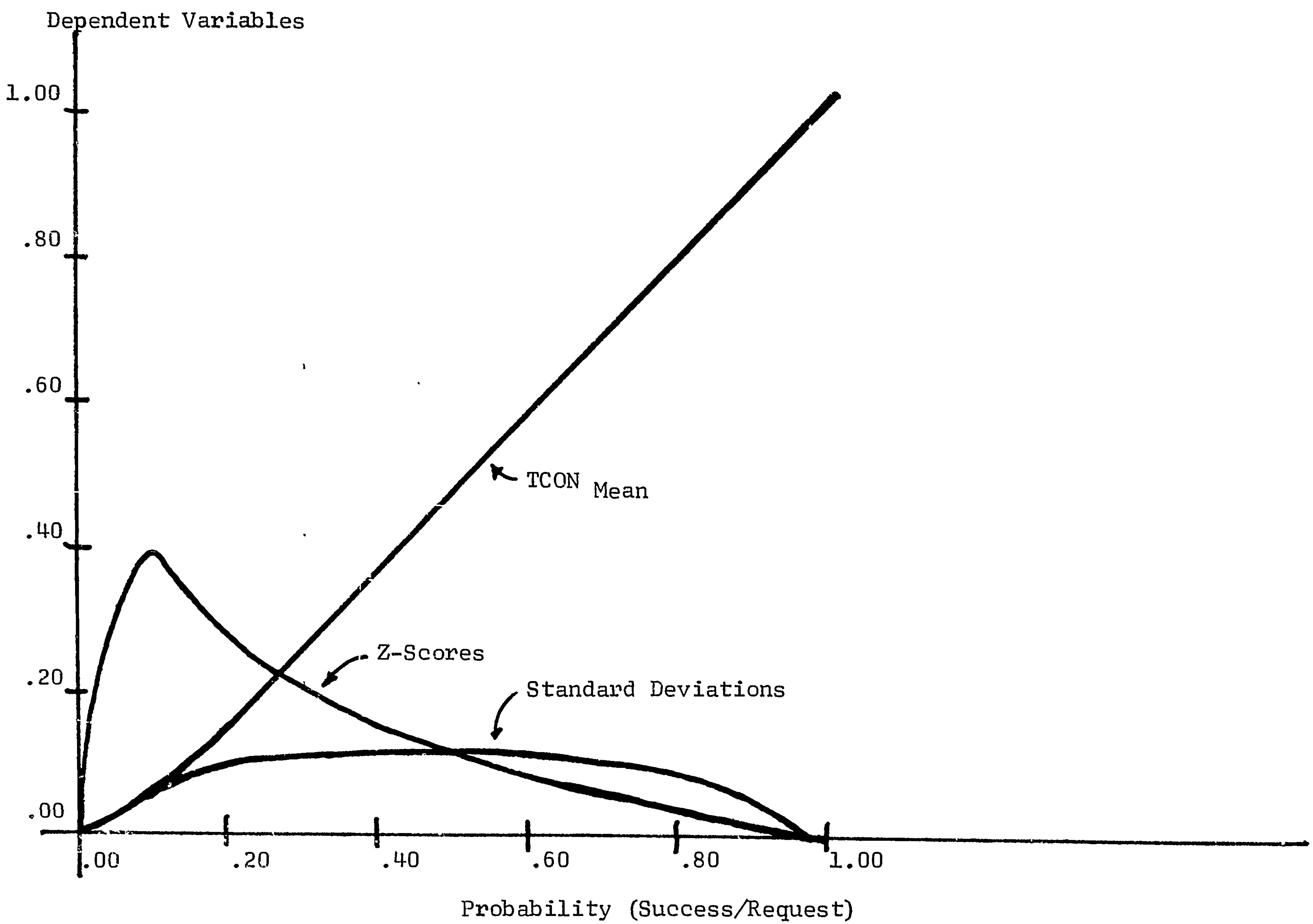

Figure 7: Mean value ($TCON_{Mean}$), and standard deviations of the distributions of consideration probability and the Z-scores for the difference of the mean values and the probability of success of a request for the complete range of the latter quantity.

$TCON_{Mean}$) for the entire range of the latter variable is shown in Figure 7. Also plotted are the deviations (standard deviations) of the consideration probability and the standard z-scores for the difference of $TCON_{Mean}$ and Prob (success/request).

Finally, it was verified that the final value of CON (averaged over a time interval) is independent of the initial value, a fact that can be proved readily by mathematical analysis. A diagram associated with this analysis was reported elsewhere (Reilly, December 1968).

C. Discussion

A couple of interesting points arise in connection with some of these results. The probability of success of a request is not increased by the user's estimation technique (i.e., use of the consideration probability). To see this in more concrete terms, let us consider an interval over which the user develops 1,000 needs. If the user were to place 1,000 requests, one for each need, he could expect good results about 600 times. Using CON he would place less than 600 requests and receive less than 360 successes. Placing a request for every need then results in far more successes. It then appears that the net effect of utilizing the consideration probability mechanism is to limit the potential gain. What then could be the basis for such a mechanism? Or are there other features of the behavior that we have not yet discussed that might make the assumption of a mechanism of this type more reasonable? Answers to both of these questions can be offered. The answer to the first question has to some extent already been treated. The assumption that a bad experience is likely to make it more unlikely for us to go to the library for service on the next opportunity has all manner of analogies; e.g., the burnt finger causes more awareness of flame for a period of time, etc. The second question, quite related to the first, calls more stringently for a deeper explanation of our views of user behavior. The mechanism we are talking about here is more on the "irrational" side of the rational-irrational-man model views since rationally it would be better dispensed with. (The reader may wish to refer to the book by Simon (1957) for a fuller discussion relating to the "models of man.") The second mechanism (the EST mechanism) is more on the "rational" side and the pair of mechanisms operating together provide us (humbly) with a total human view.

A second point is that the mean probability of consideration is less than the probability of success of a request. The reason for this is that there is slightly lower probability of making a request when the values of the consideration probability are low. Thus, there is a tendency for values lower than the probability of success to remain for more trials than for values above, the net effect being to bring the average value down and to produce the above-mentioned skew in distribution of the consideration probability.

III. ESTIMATED SERVICE TIME MODEL

In the model of the preceding section, a single parameter, the consideration probability, was used to explain the user's decision-making policies. In this section a two-parameter model is proposed. Here the mean and a measure of dispersion of an estimated service time distribution change as the user experiences good or bad service. We may, without contradiction, propose that this time-based mechanism is either in lieu of or complementary to the mechanism proposed in the previous section. In this section we take this "in lieu of" point of view. In a later section we discuss the "complementary" point of view.

A. EST Change Rule

In postulating an EST change rule, we could rely on the most simple change rule as our initial assumption. However, a rule that correlates the estimated service time with the actual (experienced) service times seems more appropriate. Such a rule of change (which we utilize) is the following:

$$MEST_{t+1} = \begin{cases} MEST_t \;, & \text{if } E_o, \\ a\ MEST_t + b\ CAST_t, & \text{if } E_1, \\ b\ MEST_t + d\ CAST_t, & \text{if } E_2, \end{cases}$$

where $MEST_t$ is the mean value of the estimated service time at time t; a, b, c, d, are constants; E_o, E_1, E_2 have the same meaning as previously; $CAST_{t-1}$ is value of the service time (a sample value from the AST distribution) on trial t-1. The values a, b, c, d are critical in determining the similarity of the MEST to the mean value of the actual service time distribution.

It is important to note a peculiar aspect of the rule of change when

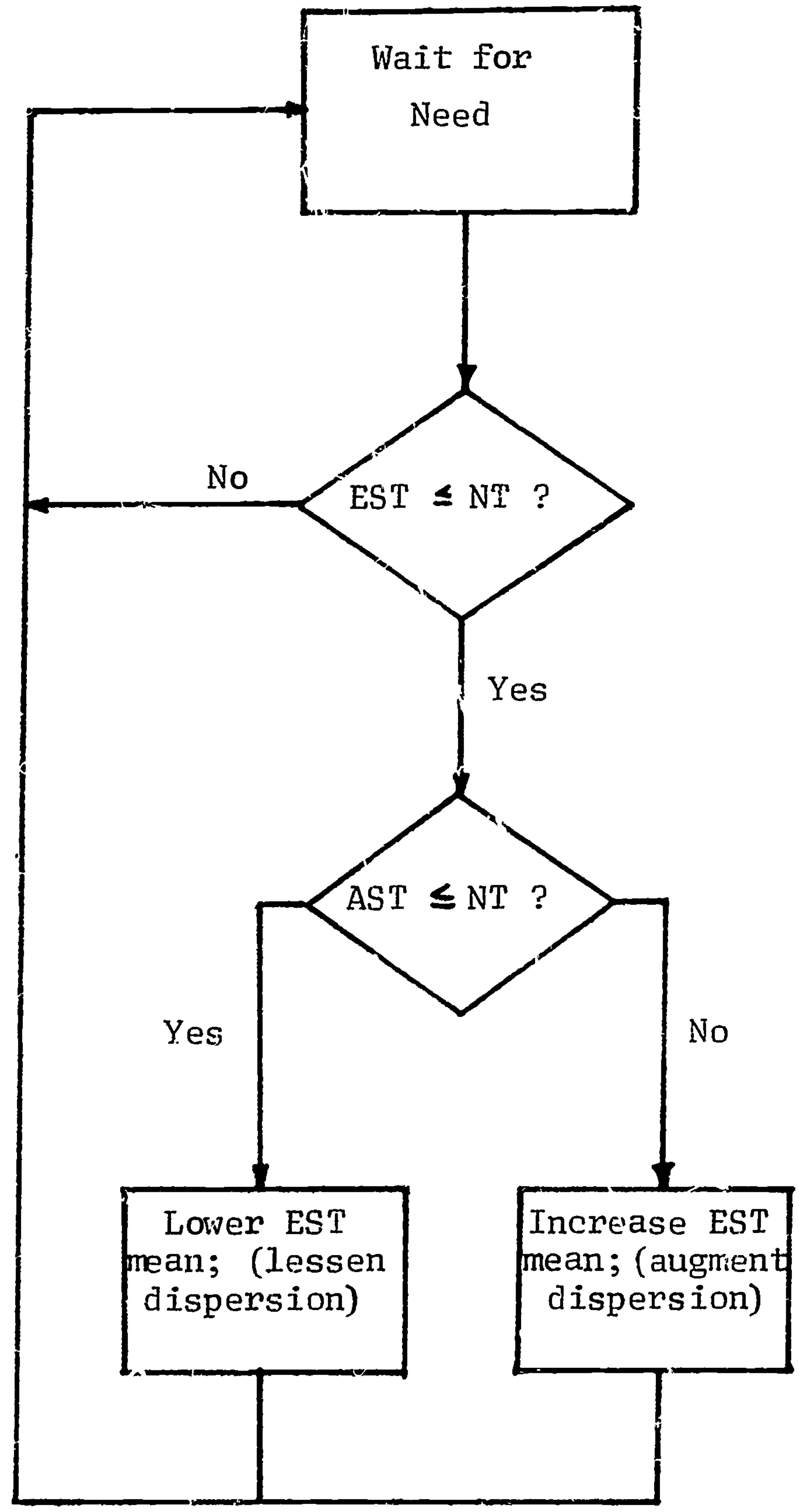

Figure 8: Flow diagram for Estimated Service Time Model.

using GPSS/360 conventions. In GPSS it is convenient to treat the probability distribution as a product of two terms: one of which is the approximate mean value of the distribution and the other a function whose mean is approximately unity. When this is done, the spread of the distribution is a function of the approximate mean so that when the approximate mean decreases the spread also decreases. Contrariwise, when the mean increases the spread also increases. Since these changes are of the type we might have postulated for the effects of good and bad service on the dispersion, we decided to utilize them as part of our initial model. This decision has the benefit that a change rule need only apply to the MEST. In a sense, then, we have here a one-parameter model, with "extras." We, of course, have to pay a price for our laziness: we have lost control over the magnitude of the dispersion changes. Dispersion control, with exceptions, e.g. normal curves, requires effort; it is necessary to utilize a GPSS HELP (an Assembly Language subroutine) block, there being no way to modify a GPSS function dynamically during a model run.

B. A Simulation Study

A model, the flow diagram of which is found in Figure 8 was run and preliminary analysis of the effect of parametric changes was undertaken. It is possible to choose a set of weights in such a way as to produce estimated service times which yield about the same overall results as in the model of the previous section. It is not possible in this special case to interpret the resultant estimator as the service time. Of more relevance then are those choices of parameters that yield a mean EST of the same order of magnitude as the AST. A simple case that produces such a result is that in which, regardless of the success or failure of the request:

$$MEST_t = MEST_{t-1} + 1/2 \quad (CAST_{t-1} \quad MEST_{t-1})$$

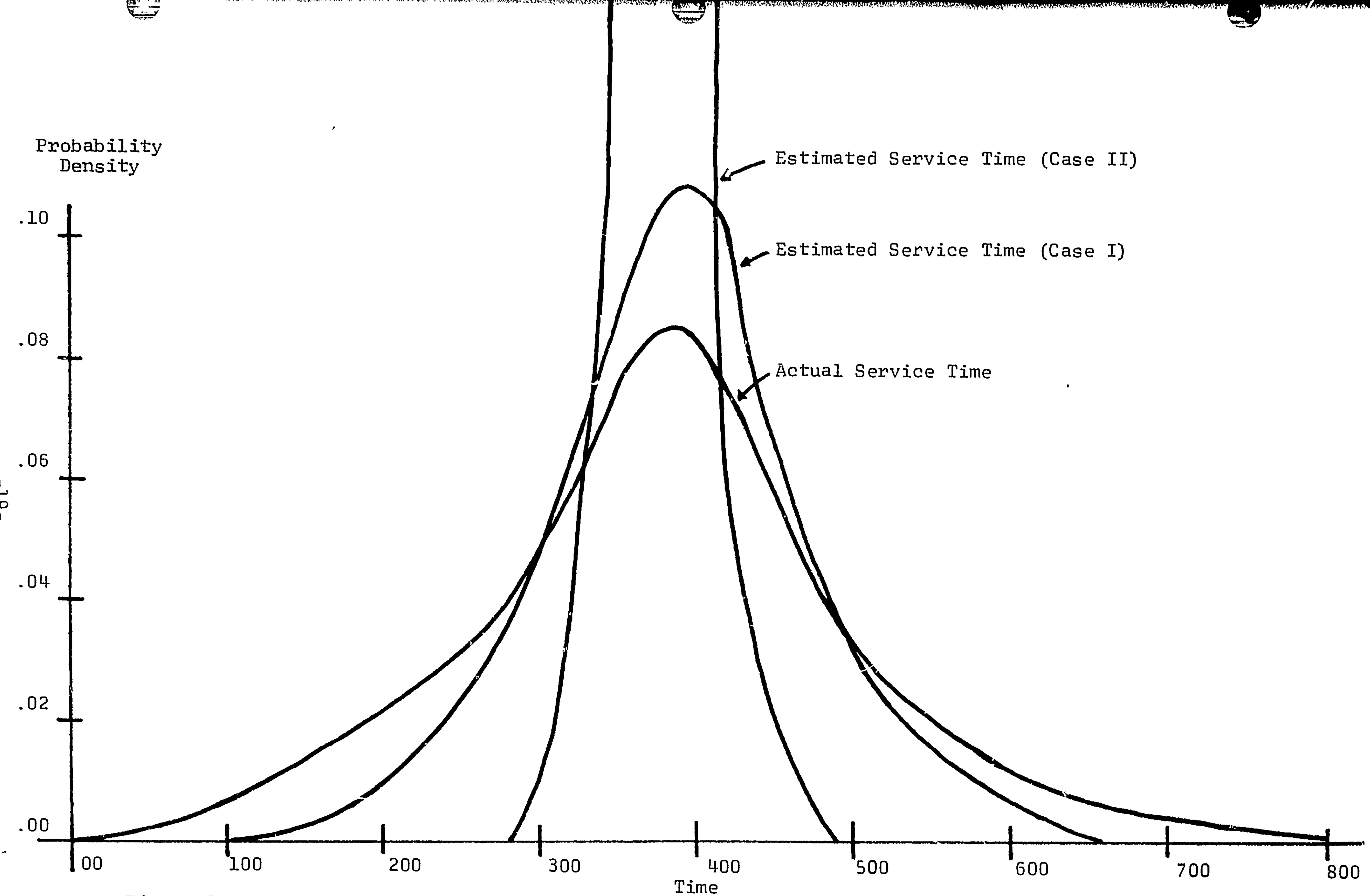

Figure 9: Actual Service Time and Estimated Service Time Distributions for a large number of trials. Case I refers to a 50-50 and Case II to a 90-10 weighting of the previous estimated service time and the actual service time (current) on each trial.

where $MEST_t$ is the mean estimated service time and $CAST_t$ is the actual service time, respectively, on the t^{th} trial.

Exercising this model proves the mean value of the estimated service time to be somewhat higher than mean actual service time. The reason for this is analogous to the consideration probability's being lower than Prob (success/request). When the estimated service time is large, there are less requests and hence the larger values of estimated (mean) service time tend to be retained for a larger number of time intervals than do the smaller values. A closer approach to the mean AST is achieved when the value d is lower (e.g., to .475) while a, b, c remain at .500. Alternatively, a closer approach appears to be achieved when a and c are large (e.g., about .900) and b and d are small (e.g., about .100).

Another result of some interest is that the final values (distribution) of EST are independent of the starting value of MEST; this result is analogous to that with CON in the previous model. An interesting fact about the deviation of the MEST distribution was also uncovered. (Realize that MEST is a distributed quantity just as is CON.) When determining an EST value on any trial we are dealing with a sample from the distribution of EST which depends on a distributed mean MEST and an (unchanging) GPSS multiplier, as described above. The deviation in MEST is less pronounced than that of AST. The reason for this is that $MEST_t$ is calculated as weighted average of $MEST_{t-1}$ and $CAST_{t-1}$. This prevents MEST from taking on the extreme values of CAST. This effect is illustrated in Figure 9 for the two cases of change rules. It is illustrated also (for one case) in Figure 10 where the interval-by-interval plots of MEST and AST are exhibited.

In a particular run of the model so arranged that the mean EST was about equal to (slightly above) the mean AST, about 56% of the information

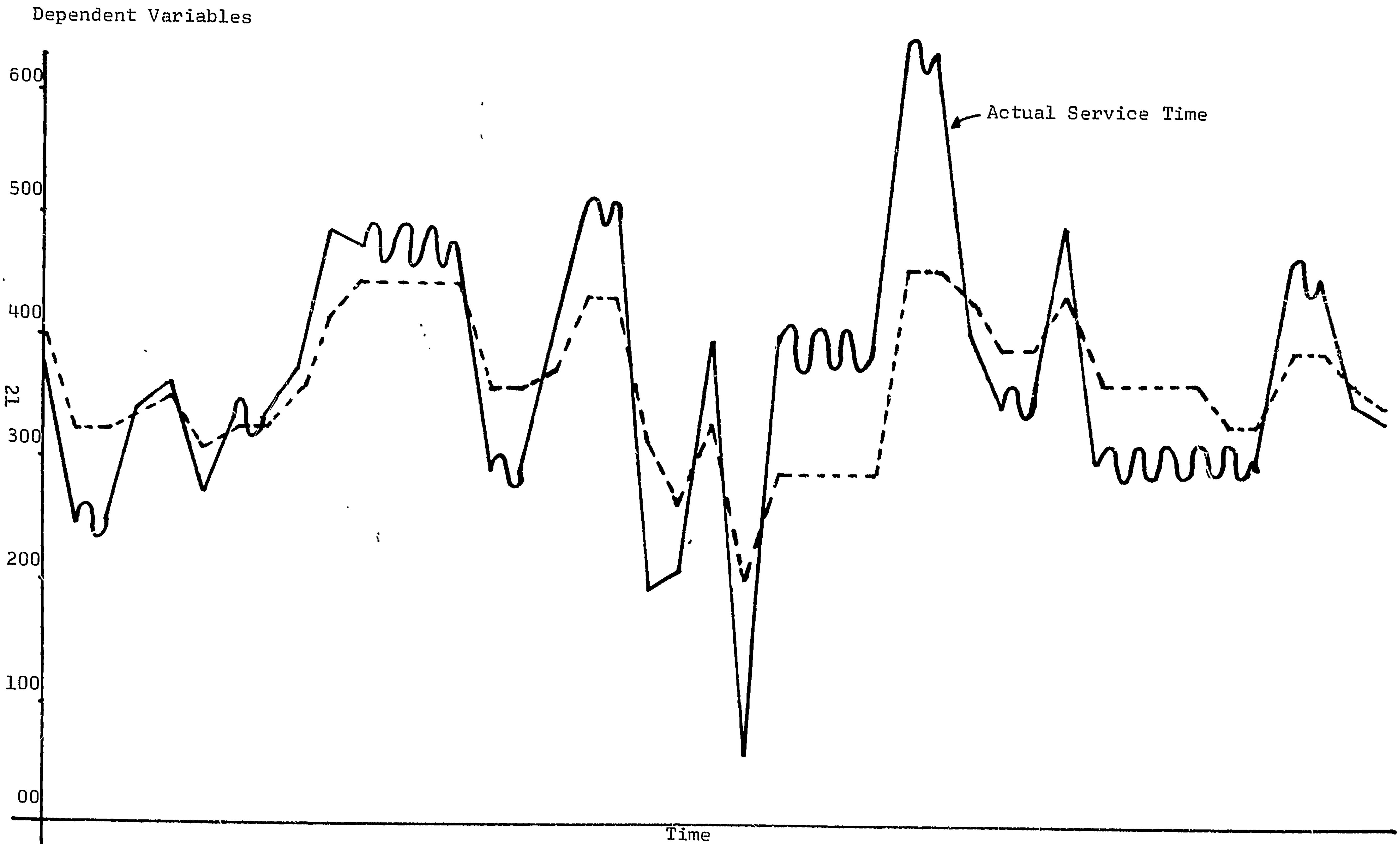

Figure 10: Interval-by-interval plot of the Actual Service Time and the mean Estimated Service Time. Wiggly lines indicate intervals over which no AST is generated.

needs culminated in requests and about 74% of these requests were successful. Therefore, the utilization of the EST device, in contradistinction to the consideration mechanism, has had the effect of increasing the odds for success when a request is made. A condition imposed here is that the EST in both mean and spread is similar to the AST. Note that no use has been made of the nature of the particular request (e.g., whether the system response to it is expected to be a long or short). Thus, the EST mechanism being used in an essentially "guessing" mode here. This, of course, makes the expectations far less accurate than might be, as we shall see later.

IV. CON/EST MODEL

The underlying mechanisms for both consideration probability and estimated service time have been presented above. Models using them have been discussed. We have already seen that the EST mechanism under one favorable (but not unreasonable) condition (i.e., that the EST distribution is similar to the AST distribution) and one unfavorable (and unreasonable) condition (i.e., that the user uses the EST distribution with no clue as to what order of magnitude of service time to expect) is superior to the CON mechanism. It, therefore, seems entirely in place for us to inquire as to what happens in the extended model in which both mechanisms are employed (when both "rational" and "irrational" behavior aspects are joined into a single picture of the user) and to observe what happens when the user drops his guessing mode and begins to exploit the information supplied to him in the form of the distribution of EST.

A. The Combined Model

The full listing of the variables that might be used in the CON/EST model is provided in Figure 11.

Probability of Consideration-to-use-the-library	CON_t
Estimated Service Time	
Mean	$MEST_t$
Measure of dispersion	$SEST_t$
Current Value	$CEST_t$
Need Time	
Mean (independent of time)	MNT
Measure of dispersion (independent of time)	SNT
Current value	CNT_t
Service Time (actual)	
Mean (independent of time)	MAST
Measure of dispersion (independent of time)	SAST
Current value	$CAST_t$
Convenience Factor	
Mean (independent of time)	MCF
Measure of dispersion (independent of time)	SCF
Current value	CCF_t

Figure 11: Concepts and symbols used in simplified user behavior model discussed in the text.

The parameters associated with the Convenience Factor have not been utilized in the current study, though addition of them would not be difficult. The convenience concept is included in the diagram (Figure 12) of the extended model.

B. A Simulation Study

Many properties already revealed in the separate models carry over to the extended model. New features, however, arise because of the interaction of the two mechanisms. The interval-by-interval plot (Figure 13) of CON and MEST reveal behaviors similar to those already seen. Decreases in CON are generally accompanied by increases in MEST and vice versa. A numerical example can illuminate why CON does not always move in a direction opposite MEST. Imagine, for a given trial, that the mean of the EST and the value of CON are both near their respective means. Imagine also that the sampled values ($CEST_t$, CAST, CNT_t) of EST, AST, and NT are all considerably below the means and that: $CEST_t \leq CNT_t$ and $CNT_t < CAST_t$. Under these conditions we have a case of "failure" to satisfy the request. CON, without doubt, decreases but the mean value of EST also decreases. The statistical properties of the overall negative correlation of CON and MEST are adequately illuminated through use of the product-moment correlation.

Both CON and MEST are distributed quantities with distributions similar to those already reported in the CON (alone) and EST (alone) cases. Again, the final values of MEST and the mean of CON are independent of the initial conditions. Also, CON values tend to run somewhat lower and EST mean values somewhat higher than what we naively might expect. The biases that we have already mentioned are, of course, the reason for this. The biases might be expected to be somewhat more exaggerated than in the CON (alone) or EST (alone) cases since lower values of CON and higher values of EST are correlated. Thus, such values might tend to hold longer than

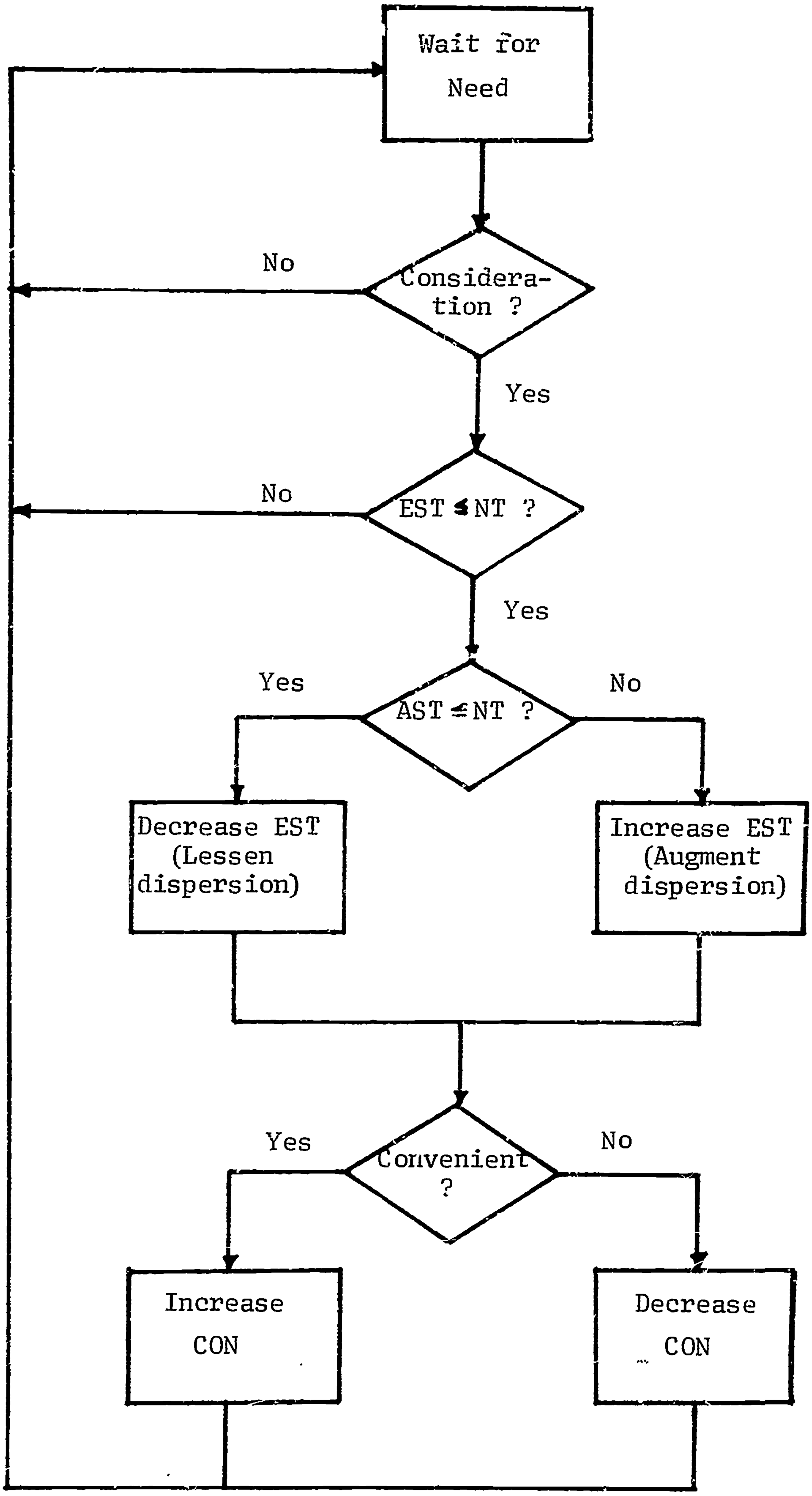

Figure 12: Flow diagram of CON/EST Model.

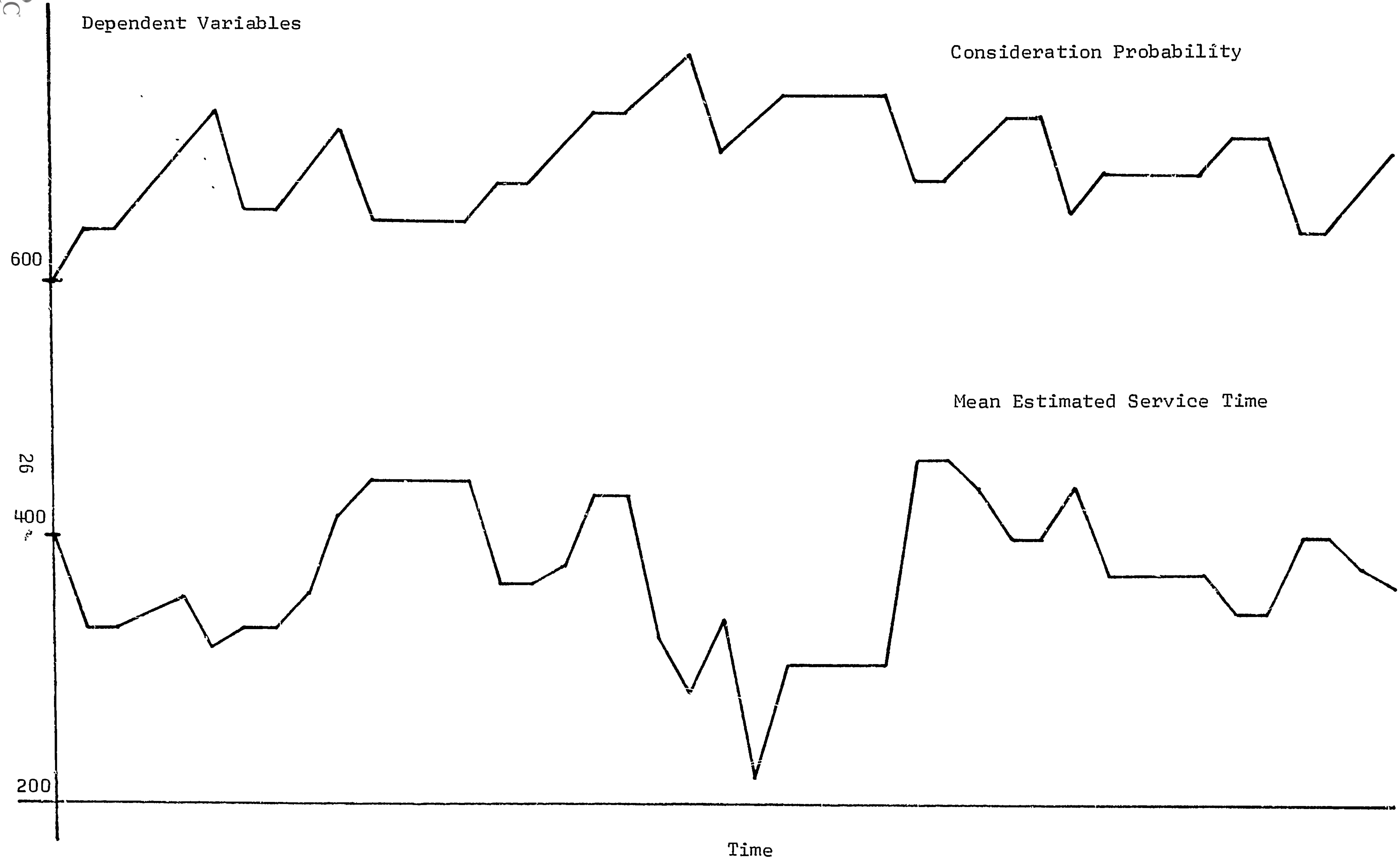

Figure 13: Interval-by-interval trace of the Consideration Probability and the mean Estimated Service Time for the "combined" model.

those in the cases when either CON or EST operate alone. In collecting CON and EST data, we must distinguish between three cases of values of these parameters: as they change; as they are utilized in decisions; as a simple time-line sampled value. The usage here is that of the middle alternative.

C. Exploiting the EST Distribution

More mileage can be extracted from the service time estimation mechanism than what we have seen so far. The basic assumption that we make is that the user can estimate for any given need the portion (or section) of the EST distribution from which his sampled value for EST is to come. In the simplest case, we postulate the existence of a single threshold, T. The user then can estimate that the expected service time is above or below this threshold value. In more complicated versions, the user may use several thresholds and divide the EST distribution up into three or four parts. All told, we consider the cases of 1-3 thresholds.

One consequence of this type of EST mechanism is that we must first (in our program) develop the AST for each need that passes the CON stage and relate it to the thresholds. Then we must constrain the EST to take up the proper disposition relative to the category of the AST. An issue at point is the programming technique to accomplish this. The simplest approach would appear to be to provide renormalized probabilities for EST in each of the categories. This approach assumes either a fixed or a reasonably small number of thresholds. Alternatively, variables could be used to renormalize at will. A third alternative exists. It seems to be about the simplest conceptually for it allows for varying the thresholds without explicit renormalization. The method is this: accept the first sampled EST value in the category supplied by the AST calculation. The question of program timing that arises here is perhaps best resolved in terms of the numbers of changes in the thresholds in the run. If the thresholds remain fixed or vary only over a fixed pattern with few alternatives, the first method would be the preferred. If the thresholds change very frequently, the third alternative would be preferred. The second alternative would be utilized for cases between the two extremes. Of course, since there is always an interplay between the number of functions, blocks, etc. available, still other considerations figure into the final choice in any particular circumstances. In our runs we took the conceptual-ease route despite the belief that it cost us a little bit of program time. We have assumed that the EST and AST categories are the same and that each potential request is determined through use of an EST derived from the same category as that of the AST for that request. These assumptions are not necessary but have the appeal that they are simple. The evaluation of the effects of this extended utilization of the EST leads directly to our next topic.

D. A Comparative Analysis of Strategies

Figure 14 illustrates some results drawn from several of the models (and partial models) that we have been exploring. Dealt with in the Figure are the CON, EST, CON/EST, and the exploited EST/CON model with 1-3 thresholds. We have converted all numbers to a base of "per 1,000 needs"; thus, the 730 requests in the first column can be translated into a CON probability (average) of .730. The third column, the first CON/EST model shows that addition of the EST mechanism in even its most inefficient form leads to a substantial improvement over the CON (alone) view. One immediate effect of the improved performance is the rise of CON from (approximately) .56 (first column) to (approximately) .73 (third column). The exploitation of the EST curve leads to successively higher values for CON reaching, for the three threshold case, a high of .91 (final column). Notice, also, the number of requests in the more complex models remains less than in the CON or EST alone cases. Each request as we go farther to the right (particularly in columns

4-6) has an increasingly higher probability of success. Thus, the overall effect of the more advanced decision rules is that the number of failures is being cut. The broaching of the subject of efficacy of the rules of decision brings us to the matter of a measure of success.

	CON	EST	CON/EST GUESS MODE	CON/EST 2 CLASSES	CON/EST 3 CLASSES	CON/EST 4 CLASSES
Needs	1,000	1,000	1,000	1,000	1,000	1,000
Considerations	560	1,000	730	843	900	907
Requests	560	560	410	528	545	558
Successes	331	417	310	454	498	515

Figure 14: Values for the number of needs, considerations, requests, and successes for a variety of different (potential) user policies.

We have already seen a measure of success, i.e., in terms of the numbers of needs, considerations, requests, and successes. We saw that the number of unsuccessful requests was lowered as the user decision policy more fully exploited the EST distribution. This reduction in unsuccessful requests can be mirrored in dollars-and-cents terms. In a most elementary sense, it costs money to make requests and successful system responses contribute financially to the requestor. Costs for making requests are generally detailed and spread out over a variety of types of expenses: time for searching, clerical aids, travelling, paper and pencils, etc. Such costs, however, present no real theoretical problems. Benefits from obtaining desired information, on the other hand, are not easy to specify. Though success on a given research project may be measured to a large degree in terms of profit, it is not easy to gauge such nonmonetary benefits such as the degree of satisfaction a piece of information gives. Also difficult to measure are delayed effects: today's new information pays off in ten years from now. Satisfaction perhaps can be written off in entertainment terms; delayed information benefits can perhaps be compared advantageously to those associated with achieving a higher education, the economic value of which has been more or less specified.

We do not propose here to model such complexities. Instead, we shall make some overly simple assumptions for illustrative purposes to exhibit how such considerations lead to explicit figures on the relative merits of user-behavior alternatives such as we have been discussing. We assume that the cost of making a request is $1.00 and that the return for a successful request is $1.66. We could assume distributions for these and develop the consequences as readily; it is perfectly proper to think of these fixed values as the means of their distributions. These particular choices were made because they provide the (approximate) break-even point for the CON-only model. Actually, such an assumption results in a fairly high rate of return for most of the policies we have been discussing (e.g., from 20 - 40%). A "pro" argument is that, in analogy to the return on education, the returns on information seeking are high. A "con" argument is that the break-even point should not be postulated for a policy so careless as that of CON (only). These considerations are, however, not critical to our purposes, since the main use to which we shall put our assumptions is more illustrative of a method of approach than of an attempt to capture full reality.

The main points that we wish to illustrate can be gathered from the curves of Figure 15 and Figure 16. These curves deal primarily with the effect of accuracy of perception of the AST on the rate of return. The first of these (Figure 15) by varying MAST shows for two cases how the maximum payoff is associated with a MEST lying somewhere between the means of the actual service time (MAST) and the need time (MNT). The second of these (Figure 16) shows a similar phenomenon for four different user models

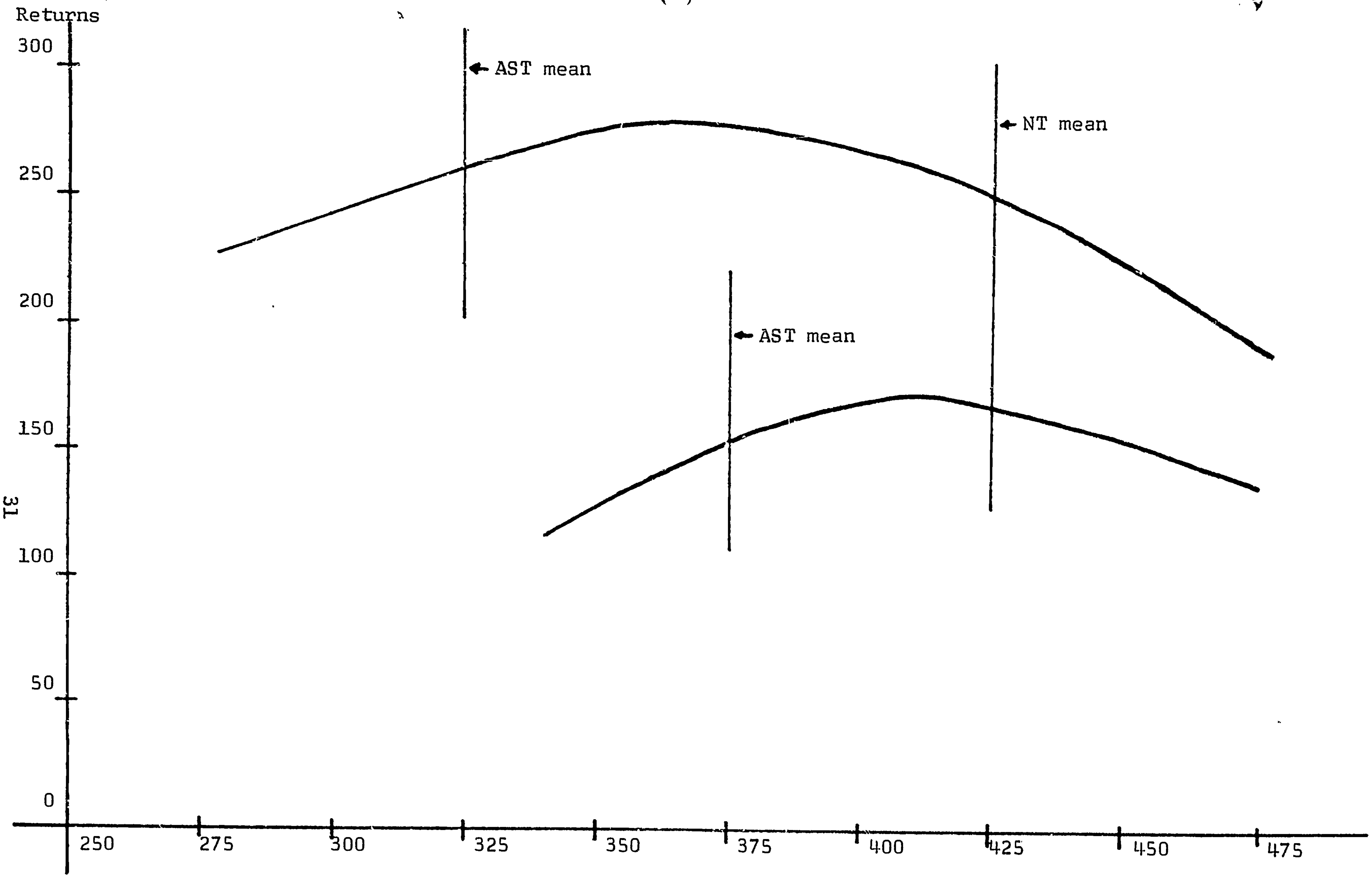

Figure 15: Illustration of the maximum pay-off region lying between the Actual Service Time and the Need Time means.

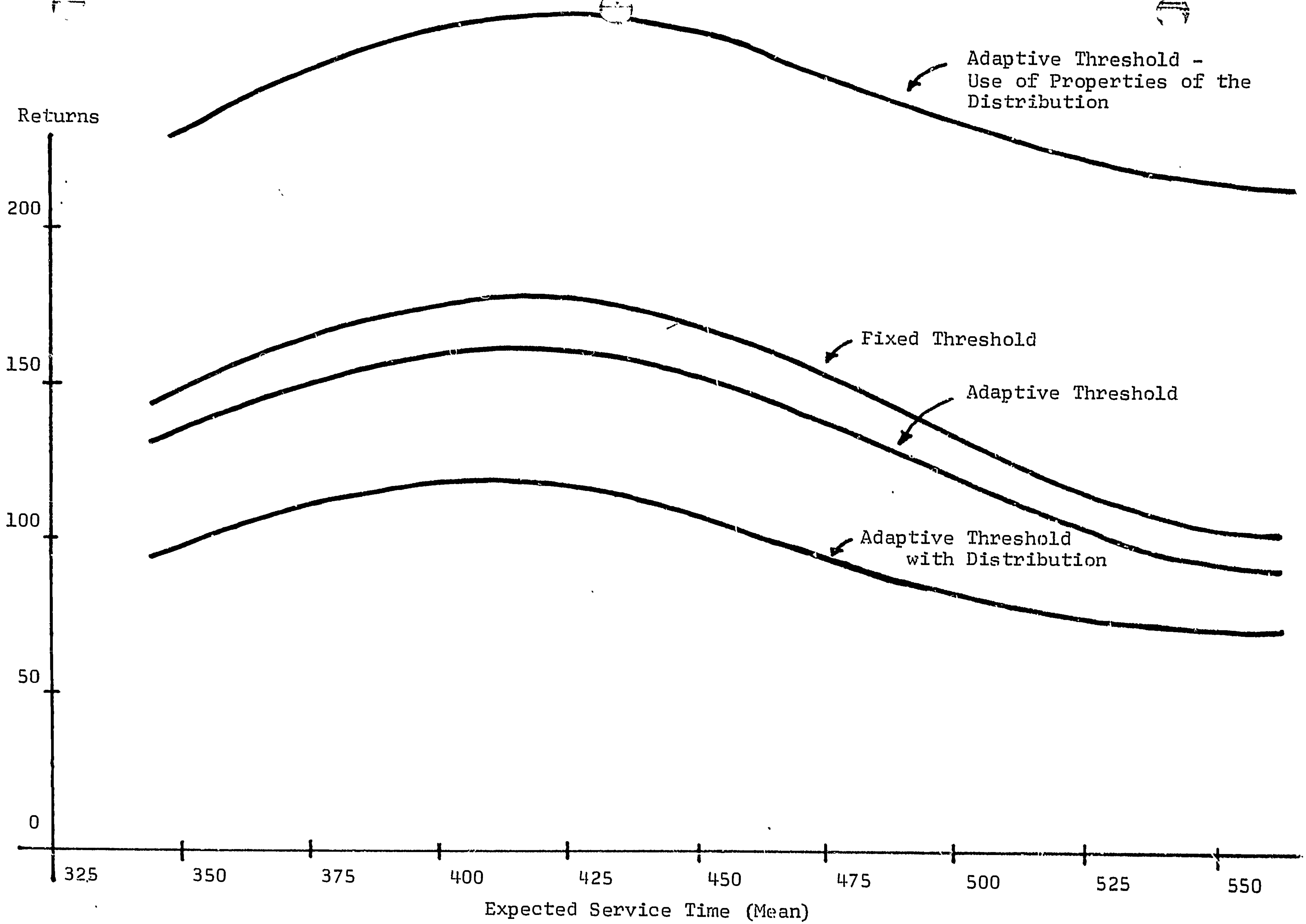

Figure 16: Net returns under different user strategies on assumption of a particular return rate. In those cases where EST is distributed the abscissa is a mean.

(potential user policies, if you will). These policies include two already discussed, namely the first CON/EST model (the lowest curve) and the CON/EST model with exploitation via a single (fixed) threshold (the highest curve). The two interior curves deal with cases in which no distribution for EST is assumed. Rather, a single parameter (also, a threshold, but not to be confused with the threshold in the EST-exploitation model) is assumed for the expected service time. This parameter is used in the obvious fashion. In one case (the higher of the two curves), the threshold parameter is assumed to be fixed and does not alter throughout the run. In the other, the threshold is allowed to vary according to the same kind of rule that was used to change the mean of the EST distribution. These cases are seen to be better than guess-mode of EST, as we would expect. The more interesting effect is that due to exploitation of the EST distribution. Under the costs/payoff regime we have assumed, a dramatic increase in payoff occurs. Of course, larger numbers of thresholds (for EST exploitation) lead to still better results. Such results are available but were not plotted.

E. A Note on the Correlation of EST and AST Values

One obvious result of the EST exploitation procedures is that the values of EST are correlated with the AST values. The mechanism that achieves this correlation is not very complex, at least in terms of what we know about human behavior. However there still seems to be some merit in looking at more simple alternatives.

A simple alternative may be proposed along the following lines. The AST value (for a given need) is calculated by the model just as in the EST exploitation model of the previous section. This value is unknown to user, of course. But, in general, he has a method of estimating it. This means is primarily a function of past experience and we saw how, above, the experience of the user might operate in forming of an EST distribution. In this model, however, the user possesses a single factor, which when multiplied by the AST, becomes his EST. This factor, on any given trial, is a value sampled from a distribution with a mean value of unity and a variable deviation parameter. The variable parameter decreases with experience (or, alternatively, decreases with good service and increases with poor service).

(The multiplication factor of this model is analogous to one of the "indices" used in multiplicative time series analysis (see, for example, Spiegel (1961), Yeomans (1968)). In fact, a conventional time series decomposition could be used in place of the assumed variable deviation parameter. If experience were to produce a unidirectional effect, a trend component would be established. Cyclic and seasonal factors useful for most library analyses could be incorporated readily. Alternatively, regression analysis could be used for relating AST to EST.)

One effect of this more simple model is that we have a less intuitive picture of the user. We have essentially given up on trying to figure out how a user comes up with reasonable EST values. We accept that ability and seek merely to tie down the correlations between AST and EST values. We have thereby (therapeutically) attenuated the experimental needs for a study.

A model of this type was run. The net payoff as a function of a particular dispersion measure (i.e., the spread of the multiplication factor) is plotted in Figure 17. The cost and return scheme of the previous section was used.

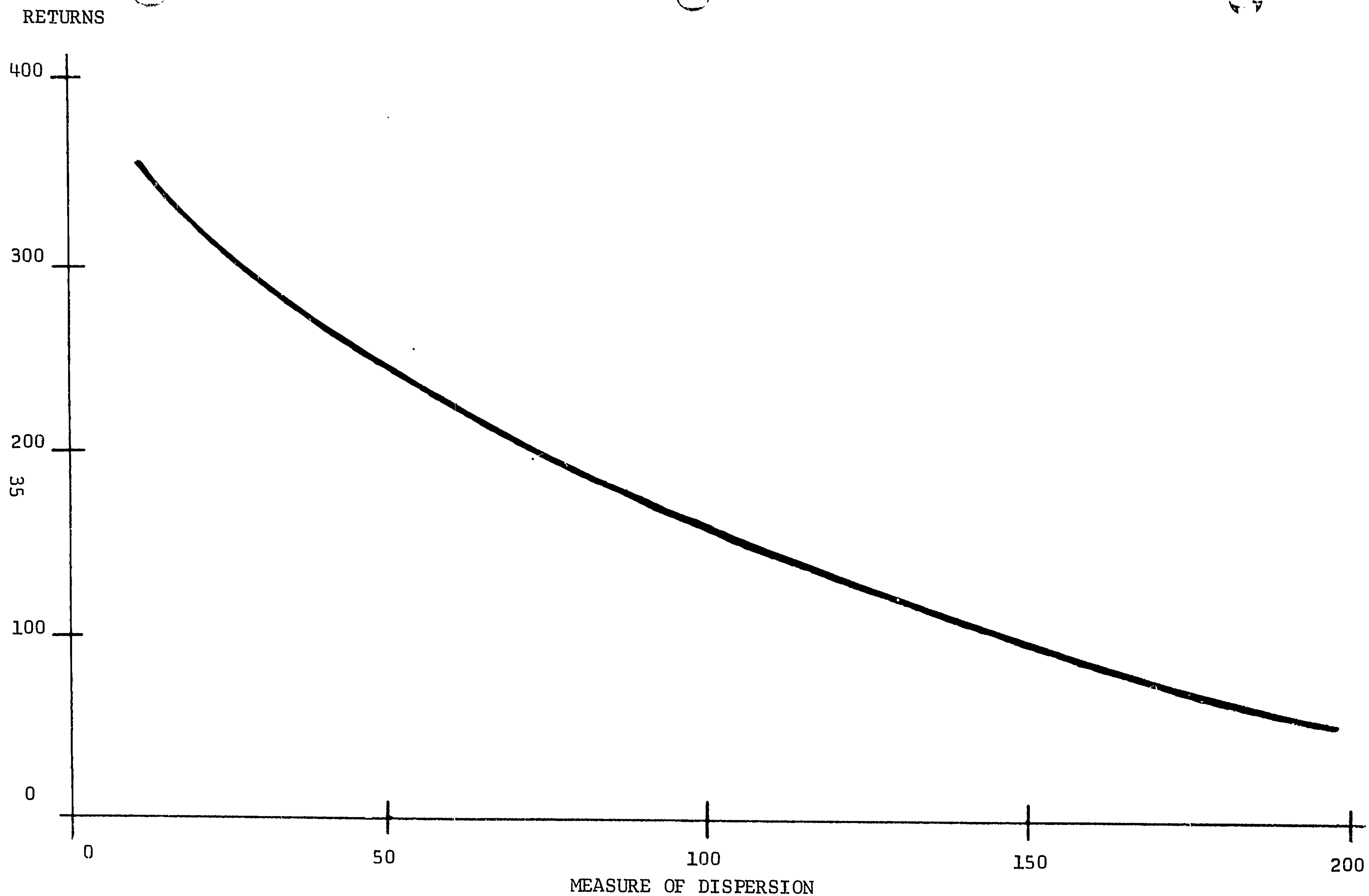

Figure 17: Net returns as a function of the measure of dispersion (spread of the distribution) of the multiplication factor in the model of Section IV-E.

V. RELATIONSHIP OF THE USER MODEL TO OTHER MODELS

Throughout this report we have restricted our attention to a single user and to a single type of service (e.g., book materials). Such a restriction must, of course, be abandoned when dealing with a real library system. This section of the report is directed toward pointing out directions our parallel (and succeeding) studies are taking and how this model fits into the larger context.

A. More Types of Service

The user-behavior (component) model is small enough that its principal features can be duplicated (without difficulty) for multiple service types. A study is now under way as to the best methods of approach with the goal being limitation of the amount of duplication. One method that has reached the near-completion stage is to consider requests of four different types (factual, single material item, survey, exhaustive search). The model may be duplicated for each of these categories. It is not necessary to do so according to material type. Corresponding to some of the categories are notions of partial satisfaction of requests with corresponding "partial" changes in user estimation parameters.

B. Different User Types

Generalization to handle many users will proceed initially along lines that have already been described. (Reilly, July 1968). Certain individualizing conditions are established so that we do not develop any consummate stereotype of "the user." Distinctions of users according to their status (research scientist, research assistant, etc.), field or area of effort, etc., are built into the model. Insofar as possible, parameters like the multiplication factor in the EST model of section 4E will be used to streamline the model.

C. The User Model in the Hierarchy of Library System Models

In a previous report (Reilly, 1969) we referred to development of a hierarchy of models . We pointed out that our efforts have been principally directed toward three levels of modelling:

1. Computer processing center activities
2. User behavior decisions
3. Delivery of (target) materials

Of special importance was mention of the fact that models at these various levels (and at levels within these levels) could be run independently of each other. That is, data characterizing computer processing and delivery-system responses to the stimuli of user requests can be developed in model runs for those systems with data relevant to the user-behavior model being written on disks or tapes for processing by the latter model. Such an integration of models is, in our opinion, essential. Later reports will deal with this issue more fully.

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